Business and consumer expectations and macroeconomic forecasts

Oscar Claveria:
Grup d'Anàlisi Quantitativa Regional (AQR)
Espai de Recerca en Economia
Facultat de Ciències Econòmiques i Empresarials, Universitat de Barcelona
E-mail: oclaveria@ub.edu
Tel: +34 93 4021825
Fax: +34 93 4021821

Ernest Pons:
Grup d'Anàlisi Quantitativa Regional (AQR)
Espai de Recerca en Economia
Facultat de Ciències Econòmiques i Empresarials, Universitat de Barcelona
E-mail: epons@ub.edu
Tel: +34 93 4021412
Fax: +34 93 4021821

Raúl Ramos:
Grup d'Anàlisi Quantitativa Regional (AQR)
Espai de Recerca en Economia
Facultat de Ciències Econòmiques i Empresarials, Universitat de Barcelona
E-mail: rramos@ub.edu
Tel: +34 93 4021984
Fax: +34 93 4021821

Address for correspondence
Grup d'Anàlisi Quantitativa Regional (AQR)
Espai de Recerca en Economia
Facultat de Ciències Econòmiques i Empresarials, Universitat de Barcelona
Avda. Diagonal 690 - 08034 Barcelona, Espanya
Tel: +34 93 4021012
Fax: +34 93 4021821

Revised version: March 2006

Biographical sketches:

Oscar Claveria:

Research fellow at the Grup d'Anàlisi Quantitativa Regional and assistant professor in the Department of Econometrics at the University of Barcelona. His teaching areas are mainly on Statistics and Econometrics. His research interests are focused on forecast quantitative and qualitative variables, econometrics and time series methods and conjuncture analysis. He has collaborated in different research projects related to the quantification of expectations and published part of his research in Cuadernos Aragoneses de Economía and Economic Issues.

Ernest Pons:

Research fellow at the Grup d'Anàlisi Quantitativa Regional and assistant professor in the Department of Econometrics at the University of Barcelona. His teaching areas are mainly on Statistics and Econometrics. His research interests are focused on the treatment of seasonality and on forecasting quantitative and qualitative variables, econometrics and time series methods and conjuncture analysis using indicators. He has collaborated in different research projects and has published his research in Economics Letters, Información Comercial Española, Revista de Economía Aplicada, Revista Asturiana de Economía and Economic Issues..

Raúl Ramos:

Research fellow at the Grup d'Anàlisi Quantitativa Regional and assistant professor in the Department of Econometrics at the University of Barcelona. His teaching areas are mainly on Statistics and Econometrics. His research interests are focused on forecasting, monetary policy and regional labour markets. He has participated in different research projects, published in Applied Economics, Economics Letters, Eastern European Economics, Papers in Regional Science, and Regional Studies, and acted as a referee of Journal of Comparative Economics, Papers in Regional Science, and Regional Studies, among others.

Business and consumer expectations and macroeconomic forecasts

Abstract:

Business and consumer surveys have become an essential tool for gathering information about different economic variables. While the fast availability of the results and the wide range of variables covered made them very useful for monitoring the current status of the economy, there is no consensus on their utility for forecasting macroeconomic developments.

The objective of the paper is to analyse the possibility of improving forecasts for selected macroeconomic variables for the euro area using the information provided by these surveys. After analyzing the potential presence of seasonality and the issue of quantification, we have tested if these indicators provide useful information to improve forecasts of the macroeconomic variables. With this aim, different sets of models have been considered (AR, ARIMA, SETAR, Markov switching regime models and VAR) to obtain forecasts for the selected macroeconomic variables. Then, information from surveys has been considered to forecast these variables in the context of the following models: autoregressive, VAR models, Markov Switching Regime models and leading indicators models. In both cases, the Root Mean Square Error (RMSE) has been computed for different forecast horizons.

The comparison of the forecasting performance of the two sets of models permit to conclude that in most cases, models that include information from the survey obtain lower RMSE than the best model without survey information. However, this reduction is only significant in a limited number of cases. In this sense, the obtained results extend the results of previous research that have considered information from business and consumer surveys to explain the behaviour of macroeconomic variables, but are not conclusive about its role.

Keywords: Macroeconomic forecasts, forecast competition, business and consumer surveys.

JEL classification: C53, C42

1. Introduction and objectives

Business and consumer surveys have become an essential tool for gathering information about different economic variables. While the fast availability of the results and the wide range of variables covered make them very useful for monitoring the current status of the economy, there is no consensus on their utility for forecasting macroeconomic developments.

