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A REVISED VERSION OF THE OPTIM MODEL

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Monthly forecasting of French GDP: A revised version of the OPTIM model [*]

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Abstract

This paper presents a revised version of the model OPTIM, proposed by Irac and Sédillot (2002), used at the Banque de France in order to predict French GDP quarterly growth rate, for the current and next quarters. The model is designed to be used on a monthly basis by integrating monthly economic information through bridge models, for both supply and demand sides of GDP. For each GDP component, bridge equations are specified by using a general-to-specific approach implemented in an automated way by Hoover and Perez (1999) and improved by Krolzig and Hendry (2001). This approach allows to select explanatory variables among a large data set of hard and soft data. The final choice of equations relies on a recursive forecast study, which also helps to assess the forecasting performance of the revised OPTIM model in the prediction of aggregated GDP. This study is based on pseudo real-time forecasts taking publication lags into account . It turns out that the model outperforms benchmark models.

Keywords: GDP forecasting, Bridge models, General-to-specific approach.
JEL Codes: C52, C53, E20.

Résumé

Cet article présente une version révisée du modèle OPTIM proposé par Irac et Sédillot (2002) et utilisé à la Banque de France afin de prévoir les taux de croissance du PIB français et de ses différentes composantes sur deux trimestres (en cours et suivant). Le modèle OPTIM est destiné à être utilisé tous les mois en intégrant de l'information économique mensuelle à l'aide d'équations d'étalonnage des variables des comptes trimestriels (côtés offre et demande). Pour chaque composante du PIB, des équations d'étalonnage sont spécifiées en utilisant une approche "general-to-specific", mise en oeuvre de manière automatique par Hoover et Perez (1999) et améliorée par Krolzig et Hendry (2001). Cette approche permet de sélectionner automatiquement des variables explicatives adéquates parmi un large ensemble d'informations économiques, comprenant des données d'enquête et des indicateurs macroéconomiques mensuels. Le choix final des équations repose sur une analyse en historique permettant également d'estimer la capacité prévisionnelle du nouveau modèle OPTIM. Cette analyse se fonde sur des prévisions récursives tenant compte des délais de publication des variables explicatives. Les résultats obtenus montrent que le modèle fournit de meilleures prévisions que des modèles statistiques simples.

Mots-clés : Prévision, taux de croissance du PIB, modèle d'étalonnage, approche "general-to-specific"
Codes JEL : C52, C53, E20

Non-technical summary

This paper presents a revised version of the model OPTIM, proposed by Irac and Sédillot (2002), used at the Banque de France in order to predict French GDP quarterly growth rate, for the current and next quarters. GDP is estimated through forecasts of the sectoral components of production, but a breakdown of GDP on the demand side (consumption, investment, exports...) is also implemented in order to serve the economic analysis. The model is designed to be used on a monthly basis by integrating monthly economic information through bridge models: series from the quarterly national accounts are modelled as functions of survey data and monthly macroeconomic indicators. For each GDP component, bridge equations are specified by using a general-to-specific approach implemented in an automated way by Hoover and Perez (1999) and improved by Krolzig and Hendry (2001). This approach allows to select explanatory variables among a large data set, using a sequence of statistical tests. The final choice of equations relies on a recursive forecast study, which also helps to assess the forecasting performance of the revised OPTIM model in the prediction of aggregated GDP. This study is based on pseudo real-time forecasts taking publication lags into account: simulations are carried out using only the information that would have been available at the time forecasts are supposed to have been conducted. This method allows choosing the best variables for forecasting, knowing that some indicators can be closely correlated to the modelled variable but less interesting than others for forecasting, due to an important publication lag. Thus, an equation relying on the industrial production index can provide better statistical properties, but less accurate forecasts than an equation based on rapidly available survey data. It turns out that the industrial production index is essential when available for two out of three months of the forecast quarter, but less interesting otherwise. Recursive forecasts also show that the model outperforms simple benchmark models (autoregressive, random walk).

Résumé non-technique

Cet article présente une version révisée du modèle OPTIM proposé par Irac et Sédillot (2002) et utilisé à la Banque de France afin de prévoir les taux de croissance du PIB français et de ses différentes composantes sur deux trimestres (en cours et suivant). Si la prévision du PIB proprement dite repose sur une modélisation des composantes sectorielles de la production, une décomposition du PIB du côté de la demande (consommation, investissement, exportations...) est également effectuée afin d'avoir une appréciation plus fine du contexte économique. Le modèle OPTIM est destiné à être utilisé tous les mois en intégrant de l'information économique mensuelle à l'aide d'équations d'étalonnage : des variables des comptes trimestriels sont estimées en fonction de données d'enquête et d'indicateurs macroéconomiques mensuels. Pour chaque composante du PIB, des équations d'étalonnage sont spécifiées en utilisant une approche "general-to-specific", mise en oeuvre de manière automatique par Hoover et Perez (1999) et améliorée par Krolzig et Hendry (2001). Cette approche permet de sélectionner automatiquement des variables explicatives adéquates parmi un large ensemble d'informations économiques, grâce à une batterie de tests statistiques. Le choix final des équations repose sur une analyse en historique permettant également d'estimer la capacité prévisionnelle du nouveau modèle OPTIM. Cette analyse se fonde sur des prévisions récursives tenant compte des délais de publication des variables explicatives : les simulations sont effectuées en utilisant uniquement l'information qui aurait été disponible au moment où les prévisions sont censées avoir été effectuées. Cette méthode permet de choisir les variables les plus pertinentes pour la prévision, sachant que certains indicateurs peuvent présenter une meilleure corrélation que d'autres avec la variable modélisée, mais être moins intéressants pour la prévision, du simple fait qu'ils sont publiés avec un retard important. Ainsi, une équation reposant sur l'indice de la production industrielle peut présenter de meilleures propriétés statistiques, mais être moins performante en prévision qu'une équation basée sur des données d'enquête publiées plus rapidement. En pratique, l'indice de la production industrielle se révèle être un indicateur incontournable lorsqu'il est disponible pour deux des trois mois du trimestre à prévoir, mais moins intéressant dans le cas contraire. Les résultats des simulations récursives montrent par ailleurs que le modèle fournit de meilleures prévisions que des modèles statistiques simples (modèle autorégressif et marche aléatoire).

1 Introduction

This paper presents a new version of the model OPTIM (Irac and Sédillot, 2002), used at the Banque de France to forecast French quarterly GDP growth and its main components. We aim at providing an accurate and timely assessment of GDP growth rate for the current and the next quarters starting from a large set of monthly hard and soft data [1]. The prediction of the current quarter can be seen as a nowcasting exercise while the prediction of the next quarter is a classical one-step-ahead forecast. In this respect, we chose to predict each of the main components of both supply and demand sides of the national accounts and then to aggregate them. This decomposition provides more precise quantitative information, allowing thus a better and earlier understanding of the economic situation.

Recently, factor models have emerged as an interesting alternative for short-term forecasting of real activity, as they can be applied to large data sets (see, e.g., Stock and Watson, 2002, 2006; Forni et al., 2003; Breitung and Schumacher, 2006; Grenouilleau, 2006; Angelini et al., 2008). However, this approach appears sometimes to practitioners as a black box in the sense that the results are difficult to interpret from an economic point of view.

In order to provide an economic interpretation of the forecasts, another often used alternative is to construct bridge models (BM, henceforth). These linear regressions "bridge" (i.e. link) monthly variables and quarterly GDP growth or other Quarterly National Account components. Such models have been widely considered in the literature especially to forecast GDP growth in national and international institutions, we refer for example to Grassman and Keereman (2001), Sédillot and Pain (2003), Rünstler and Sédillot (2003), Baffigi et al. (2004), Golinelli and Parigi (2005), Diron (2006) or Zheng and Rossiter (2006)[2].

In this paper, we propose to construct a bridge model for each of main GDP components for which input variables are selected through an automatic procedure that allows the econometrician to exploit a large number of macroeconomic time series. This procedure, called general-to-specific (Gets), has been introduced by Hendry (1979), implemented in an automated way by Hoover and Perez (1999) and improved by Krolzig and Hendry (2001). [3] These BMs are estimated using quarterly averages of monthly data as explanatory variables.

A second objective of this paper is to provide three monthly forecasting exercises of GDP growth rate for a given quarter. In this respect, we use monthly hard and soft data selected according to their publication lag in order to get early information for the quarter of interest. Several studies report that soft data contain less information beyond real activity data than hard data (e.g., Rünstler and Sédillot, 2003; Forni et al., 2003; Baffigi et al., 2004; Banerjee et al., 2005; Banbura and Rünstler, 2007)[4]. However, Banbura and Rünstler (2007) show that, once their publication

[1] A number of studies demonstrate the advantages of incorporating monthly data in forecasting GDP and other National Account components (e.g., Ingenito and Trehan, 1996; Rünstler and Sédillot, 2003; Coutinõ, 2005; Zheng and Rossiter, 2006)

[2] Note that another way to link a quarterly variable to monthly indicators is the mixed-data sampling (MIDAS) framework proposed by Ghysels et al. (2007) and applied to macroeconomic variables in Clements and Galvão (2007).

[3] Banerjee et al. (2005) employ an automated model selection procedure with a large set of indicators and find that this procedure gives quite encouraging forecasting performance.

[4] Exceptions to this general result are the studies by Giannone et al. (2005) and Hansson et al. (2005). Giannone et al. (2005) use a model-based uncertainty measure to assess the news content of data vintages that arrive within the month. They find the largest declines in uncertainty after the releases of surveys and financial

lag is taken into account, real activity data are much less relevant, while surveys take their place. More precisely, business surveys offer some clear advantages over hard data: first of all, they provide a signal that is obtained directly from the economic leaders regarding the short-term evolution of their activity; moreover, they are published very soon, in other words sooner than the main macroeconomic aggregates; lastly, the results are subject to only very minor corrections.

In this study, high attention has been paid in forecast evaluation exercises to the precise information set available in real time.

2 Modelling strategy and data selection

2.1 A detailed projection

The aim of the model is to predict French GDP growth and its main components for the current quarter and the next one. We consider GDP growth rate as released by Insee, the French national statistics institute, in the Quarterly National Account series. We make a clear distinction between the supply and the demand sides. GDP growth projections are based only on the supply side. However, demand side components are also modelled given the information they provide to economic analysis. Note that all components on both sides are not modelled. Indeed, some components which are not easily predictable with economic information have been left apart. This is notably the case of production of non-market services on the supply side and of the contribution of changes in inventories on the demand side, which is directly computed as the difference between GDP growth and the sum of the contributions of the other components. In addition, subcomponents, such as immaterial investment, are also not modelled. Precisely, the components and subcomponents that are modelled are the following :

A. On the demand side:

- Household consumption, computed by aggregation of the forecasts for:
    - Household consumption in agri-food goods
    - Household consumption in energy
    - Household consumption in manufactured goods
    - Household consumption in services
- Government consumption
- Investment, computed by aggregation of the forecasts for:
    - Corporate investment in machinery and equipment
    - Corporate investment in building
    - Household investment
    - Government investment
- Exports
- Imports

data. Hansson et al. (2005) report that the inclusion of composite index of of survey data into VAR models improves out-of-sample forecasts, but they use a small data set and only quarterly data.

B. On the supply side:

- Total Production, computed by aggregation of the forecasts for:

    Production of agri-food goods

    Production of manufactured goods

    Production of energy

    Production in construction

    Production of market services

C. Total GDP is forecast using a regression on total production.

Hence, production, household consumption and investment are aggregated through equations estimated on their modelled sub-components. The main drawback of this method is that the computed weight of a sub-component, which corresponds to its coefficient in the equation, reflects an average of the actual weights over the estimation period. Thus, if actual weights are strongly changing over time, the computed weight can be very different from the actual current weight. In order to limit this effect, short estimation samples have been chosen for aggregation equations. After various simulations, they have been set to 6 years, which leaves enough observations to have a robust estimation.

2.2 Monthly exercises

This model is designed to be used on a monthly basis. This was not the case in the previous version of the model, which was intended for quarterly forecasting exercises and was also partly relying on quarterly information. For a given quarter, six various prediction exercises will be produced to estimate GDP growth rate at this quarter. In fact, the timing of the predictions is the following (see also figure 1). Around the end of the second month of the quarter Q, an estimate of the growth rate for the current quarter Q is computed as well as the very first estimate for the next quarter $Q+1$. Then one month later, we compute an other estimate for the current quarter Q as well as a second estimate of the next quarter $Q+1$. Two months later, we publish the last estimate for the "current" quarter Q and a third one for the "next" quarter $Q+1$. Thus, the last estimate of the quarter Q is computed around 15 days before the official release of GDP figures by Insee.

When data are missing for some months of a given quarter, they are forecast using Autoregressive (AR henceforth) models. Forecasting explanatory data is standard way to deal with the problem of missing information on the recent past ("ragged-edge data"). An other solution commonly adopted is to choose, for each month, the best information available, and to regress the modelled variable on series corresponding to this information (e.g. Dubois and Michaux, 2006). For example, even if production is more correlated over the past quarters with survey data on past activity than with survey data on activity prospects, it might well be that at the beginning of a given quarter, available information on activity prospects is more useful to forecast production at this quarter than available information on past activity. In this case, a solution is to build an historical series composed with survey data on activity prospects available at the beginning of each quarter over the past and to regress production on this series. This type of modelling strategy may allow a more optimal and direct choice of explanatory variables. However, it implies a systematic change of equation from a month to an other, which might be heavy both for the construction of the model and its use in forecasting exercises, where numerous variables must be projected. Furthermore, systematic changes in equations make it more difficult to track the evolutions in the forecast from one month to the other. These are the reasons why the strategy of forecasting missing explanatory variables has been chosen, even though it implies a "double stage" forecast: in the model presented here, for a given quarter Q and for each GDP component, the same equation is generally used for all of the first three predictions (when Q is the "future" quarter) and a second equation is used for all of the next three forecasts (when Q is the "current" quarter). The only exception concerns the inclusion of the industrial production index (IPI) for the components of the supply part. It turns out that the IPI is strongly correlated with the variation of supply components. However, the IPI is published with a much longer delay than surveys. Therefore, for each supply component, we propose equations for the coincident quarter without IPI and other ones including the IPI, which can be chosen depending on the date of the forecasting exercise.

