Monthly forecasting of French GDP: a revised version of the OPTIM model (provisional draft) *

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Abstract

This paper presents a revised version of the model OPTIM, proposed by Irac and Sédillot (2002)and used at Banque de France to predict French GDP quarterly growth rate. 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. 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. A rolling forecast study is carried out to assess the forecasting performance of the revised OPTIM model in the prediction of aggregated GDP, by taking publication lags into account in order to run pseudo real-time forecasts. It turns out that the model outperforms benchmark models.

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

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] 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, factors 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; Altissimo et al., 2007). However, this approach appears 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 to 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 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).

We propose to construct BM for each of main GDP components for which input variables are selected through an automatic selection procedure that allows the econometrician to exploit the availability of 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). [2] These BMs are estimated using quarterly averages of monthly data as explanatory variables.

A second objective of this tool 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 timely publication in order to get early information for the quarter of interest. Soft data are often used to construct GDP growth indicators (e.g., Grassman and Keereman, 2001; Sédillot and Pain, 2003; Rünstler and Sédillot, 2003; Grenouilleau, 2004). Indeed, 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.

However, studies in general report that soft data contain little information beyond real activity data, but they mostly use quarterly data or ignore publication lags (e.g., Rünstler and Sédillot,

[1] A number of studies demonstrate the benefits 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] 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.

2003; Forni et al., 2003; Baffigi et al., 2004; Banerjee et al., 2005)[3]. Banbura and Rünstler (2007) also find that real activity data are the most important source of information. However, they show that, once their publication lag is taken into account, real activity data are much less relevant, while surveys take their place. In this study, high attention has been paid in forecast evaluation exercises to the precise information set that is available in real time.

2 Modelling strategy and data selection

2.1 A detailed projection

The aim of the model is to project French GDP growth and its main components for the coincident quarter. We consider GDP growth rate as released by Insee, the French national statistics institute, in the national account series. We distinguish between the supply side and the demand side, but all components on both sides are not modelled: 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 unmodelled. The components and subcomponents that are modelled are :

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

[3]Exceptions to this rule 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 data. Hansson et al. (2005) report that the inclusion of summary measures 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, three various forecasting exercises will be produced to estimate GDP growth rate at this quarter. As soon as enough information is available (around the end of the second month of the quarter), the first estimate of the growth rate for the current quarter will be computed, then one month later the second and two months later the third and last estimate. Thus, the last estimate will be computed around 15 days before the official release of GDP figures by Insee. When data are missing for some months of the last quarter, the value for the quarter is computed as the 3-month moving average of the last available observation. Generally, for each GDP component, the same equation is used for each of the three forecasts. The only exception concerns the inclusion of the 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 an equation without IPI and another one including the IPI. Depending on the date of the forecasting exercise, one of the two equations will be chosen.

2.3 A large dataset

Equations are estimated at a quarterly frequency, but as a general rule, data are only taken into account if they provide monthly information, i.e. if they are available on a monthly or higher frequency. 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 explanative variables, but financial data have not been considered. Series have been selected so that their publication lag is less than two months, in order to have fresh information on the quarter of interest. All the data are seasonally adjusted. The models should also contain a limited number of variables to prevent overspecification and to facilitate updates once the models are operative.

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[4]. 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. The 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
New cars registrations	CCFA	Hard	Monthly	+2
Electricity consumption	RTE	Hard	Daily	+1
Declared housing starts	Ministry of Equipment	Hard	Monthly	+30
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 Bank of 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 analyses, which had been 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.

[4]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 can be re-estimated without difficulty. Data selection 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.

- Relevant series are selected with an automatic model selection procedure which yields parsimonious short run dynamic adjustment equations [5]. This procedure is based on a general-to-specific (Gets) modelling strategy [6], proposed by David Hendry and which Hoover and Perez (1999) first suggested implementing in an automated way [7]. In this study, we use GROCER [8] (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 statistic 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. We choose the variables in the GUM to avoid multicolinearity problems.

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

[6] 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)

[7] 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.

[8] 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 equation relates quarterly average of the monthly explanatory variables (X) to quarterly GDP growth or National Account components Y. The general specification of the autoregressive-distributed-lag (ADL) bridge equation is as follows

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

- 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 mix of two similar sources of information (such as the Banque de France and the Insee monthly surveys on industry) has been avoided by considering alternatively each data set and by comparing resulting equations according to their statistical properties. This procedure alows to limit the risks of high correlation between explanative variables and also to shorten the data selection step.

- 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 explanative 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. A final set of approximately 1 to 5 equations is also available but not 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 rolling forecasts are carried out to determine the final equations. The rolling forecasts have been implemented over the period 2000q1-2006q4, with 3 forecasts by quarter. Coefficients are estimated at each step. This exercise takes into account the availability of data, under the assumption that a forecasting exercise will be 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 are published mid-May, and that figures for the fourth quarter of the preceding year are available mid-February, three forecasts 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 rolling forecasts, as well as in actual forecasting exercises, when data are missing for some months of the last quarter, the value for the quarter is computed as the 3-month moving average of the last available observation. As mentioned above, different equations can 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 will be kept for the three monthly projection exercises only if they bring significantly better results at the time they are being used.

3 OPTIM equations

3.1 Production

Five components of production have been modelled: agri-food goods, energy, manufactured goods, construction and market services. The sum of these five components is not equal to total production: non-market services, accounting for approximately 15% of production, is missing. However, the five modelled components account for almost all of the variance of total production (the R^2 statistic of the aggregation equation, with production explained by the modelled components, is over 0.99).

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

3.1.1 Production of agri-food goods

The production of agri-food goods has been modelled using the industrial production index in agri-food goods and the Banque de France (BdF) survey on agri-food industry. Series from the Insee survey on agri-food were also tested as explanative variables but not selected. In the first equation, the only explanative variable is the industrial production index in agri-food goods. In the second one, the selected variables are:

- changes in prices of the finished goods in agri-food industries (BdF);
- production forecasts in agri-food industries (BdF);
- changes in deliveries in agri-food industries (BdF).

3.1.2 Production of manufactured goods

Manufacturing production has been modelled using the industrial production index 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. The series included in the first equation are:

- industrial production index for manufactured goods;

- personal production outlook in manufacturing industry (Insee).

In the second equation, the following variables were selected:

- personal production outlook in manufacturing industry (Insee);
- recent changes in output (Insee);
- dummy variables for 1997q1 and 1997q2.

3.1.3 Production of energy

A first equation is directly based on the quarterly increase in the energy component of the industrial production index. Survey data offer no direct information on the energy sector. Nevertheless, RTE[9] provides a daily estimation of electricity consumption in France. A series was computed on the basis of this information and seasonally adjusted using Census X12. The second equation for production of energy is based on the quarterly changes in this series.

3.1.4 Production in construction

A first equation for this component is based on the industrial production index for construction and on data from the Insee survey in the construction sector. A second one uses exclusively data from this survey. The following series appear in the first equation:

- industrial production index for construction;
- recent changes in output in the construction sector (Insee);
- demand and order books in the construction sector (Insee).

In the second equation, the following indicators are selected:

- production outlook in the construction sector (Insee);
- demand and order books in the construction sector (Insee);
- employment outlook in the construction sector (Insee);
- recent changes in employment in the construction sector (Insee);
- price outlook in the construction sector (Insee).

3.1.5 Production of private services

Production of private services has been modelled using the industrial production index in manufactured goods, the BdF survey on services, and the Insee consumer confidence survey. Data from the INSEE survey on services were included in the selection process but not kept. The selected variables in the first equation are:

- industrial production index in manufactured goods;
- changes in activity in services (BdF);

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

- cash flow situation in services (BdF);

In the second equation, the IPI in the manufacturing sector is dropped and series from the Insee consumer confidence survey are introduced:

- changes in activity in services (BdF);
- cash flow situation in services (BdF);
- likelihood of saving (Insee);
- unemployment outlook (Insee).

3.2 Household consumption

Four components of household consumption were modelled: agri-food goods, energy, manufactured goods and services. Those four components cover all of household consumption.

3.2.1 Household consumption in agri-food goods

The Banque de France survey on manufacturing industry features series relative to the agri-food sector. One of these series, namely "expected staff levels", is selected in the final equation for household consumption in agri-food goods. The equation also relies on a series of quarterly change in agri-food goods prices, which is computed after a seasonal adjustment of the Harmonised Index of Consumption Prices series published by Eurostat.