The objective of the paper is to analyse the possibility of improving the forecasts for some selected macroeconomic variables for the euro area using the information provided by business and consumer surveys. As pointed out by Pesaran (1987), this type of data are less likely to be susceptible to sampling and measurement errors than surveys that require respondents to give point forecasts for the variables in question. One can think that the information provided by qualitative indicators could be useful to improve forecasts for quantitative variables due to two reasons. First, statistical information from business and consumer surveys is available much more in advance to quantitative statistics; and, second, these indicators are usually related with agents' expectations, so they are likely to bear a relation to future developments of macroeconomic variables.

In this paper, we have considered all the information available for the business and consumer surveys indicators in the euro area. The dataset analysed includes 38 indicators (33 of which are monthly and 5 quarterly) and 6 composite indicators. Although the starting date of these indicators differs, most of them begin in January 1985 (or in the first quarter of 1985). The latest period to be included in the analysis is December 2005 (or the last quarter of 2005).[1] More details on the dataset can be found in Table 1.

TABLE 1

The strategy to test if these indicators provide useful information to improve forecasts of the macroeconomic variables has been the following:

First, macroeconomic variables that could be related with the information provided by business and consumer surveys have been selected and statistical information for the longest time-span available has been collected from the Eurostat and the ECB databases.[2] Tables 2 and 3 show more details about this dataset of macroeconomic variables and the correspondence between the business and consumer surveys indicators and these macroeconomic variables.

TABLES 2 and 3

Second, five different sets of models have been considered (AR, ARIMA, Self-exciting threshold autoregressions –SETAR-, Markov switching regime models and vector autoregressions –VAR-) to obtain forecasts for the different quantitative variables and the Root Mean Square Error (RMSE) and the Mean Absolute Percentual Error (MAPE) have been computed for different forecast horizons. The comparison of these values with the ones obtained with models where information from business and consumer surveys has been considered would permit to assess whether these indicators permit to improve the forecasts or not.

Fourth, information from surveys is considered to forecast the quantitative variables using three different types of models:

(i) Lagged selected indicators are introduced as explanatory variables in autoregressive and VAR models. For Markov Switching Regime models, the probability of changing regime depends on the information of the qualitative indicators rather than on the own evolution of the series.

(ii) Leading indicators models are constructed for each of the quantitative variables using information from business and consumer surveys indicators.

(iii) One problem with survey data is that, in contrast to other statistical series, their results are weighted percentages of respondents expecting an economic variable to increase, decrease or remain constant. Therefore, the information refers to the direction of change but not to its magnitude. And this is the reason why we think that the considered list of qualitative indicators should be previously quantified in order to obtain more reliable forecasts of businessmen' opinions. The conversion of qualitative data into a quantitative measure of the expected rate of change provides more detailed information about agents' opinions and intentions. For this reason, a third strategy to improve quantitative forecasts from qualitative indicators would consist in quantifying the information provided by business and consumer surveys. There have been different proposals in the literature on how to obtain these quantified series of expectations. In this sense, one common feature of all them is that they permit to obtain directly one-period forecasts.

Another possibility consists in using the quantified series of expectations as explanatory variables of the related quantitative variable.

One additional aspect that has also been considered is whether raw data or seasonal adjusted data from business and consumer surveys should be used in order to improve forecasts of the selected macroeconomic variables.

The structure of the paper is as follows. In the next section our methodological approach is described, including both benchmark models and models where business and consumer surveys information is included. Next, results of the forecasting competition are discussed in Section 3. Last, conclusions are given in Section 4.

2. Methodology

2.1. Benchmark models

The five proposed models (AR, ARIMA, SETAR, Markov switching regime models and VAR models) have been applied to obtain forecasts for the quantitative variables (expressed as year-on-year growth rates.

2.1.1. Autoregressions

The widely known autoregressive model (also known as distributed-lags model) explains the behaviour of the endogenous variable as a linear combination of its own past values:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + ... + \phi_p x_{t-p} + \varepsilon_t \qquad (1)$$

The key question is how to determine the number of lags that should be included in the model. For monthly data, we have considered different models with a minimum number of 1 lag up to a maximum of 24 (including all the intermediate lags), selecting that model with the lowest value of the Akaike Information Criteria (AIC). For quarterly data, we have considered a maximum number of lags equals to 8.

2.1.2. ARIMA models

Since the work by Box and Jenkins (1970), ARIMA models have been widely used and their forecast performance has also been confirmed.