Figure 1 describes the calendar for the different forecasts of GDP growth at the first quarter of a given year n.

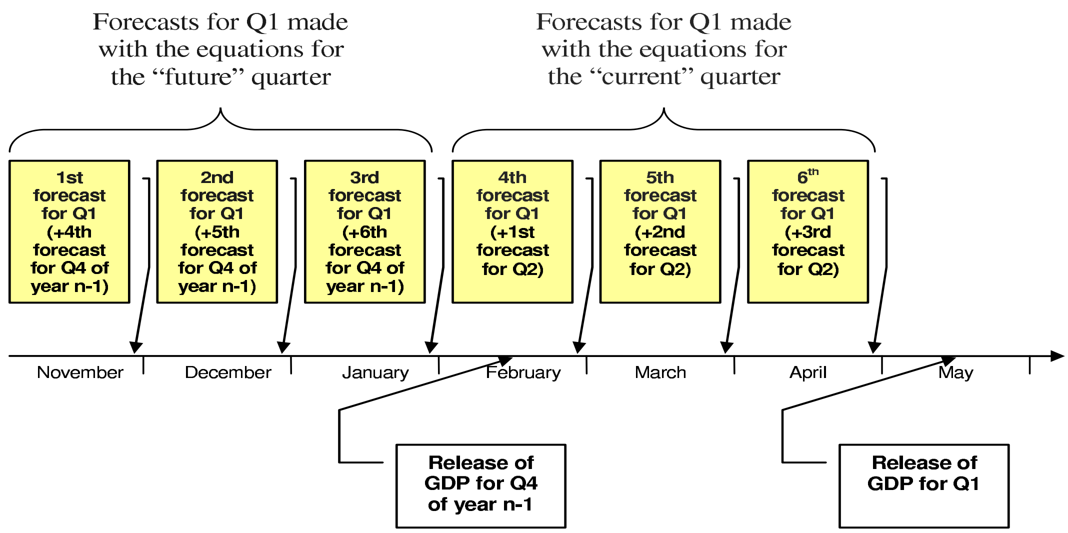

Figure 1: Calendar for the forecasts of GDP growth at the first quarter of a given year n.

2.3 A large dataset

Equations are estimated at a quarterly frequency, but as a general rule, explanatory variables are only taken into account if they provide monthly information (i.e. if they are available on a monthly or higher frequency) and if their publication lag is less than two months, in order to have timely information on the quarter of interest. For example, data such as employment have been disregarded because they are only available on a quarterly basis. Hard data as well as soft data (surveys) have been used as explanatory variables. A few financial data, such as interest rates, have been tested, but not kept : though these variables might be useful to assess and forecast medium-term developments, they seem to provide a less reliable message for short-term prospects than survey data or monthly macroeconomic indicators. All series are seasonally adjusted.

As regards the equations for imports and exports, a specific treatment has been applied to the series of the European Commission survey data. For a given question of the survey, the corresponding series for the various countries are not considered separately, but summed up into one series, weighted by the share of each country in France's imports. Only data relative to the major European partners of France in international trade are used (56.3% of exports and 59.3% of imports). Weights are computed with series from the CHELEM database[5]. They refer to 2004, which is the last year available in this database. Weights are rather stable over time and comparable for imports and exports.

Data sources are presented in table 1.

Name	Source	Data type	Frequency	Publication lag
Quarterly National Accounts	Insee	Hard	Quarterly	+45
Industrial Production Index	Insee	Hard	Monthly	+40
Consumption in manufatured goods	Insee	Hard	Monthly	+25
HICP in agri-food	Eurostat	Hard	Monthly	+20
Electricity consumption	RTE	Hard	Daily	+1
Declared housing starts	Ministry of Equipment	Hard	Monthly	+30
Euro-dollar exchange rate	ECB	Hard	Monthly	+1
External trade in value	Customs	Hard	Monthly	+45
Business surveys in industry	Banque de France	Soft	Monthly	+15
Business surveys in retail trade	Banque de France	Soft	Monthly	+15
Business surveys in services	Banque de France	Soft	Monthly	+15
Business surveys in industry	Insee	Soft	Monthly	+0
Business surveys in retail trade	Insee	Soft	Monthly	+0
Business surveys in services	Insee	Soft	Monthly	+0
Business surveys in construction	Insee	Soft	Monthly	+0
Consumer surveys	Insee	Soft	Monthly	+0
Survey on public works	FNTP	Soft	Monthly	+35
Business and consumer surveys	European Commission	Soft	Monthly	+0

Table 1: Information sources. Publication lags correspond to the number of days after the end of the reference period. In the Banque de France survey, answers refer to the economic situation on the previous month, while in the Insee and European Commission surveys, answers refer to the economic situation over the recent period (usually 3 months) including the current month.

2.4 Emphasis on the economic content of equations

Though OPTIM is not a structural model, the economic meaning of equations is taken into account, so that the results of the forecasting exercises can be interpretable from an economic point of view. Indeed, the purpose is not only to make reliable forecasts but also to build a consistent economic scenario. Hence, estimated coefficients must show the expected sign (for example, a negative relation between unemployment and consumption). This is also a way to avoid spurious regressions and to ensure a better stability of econometric relationships. Principal component analysis, which were used in the previous version of the model, are generally avoided in this study. Our view is that synthetic indicators reflect pretty well the economic activity and contain limited noise but offer less accuracy and flexibility for economic interpretation. Furthermore, data selection exercises have shown no evidence that models based on factors perform significantly better than models based on individual series.

[5]http://www.cepii.fr/anglaisgraph/bdd/chelem.htm.

2.5 A systematic method for data selection

The data selection method has been designed to be as robust as possible and easily replicable. The statistical quality of the equations can erode with time and it is important that equations could be re-estimated without difficulty. The equations should feature a limited number of variables, in order to prevent over-parametrization and to facilitate updates once the models are operative. The selection of the explanatory variables follows a step process:

- a main block of series is first selected from one particular source, which brings *a priori* good information on the behaviour of the estimated series (for example, the Banque de France survey on services for consumption in services). Only a few series are selected, on the basis of two criteria: they must be strongly correlated with the data of interest and not too correlated with each other, in order to avoid multicolinearity problems.

- Relevant series are selected with an automatic model selection procedure which yields parsimonious short-run dynamic adjustment equations [6]. This procedure is based on a general-to-specific (Gets) modelling strategy [7], proposed by David Hendry and which Hoover and Perez (1999) first suggested implementing in an automated way [8]. In this study, we use GROCER [9] (Dubois, 2003), a computer program which implements the Gets modelling. This automatic model selection procedure has four basic stages in its approach to select a parsimonious undominated representation of an overly general initial model, denoted the general unrestricted model (GUM) containing all variables likely (or specified) to be relevant, including the maximum lag length of the independent and dependent variables: (i) estimation and testing of the GUM; (ii) a pre-search process to remove insignificant variables in the GUM; (iii) a multipath search procedure which checks the validity of each reduction until terminal selections using diagnosis - these terminal models are tested against their union until a unique undominated congruent model is selected; and (iv) a post-search evaluation to check the reliability of the selection using overlapping sub-samples (refer to Hendry and Krolzig (2001) for further details). The following statistical tests, suggested by Hendry and Krolzig (2001), are implemented in the automatic model selection procedure: Godfrey (1978) Lagrange Multiplier test for serial correlation in the residuals up to 5 lags [LM(5)], Doornik and Hansen (1994) normality test [DH], Nicholls et Pagan (1983) test for quadratic heteroscedasticity between regressors [NP] and Chow in-sample predictive failure test on 50% [Chow(50%)] and 90% [Chow(90%)] of the sample. A multicollinearity diagnostic [BKW] is also displayed (Besley et al., 1980).

  We include in the selection procedure as many variables (and lagged terms) as possible in the GUM, i.e. a maximum of around 20 series.

[6]Golinelli and Parigi (2005) also used an automatic model selection procedure to build their bridge models.

[7]An overview of the literature, and the developments leading to Gets modelling in particular, is provided by Campos, Ericsson and Hendry (2004). Finite-sample behaviour is examined in Krolzig and Hendry (2001) and Hendry and Krolzig (2004)

[8]Perez-Amaral et al. (2003) also proposed another automatic modelling method, called RETINA (relevant transformation of the inputs network approach, based on specific-to-general strategy. Perez-Amaral et al. (2005) and Castle (2005) compared the characteristics of the both strategies. They showed that Gets strategy may be more appropriate when there is a desire to conform to economic interpretation.

[9]GROCER is an open source econometric toolbox for the software Scilab, developed by E. Dubois and E. Michaux. For more information, refer to http://dubois.ensae.net/grocer.html. Krolzig and Hendry (2001) implemented Gets modelling in the computer program PcGets.

The bridge equations relate quarterly average of the monthly explanatory variables $(X_t)_t$ to the quarterly growth rate of a National Account series $(Y_t)_t$. The general specification of the autoregressive-distributed-lag (ADL) bridge equation is as follows

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{q} \sum_{i=1}^{k} \delta_{j,i} X_{j,t-i} + \varepsilon_t \quad (1)$$

- A new block of series can be selected from another source of information and merged with the series selected by GROCER in a new set, which will in turn be tested with GROCER and deliver a second subset of series. This operation can be replicated several times. The choice of this type of iterative procedure is due to the fact that the number of series that can be included in the GUM is limited. The mix of two similar sources of information (such as the Banque de France and the Insee monthly surveys on industry) has been avoided: each data set is considered alternatively and the resulting equations are compared according to their statistical properties. This procedure allows to limit the risks of high correlation between explanatory variables and also to shorten the data selection process.

- Among equations selected by GROCER, only a few are kept, depending on their statistical properties (adjusted R^2, AIC and Schwartz information criteria, CUSUM stability tests, residuals tests and correlograms ...) and their economic content. Equations with illogical coefficient signs are dropped. An equation is preferred to another if it covers a wider spectrum of information. For instance, having information on prices, unemployment and activity through the explanatory variables in a consumption equation is considered preferable than having solely information on activity. Equations might be slightly modified to take the lag structure of variables into account: as a general rule, levels (and not differences) of variables are introduced in the equations; however, if a variable appears in an equation with a coefficient $\hat{\beta}$ and its first lag with a coefficient close to $-\hat{\beta}$, the same equation is tested with the first difference of this variable. Additional lags of the dependent variable can be added to eliminate serial correlation in the residuals. If heteroskedasticity is detected, the Newey-West HAC estimator is applied. For each modelled series, a set of approximately 1 to 5 equations is thus selected at this stage, though only one final equation is generally discussed in the remaining of the paper. A rather large set of equations can be chosen, bearing in mind that an equation based on data with a short publication lag might perform better in forecasting, even if it proves less reliable than equations based on other data over the past.

- Out-of-sample recursive forecasts are carried out to determine the final equation for each modelled series. The recursive forecasts have been implemented over the period 2000q1-2006q4, with three predictions for a given quarter. Coefficients are estimated at each step. This exercise takes the availability of the data into account, under the assumption that one forecasting exercise is implemented at each end of month (i.e. just after the publication of Insee and EC survey data and just before the ECB Governing Council). For example, considering the fact that GDP figures for the first quarter of a given year are published mid-May, and that figures for the fourth quarter of the preceding year are available mid-February, three "nowcasts" will be made for the first quarter in February, March and April. The industrial production index for January, which is published with a 40 days lag, can not be used in the forecast made in February, but can be used in the forecast made at the end of March. In the recursive forecasts, as well as in actual forecasting exercises, when data are missing for some months of the last quarter, they are forecast using AR models. As mentioned above, different equations can theoretically be selected for the different forecasts of the same quarter: an equation can have a relatively high Root Mean Squared Error (RMSE) in the forecasts made in February, May, August and November, but a relatively low RMSE in the forecasts made in March, June, September and December. However, having different equations for the different forecasts of a GDP component at a particular quarter makes it more difficult to understand revisions of forecast from a month to another. Therefore, various equations are kept for the monthly projection exercises only if they bring significantly better results at the time they are being used.

3 OPTIM equations

In this section, we describe the coincident and future equations that we propose for both supply and demand sides of the OPTIM model. We briefly present the data involved in equations as well as the main stylized facts of those equations. Note that all equations and variables are presented in annex. Forecasting results are discussed in the next section.

3.1 Production

As regards production, five components have been modelled: agri-food goods, energy, manufactured goods, construction and private services. The sum of these five components is not equal to total production because non-private services, which account for approximately 15% of production, are missing. However, the five modelled components account for almost all of the variance of total production. Indeed, the R^2 statistic of the aggregation equation in which production is explained by the modelled components is over 0.99.

Generally, taking the Industrial Production Index (IPI henceforth) into account provides a better fitting, but its strongly delayed publication (around 40 days after the end of the month) makes it less useful for early forecasting exercises. For example, no IPI data is available when the first nowcast of the current quarter and the first forecast of the next quarter are made. Hence, for each component, two equations are specified, one with IPI and the other without (for each sector of industry, the corresponding component of the IPI is selected and for market services the IPI in manufactured goods is selected).

3.1.1 Production of agri-food goods

The production of agri-food goods has been modelled using the IPI in agri-food goods and the Banque de France (BdF) survey on agri-food industry. All the equations contain the lagged production of agri-food goods. For coincident models, the first equation is based on the IPI and "production expectations" extracted from the BdF survey on agri-food goods. The second equation integrates only this latter variable. For the future model, we retain the same variables as in the coincident equation with IPI, but with different lags.

3.1.2 Production of manufactured goods

Manufacturing production has been modelled using the IPI in the manufacturing sector and the Insee survey on industry. Equations with the BdF survey for the manufacturing industry were tried but not retained. In the equation without IPI, dummy variables were introduced in order to take into account a strong increase in production in the first half of 1997 that was not reflected by survey data. As regards the coincident equation, the series included in the first equation are the IPI for manufactured goods and "personal production outlook in manufacturing industry" (Insee). In the second equation, "personal production outlook in manufacturing industry" (Insee) and "recent changes in output" (Insee) were selected. For the future equation, "personal price outlook in manufacturing industry" (Insee), "personal outlook in industry", as well as the difference between "general" and "personal outlook in industry" (Insee) are used.