3.2.2 Household consumption in energy

The forecast of household consumption in energy is obtained with an equation on the RTE series of electricity consumption (also used in one of the equations for production of energy, see above section 3.1.). A regression on the industrial production index for energy was tested but rejected.

3.2.3 Household consumption in manufactured goods

This component is directly obtained from the monthly indicator of 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. It is available 25 days after the end of month. When monthly data are missing for the current quarter, they are forecast using an AR model. An alternative equation, based on Banque de France survey components relative to retail trade and consumption goods, showed satisfying statistics, but provided worse RMSE in the rolling forecast exercises.

3.2.4 Household consumption in services

Two main data sources have been separately tested for estimating consumption in services: the Banque de France survey on services and the Insee survey on services. Equations were first selected on 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 equation uses data from the Banque de France survey on services plus data from the Insee survey on households. Explanative variables are the following:

- changes in activity in services (BdF);

- cash flow situation in services (BdF);
- likelihood of buying (Insee);
- unemployment outlook (Insee).

3.3 Government consumption

Government consumption is forecast with an auto-regressive model. In fact, no better equation based on economic variables was found. In national accounts, Government consumption is calculated from Government production, which is estimated at factor costs, and is therefore corresponding 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 components, 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 of the aggregation equation is close to 0.9. For all components of investment, only survey data were selected.

3.4.1 Corporate investment in equipment

Forecast of equipment investment is based on the Banque de France survey on industry, and notably on answers from capital good industry companies. Series of company car registrations were also tested but not kept. The selected variables are:

- changes in deliveries, capital goods (BdF);
- capacity utilisation rate, total industry (BdF).

3.4.2 Corporate investment in construction

Forecasts of investment in construction are based on the Insee survey in the construction sector. The following series were selected:

- demand and order books in the construction sector (Insee);
- employment outlook in the construction sector (Insee).

3.4.3 Household investment

As in the case for corporate investment in construction, household investment is modelled with variables from the Insee survey on building industry. A series of declared housing starts, published by the Ministry of Equipment with a lag of 30 days is also taken into account. In the final equation, the following variables are used:

- production outlook in the construction sector (Insee);
- employment outlook in the construction sector (Insee);
- housing starts (Ministry of Equipment).

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 month. It is noteworthy that this series is directly used by Insee to compute Government investment.

3.5 External trade

Though data selection methods were separately applied to the imports and exports equations, they led to very similar sets of explanative variables, suggesting thus robustness of the relationships. This result is all the more impressive as many data sources were included in the selection process: Banque de France surveys on industry and retail trade, Insee surveys on industry and retail trade and EU Commission business survey. In the final equations, only data from the Banque de France survey on industry and from the EU Commission survey were selected.

For the import equation, variables are the following:

- changes in order books, total industry (BdF);
- production expectations for the months ahead (European Commission)

For exports, selected variables are:

- changes in foreign order books , total industry (BdF);
- production expectations for the months ahead (European Commission)

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" both for 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

The results presented in this section correspond to the rolling forecast exercise detailed in section 2.5. Benchmark results correspond to AR models and to naïve projections (the forecast is equal to the last observation). The AR models have been estimated over the longest possible sample. Significant lags up to the 4th order with an associated probability of the t-stat of less than 10% were kept. Results are presented in table 2.

For all equations, the root mean-squared errors (RMSE, henceforth) are lower than those of the AR and naïve predictors. As expected, the accuracy of projections generally increases with each forecast: in most cases, the smallest RMSE are observed for the third forecast.

For the production components, equations based on the industrial production indexes 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

Component		First	Second	Third	AR	Naive
GDP	with IPI	0.32	0.31	0.23	0.38	0.51
	without IPI	0.27	0.25	0.25		
Production Agri-food	with IPI	0.49	0.47	0.45	0.57	0.68
	without IPI	0.54	0.54	0.54		
Production Manufactured	with IPI	1.14	1.07	0.71	1.28	1.73
	without IPI	0.82	0.79	0.79		
Production Energy	with IPI	1.56	1.48	1.21	1.44	2.52
	without IPI	1.44	1.34	1.34		
Production Construction	with IPI	0.63	0.57	0.55	0.67	0.76
	without IPI	0.62	0.60	0.60		
Production Services	with IPI	0.41	0.41	0.34	0.45	0.59
	without IPI	0.44	0.39	0.37		
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		0.80	0.77	0.71	0.87	1.24
Imports		1.23	1.13	1.13	1.31	1.54
Exports		1.46	1.32	1.27	1.62	2.07

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

selected for the different forecasts.

For the aggregated GDP, RMSEs are obtained for the first and second forecasts with an equation aggregating the components but without IPI and for the third forecast with an equation including IPI. [10] The estimated RMSEs for the first, second and third forecasts are respectively 0.27 percentage point, 0.25 pp and 0.23 pp. This result seems satisfying in the sense that the RMSEs of Insee GDP forecasts, [11] which are implemented two months before GDP releases, has actually attained 0.29 pp over the same period, and the RMSE of the Banque de France GDP forecasts [12], made one month before GDP releases, has attained 0.26 pp.
Diebold-Mariano tests of equality of forecast performance are carried out (see results in table 3). The modified Diebold-Mariano test of Harvey, Leybourne and Newbold (1997) is to be implemented. However, due to the short forecast horizon, $h = 1$, and to the relatively large number of forecast, $n = 28$, results should not be strongly different. Except for production of energy and construction without IPI, DM tests indicate that the third forecasts significantly outperfom benchmark AR forecasts, with a confidence level of $1 - \alpha = 0.90$. Especially, GDP forecasts (without IPI for first and second and with IPI for the third) are strongly better than the benchmark with a confidence level $1 - \alpha = 0.99$.

[10] 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.

[11] The Insee quarterly GDP forecasts are presented in the "Note de Conjoncture" or "Point de Conjoncture".

[12] Those forecasts correspond to the monthly index of business activity (MIBA), presented each month with the Banque de France monthly business survey and computed solely on the basis of the Banque de France survey results.

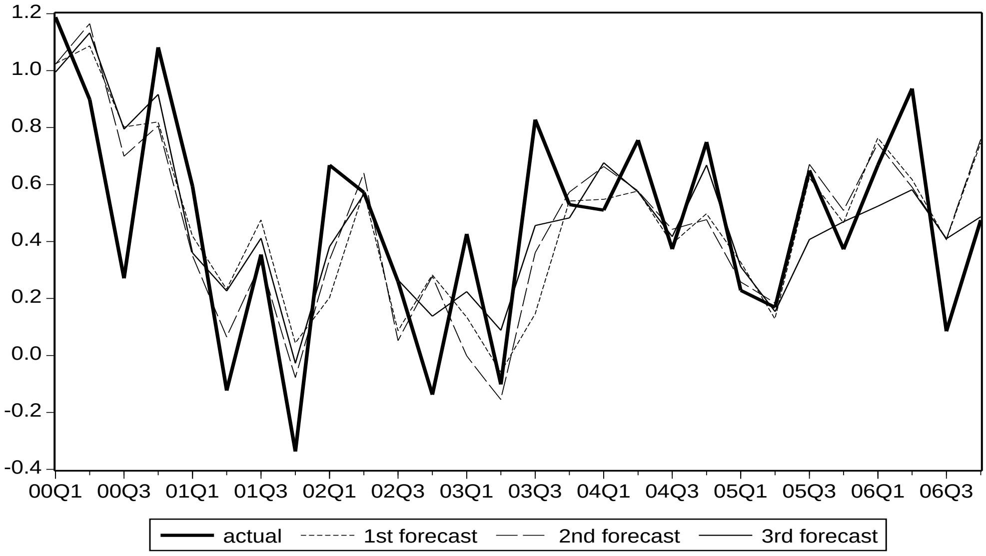

Figure 1: Realised GDP and forecasts for the 1st, 2nd and 3rd months

Component		First	Second	Third
GDP	with IPI	0.0626	0.0344	0.0009
	without IPI	0.0063	0.0033	0.0037
Production Agri-food	with IPI	0.0675	0.0360	0.0257
	without IPI	0.0633	0.0613	0.0777
Production Manufactured	with IPI	0.1000	0.0203	0.0001
	without IPI	0.0021	0.0022	0.0022
Production Energy	with IPI	0.8569	0.6598	0.0442
	without IPI	0.4723	0.2002	0.2002
Production Construction	with IPI	0.1353	0.0699	0.0615
	without IPI	0.3121	0.2560	0.2560
Production Services	with IPI	0.0449	0.1290	0.0023
	without IPI	0.4305	0.1379	0.0602
Household Consumption		0.0268	0.0002	0.0000
Investment		0.2193	0.1389	0.0696
Imports		0.2121	0.0642	0.0642
Exports		0.1599	0.0212	0.0057

Table 3: P-values of Diebold-Mariano tests 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 and thus that we accept the fact that the considered model outperforms significantly the benchmark AR model.