The general expression of an ARIMA model is the following:

$$x_t^{\lambda} = \frac{\Theta_s\left(L^s\right)\theta(L)}{\Phi_s\left(L^s\right)\phi(L)\Delta_s^D\Delta^d}\varepsilon_t \qquad (2)$$

where

$$\Theta_s\left(L^s\right) = \left(1 - \Theta_s L^s - \Theta_{2s} L^{2s} - \ldots - \Theta_{Qs} L^{Qs}\right) \qquad (3)$$

is a seasonal moving average polynomial,

$$\Phi_s\left(L^s\right) = \left(1 - \Phi_s L^s - \Phi_{2s} L^{2s} - \ldots - \Phi_{Ps} L^{Ps}\right) \qquad (4)$$

is a seasonal autoregressive polynomial,

$$\theta(L) = \left(1 - \theta_1 L^1 - \theta_2 L^2 - \ldots - \theta_q L^q\right) \qquad (5)$$

is a regular moving average polynomial,

$$\phi(L) = \left(1 - \phi_1 L^1 - \phi_2 L^2 - \ldots - \phi_p L^p\right) \qquad (6)$$

is a regular autoregressive polynomial, λ is the value of the Box-Cox (1964) transformation, Δ_s^D is the seasonal difference operator, Δ^d is the regular difference operator, *S* is the periodicity of the considered time series, and ε_t is the innovation which is assumed to behave as a white noise.

In order to use this kind of models with forecasting purposes it is necessary to identify the best suited model (i.e., to give values to the order of the different polynomials, to the difference operator, etc.). For monthly data, we have considered models with up to 12 AR and MA terms (4 in the case of quarterly data) selecting the model with the lowest value of the AIC. The statistical goodness of the selected model has also been checked.

2.1.3. TAR models

In the case of the ARIMA model the relationship between the current value of a variable and its lags is supposed to be linear and constant over time. However, when looking at real data it can be seen that expansions are more prolonged over time than recessions (Hansen, 1997). In fact, in the behaviour of most economic variables there seems to be a cyclical asymmetry that lineal models are not able to capture (Clements and Smith, 1999).

A Self-Excited Threshold Autoregressive model (SETAR) for the time series x_t can be summarised as follows:

$$B(L)\cdot x_t + u_t \text{ if } x_{t-k} \leq x \quad (7)$$

$$\zeta(L)\cdot s_t + v_t \text{ if } x_{t-k} > x \quad (8)$$

where u_t and v_t are white noises, $B(L)$ and $\zeta(L)$ are autoregressive polynomials, the value k is known as delay and the value x is known as threshold.

This two-regime self-exciting threshold autoregressive process is estimated using monthly and quarterly data for each indicator and the Monte Carlo procedure is used to generate multi-step forecasts.

The selected values of the delay are those minimising the sum of squared errors among values between 1 and 12 for monthly data and 1 and 4 for quarterly data. The values of the threshold are given by the variation of the analysed variable.

2.1.4. Markov switching regime models

Threshold autoregressive models are perhaps the simplest generalization of linear autoregressions. In fact, these models were built on developments over traditional ARMA time series models. As an alternative to these models, time series regime-switching models assume that the distribution of the variable is known conditional on a particular regime or state occurring. When the economy changes from one regime to another, a substantial change occurs in the series.

Hamilton (1989) presented the Markov regime-switching model in which the unobserved regime evolves over time as a 1st-order Markov process. The regime completely governs the dynamic behaviour of the series. This implies that once we condition on a particular regime occurring, and assume a particular parameterization of the model, we can write down the density of the variable of interest. However, as the regime is strictly unobservable, it is necessary to draw statistical inference regarding the likelihood of each regime occurring at any point in time. So, it is necessary to obtain the transition probabilities from one regime to the other.

There have been three different approaches to estimating these models (Potter, 1999). First, Hamilton (1989) developed a nonlinear filter to evaluate the likelihood function of the model and then directly maximized the likelihood function. Second, in a later article, Hamilton (1990) constructed an EM algorithm that is particularly useful for the case where all the parameters switch. Finally, Albert and Chib (1993) developed a Bayesian approach to estimation.

In this work, we employ a Markov-switching threshold autoregressive model (MK-TAR) where we allow for different regime-dependent intercepts, autoregressive parameters, and variances. The estimation of the models is carried out by maximum likelihood using the Hamilton (1989) filter [3] together with the smoothing filter of Kim (1994).

Once we have estimated the probabilities of expansion and recession, we construct the following model for the time series x_t using the estimated probabilities of changing regime:

$$B(L)\cdot x_t + u_t \text{ if } P\left[Expansion / x_{t-k}\right] \leq P \tag{9}$$

$$\zeta(L)\cdot x_t + v_t \text{ if } P\left[Expansion / x_{t-k}\right] > P \tag{10}$$

where, as in SETAR models, u_t and v_t are white noises, $B(L)$ and $\zeta(L)$ are autoregressive polynomials, the value k is known as delay and the value P is known as threshold.[4] The selected values of the delay are those minimising the sum of squared errors among values between 1 and 12 for monthly data and 1 and 4 for quarterly data. The values of the threshold are given by the variation of the probability.