3.1.3 Production of energy

A first coincident equation is directly based on the quarterly increases in the energy component of the IPI. Survey data offer no direct information on the energy sector. Nevertheless, RTE[10] provides a daily estimation of electricity consumption in France. A monthly series has been first computed by aggregation of this information and then seasonally adjusted using Census X12. The second coincident equation for production of energy is based on the quarterly changes in this series. The future equation includes also the lagged value of the production of energy.

3.1.4 Production in construction

A first coincident equation for this component is based on theIPI for construction, on data from the Insee survey in the construction sector, namely "recent changes in output", and on survey data on public works. A second one uses data from the Insee survey in the construction sector, namely "production outlook", and survey data on public works. The future equation includes Insee survey data on the outlook for production and employment.

3.1.5 Production of private services

Production of private services has been modelled using the IPI in manufactured goods, the BdF survey on services and the Insee consumer confidence survey. All equations contain the lagged production of private services. The first coincident equation is specified with IPI in manufactured goods and a variable from the BdF survey on services ("changes in activity"). The second coincident equation is based on this latter variable plus an other series from the same survey ("cash flow situation") and two series from the Insee consumer confidence survey ("unemployment outlook" and "likelihood of buying"). Finally, the future model includes, as explanatory variables, "likelihood of buying" (Insee consumer survey), "cash flow situation" and "forecast staff level" (both from the BdF survey on services).

3.2 Household consumption

Four components of household consumption were modelled: agri-food goods, energy, manufactured goods and services. The whole household consumption is covered by those four components.

3.2.1 Household consumption in agri-food goods

The BdF survey on manufacturing industry features series relative to the agri-food sector that are useful to model this component. One of these series, namely "expected staff levels", is selected in the coincident equation for household consumption in agri-food goods. The coincident

[10]RTE is the company responsible for operating, maintaining and developing the French electricity transmission network. http://www.rte-france.com.

equation also relies on a series of quarterly changes in agri-food good prices, which is computed after a seasonal adjustment of the Harmonized Index of Consumption Prices series published by Eurostat. The future equation also includes "evolution of commands in the agri-food sector" as well as "production evolution" and the capacity utilization rate (evolution over two quarters).

3.2.2 Household consumption in energy

The nowcast of household consumption in energy is obtained through an equation using the RTE series of electricity consumption as exogenous variable (also used in one of the equations for production of energy, see above section 3.1.3.). The inclusion of IPI for energy was tested but rejected. The future equation is based on an autoregressive (AR) model with two lags.

3.2.3 Household consumption in manufactured goods

This component is directly obtained from the monthly indicator of the household consumption in manufactured goods published by Insee. On a quarterly basis, this series is strictly equal to the series of household consumption in manufactured goods featured in the national accounts. This monthly indicator is available 25 days after the end of the reference month. When monthly data are missing for the current quarter, they are forecast using an AR model. An alternative equation was also estimated, based on BdF survey components relative to retail trade and consumption goods. This equation was statistically significant but provided worse RMSE in the recursive forecast exercises. The equation for the future quarter is also based on monthly data on consumption in manufactured goods, but feature other explanatory variables, namely "level of order books for consumption goods","clothing retail sales in volume" and "production expectations in industry", all provided by BdF surveys.

3.2.4 Household consumption in services

Series from the BdF and Insee surveys on services have been separately tested in the estimation of consumption in services: . Equations were first selected with data exclusively taken from these two sources, then with data added from the Insee household survey and finally with data added from the Insee household survey plus monthly consumption in manufactured products. The selected coincident equation uses data from the BdF survey on services ("changes in activity" and "cash flow situation") plus data from the Insee survey on households ("likelihood of buying" and "unemployment outlook"). In the future equation, "changes in activity" was replaced by "forecast staff level". Most of the series included in the equations for household consumption in services are laso included in the equations for services production. This result is coherent, as changes in consumption of services are close to changes in production of services, notably due to the fact that some data are used on both sides in the national account calculations.

3.3 Government consumption

Government consumption is forecast with an AR model. In fact, no better equation based on economic variables was found. In the national accounts, Government consumption is calculated from Government production, which is estimated at factor costs, and therefore corresponds for its main part to civil servant compensations. Government consumption is far from being negligible, as it accounts for almost 25% of GDP, but it is one of the less volatile components of GDP.

3.4 Investment

Investment is split into three main components: household investment (based on investment in construction), corporate investment and Government investment. In addition, corporate investment is divided in two subcomponents, equipment and building. The sum of these components do not equal total investment: about 20% is lacking, corresponding mainly to firm investment in services ("immaterial investment"). However the R^2 statistic stemming from the aggregation equation through a regression model is close to 0.9.

3.4.1 Corporate investment in equipment

Equations for equipment investment are based on the BdF survey on industry, and notably on answers from capital good industry companies. Series of company car registrations were also tested but not kept. The coincident equation includes "changes in deliveries of capital goods" and the capacity utilization rate for total industry. In the future equation, "changes in deliveries of capital goods" are dropped.

3.4.2 Corporate investment in construction

Equations of investment in construction are based on the Insee survey in the construction sector. Both future and coincident equations contain the variables "order books" and "employment outlook in the construction sector".

3.4.3 Household investment

A series of declared housing starts, published by the Ministry of Equipment with a lag of 30 days, is the only explanatory variables taken into account in the equation for the coïncident quarter. A weighted sum of the current and past values of this series is actually used in the national accounts to compute households'investment. For the future quarter, as in the case for corporate investment in construction, household investment is modelled with a variable from the Insee survey on building industry ("production outlook in industry").

3.4.4 Government investment

Government investment is modelled with a series of achieved public works, taken from a monthly survey made by the national public works federation (FNTP) and published 35 days after the end of the reference month. It is noteworthy that this series is directly used by Insee to compute Government investment. This series is included in both coincident and future equations.

3.5 External trade

Though data selection methods were separately applied to the imports and exports equations, they led to very similar sets of explanatory variables, suggesting thus robustness of the relationships. This result is all the more impressive as many data sources were included in the selection process: BdF surveys on industry and retail trade, Insee surveys on industry and retail trade, European Commission (EC) business survey, customs series on external trade in value and exchange rates. In the final equations, customs series, exchange rates and data from the BdF survey on industry and from the EC survey were selected.

As regards the import component, the coincident equation contains four variables: "changes in order books in total industry" (BdF), "production expectations for the months ahead" (EC), quarterly changes in exports in value (customs) and the euro-dollar exchange rate. In the future equation, the fourth-order lag of the modelled variable was added and the variable from the EC survey was dropped. For exports, in the coincident equation, the variable "'changes in order books"' was replaced by "changes in foreign orders" and the first lag of the endogeneous variable was added. The future equation contains lags of the endogeneous variable, "changes in foreign orders", the euro-dollar exchange rate but also two variables related to exportations, namely "changes in foreign orders books" and "inventories forecast in the intermediate goods" (BdF).

The selection of variables like "changes in order books" for imports and "changes in foreign order books" for exports appears logical. The selection of the same variable of "production expectations" (from the EC survey) for both imports and exports is more puzzling. The link with exports is quiet direct, as this variable refers to activity of France's economic partners and is thus a proxy for demand from European countries addressed to France. The link with imports is less obvious, but can correspond to the fact that more imports from France will boost activity of trade partners and also to the fact that the economic cycles of European countries are quite close.

4 Forecasting results

The results presented in this section correspond to the recursive forecast exercise detailed in section 2.5. For each quarter t, we provide with three forecasts for the current quarter (or nowcasts), $\hat{Y}_t^i$, for $i = 1, 2, 3$, and three forecasts for the next quarter $\hat{Y}_{t+1}^i$, for $i = 1, 2, 3$. The root mean-squared error (RMSE, henceforth) for the i^{th} forecast is defined by the following equation:

$$RMSE(i) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t^i)^2}, \tag{2}$$

where n is the number of quarters considered in the recursive forecast exercise ($n = 28$ from Q1 2000 to Q4 2006), where Y_t is the actual value of the macroeconomic variable that we aim to forecast for the quarter t. The chain-linked values released in August 2007 by the quarterly national accounts of the French statistical institute are used as actual values. Our first aim was to use as actual values $(Y_t)_t$ the first releases of GDP growth published by the Insee, but because of the changes in the quarterly national accounts methodology we choose to use as actual values the chain-linked GDP growth rates.

Benchmark forecasting results correspond to AR models and to naive projections. The AR models have been estimated over the longest possible sample. Significant lags up to the 4^{th} order with an associated probability of the t-stat of less than 10% were kept. Forecasts with the AR models present the following form, for all t:

$$\hat{Y}_t = \hat{\phi}_0 + \hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2} + \hat{\phi}_3 Y_{t-3} + \hat{\phi}_4 Y_{t-4}, \tag{3}$$

where the $\hat{\phi}_i$ are the estimated parameters. The naive projections are estimated by taking the last observation as the forecast, that is for all t:

$$\hat{Y}_t = Y_{t-1}. \tag{4}$$

For the two benchmark approaches, there is a single forecast by quarter as we do not include any monthly information. Results in terms of RMSE are presented in Table 2.

Component		First	Second	Third	AR	Naive
GDP	with IPI	0.36	0.28	0.20	0.38	0.51
	without IPI	0.26	0.25	0.25		
Production Agri-food	with IPI	0.49	0.46	0.46	0.57	0.68
	without IPI	0.56	0.56	0.56		
Production Manufactured	with IPI	1.26	1.00	0.60	1.28	1.73
	without IPI	0.74	0.78	0.78		
Production Energy	with IPI	1.53	1.29	1.12	1.44	2.52
	without IPI	1.30	1.34	1.34		
Production Construction	with IPI	0.60	0.49	0.46	0.67	0.76
	without IPI	0.57	0.51	0.50		
Production Services	with IPI	0.48	0.41	0.33	0.45	0.59
	without IPI	0.39	0.36	0.35		
Household Consumption		0.26	0.19	0.19	0.33	0.45
Government Consumption		0.23	0.23	0.23	0.23	0.28
Investment		0.81	0.79	0.73	0.87	1.24
Imports		1.08	0.98	0.92	1.31	1.54
Exports		1.36	1.13	1.04	1.62	2.07

Table 2: RMSEs for the coincident quarter by components for the first, second and third forecasts and for the AR and naive models, over the period Q1 2000 - Q4 2006

For all components, the RMSEs produced by the equations are generally lower or equal to those of the AR and naive predictors. However, a few exceptions appear. Firstly, production of energy and production of market services are more precisely forecast with an AR model than with the equations with IPI for the first forecast on the coincident quarter. Nevertheless, if we do not include the information conveyed by the IPI, the equation performs better than the AR model. Secondly, in the first forecast on the future quarter, the model forecasts for households' consumption and production of services are outperformed by the AR. Thirdly, as mentioned above, Government consumption is forecast directly by an AR model, implying obviously that the results are the same for each forecast. It is also noteworthy that AR forecasts are always more accurate than naive projections, meaning that information is present inside data taking the form of non-null autocorrelations. Last, as expected, the accuracy of projections generally increases with each forecast: in most cases, the smallest RMSEs are observed for the third forecast $\hat{Y}_t^3$.

For the production components, equations based on the IPI always display the smallest RMSE for the third forecasts, but this is not systematically the case for the first and second forecasts. This result implies that different production equations should be selected for the different forecasts.

For the aggregated GDP, the lowest RMSEs are obtained for the first and second forecasts with an aggregation of sectoral production forecasts obtained with equations excluding the IPI and for the third forecast with an aggregation of production forecasts obtained with equations including the IPI [11]. The estimated RMSEs for the first, second and third forecasts are respectively 0.24 percentage point (pp hereafter), 0.24 pp and 0.20 pp.

Diebold-Mariano tests of equality of forecast performance are carried out (see results in Table 4). The modified Diebold-Mariano test of Harvey, Leybourne and Newbold (1997) has been

[11] On the studied sample, this method delivers approximately the same RMSE for GDP than an aggregation of forecasts of the equations that display the lowest RMSE for each component on each month.

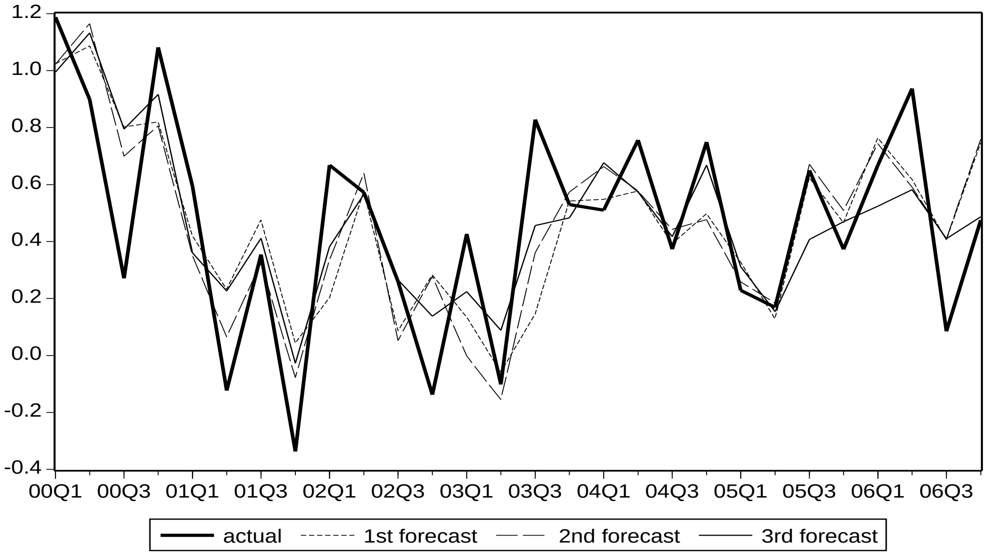

Figure 2: Realized GDP and forecasts for the 1st, 2nd and 3rd months

implemented in order to take the small number of forecasts into account ($n = 28$). Except for production of energy and construction without IPI, the tests indicate that the third forecasts significantly outperform benchmark AR forecasts, with a confidence level of 90%. Especially, GDP forecasts (without IPI for first and second and with IPI for the third) are strongly better than those obtained by the benchmark model, with a confidence level 99%.