5 Conclusions

In this paper, a revised version of the OPTIM model has been proposed. Bridge equations for French GDP growth and its main components at the current quarter have been presented. The main new features are: a monthly frequency for forecasting exercises, a general-to-specific selection of equations, and a rolling forecast exercise taking the availability of data into account. In terms of Root Mean Squared Errors, the new equations outperform benchmark models.

Nevertheless, this work is still in progress. First, equations have only been proposed for the current quarter, but new equations for the next quarter will also be estimated in a future work. Second, GDP is forecast on the basis of supply equations. On the demand side, the contribution of changes in inventories is computed as the difference between GDP forecast and the demand component forecasts. However, with this method, strong contributions of changes in inventories can be forecast if supply and demand equations provide different diagnosis. This type of result is not easy to handle. As a solution, the previous version of the OPTIM model (Irac and Sédillot, 2002) suggests a procedure for matching of supply and demand approaches, based on the magnitude of the equation residuals. It could be interesting to keep this procedure, which has not been presented here.

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6 Annexes

Production of Agri-food Goods (with IPI)

Table 4: Model for production of agri-food goods with IPI (PIAA_GT)

Variable	Coefficient	t-stat
PIAA_GT (t-1)	0.838	12.03
PIAA_GT (t-3)	-0.422	-6.54
IPI_IAA_GT (t)	0.132	3.50
IPI_IAA_GT (t-1)	-0.191	-4.88
α	0.124	2.53
$\bar{R}^2 = 0.76$ – SE = 0.37 – DW = 1.99 – BKW = 2		
LM(5) = 0.69 [0.63] – DH = 1.34 [0.51]		
NP = 0.37 [0.93] – Chow(50%) = 1.66 [0.09]		
Chow(90%) = 1.16 [0.34]		

P-values of test statistics are in brackets. $PIAA\_GT$: production of agri-food goods (q-o-q); IPI_MANUF_GT: industrial production index in agri-food goods (q-o-q). Estimation period: 1991 Q2 - 2006 Q4.

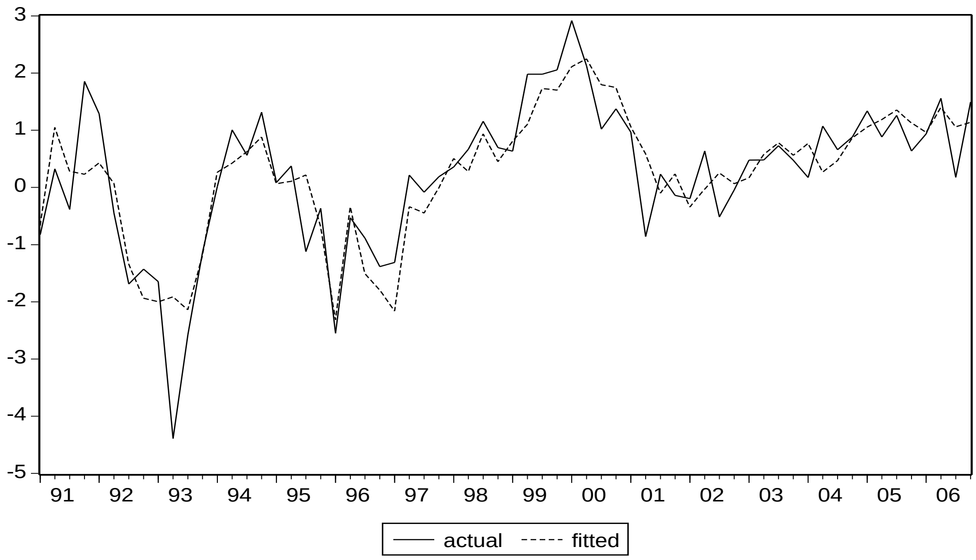

Figure 2: Production of agri-food goods (with IPI): Actual and fitted values

Production of Agri-food Goods (without IPI)

Table 5: Model for production of agri-food goods without IPI (PIAA_GT)

Variable	Coefficient	t-stat
PIAA_GT (t-1)	0.523	5.17
PIAA_GT (t-3)	-0.242	-2.05
PIAA_GT (t-4)	-0.296	-2.63
EVPRPF_IAA (t)	-0.041	-2.16
PREVPRO_IAA (t-1)	0.041	2.74
EVLIV_IAA (t-1)	-0.030	-2.46
α	0.057	0.25
$\bar{R}^2 = 0.61$ – SE = 0.47 – DW = 1.92 – BKW = 6		
LM(5) = 4.22 [0.52] – DH = 0.91 [0.63]		
NP = 0.48 [0.87] – Chow(50%) = 1.39 [0.20]		
Chow(90%) = 1.25 [0.30]		

P-values of test statistics are in brackets. $PIAA\_GT$: production of agri-food goods (q-o-q); $EVPRPF\_IAA$: changes in prices of the finished goods in agri-food industries (BdF); $PREVPRO\_IAA$: production forecasts in agri-food industries (BdF); $EVLIV\_IAA$: changes in deliveries in agri-food industries (BdF). Estimation period: 1991 Q2 - 2006 Q4.

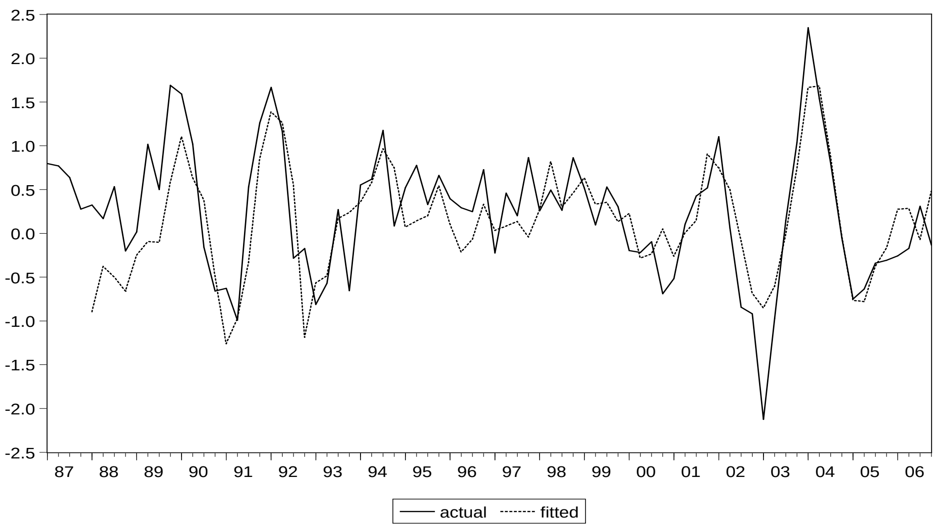

Figure 3: Production of agri-food goods (without IPI): Actual and fitted values

Production of manufactured goods (with IPI)

Table 6: Model for manufacturing production with IPI (PMANU_GT)

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). Estimation period: 1991 Q2 - 2006 Q4.