2.1.5. VAR models

The VAR models that have been specified try to pick up, as far as possible, the classical Economic Theory assumptions in order to reflect the economic dynamic. In this sense, the VAR models that have been estimated could be defined as “total of the economy”, “supply”, “industry”, “construction” and, by the demand side, “exports”, “consumption” and “saving”. In particular, the considered quantitative VAR models are shown in table 4.

TABLE 4

2.2. Models where business and consumer surveys information is incorporated

2.2.1. “Augmented” autoregression, Markov switching regime and VAR models

One way to use the information of the qualitative indicators to improve the forecasts of the quantitative variables consists in introducing selected indicators as explanatory variables in autoregressions and VAR models. Recently, different works have estimated autoregressive and VAR models for some target variable (consumer spending, GNP), adding current and lagged values of a consumer confidence index to the models in order to test its significance and consider the extent of its effects. The approach applied in this section is quite similar. In this sense, it is worth mentioning that, as shown in table 2, more than one quantitative variable could be related to the evolution of the considered indicators. So, different possibilities have been considered for each autoregressive model. For the case of “augmented” VAR models, the strategy has been slightly different: only selected indicators have been included. This information is shown in table 5.

TABLE 5

2.2.2. Leading indicators models

In spite of their well-known limitations pointed by the literature, leading indicators can also provide reliable forecasts of the analysed quantitative variables considering the whole set of information of business and consumer surveys.

According to Clements and Hendry (1998), p. 207 “an indicator is any variable believed informative about another variable of interest”. In this context, a leading indicator is any variable whose outcome is known in advance of a related variable which is desired to forecast. Usually, there are several leading indicators for every variable to be forecasted and, for this reason, composite leading indicators are constructed. A composite leading index is a combination (e.g. a weighted average) of this set of simple leading indicators. Composite leading indicators are useful to provide estimates of the current state and short-term forecasts of the analysed economy. The main advantage of composite leading indicators in relation to other methods is that it is not necessary to obtain forecasts for exogenous variables as their lagged values are known in advance. Of course, leading indicators will only provide reasonably accurate short term forecasts. However, we extend the analysis up to two years as an additional benchmark for the results using other procedures.

The procedure for the selection of the simple leading indicators for each endogenous variable is based on the bilateral correlations between different lags of each of the variables in the business and consumer surveys indicators and the endogenous variable. The simple leading indicators have been chosen among those with highest values of the correlation coefficient. The length of the lead has been determined by cross-correlation analysis. In this sense, as an automatic identification procedure, different values of the bilateral correlation coefficient have been explored as a limit for a variable to be considered as a leading indicator. These values range from zero (all explanatory variables would be considered as leading indicators) to 0.8 (only variables with a strong correlation with the endogenous would be considered). Eventually we fixed this limit at 0.5.

As there could be several simple leading indicators for every endogenous variable and the available sample is quite short, it is necessary to reduce the dimensionality of the exogenous variables matrix before using this information set to obtain the desired forecasts. It is also necessary to eliminate from this set of simple leading indicators, the part of their behaviour attributable to noise which would not be useful to forecast the endogenous variables (the noise would be higher with lower values of the correlation coefficient). With this aim, we extracted the principal components of the explanatory variables. The idea is that the first principal components capture the commonalities in the set of simple leading indicators (the relevant information to forecast the endogenous variables). After experimenting with different values, we retain as many components as necessary to explain 70% of the total variance of the simple leading indicators.

Once the simple leading indicators have been selected and have been summarised in a few components (in most cases, the number of considered components ranges from one to three), these components are used as explanatory variables in the forecasting equations.

The description of the leading indicators models applied in this case and their selected variables are available from the authors on request.

2.3. Other aspects related to the nature of business and consumer surveys indicators

2.3.1. Seasonal patterns

One feature of business and consumer survey data is the presence of seasonal patterns. The treatment of seasonal patterns is relevant in our context in order to determine whether is better to forecast macroeconomic variables using raw data or seasonal adjusted data. In order to verify the importance of seasonality, we computed the Kruskal-Wallis test for all the indicators in our database. Table 6 summarises the obtained results (more details are given in Annex A). As it can be seen in this table, in almost an 80% of the cases, the null hypothesis of non-seasonality was not rejected, that is, most series did not present a seasonal component. Taking into account these results, and in order to keep homogeneity, in our forecasting competition we decided to use raw data for all the indicators obtained from the surveys.