As regards future equations, RMSEs are generally higher, reflecting the larger risk of prediction error when the horizon increases (see Table 3). Moreover, contrarily to the coincident forecasts, we observe that there is few decrease in time in RMSEs when monthly information is incorporated. GDP is one of the most accurately forecast variable with a RMSE of around 0.28 over the period. Among all components, household and government consumptions present also the lowest RMSEs (0.33 and 0.24, respectively, for the third forecast). This phenomenon is due to the strong persistence of those series. On the opposite, external trade variables are extremely difficult to forecast one-quarter-ahead because of their strong volatility (RMSEs of imports and exports are not lower than 1.21 and 1.17 respectively). This high volatility from one quarter to the other may be partly due to the strong sensibility of those components to the international and conjunctural environment (oil prices, exchange rates, financial markets ...). Inventories management may also plays a role in those large quarterly variations. Anyway, the modified Diebold-Mariano test of equality of forecast shows that the model for exports clearly outperform a simple AR model, even with a very low risk of 1% (see Table 5). The most volatile variable is the production of energy that displays a RMSE of 1.51. Actually energy production is strongly linked to the climatic situation, whose evolutions are rather erratic and therefore tricky to anticipate.

5 Conclusions

In this paper, a revised version of the OPTIM model has been proposed, in order to forecast French GDP growth and its main components for the current quarter, as well as for the next quarter. Bridge equations for GDP and its main components are specified and estimated, using

Component	First	Second	Third	AR	Naive
GDP	0.29	0.28	0.28	0.37	0.48
Production Agri-food	0.63	0.64	0.65	0.77	1.08
Production Manufactured	1.08	1.06	1.06	1.24	1.57
Production Energy	1.51	1.51	1.51	1.51	2.07
Production Construction	0.70	0.71	0.71	0.72	0.77
Production Services	0.46	0.44	0.44	0.45	0.54
Household Consumption	0.36	0.33	0.33	0.33	0.48
Government Consumption	0.24	0.24	0.24	0.24	0.28
Investment	0.79	0.82	0.78	0.85	1.24
Imports	1.40	1.37	1.21	1.41	1.54
Exports	1.37	1.29	1.17	1.75	2.33

Table 3: RMSEs for the future quarter by components for the first, second and third forecasts and for the AR and naive models, over the period Q1 2000 - Q4 2006

monthly information based on soft and hard data. Both supply and demand sides are considered. The main new features are: a monthly frequency for forecasting exercises, a general-to-specific selection of equations and a recursive forecast exercise taking the availability of data into account. In terms of root mean squared errors, the new equations provide satisfactory results and clearly outperform benchmark models.

Since September 2007, the revised OPTIM model is used each end of the month at the Banque de France in order to provide GDP growth estimates for the coincident and the next quarter. The first *true real-time* results were encouraging, insofar as at the end of September, we nowcast a value of 0.6% for the third quarter 2007 (2nd forecast), that was revised upward at 0.7% at the end of October (3rd forecast). Finally, the first GDP growth estimate was released at 0.7% by the Insee mid-November. As regards the last quarter of 2007, the first nowcast in November was of 0.5%, remaining unchanged in December. Then, the last nowcast of Q4 2007 at the end of January 2008 was estimated at 0.4%. The first estimate of the Insee, released February 14, was of 0.3% for Q4 2007. For Q1 2008, the three consecutive nowcasts were respectively 0.4%, 0.4% and 0.5% and the published GDP growth was 0.6%.

As further research, our aim is to improve the way to bridge from monthly to quarterly information. That is, the question is how to complete the value of an explanatory variable for a given quarter when only one or two months are known. Currently, missing monthly data are forecast using AR models. However, around turning points this method may lead to unrealistic results, that need to be modified through expert claims. One direction for further improvements would be to use more sophisticated equations, for example integrating explanatory variables such as survey data on activity prospects. At first, only the most useful variables for GDP modelling (and in particular the IPI, to begin with) could be forecast on the missing months with this type of equations.

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6 Annexes

Component		First	Second	Third
GDP	with IPI	0.2553	0.0332	0.0016
	without IPI	0.0101	0.0089	0.0091
Production Agri-food	with IPI	0.0732	0.0301	0.0348
	without IPI	0.2776	0.2776	0.2776
Production Manufactured	with IPI	0.4126	0.0424	0.0007
	without IPI	0.0047	0.0045	0.0045
Production Energy	with IPI	0.2637	0.1546	0.0347
	without IPI	0.1527	0.2123	0.2123
Production Construction	with IPI	0.0427	0.0221	0.0262
	without IPI	0.1342	0.0617	0.0923
Production Services	with IPI	0.2118	0.1766	0.0016
	without IPI	0.0747	0.0245	0.0158
Household Consumption		0.0264	0.0001	0.0001
Investment		0.2719	0.1763	0.0782
Imports		0.0144	0.0229	0.0195
Exports		0.0716	0.0044	0.0012

Table 4: P-values of Modified Diebold-Mariano tests (Harvey, Leybourne and Newbold, 1997) against the AR model, over the period Q1 2000 - Q4 2006 ($n = 28$ observations). If the P-value is lower than the type I risk α equal to, for example, 0.05, it means that we can reject the null hypothesis of equality of expected forecast performance with a risk α.

Component		First	Second	Third
GDP	with IPI	0.0428	0.0329	0.0322
Production Agri-food	with IPI	0.0199	0.0598	0.0958
Production Manufactured	with IPI	0.1347	0.1098	0.1098
Production Energy	with IPI	0.4792	0.4792	0.4792
Production Construction	with IPI	0.4391	0.4669	0.4669
Production Services	with IPI	0.4575	0.4684	0.4687
Household Consumption		0.2820	0.4826	0.4822
Investment		0.2561	0.2571	0.2428
Imports		0.4906	0.4109	0.1322
Exports		0.0069	0.0060	0.0021

Table 5: P-values of Modified Diebold-Mariano tests (Harvey, Leybourne and Newbold, 1997) against the AR model, over the period Q2 2000 - Q4 2006 ($n = 27$ observations), for the future quarter. If the P-value is lower than the type I risk α equal to, for example, 0.05, it means that we can reject the null hypothesis of equality of expected forecast performance with a risk α.

Production of Agri-food Goods (with IPI)

Table 6: Model for production of agri-food goods with IPI (PIAA_GT)

Coincident equation

Variable	Coefficient	t-stat
PIAA_GT (t-1)	0.791	11.44
PIAA_GT (t-3)	-0.406	-5.36
Δ(IPI_IAA_GT) (t)	0.158	7.25
PREVPRO_IAA (t-1)	0.017	2.22
α	-0.108	-0.94
$\bar{R}^2 = 0.76$ – SE = 0.36 – DW = 1.92 – BKW = 4		
LM(5) = 3.72 [0.59] – DH = 1.77 [0.41] – NP = 0.32 [0.94]		
Chow(50%) = 1.85 [0.05] – Chow(90%) = 0.87 [0.52]		

Future equation

Variable	Coefficient	t-stat
PIAA_GT (t-1)	0.843	11.91
PIAA_GT (t-3)	-0.508	-7.41
IPI_IAA_GT (t-1)	-0.252	-7.34
IPI_IAA_GT (t-3)	0.090	2.66
PREVPRO_IAA (t-1)	0.026	2.34
α	-0.205	-1.30
$\bar{R}^2 = 0.75$ – SE = 0.37 – DW = 1.96 – BKW =		
LM(5) = 1.29 [0.29] – DH = 4.53 [0.10] – NP = 0.77 [0.64]		
Chow(50%) = 2.36 [0.02] – Chow(90%) = 1.10 [0.38]		

P-values of test statistics are in brackets. PIAA_GT: production of agri-food goods (q-o-q); IPI_IAA_GT: index of industrial production in agri-food goods (q-o-q, Insee). PREVPRO_IAA: forecasted production in agri-food goods (BdF); Estimation period: 1991 Q1 - 2006 Q4.

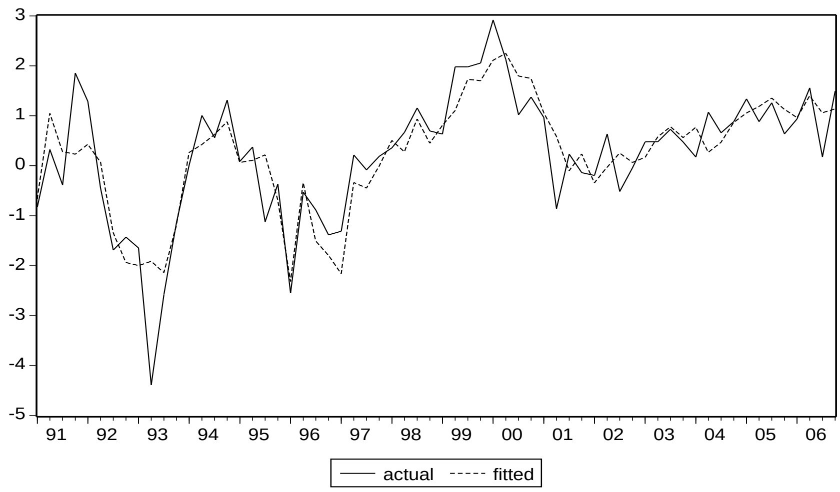

Figure 3: Production of agri-food goods (with IPI): Actual and fitted values

Production of Agri-food Goods (without IPI)

Table 7: Model for production of agri-food goods without IPI (PIAA_GT)

Coincident equation

Variable	Coefficient	t-stat
PIAA_GT (t-1)	0.489	6.26
PIAA_GT (t-4)	-0.409	-5.04
PREVPRO_IAA (t-1)	0.025	2.03
α	-0.126	-0.72
$\bar{R}^2 = 0.53$ – SE = 0.50 – DW = 1.96 – BKW = 4		
LM(5) = 4.40 [0.49] – DH = 1.78 [0.41] – NP = 0.07 [1.00]		
Chow(50%) = 0.96 [0.55] – Chow(90%) = 0.43 [0.90]		

P-values of test statistics are in brackets. PIAA_GT: production of agri-food goods (q-o-q); PREVPRO_IAA: forecasted production in agri-food goods (BdF); Estimation period: 1991 Q1 - 2006 Q4.

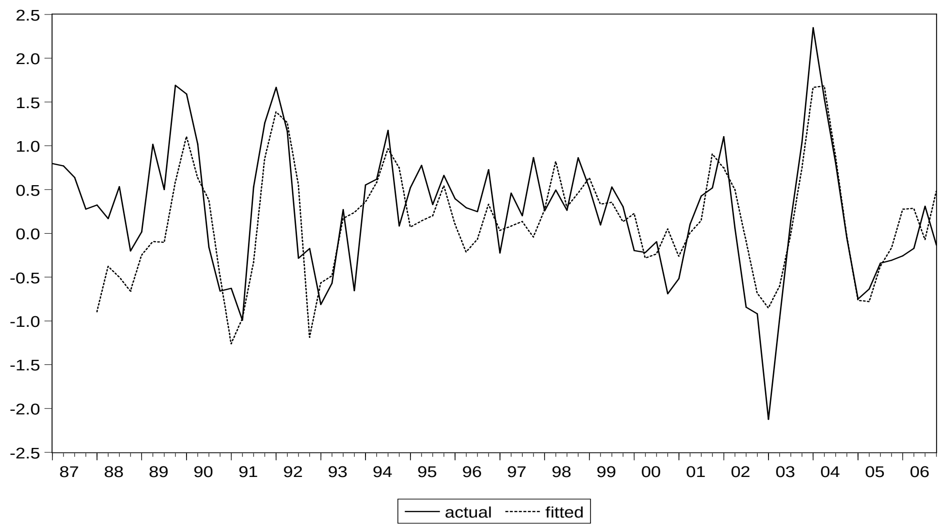

Figure 4: Production of agri-food goods (without IPI): Actual and fitted values

Production of manufactured goods (with IPI)

Table 8: Model for manufacturing production with IPI (PMANU_GT)

Coincident equation

Variable	Coefficient	t-stat
PMANU_GT (t-4)	0.371	7.099
IPI_MANUF_GT (t)	0.910	13.980
Δ(PRODPREV_MANUF) (t)	0.038	3.334
α	0.082	0.989
$\bar{R}^2 = 0.83$ – SE = 0.55 – DW = 2.27 – BKW = 2		
LM(5) = 6.38 [0.27] – DH = 0.66 [0.72] NP = 0.25 [0.96]		
Chow(50%) = 0.51 [0.97] – Chow(90%) = 1.03 [0.42]		

P-values of test statistics are in brackets. PMANU_GT: manufacturing production (q-o-q); IPI_MANUF_GT: industrial production index in manufactured goods (q-o-q); PRODPREV_MANUF: personal production outlook in manufacturing industry (INSEE); PREVPRO_I: production forecasts, total industry (BdF). Estimation period: 1991 Q2 - 2006 Q4.