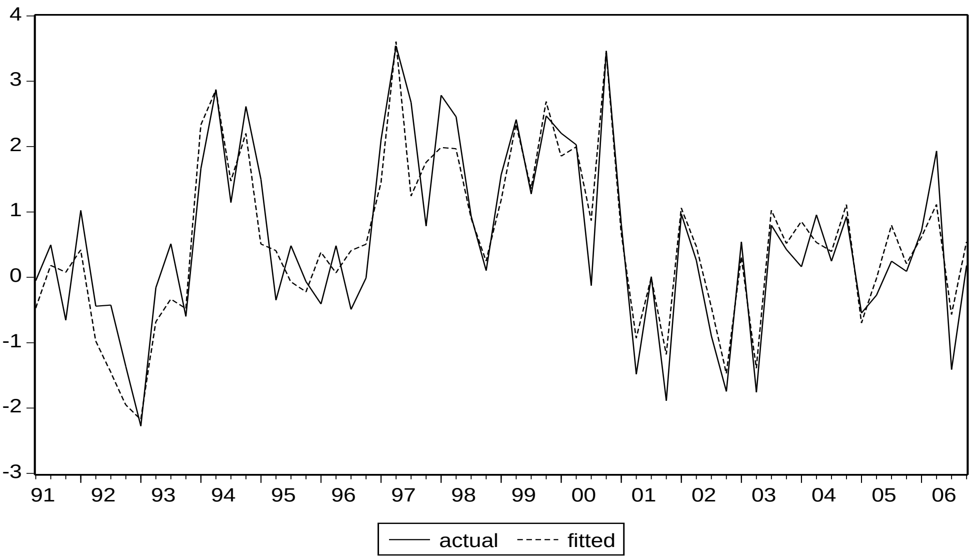

Figure 4: Production of manufactured goods (with IPI): Actual and fitted values

Production of manufactured goods (without IPI)

Table 7: Model for manufacturing production without IPI (PMANU_GT)

Variable	Coefficient	t-stat
PMANU_GT (t-3)	0.436	6.431
PMANU_GT (t-4)	0.394	4.724
Δ(PRODPREV_MANUF) (t)	0.135	8.453
Δ(PRODPASS_MANUF) (t)	0.055	3.623
DUM972	3.187	15.111
DUM973	1.984	18.648
α	-0.055	-0.769
$\bar{R}^2 = 0.72$ – 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]		

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); $DUM972$: dummy 97Q2; $DUM973$: dummy 97Q3. Estimation period: 1991 Q2 - 2006 Q4.

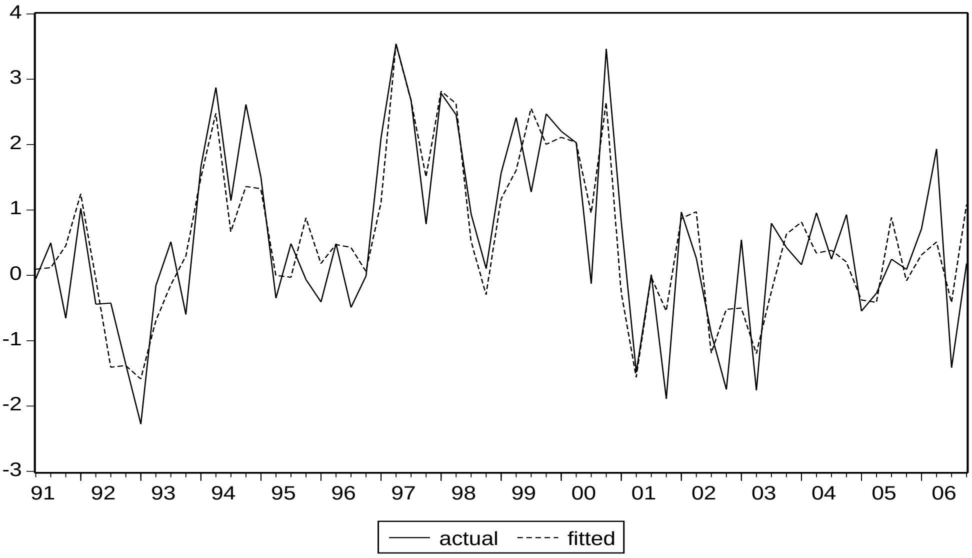

Figure 5: Production of manufactured goods (with IPI): Actual and fitted values

Production of energy (with IPI)

Table 8: Model for production of energy with IPI (PENER_GT)

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]		

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.

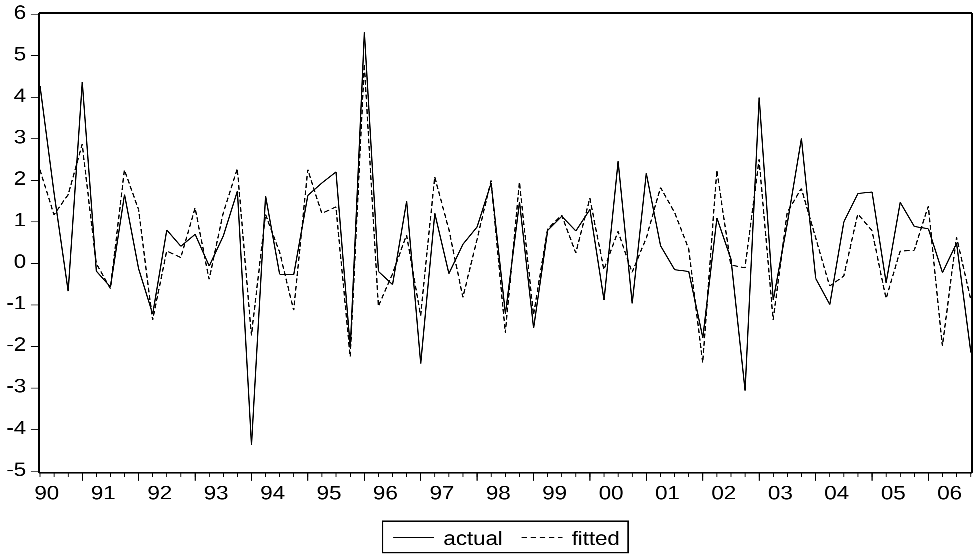

Figure 6: Production of energy (with IPI): Actual and fitted values

Production of energy (without IPI)

Table 9: Model for production of energy without IPI (PENER_GT)

Variable	Coefficient	t-stat
RTE_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_GT: electricity consumption (q-o-q). Estimation period: 1996 Q1 - 2006 Q4.

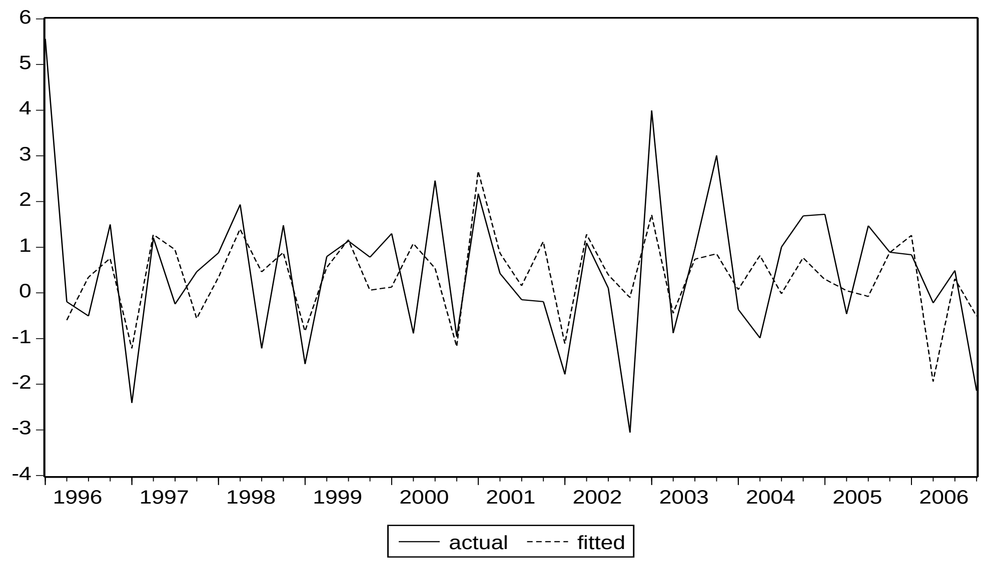

Figure 7: Production of energy (without IPI): Actual and fitted values

Production in construction (with IPI)

Table 10: Model for production in construction with IPI (PBAT_GT)

Variable	Coefficient	t-stat
PBAT_GT(t-1)	0.252	3.499
IPI_CONST_GT(t)	0.267	7.679
ACTPASS_BAT(t)	0.018	6.959
α	0.229	2.651
$\bar{R}^2 = 0.76$ – SE = 0.64 – DW = 1.98 – BKW = 3		
LM(5) = 1.57 [0.90] – DH = 13.9 [0.00]		
NP = 0.62 [0.68] – Chow(50%) = 0.487 [0.97]		
Chow(90%) = 0.567 [0.69]		

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. Estimation period: 1991 Q1 - 2006 Q4.