TABLE 6

2.3.2. Quantification of expectations

An additional problem with survey data is that, in contrast to other statistical series, their results are weighted percentages of respondents expecting an economic variable to increase, decrease or remain constant. Therefore, the information refers to the direction of change but not to its magnitude. In the literature, different methods have been proposed in order to convert qualitative data into a quantitative measure of agents' opinions and intentions. The problem with these methods is that only one-period forecasts can be directly computed (for further details, see Claveria et al., 2006), and for this reason, in this paper, the quantification of expectations will only be used to transform survey indicators before including them as regressors in autoregressions and VAR models. With this aim, six different possibilities are considered: the balance, the principal components based procedure, the Anderson procedure, the Carlson-Parkin and Augmented Carlson-Parkin methods and State-Space models.

Assuming that the percentage change expected remains constant in time for the categories expecting an increase and a decrease of the variable, Anderson (1951) defined the balance statistic as a measure of the average changes expected in the variable. Ever since, the balance statistic has been widely used as a short-term forecast as well as for the construction of several economic indicators.

There have been a variety of quantification methods proposed in the literature. These methods are based on the assumption that respondents base their answer on a subjective probability distribution defined over future changes in the variable and conditional to the information available up to that moment, which has the same form for all agents. Differences between methods have usually been related to theoretical considerations regarding rationality tests rather than based on their forecasting ability.

The accuracy of the balance statistic as a means for extracting the maximum degree of information from survey data on the direction of change has been widely studied since the introduction of this new source of information in Europe by the IFO-Institut für Wirtschaftsforschung at the beginning of the fifties, for example by Anderson (1951, 1952), Theil (1952, 1955), Anderson, Bauer and Fels (1954), De Menil and Bhalla (1975) and Defris and Williams (1979). This line of research has led some authors to look for alternative procedures and statistics oriented towards the conversion of qualitative data into quantitative series of expectations.

While most of the emphasis was given to the justification of the balance statistic within a theoretical framework and the evaluation of its performance as predictor of inflation and economic activity, as well as to the analysis of the rationality and the formation of expectations (i.e. Papadia, 1983), some other studies have been more empirically oriented. The fact that business and consumer surveys seem to be a valuable tool for anticipating economic activity has given rise to a line of research more focused on the construction of indexes and indicators of activity with survey data.

In spite of the valuable information contained in the balance statistic, our experience with this type of data has led us to find some limitations of the balance statistic as a forecasting measure. Some of these shortcomings concerning the degree of response, the relative importance of each category for every question, etc. depend to a large extent on the specific features of the survey under consideration. Some other problems, such as the volatility and the escalation of the series, are related to the nature of the data on the direction of change.

For this reason, we have considered other possibilities of "quantifying" the information from business and consumer surveys. A first possibility consists in summarising all the possible answering categories contained in the business and consumer surveys in an indicator that also takes account of the percentage of "stable" answers. This indicator can be constructed using a principal component analysis (PCA) of all the answers for each question, which shows the linear combination of the three/five/six percentages that captures the most variability between the successive surveys.

But, the strong correlation of the balance statistic with the percentage changes of its corresponding quantitative index of reference found by Anderson (1952) opened the door for the quantification of ordinal responses using more complex methods. Theil (1952) suggested a theoretical framework, later referred as the subjective probability approach, to convert qualitative responses of the direction of change into quantitative expectations, $\bar{x}_{t+1}^{e}$. The basic idea behind the method is that there is some indifference interval around zero within which respondents report "no change", whereas outside they report a change in the variable.

Let x_{t+1} be the percentage change of the variable from period t to period $t+1$ and $\bar{x}_{t+1}^{e}$ its expectation conditional on the respondent's information set. Hence, an expected increase is reported if $\bar{x}_{t+1}^{e} > \delta_a$ with a relative frequency A_t^{t+1} and an expected decrease $\bar{x}_{t+1}^{e} < \delta_b$ with a relative frequency B_t^{t+1}. Assuming the standard normal distribution one can derive:

$$\bar{x}_{t+1}^{e} = \hat{\delta} g_t^{t+1} \tag{11}$$

where $g_t^{t+1} = \dfrac{b_t^{t+1} + a_t^{t+1}}{b_t^{t+1} - a_t^{t+1}}$ and $\begin{cases} b_t^{t+1} = \Phi^{-1}\left(B_t^{t+1}\right) = \dfrac{-\delta - \bar{x}_{t+1}^{e}}{\sigma_{t+1}^{e}} \\ a_t^{t+1} = \Phi^{-1}\left(1 - A_t^{t+1}\right) = \dfrac{\delta - \bar{x}_{t+1}^{e}}{\sigma_{t+1}^{e}} \end{cases}$.