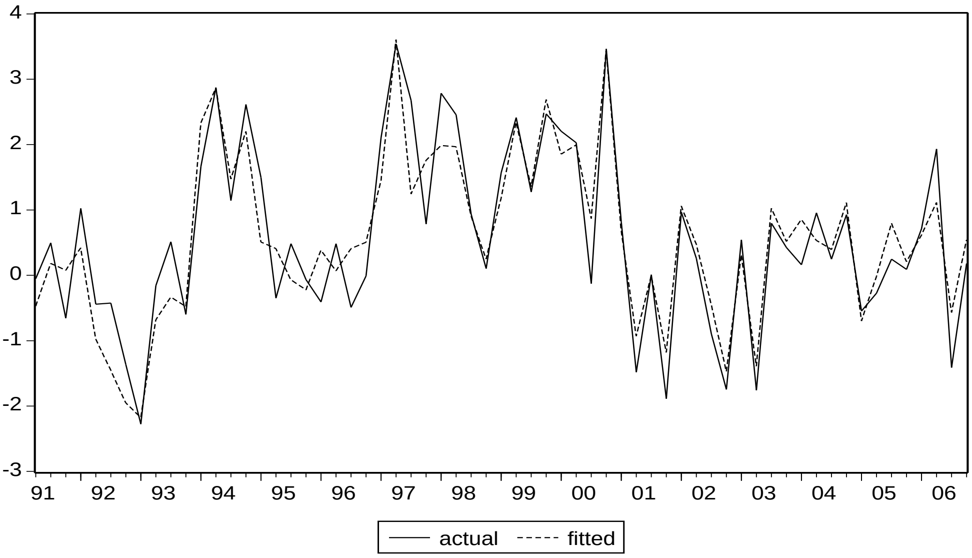

Figure 5: Production of manufactured goods (with IPI): Actual and fitted values

Production of manufactured goods (without IPI)

Table 9: Model for manufacturing production without IPI (PMANU_GT)

Coincident equation

Variable	Coefficient	t-stat
PMANU_GT (t-3)	0.436	6.43
PMANU_GT (t-4)	0.394	4.72
Δ(PRODPREV_MANUF) (t)	0.135	8.45
Δ(PRODPASS_MANUF) (t)	0.055	3.62
DUM972	3.187	15.11
DUM973	1.984	18.65
α	-0.055	-0.77
$\bar{R}^2 = 0.72$ – SE = 0.72 – DW = 2.35 – BKW = 3		
LM(5) = 5.74 [0.33] – DH = 1.13 [0.57] – NP = 0.59 [0.81]		
Chow(50%) = 1.30 [0.25] – Chow(90%) = 1.47 [0.21]		

Future equation

Variable	Coefficient	t-stat
Δ(PRODPREV_MANUF) (t-1)	0.060	2.65
VOLPREV_MANUF- PRODPREV_MANUF (t-1)	0.045	5.03
PRIXPREV_MANUF (t-1))	-0.059	-4.14
α	0.934	5.64
$\bar{R}^2 = 0.44$ – SE = 1.01 – DW = 2.14 – BKW = 2		
LM(5) = 2.12 [0.83] – DH = 0.33 [0.85] – NP = 0.55 [0.73]		
Chow(50%) = 1.09 [0.41] – Chow(90%) = 0.68 [0.68]		

P-values of test statistics are in brackets. PMANU_GT: manufacturing production (q-o-q); PRODPREV_MANUF: personal production outlook in manufacturing industry (INSEE); PRODPASS_MANUF: recent changes in output (INSEE); VOLPREV_MANUF: general production outlook in manufacturing industry (INSEE); DUM972 : dummy 97Q2 ; DUM973 : dummy 97Q3; PRIXPREV_MANUF: personal price outlook in manufacturing industry (INSEE); Estimation period: 1991 Q2 - 2006 Q4.

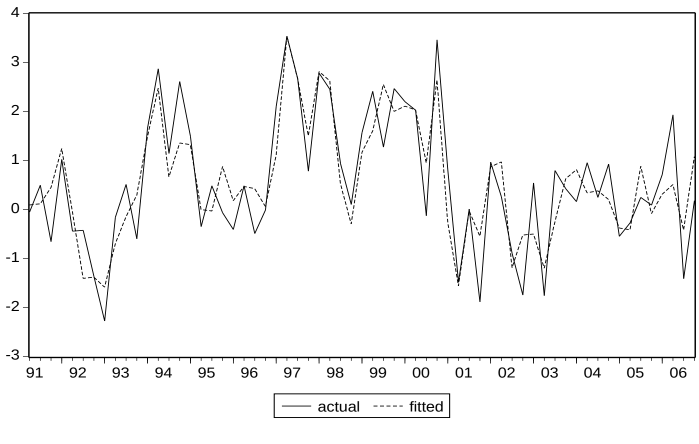

Figure 6: Production of manufactured goods (with IPI): Actual and fitted values

Production of energy (with IPI)

Table 10: Model for production of energy with IPI (PENER_GT)

Coincident equation

Variable	Coefficient	t-stat
IPI_ENER_GT	0.613	10.83
α	0.276	2.15
$\bar{R}^2 = 0.64$ – SE = 1.03 – DW = 2.28 – BKW = 1		
LM(5) = 2.42 [0.79] – DH = 2.86 [0.24]		
NP = 0.17 [0.84] – Chow(50%) = 1.09 [0.40]		
Chow(90%) = 0.95 [0.48]		

Future equation

Variable	Coefficient	t-stat
PENER_GT (t-1)	-0.407	-3.56
IPI_ENER_GT (t-3)	0.175	2.05
α	0.577	2.87
$\bar{R}^2 = 0.23$ – SE = 1.49 – DW = 1.89 – BKW = 1		
LM(5) = 3.47 [0.63] – DH = 2.68 [0.26] – NP = 0.03 [0.99]		
Chow(50%) = 0.63 [0.89] – Chow(90%) = 0.64 [0.88]		

P-values of test statistics are in brackets. PENER_GT: production of energy (q-o-q); IPI_ENER_GT: industrial Production index in energy (q-o-q). Estimation period: 1990 Q2 - 2006 Q4 (coincident); 1991 Q1 - 2006 Q4 (future).

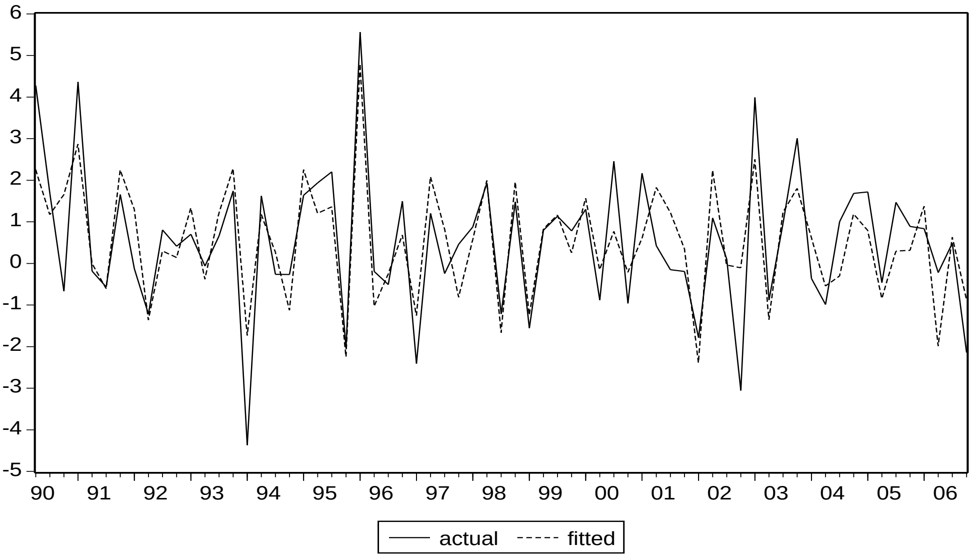

Figure 7: Production of energy (with IPI): Actual and fitted values

Production of energy (without IPI)

Table 11: Model for production of energy without IPI (PENER_GT)

Coincident equation

Variable	Coefficient	t-stat
RTE_SA_GT	0.416	4.85
α	0.224	3.48
$\bar{R}^2 = 0.35$ – SE = 1.17 – DW = 2.52 – BKW = 1		
LM(5) = 5.08 [0.41] – DH = 0.37 [0.83]		
NP = 0.04 [0.96] – Chow(50%) = 1.81 [0.09]		
Chow(90%) = 1.13 [0.36]		

P-values of test statistics are in brackets. PENER_GT: production of energy (q-o-q); RTE_SA_GT: electricity consumption (q-o-q). Estimation period: 1996 Q1 - 2006 Q4.

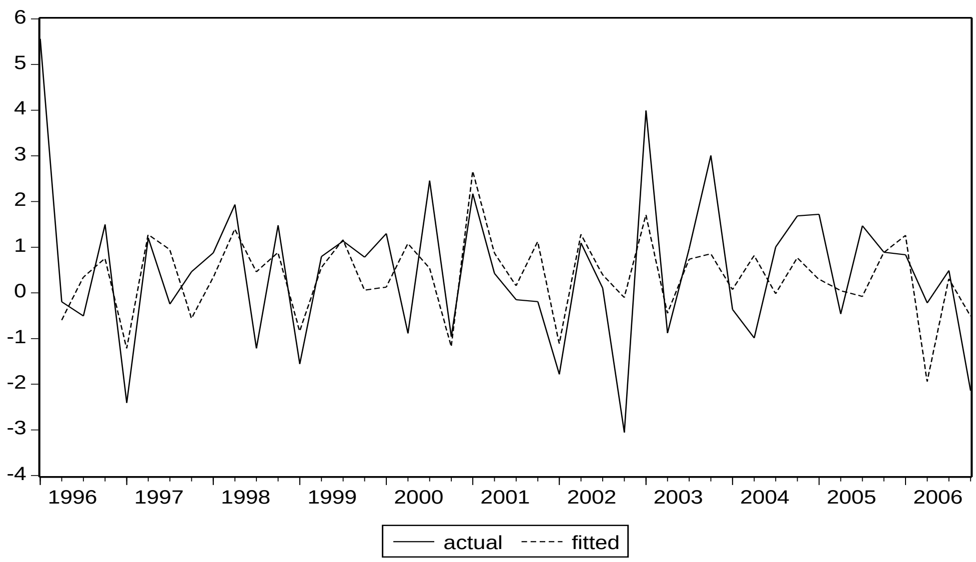

Figure 8: Production of energy (without IPI): Actual and fitted values

Production in construction (with IPI)

Table 12: Model for production in construction with IPI (PBAT_GT)

Coincident equation

Variable	Coefficient	t-stat
PBAT_GT(t-1)	0.360	3.68
IPI_CONST_GT(t)	0.189	4.09
ACTPASS_BAT(t)	0.014	2.88
FNTP_GT(t)	0.089	3.44
α	0.181	2.00
$\bar{R}^2 = 0.78$ – SE = 0.59 – DW = 1.92 – BKW = 3		
LM(5) = 3.68 [0.60] – DH = 42.3 [0.00]		
NP = 1.33 [0.25] – Chow(50%) = 0.35 [1.00]		
Chow(90%) = 0.38 [0.89]		

P-values of test statistics are in brackets. PBAT_GT: production in construction (q-o-q); IPI_CONST_GT: industrial production index in construction (q-o-q); ACTPASS_BAT: Production trend observed in recent months in construction; FNTP_GT: achieved public works (q-o-q). Estimation period: 1991 Q1 - 2006 Q4.

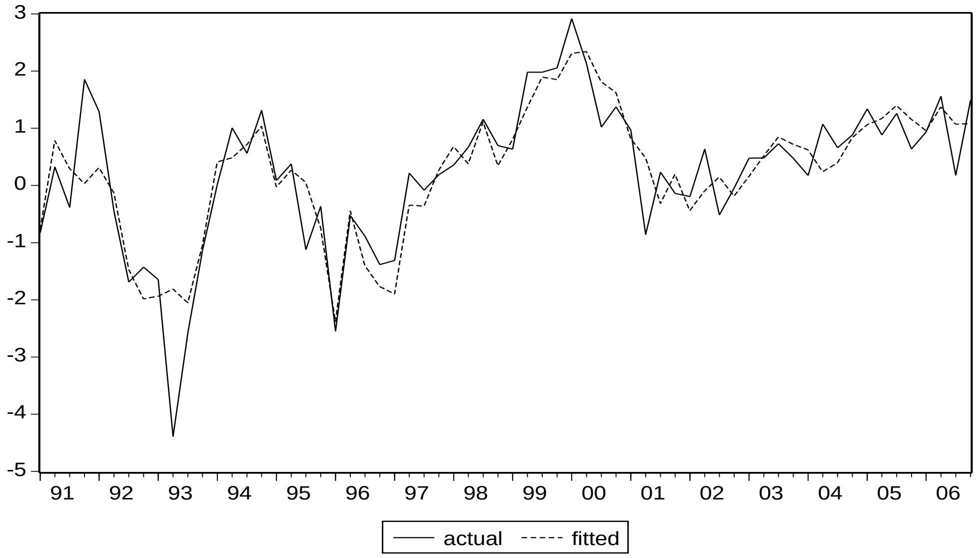

Figure 9: Production of building (with IPI): Actual and fitted values

Production in construction (without IPI)

Table 13: Model for production in construction without IPI (PBAT_GT)

Coincident equation

Variable	Coefficient	t-stat
PBAT_GT(t-1)	0.389	4.15
ACTPREV_BAT(t)	0.019	3.27
FNTP_GT(t)	0.154	6.35
α	0.285	2.65
$\bar{R}^2 = 0.72$ – SE = 0.69 – DW = 1.84 – BKW = 2		
LM(5) = 4.81 [0.44] – DH = 39.7 [0.00]		
NP = 0.95 [0.46] – Chow(50%) = 0.24 [1.00]		
Chow(90%) = 0.70 [0.65]		

Future equation

Variable	Coefficient	t-stat
PBAT_GT(t-1)	0.298	2.59
ACTPREV_BAT(t-1)	0.025	3.76
Δ(EFFPREV_BAT)(t-1)	0.067	2.94
α	0.391	3.10
$\bar{R}^2 = 0.63$ – SE = 0.77 – DW = 2.04 – BKW = 2		
LM(5) = 3.31 [0.65] – DH = 22.5 [0.00] – NP = 1.26 [0.30]		
Chow(50%) = 0.37 [1.00] – Chow(90%) = 0.54 [0.78]		

P-values of test statistics are shown in brackets. ACTPREV_BAT: production outlook in building industry (Insee); FNTP_GT: achieved public works (q-o-q); EFFPREV_BAT: employment outlook in building industry (Insee); Estimation periods: 1988 Q3 - 2006 Q4 (coincident); 1991 Q1 - 2006 Q4 (future).