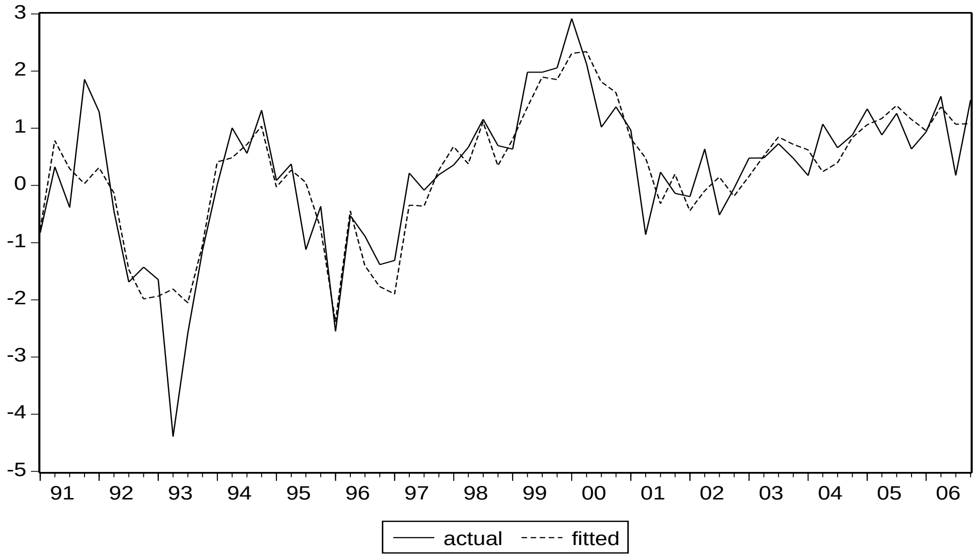

Figure 8: Production of building (with IPI): Actual and fitted values

Production in construction (without IPI)

Table 11: Model for production in construction without IPI (PBAT_VT)

Variable	Coefficient	t-stat
ACTPREV_BAT(t)	0.034	3.017
Δ(CARNET_BAT)(t-1)	0.052	2.974
EFFPREV_BAT(t)	-0.046	-2.845
EFFPASS_BAT(t)	0.054	4.048
Δ^2(EVPRIX_BAT)(t-1)	-0.035	-3.05
α	0.534	12.560
$\bar{R}^2 = 0.50$ – SE = 0.97 – DW = 2.05 – BKW = 9		
LM(5) = 13.91 [0.02] – DH = 8.48 [0.01]		
NP = 2.99 [0.01] – Chow(50%) = 0.337 [0.99]		
Chow(90%) = 0.151 [0.99]		

P-values of test statistics are shown in brackets. *ACTPREV_BAT*: production outlook in building industry (Insee); *CARNET_BAT*: demand and order levels in building industry (Insee); *EFFPREV_BAT*: employment outlook in building industry (Insee); *EFFPASS_BAT*: recent changes in employment in building industry (Insee); *EVPRIX_BAT*: price outlook in building industry (Insee). Estimation period: 1979 Q1 - 2006 Q4.

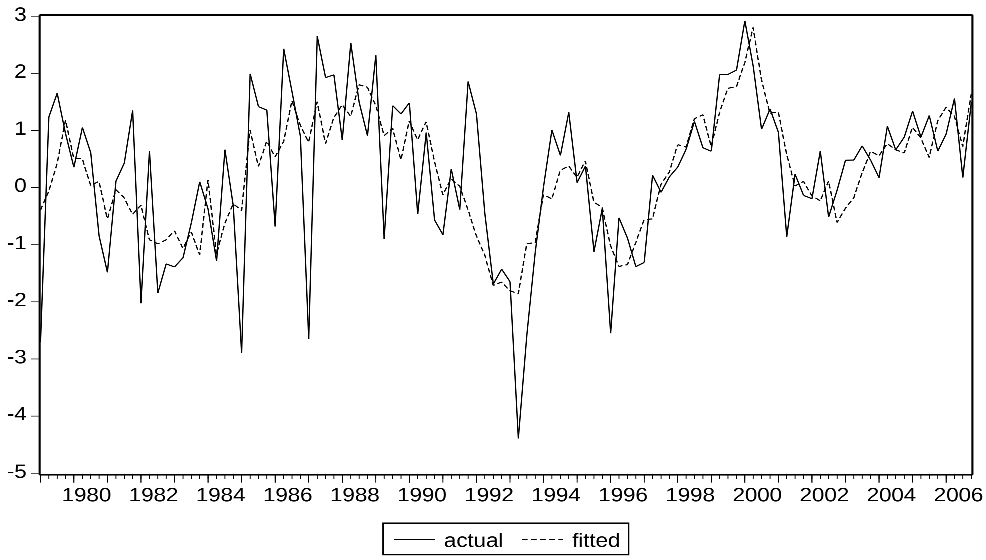

Figure 9: Production of building (without IPI): Actual and fitted values

Production of services (with IPI)

Table 12: Model for production of private services with IPI (PSERM_GT)

Variable	Coefficient	t-stat
PSERM_GT (t-1)	0.370	4.15
PSERM_GT (t-2)	0.256	3.18
Δ(EVACT_SV) (t)	0.016	2.36
Δ(NIVTRES_SV) (t-1)	-0.026	-2.89
IPI_MANUF_GT (t)	0.242	7.01
α	0.195	3.26
$\bar{R}^2 = 0.76$ – SE = 0.28 – DW = 2.16 – BKW = 4		
LM(5) = 3.62 [0.61] – DH = 0.93 [0.63]		
NP = 0.39 [0.95] – Chow(50%) = 0.87 [0.66]		
Chow(90%) = 0.63 [0.73]		

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

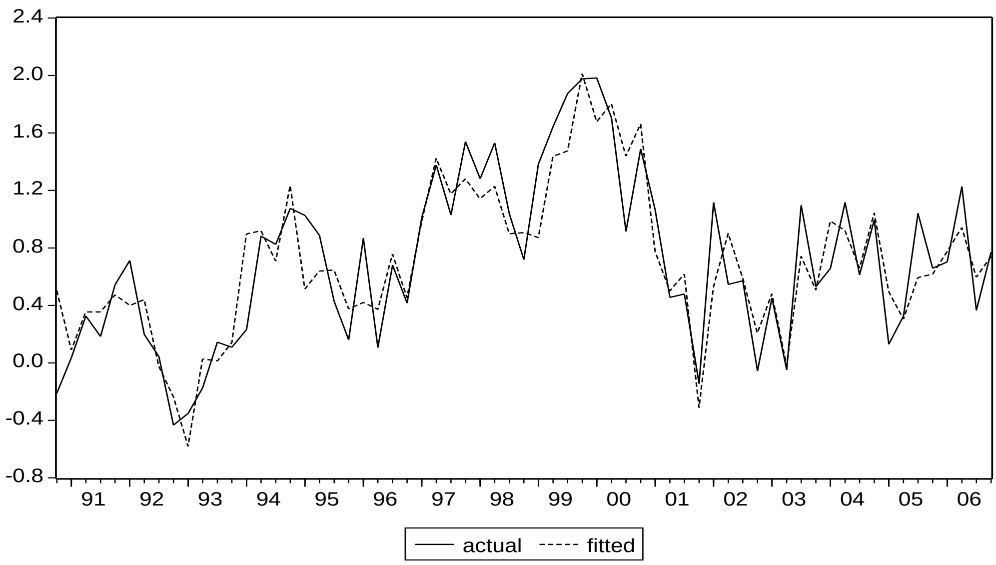

Figure 10: Production of services (with IPI): Actual and fitted values

Production of services (without IPI)

Table 13: Model for production of private services without IPI (PSERM_GT)

Variable	Coefficient	t-stat
PSERM_GT (t-1)	0.240	2.11
PSERM_GT (t-4)	-0.203	-2.10
Δ(EVACT_SV) (t)	0.036	5.21
Δ(NIVTRES_SV) (t-1)	0.032	3.22
OPPEPAR (t)	-0.020	-3.47
CHOMPREV (t)	-0.012	-4.55
α	1.533	5.69
$\bar{R}^2 = 0.71$ – SE = 0.31 – DW = 1.96 – BKW = 6		
LM(5) = 4.22 [0.52] – DH = 0.91 [0.63]		
NP = 0.48 [0.87] – Chow(50%) = 1.39 [0.20]		
Chow(90%) = 1.25 [0.30]		

P-values of test statistics are in brackets. $PSERM\_GT$: production of private services (q-o-q); $EVACT\_SV$: changes in activity in services (BdF); $NIVTRES\_SV$: cash flow situation in services (BdF); $OPPEPA$: likelihood of saving (Insee); $CHOMPREV$: unemployment outlook (Insee). Estimation period: 1990 Q4 - 2006 Q4.