Φ^{-1} stands for the inverse of the cumulative standard normal distribution. As pointed out by Zimmermann (1999), the logistic and the scaled-t have also been used in the literature, usually leading to very similar results. Since the limit of the interval of indifference δ is unknown, Carlson and Parkin (1975) used the following method of escalation:

$$\hat{\delta} = \frac{\sum_{t=1}^{n} x_{t+1}}{\sum_{t=1}^{n} g_t^{t+1}} \tag{12}$$

This method was first applied by Carlson and Parkin (1975) and widely employed in the literature ever since. Recent contributions have relaxed the assumption of a symmetric indifference interval and the unbiasedness condition introduced by Carlson-Parkin escalating procedure:

$$x_{t+1}^{e} = \hat{\delta}_b e_t^{t+1} + \hat{\delta}_a f_t^{t+1} \tag{13}$$

where $e_t^{t+1} = \dfrac{b_t^{t+1}}{b_t^{t+1} - a_t^{t+1}}$ and $f_t^{t+1} = \dfrac{a_t^{t+1}}{b_t^{t+1} - a_t^{t+1}}$.

As parameters δ_b and δ_a are unknown they have to be estimated usually by the following OLS regression $x_t = \delta_b e_t^{t-1} + \delta_a f_t^{t-1} + u_t$. This alternative procedure implies that the aggregate distribution and the indifference intervals for both expectations and realizations are the same. As it happened with Carlson-Parkin method, this may cause problems when using the derived data for testing the rationality of expectations.

Recent econometric techniques have been incorporated in the methodology in order to overcome some of its shortcomings, basically the restrictive assumptions on which it is based. As a result, new methods have been suggested and applied with the aim of obtaining accurate series of expectations. Recent papers have focused in the possibility of using State-Space models to estimate series of expectations and to forecast reference quantitative variables. For example, Seitz (1988) applied the time-varying parameter model of Cooley and Prescott (1976) and used the Kalman filter to derive a dynamic and asymmetric indifference interval.

Our proposal consists in using a State-Space model where the Kalman filter is used to estimate time varying and asymmetric indifference intervals that can be used to obtain series of expectations but also to forecast reference quantitative series.

By relaxing the assumption that thresholds $\delta_{a,t+1}$ and $\delta_{b,t+1}$ are symmetric and are fixed across time, the asymmetric Carlson-Parkin conversion equation turns into:

$$x_{t+1}^{e} = \hat{\delta}_b e_t^{t+1} + \hat{\delta}_a f_t^{t+1} \tag{14}$$

where $e_t^{t+1} = \dfrac{b_t^{t+1}}{b_t^{t+1} - a_t^{t+1}}$ and $f_t^{t+1} = \dfrac{a_t^{t+1}}{b_t^{t+1} - a_t^{t+1}}$.

Instead of using the Cooley and Prescott time-varying parameter model and regressing the outturn on retrospective survey responses in order to obtain estimates of $\bar{x}_{t+1}^{e}$ as done by Seitz (1988), we purpose a more general state-space representation for the threshold parameters that would include Seitz's method as a particular case:

$$\bar{x}_t = \delta_{a,t} e_{t-1}^{t} - \delta_{b,t} f_t^{t+1} + u_t \tag{15}$$

where $u_t \sim N\left(0, \sigma_u^2\right)$, and

$$\begin{cases} \delta_{a,t} = \alpha \delta_{a,t-1} + v_t \\ \delta_{b,t} = \beta \delta_{b,t-1} + w_t \end{cases} \tag{16}$$

where α and β are the autoregressive parameters and v_t and w_t are two independent and normally distributed disturbances with mean zero and variance σ_v^2 and σ_w^2, respectively. The relationship between x_t and the response thresholds is linear and it is expressed in the measurement equation. The unknown state is supposed to vary in time according to the linear transition equation. In order to estimate the variances and the autoregressive parameters and derive estimates of x_{t+1}^{e} the Kalman filter is used.

This generalization of the probability approach introduces a more flexible representation, allowing for asymmetric and dynamic response thresholds generated by a first-order Markov process. Additionally, estimates of $\bar{x}_{t+1}^{e}$ can be derived by means of just survey responses about expectations, without the need of perceptions about past changes of the variable.

We also consider a particular case of this general model where threshold parameters follow a random walk instead of an autoregressive process. Therefore, α and β are supposed to be zero and the state-space representation of the model is:

$$\bar{x}_t = \delta_{a,t} e_{t-1}^{t} - \delta_{b,t} f_t^{t+1} + u_t \qquad (17)$$

where $u_t \sim N\left(0, \sigma_u^2\right)$ and

$$\begin{cases} \delta_{a,t} = \delta_{a,t-1} + v_t \\ \delta_{b,t} = \delta_{b,t-1} + w_t \end{cases} \qquad (18)$$

When initialising the Kalman filter two options have been considered. First, we have supposed that the initial conditions of the filter are obtained by regressing $\bar{x}_t$ on e_t^{t+1} and f_t^{t+1} in the first fourth of the sample. We have also supposed that both initial conditions are equal to zero. As a result, we end up with four different state-space representations:

SS1: autoregressive process with initial conditions estimated by OLS regression.
SS2: random walk process with initial conditions estimated by OLS regression.
SS3: random walk process with null initial conditions.
SS4: autoregressive process with null initial conditions.