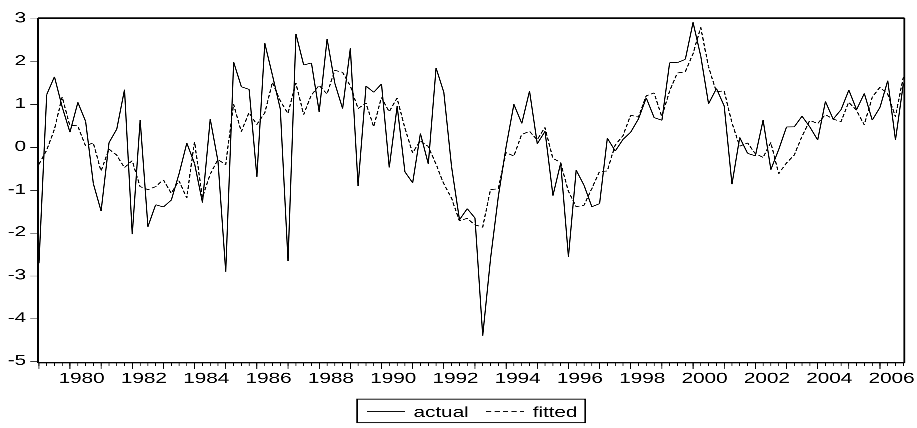

Figure 10: Production of building (without IPI): Actual and fitted values

Production of Services (with IPI)

Table 14: Model for production of private services with IPI (PSERM_GT)

Coincident equation

Variable	Coefficient	t-stat
PSERM_GT (t-1)	0.293	3.31
PSERM_GT (t-2)	0.322	3.95
Δ(EVACT_SV) (t)	0.015	2.12
IPI_MANUF_GT (t)	0.224	6.24
α	0.209	3.31
$\bar{R}^2 = 0.73$ – SE = 0.30 – DW = 2.09 – BKW = 4		
LM(5) = 1.48 [0.92] – DH = 0.55 [0.76] – NP = 0.61 [0.76]		
Chow(50%) = 1.20 [0.31] – Chow(90%) = 0.66 [0.71]		

P-values of test statistics are in brackets. PSERM_GT: production of private services (q-o-q); EVACT_SV: activity in private services (BdF); IPI_MANUF_GT: index of industrial production in manufactured goods (q-o-q, Insee). Estimation period: 1990 Q2 - 2006 Q4.

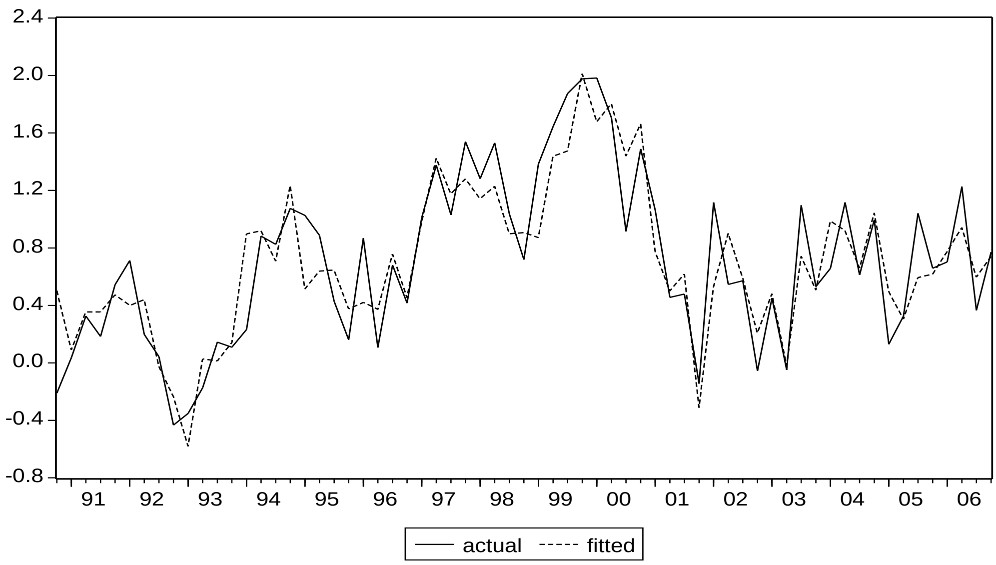

Figure 11: Production of services (with IPI): Actual and fitted values

Production of Services (without IPI)

Table 15: Model for production of private services without IPI (PSERM_GT)

Coincident equation

Variable	Coefficient	t-stat
PSERM_GT (t-1)	0.389	3.78
Δ(EVACT_SV) (t)	0.035	5.14
NIVTRES_SV (t)	0.016	3.70
Δ^2(NIVTRES_SV) (t)	0.028	3.78
OPPACHA (t-1)	0.010	2.53
Δ(CHOMPREV) (t)	-0.008	-2.33
α	0.420	3.66
$\bar{R}^2 = 0.75$ – SE = 0.30 – DW = 2.17 – BKW = 4		
LM(5) = 5.83 [0.32] – DH = 2.04 [0.36] – NP = 0.85 [0.57]		
Chow(50%) = 1.32 [0.24] – Chow(90%) = 1.29 [0.28]		

Future equation

Variable	Coefficient	t-stat
PSERM_GT (t-1)	0.300	2.11
Δ(PREVEFF_SV) (t-1)	0.057	3.43
Δ^4 (OPPACHA) (t-1)	0.018	3.24
Δ(NIVTRES_SV) (t-3)	0.015	3.00
α	0.392	4.87
$\bar{R}^2 = 0.57$ – SE = 0.37 – DW = 2.09 – BKW = 3		
LM(5) = 3.48 [0.63] – DH = 1.28 [0.53] – NP = 2.73 [0.016]		
Chow(50%) = 1.83 [0.05] – Chow(90%) = 0.86 [0.54]		

P-values of test statistics are in brackets. PSERM_GT: production of private services (q-o-q); EVACT_SV: activity in private services (BdF); NIVTRES_SV: treasury in private services (BdF); OPPACHA: likelihood of buying (Insee); CHOMPREV: prospects for evolution in unemployment (Insee); PREVEFF_SV: forecast staff levels in services (BdF); Estimation period: 1990 Q4 - 2006 Q4 (coincident); 1991 Q1 - 2006 Q4 (future).

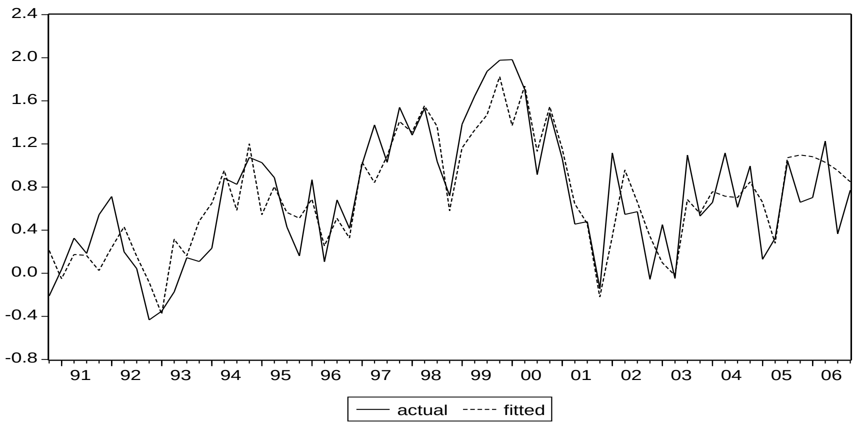

Figure 12: Production of services (without IPI): Actual and fitted values

Consumption of agri-food goods

Table 16: Model for consumption of agri-food (CIAA_GT)

Coincident equation

Variable	Coefficient	t-stat
CIAA_GT (t-1)	-0.432	-6.15
IPCH_AGRO_GT (t)	-0.425	-3.29
IPCH_AGRO_GT (t-1)	-0.529	-4.84
EVEFF_IAA (t)	0.134	5.13
α	0.641	7.22

$\bar{R}^2 = 0.43$ – SE = 0.65 – DW = 2.12 – BKW = 3
LM(5) = 4.99 [0.42] – DH = 0.95 [0.62] – NP = 0.83 [0.58]
Chow(50%) = 0.87 [0.64] – Chow(90%) = 1.03 [0.41]

Future equation

Variable	Coefficient	t-stat
EVCOM_IAA (t)	-0.050	-2.47
Δ IPCH_AGRO_GT (t-2)	-0.436	-2.52
EVPRO_IAA (t-3)	0.035	2.09
TUC_IAA(t-2)-TUC_IAA(t-4)	0.339	2.82
α	0.647	2.04

$\bar{R}^2 = 0.30$ – SE = 0.71 – DW = 2.62 – BKW = 4
LM(5) = 5.97 [0.31] – DH = 2.23 [0.33] – NP = []
Chow(50%) = 0.72 [0.80] – Chow(90%) = 0.72 [0.81]

P-values of test statistics are in brackets. CIAA_GT: consumption of agri-food (q-o-q); IPCH_AGRO_GT: consumer price index in agri-food (Eurostat, q-o-q); EVEFF_IAA: evolution staff levels in agri-food industry (BdF); EVCOM_IAA: commands evolution in agri-food industry (BdF); EVPRO_IAA: production evolution in agri-food industry (BdF); TUC_IAA: capacity utilization rate in agri-food industry (BdF); Estimation period: 1994 Q1 - 2006 Q4 (coincident); 1991 Q2 - 2006 Q4 (future).

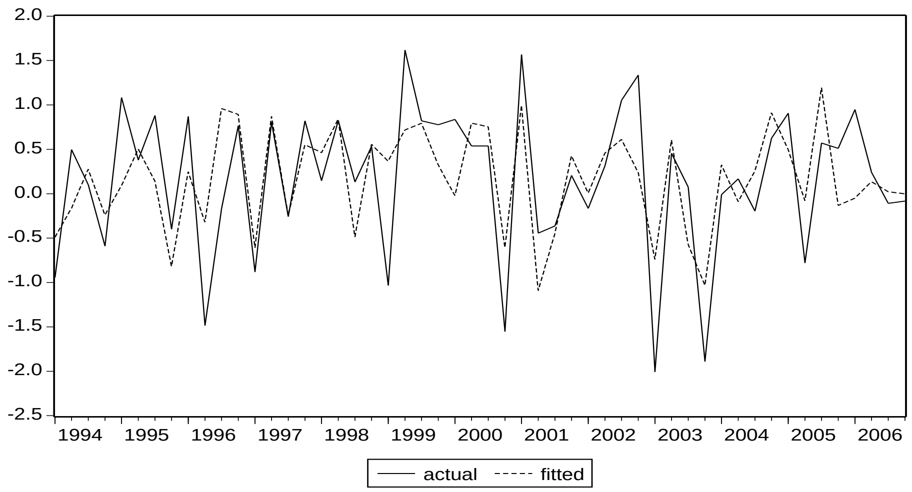

Figure 13: Consumption of agri-food: Actual and fitted values

Consumption of manufactured goods

Table 17: Model for consumption of manufactured goods (CMANU_GT)

Future equation

Variable	Coefficient	t-stat
CONSO_MANUF_GT (t-1)	-0.317	-2.77
ETCC_BC (t-1)	0.045	3.88
IVOL_TEXT_GT (t-1)	-0.175	-2.66
Δ^2 (PREVPRO_I) (t-1)	0.054	2.06
α	0.544	3.19
$\bar{R}^2 = 0.34$ – SE = 1.22 – DW = 2.15 – BKW = 2		
LM(5) = 4.55 [0.47] – DH = 5.90 [0.05] – NP = 2.88 [0.01]		
Chow(50%) = 0.22 [1.00] – Chow(90%) = 0.18 [1.00]		

P-values of test statistics are in brackets. CMANU_GT: consumption of manufactured goods (q-o-q); CONSO_MANUF_GT: monthly consumption of manufactured goods (q-o-q); ETCC_BC: level of order books for consumption goods (BdF); IVOL_TEXT_GT: clothing retail sales in volume (BdF,q-o-q); PREVPRO_I: production expectations in industry (BdF). Estimation period: 1991 Q1 - 2006 Q4.

Consumption of Energy

Table 18: Model for consumption of energy (CENER_GT)

Coincident equation

Variable	Coefficient	t-stat
RTE_SA_GT (t)	0.760	5.47
RTE_SA_GT (t-1)	0.184	3.96
α	-0.300	-2.83
$\bar{R}^2 = 0.50$ – SE = 1.56 – DW = 2.52 – BKW = 1		
LM(5) = 10.6 [0.06] – DH = 0.37 [0.83] – NP = 1.30 [0.29]		
Chow(50%) = 0.95 [0.55] – Chow(90%) = 1.41 [0.25]		

Future equation

Variable	Coefficient	t-stat
CENER_GT (t-1)	-0.621	-6.75
CENER_GT (t-2)	-0.356	-3.87
α	0.510	2.164
$\bar{R}^2 = 0.29$ – SE = 2.43 – DW = 2.04 – BKW = 2		
LM(5) = 4.67 [0.45] – DH = 0.83 [0.660] – NP = []		
Chow(50%) = 0.758 [0.80] – Chow(90%) = 0.436 [0.998]		

P-values of test statistics are in brackets. CENER_GT: consumption of energy (q-o-q); RTE_SA_GT: consumption of electricity (q-o-q). Estimation period: 1996 Q2 - 2006 Q4 (coincident); 1979 Q2 - 2006 Q4 (future).

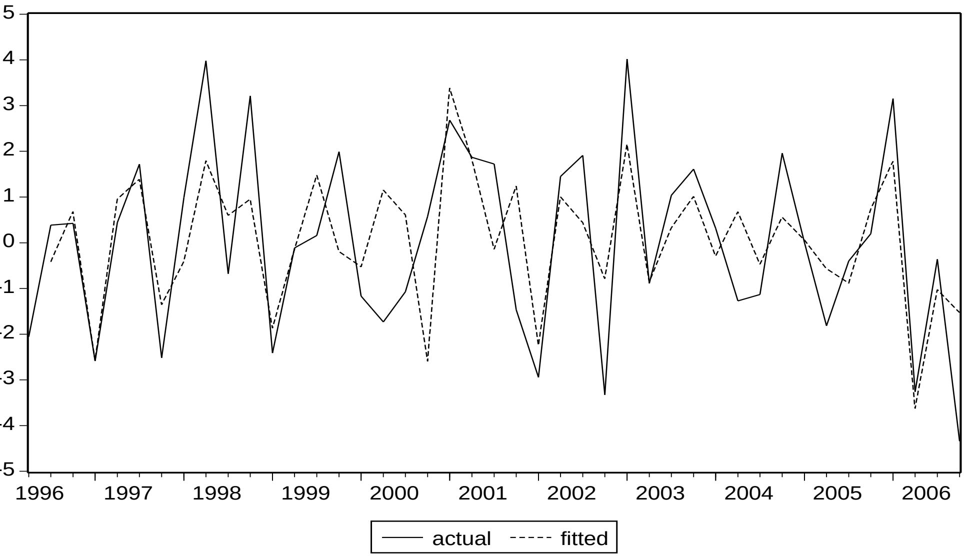

Figure 14: Consumption of energy: Actual and fitted values

Consumption of services

Table 19: Model for household consumption in services (CSERV_GT)

Coincident equation

Variable	Coefficient	t-stat
Δ(EVACT_SV) (t)	0.019	3.49
NIVTRES_SV (t)	0.012	3.94
Δ^2(NIVTRES_SV) (t)	0.018	3.26
OPPACHA (t-1)	0.012	3.96
Δ(CHOMPREV) (t)	-0.006	-2.45
α	0.654	9.52
$\bar{R}^2 = 0.54$ – SE = 0.25 – DW = 1.88 – BKW = 2		
LM(5) = 5.09 [0.41] – DH = 0.12 [0.94] – NP = 0.71 [0.70]		
Chow(50%) = 0.72 [0.82] – Chow(90%) = 0.78 [0.61]		

Future equation

Variable	Coefficient	t-stat
CSERV_GT (t-4)	-0.275	-2.42
NIVTRES_SV (t-3)	0.015	4.00
Δ(PREVEFF_SV) (t-1)	0.033	2.83
OPPACHA (t-2)	0.012	3.09
Δ(CHOMPREV) (t-1)	-0.006	-2.04
α	0.79	6.85
$\bar{R}^2 = 0.45$ – SE = 0.27 – DW = 2.07 – BKW = 4		
LM(5) = 3.31 [0.65] – DH = 3.08 [0.21] – NP = 1.22 [0.30]		
Chow(50%) = 0.922 [0.60] – Chow(90%) = 0.798 [0.74]		

P-values of test statistics are in brackets. CSERV_GT: household consumption in services (q-o-q); EVACT_SV: changes in activity in services (BdF); NIVTRES_SV: cash flow situation in services (BdF); PREVEFF_SV: forecast staff levels in services (BdF); OPPACHA: likelihood of buying (Insee); CHOMPREV: unemployment outlook (Insee). Estimation period: 1990 Q1 - 2006 Q4.