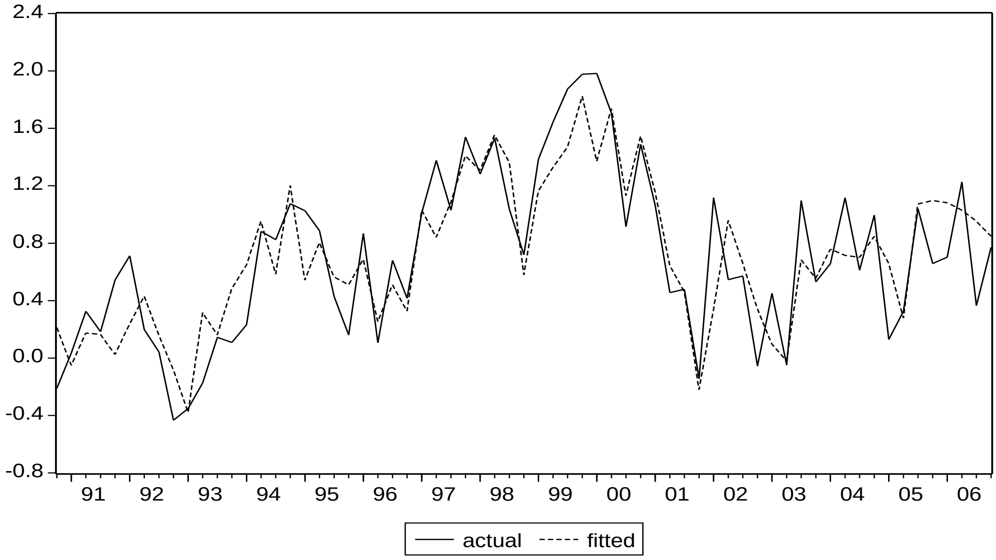

Figure 11: Production of services (without IPI): Actual and fitted values

Consumption of agri-food goods

Table 14: Model for consumption of agri-food (CIAA_GT)

Variable	Coefficient	t-stat
CIAA_GT (t-1)	-0.432	-6.15
IPCH_AGRO_VT (t)	-0.425	-3.29
IPCH_AGRO_VT (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]		

P-values of test statistics are in brackets. *CIAA_GT*: consumption of agri-food (q-o-q); *IPCH_AGRO_VT*: consumer price index in agri-food (Eurostat, q-o-q); *EVEFF_IAA*: forecast staff levels in agri-food industry (BdF). Estimation period: 1994 Q1 - 2006 Q4.

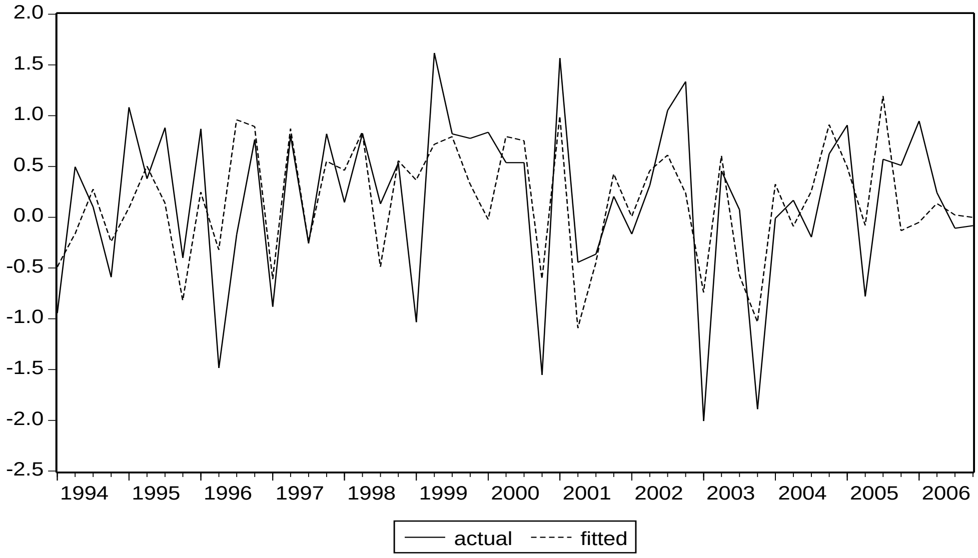

Figure 12: Consumption of agri-food: Actual and fitted values

Consumption of Energy

Table 15: Model for consumption of energy (CENER_GT)

Variable	Coefficient	t-stat
RTE_SA_VT (t)	0.760	5.47
RTE_SA_VT (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]		

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

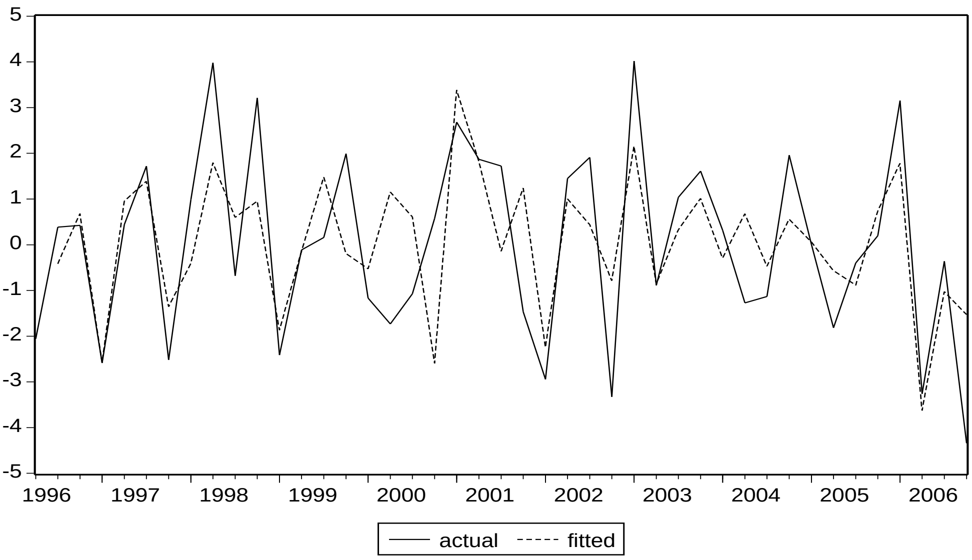

Figure 13: Consumption of energy: Actual and fitted values

Consumption of services

Table 16: Model for household consumption in services (CSERV_GT)

Variable	Coefficient	t-stat
Δ(EVACT_SV) (t)	0.018	3.31
NIVTRES_SV (t)	0.011	3.75
Δ^2(NIVTRES_SV) (t)	0.020	3.50
OPPACHA (t-2)	0.012	3.97
Δ_2(CHOMPREV) (t)	-0.004	-2.59
α	0.657	9.60
$\bar{R}^2 = 0.55$ – SE = 0.24 – DW = 1.84 – BKW = 2		
LM(5) = 7.35 [0.20] – DH = 0.27 [0.87]		
NP = 0.76 [0.64] – Chow(50%) = 0.69 [0.85]		
Chow(90%) = 0.45 [0.87]		

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); $OPPACHA$: likelihood of buying (Insee); $CHOMPREV$: unemployment outlook (Insee). Estimation period: 1990 Q1 - 2006 Q4.