Further details on the estimation procedure can be found in Harvey (1982) and (1987).

The output of these quantification procedures can be considered as one period ahead forecasts of the quantitative variable used in the analysis or as exogenous proxies (quantified indicators) introduced in AR and VAR models to forecast quantitative variables. This second alternative is the one considered in this paper.

3. Results of the forecasting competition

In order to evaluate the relative forecasting accuracy of the models, for each variable to be forecasted all models were estimated until 2001.12 (or 2001.III or IV for quarterly indicators) and forecasts for 1,2,3,6 and 12 months (or 1,2,4 quarters) ahead were computed. The specifications of the models are based on information up to that date and, then, models are re-estimated in each month or quarter and forecasts are computed. Given the availability of actual values until 2005.12 or 2005.III or IV, forecast errors for each indicator and method can be computed in a recursive way (i.e., for the 1 month forecast horizon, 48 forecast errors can be computed for each indicator or 16 for the 1 quarter forecast horizon). In order to summarise this information, the Root Mean Squared Error (RMSE) has been computed. These values provide useful information in order to analyse the forecast accuracy of each method, so methods can be ranked according to their values. It is worth mentioning that in all cases we have assumed that the information of business and consumer surveys is known in advance, which is not a strong assumption for shorter forecasting horizons but it could be for longer ones. A possible strategy that is beyond the scope of this paper is to apply univariate forecasting methods to business and consumer surveys indicators (see Clar et al., 2006).

The results of our forecasting competition are shown in tables B.1 to B.19 of appendix B. These tables present the values of the Root of the Mean Squared Error (RMSE) obtained from recursive forecasts for 1,2,3,6 and 12 months during the period 2002.1-2005.12 or for 1,2 and 4 quarters during the period 2002.I-2005.IV for both, the benchmark models and the models including information from surveys.

The obtained results permit to conclude that, as expected, forecasts errors increase for longer horizons in most cases. Regarding the forecast accuracy of the different methods, in most cases the autoregressions, leading indicators models and VAR models are not outperformed by the rest of the methods, being the ARIMA and the modified Markov model the ones usually displaying the highest RMSE values.

But, do models with information from business and consumer surveys improve the forecasting performance of models that do not? Table 7 summarises the results from the forecasting competition. In particular, it shows for each variable which is the model with the lower value of the RMSE for every forecasting horizon. As we can see, when comparing the performance of the models including survey data to the ones that do not, the conclusion seems to be that in most cases some model that includes information from the survey obtains lower RMSE than the best model without survey information.

TABLE 7

In particular, for monthly variables (top panel of table 7) only for forecasting horizons of 1, 2 and 3 months, models without survey information show lower values of the RMSE than models with survey information. The exceptions are the number of persons employed in construction (qv2), the industry production index (qv4) and the number of new car registrations (qv6). For 6 and 12 months forecasting horizons, augmented AR models, augmented VAR models and leading indicator models show a better forecasting performance.

For quarterly variables (bottom panel of table 7), the results show a similar pattern: models with survey information show lower values of the RMSE with some exceptions for 1 quarter forecasting horizon. In particular, autoregressions and VAR models without survey information achieve better results for gross domestic product (qv14), gross fixed capital formation: construction work - other constructions (qv15) and final consumption expenditure: household and NPISH (qv18).

However, one key aspect that should be addressed is if the reduction in RMSE when comparing models with and without survey information is statistically significant.[5] With this aim, we have calculated the measure of predictive accuracy proposed by Diebold-Mariano (1995) between the two best models with and without survey information for the first 12 months or the first 4 quarters of the forecasting horizon. Given these two competing forecasts and the actual series for each quantitative variable, we have calculated the S(1) measure which compares the mean difference between a loss criteria (in this case, the root of the mean squared error) for the two predictions using a long-run estimate of the variance of the difference series.[6] In order to estimate this long-run variance from its autocovariance function, we have used the Bartlett kernel, as it guarantees that variance estimates are positive definite, while the maximum lag order has been calculated using the Schwert criterion as a function of the sample size. These results are shown in table 8.

TABLE 8

If we look at the results from table 8, we can see that in 9 out of 19 cases there is no significant difference between both forecasts. However, in ten cases, the difference is significant and in five of them, this difference is in favour of models with survey information[7]. The actual values and the two competing forecasts for these seven series where the difference is significant are shown in figure 1.