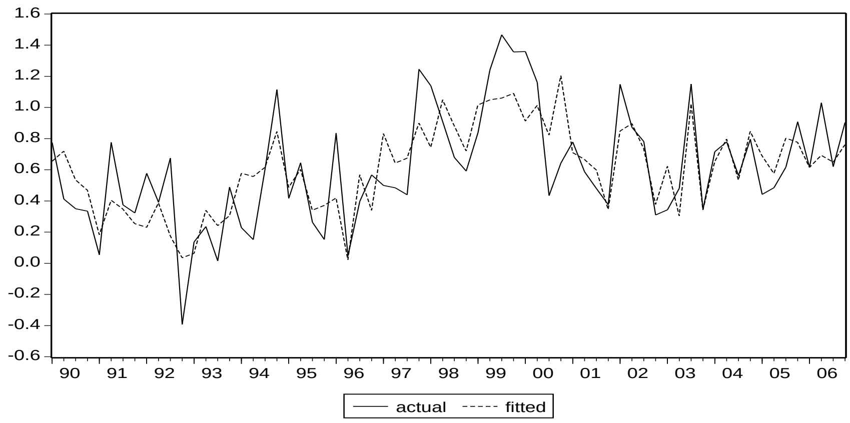

Figure 15: Consumption of services: Actual and fitted values

Government Consumption

Table 20: Model for government consumption (CAPU_GT)

Coincident and Future equation

Variable	Coefficient	t-stat
CAPU_GT (t-1)	0.244	2.76
CAPU_GT (t-2)	0.497	4.99
CAPU_GT (t-4)	-0.171	-1.84
α	0.224	3.48
$\bar{R}^2 = 0.31$ – SE = 0.33 – DW = 1.99 – BKW = 4		
LM(5) = 2.20 [0.82] – DH = 3.23 [0.20]		
NP = 6.96 [0.96] – Chow(50%) = 0.85 [0.71]		
Chow(90%) = 0.48 [0.91]		

P-values of test statistics are shown in brackets. CAPU_GT: Government consumption (q-o-q). Estimation period: 1980 Q2 - 2006 Q4.

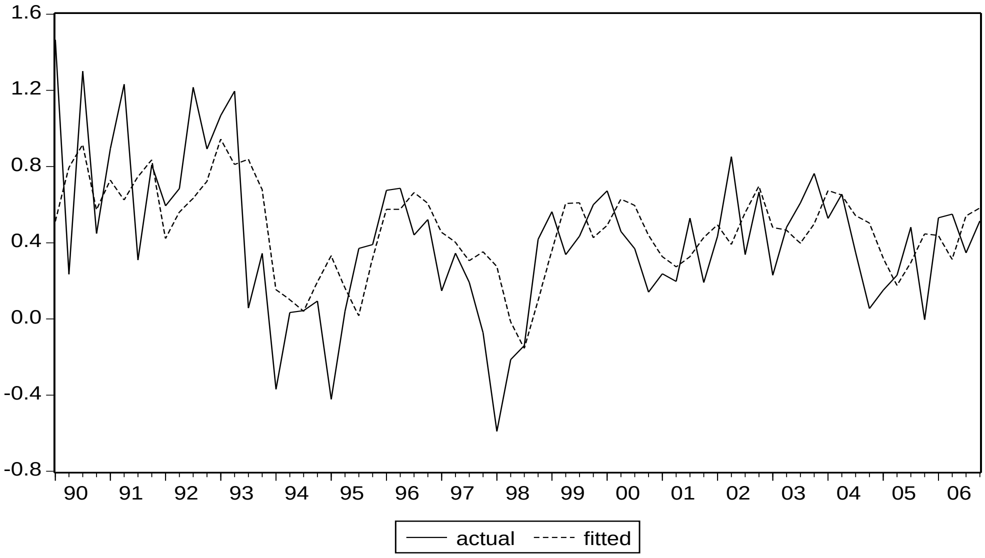

Figure 16: Government consumption: Actual and fitted values

Investment in Material

Table 21: Model for investment in equipment (INVSNFEI_MAT_GT)

Coincident equation

Variable	Coefficient	t-stat
INVSNFEI_MAT_GT(t-2)	0.259	3.099
EVLIV_BE(t-1)	0.115	3.665
D(TUC_I)(t)	0.611	3.650
α	-0.604	-2.286
$\bar{R}^2 = 0.464$ – SE = 1.43 – DW == 2.17 – BKW = 3		
LM(5) = 4.57 [0.46] – DH = 0.07 [0.96]		
NP = 0.86 [0.52] – Chow(50%) = 0.86 [0.64]		
Chow(90%) 0.75= [0.66]		

Future equation

Variable	Coefficient	t-stat
INVSNFEI_MAT _GT (t-2)	0.422	3.68
delta(TUC_I) (t-1)	0.744	3.26
α	0.532	2.163
$\bar{R}^2 = 0.34$ – SE = 1.58 – DW = 1.97 – BKW = 1		
LM(5) = 2.67 [0.02] – DH = 0.28. [0.867] – NP = 1.31 [0.27]		
Chow(50%) = 1.233 [0.32] – Chow(90%) = 1.183 [0.307]		

P-values of test statistics are in brackets. INVSNFEI_MAT_GT: corporate investment in equipment (q-o-q); EVLIV_BE: changes in deliveries, capital goods (BdF); TUC_I: capacity utilisation rate, total industry (BdF). Estimation period: 1987 Q4 - 2006 Q4.

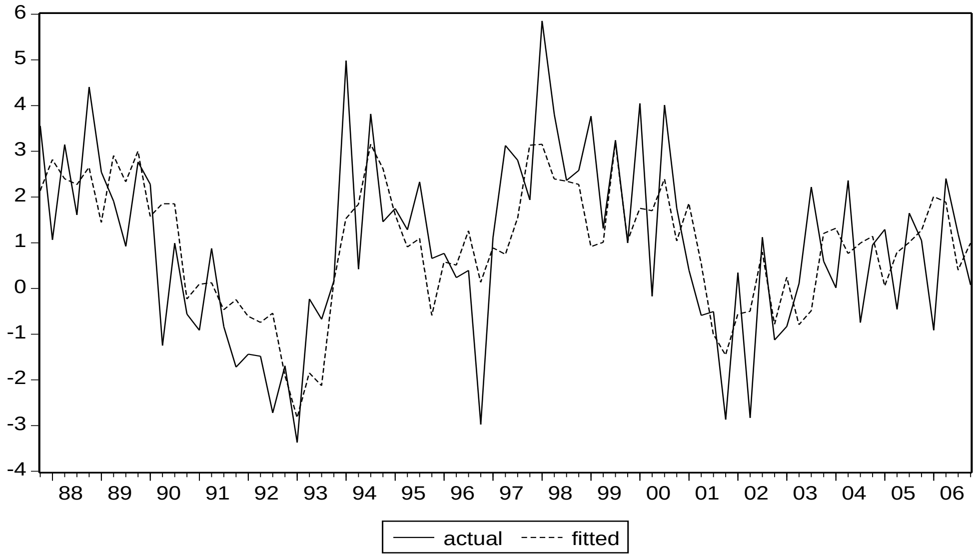

Figure 17: Investment in material: Actual and fitted values

Investment in construction

Table 22: Model for investment in construction (INVSNFEI_BAT_GT)

Coincident equation

Variable	Coefficient	t-stat
Δ(CARNET_BAT) (t-2)	0.098	3.87
EFFPREV_BAT (t)	0.065	11.37
α	0.319	1.67
$\bar{R}^2 = 0.57$ – SE = 1.46 – DW = 2.12 – BKW = 1		
LM(5) = 2.80 [0.72] – DH = 1.10 [0.57] – NP = 0.42 [0.73]		
Chow(50%) = 0.58 [0.94] – Chow(90%) = 0.62 [0.87]		

Future equation

Variable	Coefficient	t-stat
EFFPREV_BAT (t-1)	0.060	9.61
Δ(CARNET_BAT) (t-2)	0.120	3.92
α	0.301	1.61
$\bar{R}^2 = 0.53$ – SE = 1.49 – DW = 2.02 – BKW = 1		
LM(5) = 1.60 [0.90] – DH = 0.69 [0.70] – NP = 1.45 [0.23]		
Chow(50%) = 0.73 [0.80] – Chow(90%) = 0.63 [0.89]		

P-values of test statistics are in brackets. INVSNFEI_BAT_GT : corporate investment in construction (q-o-q); CARNET_BAT: Demand and order levels in building industry (Insee); EFFPREV_BAT: employment outlook in building industry (Insee). Estimation period: 1989 Q4 - 2006 Q4.

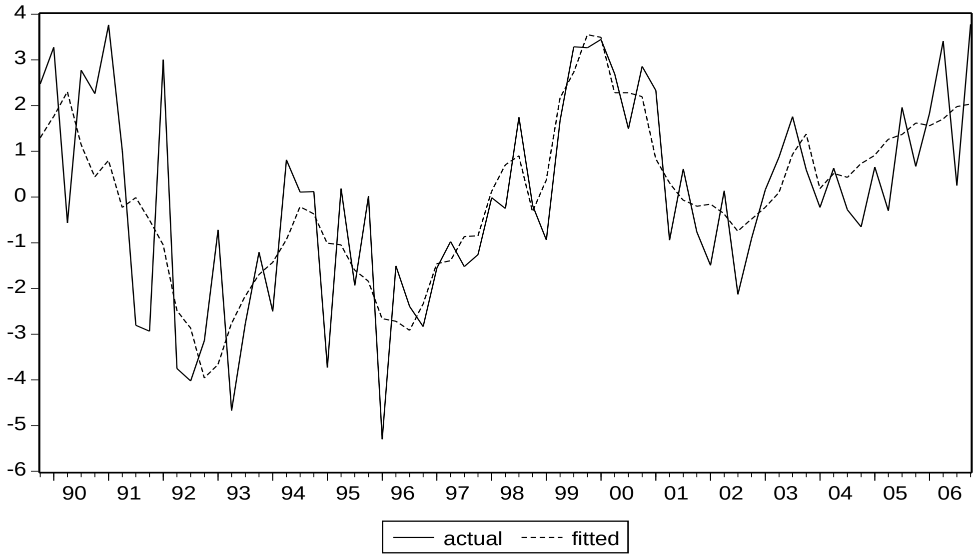

Figure 18: Investment in building: Actual and fitted values

Households Investment

Table 23: Model for household investment (INVMEN_GT)

Coincident equation

Variable	Coefficient	t-stat
LOGEMENTS_SA_GT (t)	11.395	3.98
LOGEMENTS_SA_GT (t-1)	9.822	3.25
LOGEMENTS_SA_GT (t-2)	9.401	3.10
LOGEMENTS_SA_GT (t-3)	8.066	2.90
LOGEMENTS_SA_GT (t-4)	8.012	3.12
α	0.043	0.22
$\bar{R}^2 = 0.26$ – SE = 1.61 – DW = 2.32 – BKW = 2		
LM(5) = 9.76 [0.08] – DH 2.47= [0.29] – NP 1.55= [0.14]		
Chow(50%) = 0.40 [1.00] – Chow(90%) = 0.22 [0.99]		

Future equation

Variable	Coefficient	t-stat
ACTPREV_BAT (t-1)	0.079	4.09
ACTPREV_BAT (t-3)	-0.070	-3.56
α	0.368	1.61
$\bar{R}^2 = 0.18$ – SE = 1.75 – DW = 2.04 – BKW = 4		
LM(5) = 2.67 [0.75] – DH = 0.44 [0.80] – NP = 2.90 [0.06]		
Chow(50%) = 0.62 [0.91] – Chow(90%) = 0.31 [0.94]		

P-values of test statistics are in brackets. INVMEN_GT : household investment (q-o-q); LOGEMENTS_SA_GT : declared housings starts (Ministry of Equipment, q-o-q); ACTPREV_BAT: production outlook in building industry (Insee). Estimation period: 1987 Q2 - 2006 Q4 (coincident); 1989 Q4 - 2006 Q4 (future).