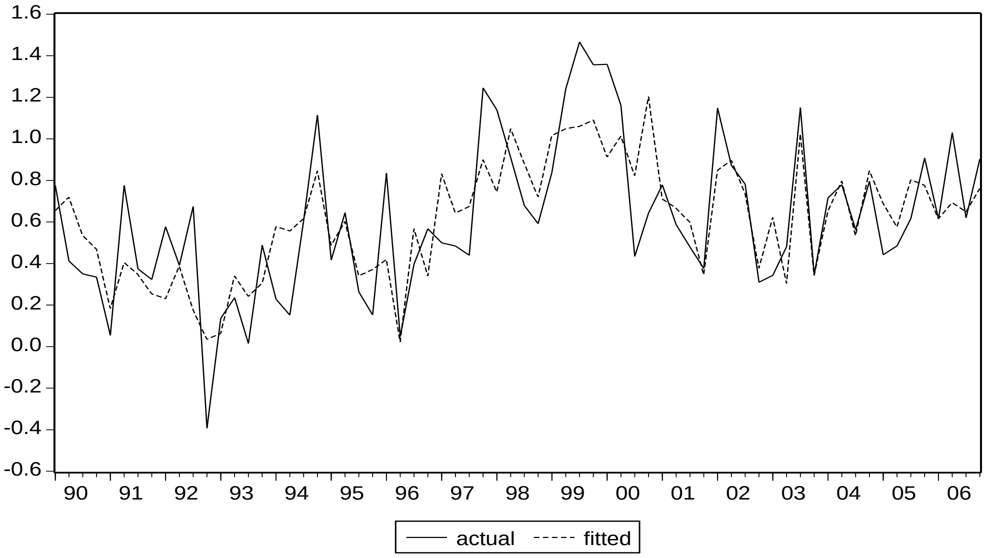

Figure 14: Consumption of services: Actual and fitted values

Government Consumption

Table 17: Model for government consumption (CAPU_GT)

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.

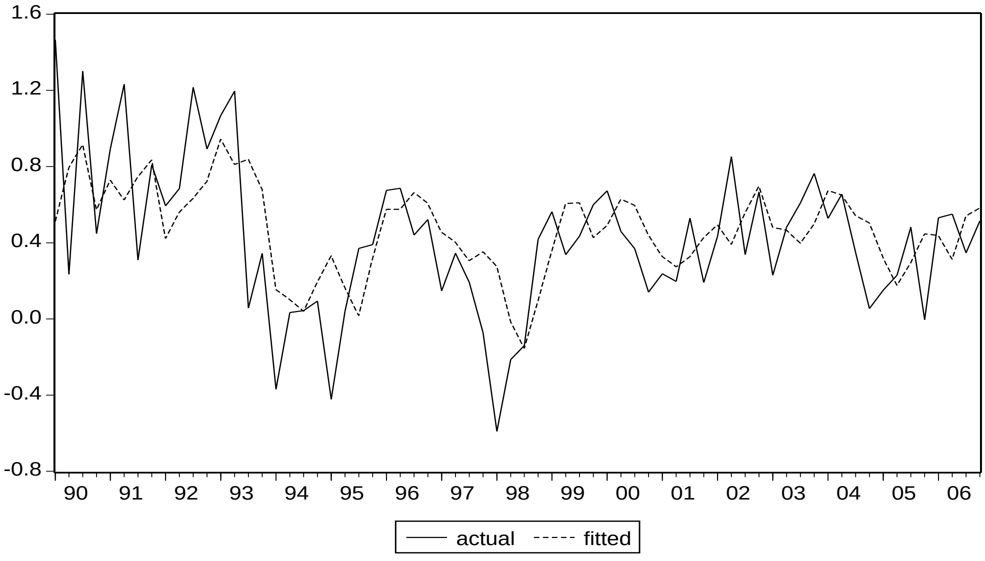

Figure 15: Government consumption: Actual and fitted values

Investment in Material

Table 18: Model for investment in equipment (INVSNFEI_MAT_GT)

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]		

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.

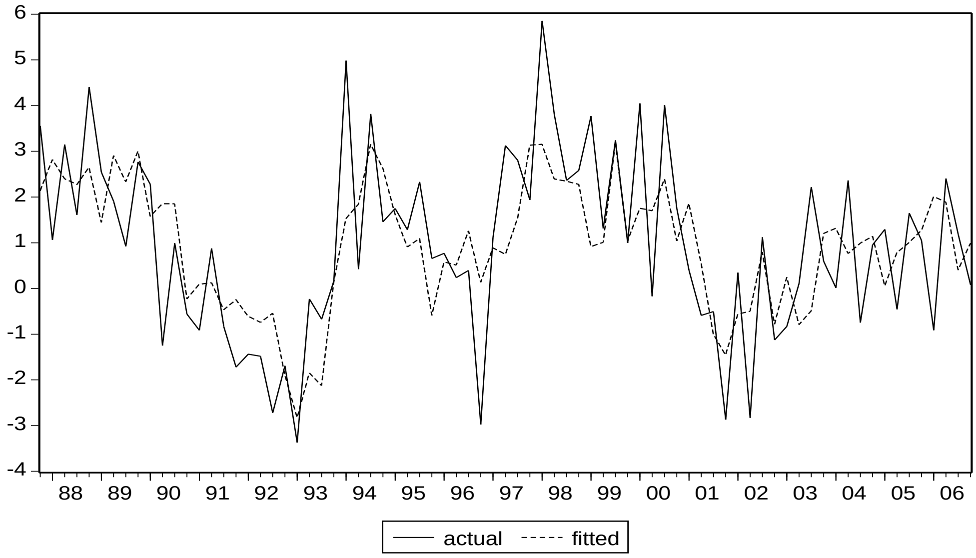

Figure 16: Investment in material: Actual and fitted values

Investment in construction

Table 19: Model for investment in construction (INVSNFEI_BAT_GT)

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]		

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.

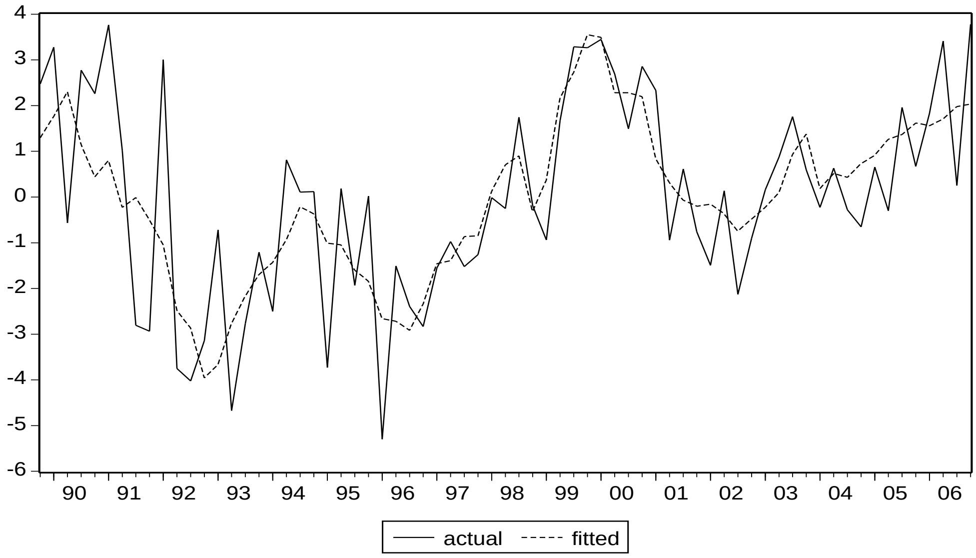

Figure 17: Investment in building: Actual and fitted values

Households Investment

Table 20: Model for household investment (INVMEN_GT)

Variable	Coefficient	t-stat
ACTPREV_BAT(t-1)	0.19	5.71
EFFPREV_BAT (t-1)	0.12	6.64
LOGEMENTS_SA_GT (t)	0.12	6.64
α	0.23	1.47
$\bar{R}^2 = 0.24$ – SE = 1.67 – DW = 2.14 – BKW = 5		
LM(5) = 3.034 [0.69] – DH 0.070= [0.96]		
NP 1.979= [0.126] – Chow(50%) = 0.49 [0.97]		
Chow(90%) = 0.27 [0.95]		

P-values of test statistics are in brackets. $INVMEN\_GT$: household investment (q-o-q); $ACTPREV\_BAT$: production outlook in building industry (Insee); $EFFPREV\_BAT$: employment outlook in building industry (Insee); $LOGEMENTS\_SA\_GT$: declared housings starts (Ministry of Equipment, q-o-q). Estimation period: 1989 Q4 - 2006 Q4.

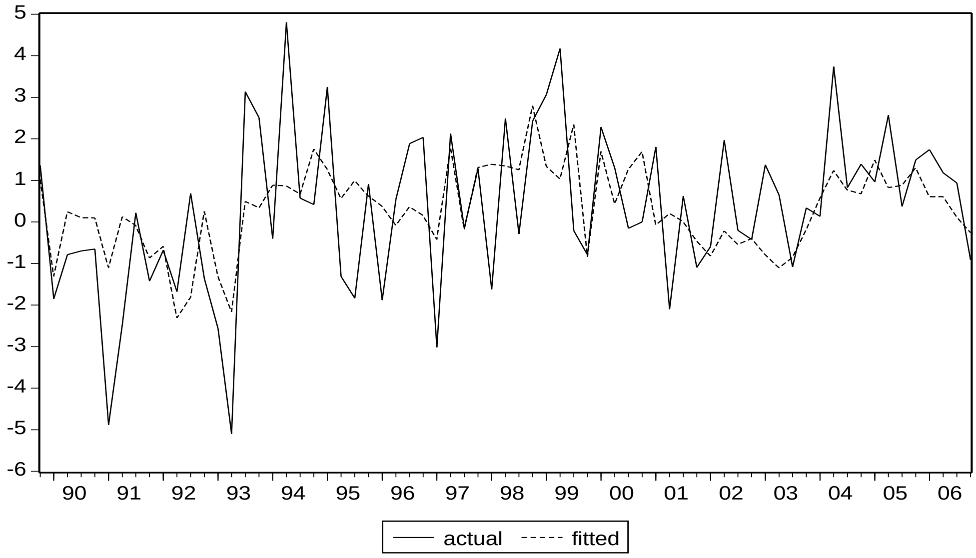

Figure 18: Household investment: Actual and fitted values

Government investment

Table 21: Model for government investment (INVAPU_GT)

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]		

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.

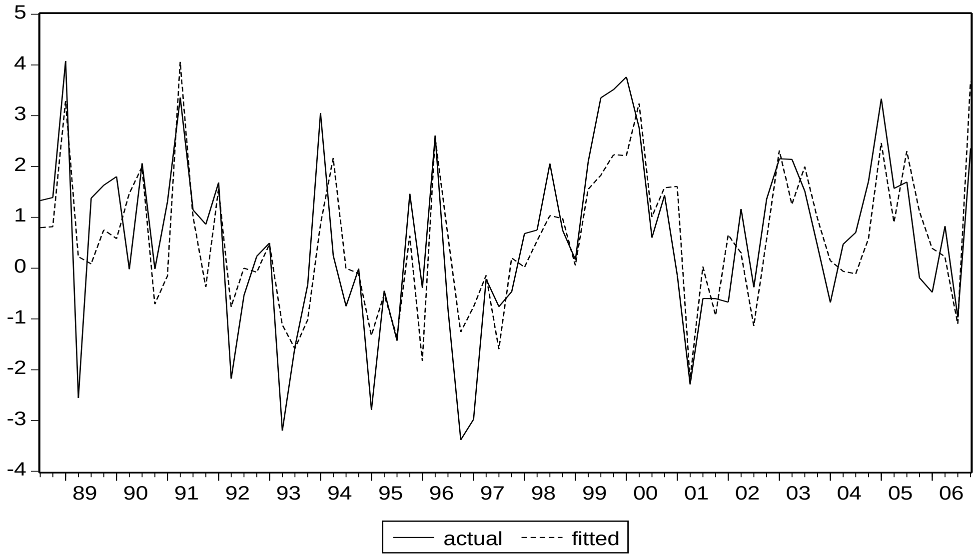

Figure 19: Government investment: Actual and fitted values

Imports

Table 22: Model for imports (IMPORT_GT)

Variable	Coefficient	t-stat
Δ(EU5) (t)	0.193	5.71
EVCOM_I (t-1)	0.125	6.64
α	0.234	1.47
$\bar{R}^2 = 0.56$ – SE = 1.09 – DW = 1.89 – BKW = 1		
LM(5) = 1.58 [0.18] – DH = 0.19 [0.90]		
NP = 0.08 [0.98] – Chow(50%) = 0.83 [0.68]		
Chow(90%) = 1.18 [0.32]		

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). Estimation period: 1991 Q1 - 2006 Q4.

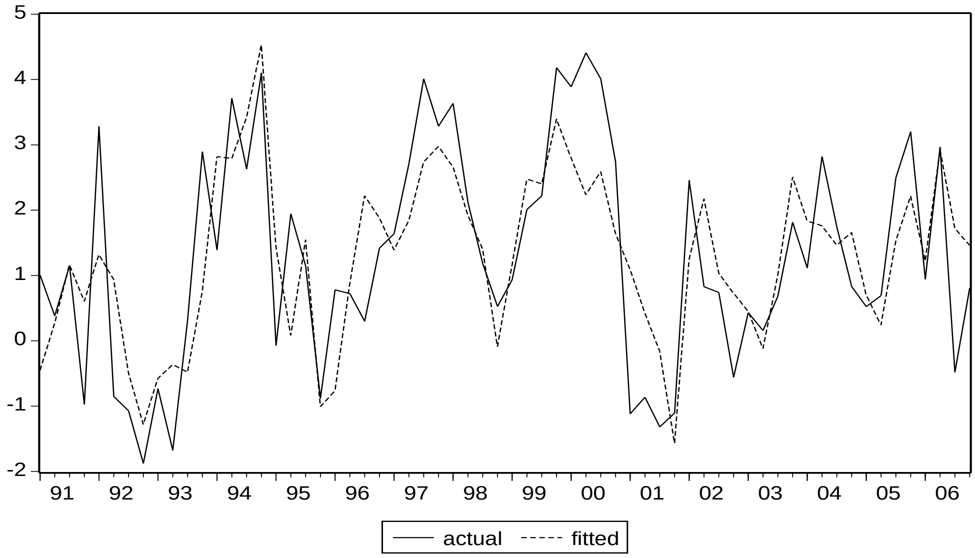

Figure 20: Imports: Actual and fitted values

Exports

Table 23: Model for exports (EXPORT_GT)

Variable	Coefficient	t-stat
EU(5) (t-1)	-0.070	-2.53
EVCOME_I (t)	0.203	9.44
α	-0.115	-0.59
$\bar{R}^2 = 0.48$ – SE = 1.31 – DW = 2.16 – BKW = 2		
LM(5) = 4.15 [0.52] – DH 0.14 = [0.93]		
NP = 1.16 [0.33] – Chow(50%) 1.09 = [0.40]		
Chow(90%) 2.25 = [0.05]		

P-values of test statistics are in brackets. *EXPORT_GT*: exports (q-o-q); *EU*5: production expectations for the months ahead (Eurostat); *EVCOME_I*: changes in foreign orders, total industry (BdF). Estimation period: 1991 Q1 - 2006 Q4.

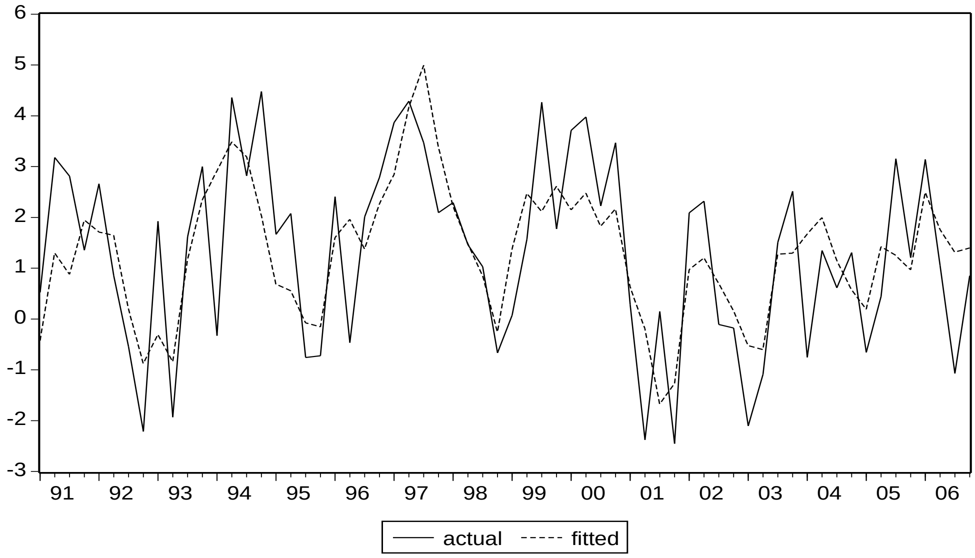

Figure 21: Exports: Actual and fitted values

Production aggregation

Table 24: 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 25: 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 26: 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 27: 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.