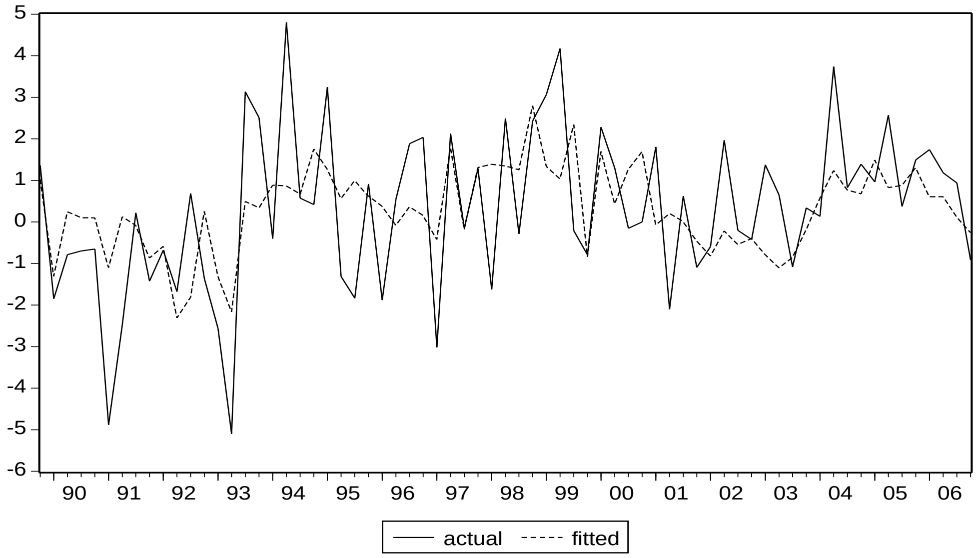

Figure 19: Household investment: Actual and fitted values

Government investment

Table 24: Model for government investment (INVAPU_GT)

Coincident equation

Variable	Coefficient	t-stat
INVAPU_GT (t-1)	0.593	5.96
FNTP_GT (t)	0.280	7.63
FNTP_GT (t-1)	-0.161	-3.18
α	0.182	1.36
$\bar{R}^2 = 0.60$ – SE = 1.07 – DW = 1.72 – BKW = 2		
LM(5) = 8.99 [0.11] – DH = 5.42 [0.07] – NP = 2.00 [0.08]		
Chow(50%) = 0.50 [0.98] – Chow(90%) = 0.74 [0.64]		

Future equation

Variable	Coefficient	t-stat
INVAPU_GT (t-1)	0.661	5.13
(FNTP_GT) (t-1)	-0.223	-3.66
α	0.277	1.55
$\bar{R}^2 = 0.23$ – SE = 1.47 – DW = 2.00 – BKW = 2		
LM(5) == 2.61 [0.75] – DH = 3.17 [0.20] – NP = 0.54 [0.74]		
Chow(50%) = 0.457 [0.98] – Chow(90%) = 0.435 [0.87]		

P-values of test statistics are in brackets. INVAPU_GT: Government investment (q-o-q); FNTP_GT: achieved public works (q-o-q). Estimation period: 1988 Q3 - 2006 Q4.

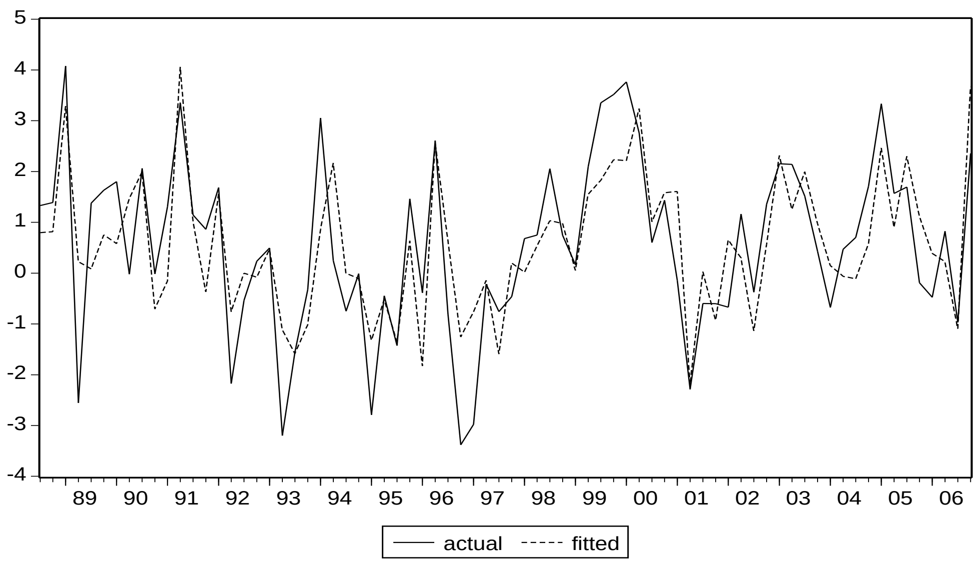

Figure 20: Government investment: Actual and fitted values

Imports

Table 25: Model for imports (IMPORT_GT)

Coincident equation

Variable	Coefficient	t-stat
Δ(EU5) (t)	0.125	3.68
EVCOM_I (t-1)	0.088	4.71
IMP_DOUANES_GT (t)	0.249	4.27
Δ(EUUSD) (t)	-4.198	-2.03
α	0.184	1.40
$\bar{R}^2 = 0.72$ – SE = 0.89 – DW = 2.27 – BKW = 3		
LM(5) = 6.56 [0.26] – DH = 0.88 [0.64] – NP = 0.75 [0.61]		
Chow(50%) = 0.60 [0.91] – Chow(90%) = 1.16 [0.34]		

Future equation

Variable	Coefficient	t-stat
IMPORT_GT (t-4)	-0.313	-3.54
EVCOM_I (t-1)	0.119	4.80
IMP_DOUANES_GT (t-1)	0.155	2.36
Δ(EUUSD) (t-1)	-8.036	-2.67
α	0.509	2.23
$\bar{R}^2 = 0.58$ – SE = 1.08 – DW = 2.14 – BKW = 3		
LM(5) = 9.53 [0.09] – DH = 2.15 [0.34] – NP = 0.67 [0.67]		
Chow(50%) = 1.21 [0.32] – Chow(90%) = 0.76 [0.59]		

P-values of test statistics are in brackets. IMPORT_GT: imports (q-o-q); EU5: production expectations for the months ahead (Eurostat); EVCOM_I: changes in orders, total industry (BdF); IMP_DOUANES_GT: monthly imports in value (customs); EUUSD: euro-dollar exchange rate. Estimation period: 1992 Q2 - 2006 Q4 (coincident); 1992 Q3 - 2006 Q4 (future) .

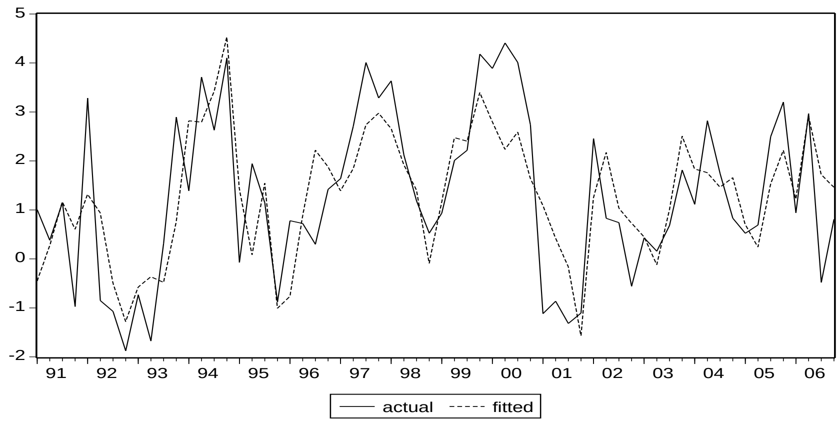

Figure 21: Imports: Actual and fitted values

Exports

Table 26: Model for exports (EXPORT_GT)

Coincident equation

Variable	Coefficient	t-stat
EXPORT_GT (t-1)	-0.235	-2.34
Δ(EU5) (t)	0.070	2.18
EVCOME_I (t)	0.138	4.33
EXP_DOUANES_GT (t)	0.210	2.13
Δ(EUUSD) (t-1)	-9.111	-2.40
α	0.064	0.38
$\bar{R}^2 = 0.68$ – SE = 1.04 – DW = 2.04 – BKW = 3		
LM(5) = 5.32 [0.38] – DH 2.21 = [0.33] – NP = 0.69 [0.82]		
Chow(50%) 0.70 = [0.82] – Chow(90%) 1.41 = [0.23]		

Future equation

Variable	Coefficient	t-stat
EXPORT_GT (t-1)	-0.236	-2.18
EXPORT_GT (t-4)	-0.443	-4.61
EVCOME_I (t-1)	0.141	4.25
PREVSTPF_BI (t-2)	-0.284	-3.16
CARNET_ETR_I (t-1)	0.031	2.36
Δ(EUUSD) (t-1)	-10.600	-2.98
α	0.143	0.27
$\bar{R}^2 = 0.13$ – SE = 1.29 – DW = 1.81 – BKW = 6		
LM(5) = 8.48 [0.33] – DH = 1.32 [0.52] – NP = 0.54 [0.84]		
Chow(50%) = 0.65 [0.88] – Chow(90%) = 0.68 [0.66]		

P-values of test statistics are in brackets. EXPORT_GT: exports (q-o-q); EU5: production expectations for months ahead (Eurostat); EVCOME_I: changes in foreign orders, industry (BdF); EXP_DOUANES_GT: exports in value (customs); EUUSD: euro-dollar exchange rate. Estimation period: 1992 Q2 - 2006 Q4 (coincident); 1991 Q1 - 2006 Q4 (future).

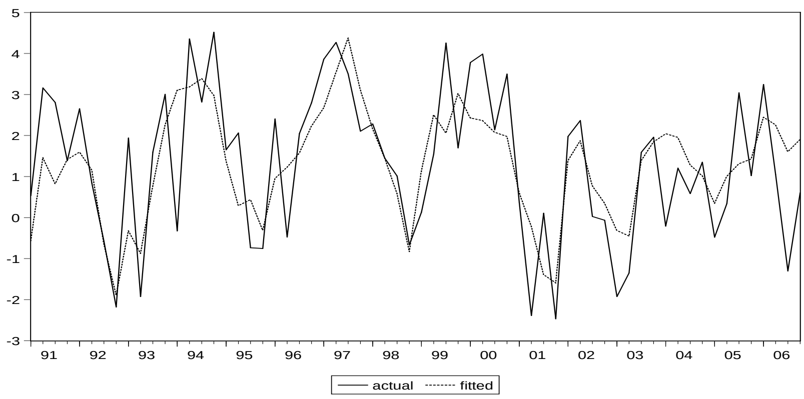

Figure 22: Exports: Actual and fitted values

Production aggregation

Table 27: Model for production aggregation (PTOT_GT)

Variable	Coefficient	t-stat
PIAA_GT (t)	0.088	12.27
PMANU_GT (t)	0.224	15.68
PENER_GT (t)	0.035	8.51
PBAT_GT (t)	0.090	7.17
PSERM_GT (t)	0.449	14.27
α	0.049	2.07
$\bar{R}^2 = 0.996$ – SE = 0.027 – DW = 1.49 – BKW = 3		
LM(5) = 3.54 [0.62] – DH 0.97 = [0.62]		
NP = 0.53 [0.83] – Chow(50%) 0.64 = [0.76]		
Chow(90%) 2.67 = [0.10]		

P-values of test statistics are in brackets. PTOT_GT: total production (q-o-q); PIAA_GT: production of agri-food goods(q-o-q); PMANU_GT: production of manufactured goods (q-o-q); PENER_GT: production of energy (q-o-q); PBAT_GT: production in construction (q-o-q); PSERM_GT: production of market services (q-o-q). Estimation period: 2001 Q1 - 2006 Q4.

GDP

Table 28: Model for GDP (PIB_GT)

Variable	Coefficient	t-stat
PIB_GT (t-4)	-0.135	-3.75
PTOT_GT (t)	0.682	22.76
α	0.196	7.77
$\bar{R}^2 = 0.96$ – SE = 0.066 – DW = 1.58 – BKW = 2		
LM(5) = 3.32 [0.65] – DH 0.86 = [0.65]		
NP = 0.27 [0.89] – Chow(50%) 0.42 = [0.92]		
Chow(90%) 0.10 = [0.91]		

P-values of test statistics are in brackets. PIB_GT: Gross Domestic Product (q-o-q); PTOT_GT: total production (q-o-q). Estimation period: 2001 Q1 - 2006 Q4.

Household consumption aggregation

Table 29: Model for household consumption aggregation (CMEN_GT)

Variable	Coefficient	t-stat
CIAA_GT (t)	0.124	10.05
CMANU_GT (t)	0.261	12.28
CENER_GT (t)	0.073	14.62
CSERV_GT (t)	0.441	10.06
α	0.067	2.17
$\bar{R}^2 = 0.97$ − SE = 0.048 − DW = 0.94 − BKW = 4		
LM(5) = 7.55 [0.18] − DH 0.69 = [0.71]		
NP = 0.70 [0.69] − Chow(50%) 0.72 = [0.70]		
Chow(90%) 0.62 = [0.55]		

P-values of test statistics are in brackets. CMEN_GT: household consumption (q-o-q); CIAA_GT: household consumption of agri-food goods(q-o-q); CMANU_GT: household consumption of manufactured goods (q-o-q); CENER_GT: household consumption of energy (q-o-q); CSERV_GT: household consumption of services (q-o-q). Estimation period: 2001 Q1 - 2006 Q4.

Investment aggregation

Table 30: Model for investment aggregation (INV_GT)

Variable	Coefficient	t-stat
INVMEN_GT (t)	0.203	3.56
INVSNFEI_BAT_GT (t)	0.180	3.24
INVSNFEI_MAT_GT (t)	0.389	7.10
INVAPU_GT (t)	0.141	2.41
α	0.197	2.35
$\bar{R}^2 = 0.86$ − SE = 0.345 − DW = 2.60 − BKW = 2		
LM(5) = 3.29 [0.66] − DH 1.89 = [0.39]		
NP = 0.92 [0.53] − Chow(50%) 2.86 = [0.09]		
Chow(90%) 0.51 = [0.61]		

P-values of test statistics are in brackets. INV_GT: total investment (q-o-q); INVSNFEI_MAT_GT: corporate investment in equipment (q-o-q); INVSNFEI_BAT_GT: corporate investment in construction (q-o-q); INVMEN_GT: household investment (q-o-q); INVAPU_GT: government investment (q-o-q). Estimation period: 2001 Q1 - 2006 Q4.

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