FIGURE 1

As we can see from table 8 and figure 1, the consideration of information from business and consumer surveys improves significantly the forecasting performance of the considered models but in a similar number of cases than models without survey information. These results are in line with the ones shown in table 7 and in the annex B.

However, looking at figure 1, it can also be observed that information from business and consumer surveys is particularly helpful in the presence of turning points in the forecasting horizon. For example, in the case of the savings rate (qv13), the leading indicator models with survey information is able to capture more quickly the downward trend in its evolution. A similar result is obtained for the gross fixed capital formation (qv15) when the construction confidence indicator (v28) is included as an exogenous variable in a VAR model.

Summarising, the comparison of the forecasting performance of the two sets of models permit to conclude that in most cases, models that include information from the survey obtain lower RMSE than the best model without survey information, particularly at longer forecasting horizons. However, this reduction is only significant in a limited number of cases. In this sense, the obtained results extend the results of previous research that have considered information from business and consumer surveys to explain the behaviour of macroeconomic variables, but are not conclusive about its role.

4. Conclusions

The objective of the paper was to analyse the possibility of improving the forecasts for some selected macroeconomic variables for the euro area using the information provided by business and consumer surveys. With this aim, we have carried out a forecasting competition between models with and without survey information and considering the presence or not of seasonal patterns in the data and the need of quantification the information from surveys.

The obtained results allow us to conclude that, only in a limited number of cases, the consideration of information from business and consumer surveys has improved significantly the forecasting performance of the different models for the considered macroeconomic variables.

Last, it is important to highlight that we have extended in a more systematic way[8] the results of previous research[9] that have considered information from business and consumer surveys to explain the behaviour of macroeconomic variables. As previously mentioned, the consideration of business and consumer surveys reduces the value of the RMSE in nearly the 80% of cases, but the results are not conclusive in a statistical sense (the reduction of forecasts errors is only significant in a limited number of cases). Moreover, the economic interpretation of the results is not always clear: for example, in the case of the number of persons employed in construction (qv2) when employment expectations for the months ahead (v31) is included as an additional explanatory variable, a significant improvement is achieved in forecasting the future evolution of the macroeconomic variable, which is the expected result. However, in other cases, such as the evolution of industrial production (qv4) and production expectations for the months ahead (v7), although RMSE is reduced, the differences are not significant. Why some survey indicators help to improve forecasts and why others do not is an aspect that will be considered in further research.

Acknowledgements

The results presented here were obtained under the contract "Forecasting models currently applied to indicators computed on the basis of surveys results" (ECFIN/2002/A3-01), directed by Manuel Artís and Jordi Suriñach, and the full report is available at the following internet address http://europa.eu.int/comm/economy_finance/indicators/business_consumer_surveys/studies/ub_aqr_final_report.pdf. We would like to thank the editors and an anonymous referee for their helpful comments and also the staff from the DG ECFIN of the European Commission and, particularly, Peter Weiss and Pilar Bengoechea for their suggestions and support. Raúl Ramos gratefully acknowledges support received from CICYT SEJ2005-04348/ECON. The usual disclaimer applies.

References

Albert, J. and Chib, S. (1993). Bayesian inference via Gibbs sampling of autoregressive time series subject to Markov mean and variance shifts. *Journal of Business and Economic Statistics, 11,* 1-15.

Anderson, O. (1951). Konjunkturtest und Statistik. *Allgemeines Statistical Archives, 35,* 209-20.

Anderson, O. (1952). The business test of the IFO-Institute for economic research, Munich, and its theoretical model. *Revue de l'Institut International de Statistique, 20,* 1-17.

Anderson, O., Bauer, R. K. and Fels, E. (1954). On the accuracy of short-term entrepreneurial expectations. Paper presented at the Montreal Meeting of the American Statistical Association.

Bodo, G., Golinelli, R. and Parigi, G. (2000). Forecasting Industrial Production in the Euro Area. *Empirical Economics, 25,* 541-561.

Box, G. and Cox, D. (1964). An Analysis of Transformation. *Journal of the Royal Statistical Society Series B,* 211-264.

Box, G. E. P. and Jenkins, G. M. (1970). *Time Series Analysis: Forecasting and Control*. Holden-Day, San Francisco.

Carlson, J. A. and Parkin, M. (1975). Inflation expectations. *Economica, 42,* 123-38.

Clar, M., Duque, J. C., Moreno, R. (2006), Forecasting Business and Consumer Surveys Indicators. A Time Series Models Competition. *Applied Economics*, forthcoming.

Claveria, O., Pons, E., Surinach, J. (2006), Quantification of Expectations. Are They Useful for Forecasting Inflation?. *Economic Issues*, forthcoming.

Clements, M. and Hendry, D. (1998). *Forecasting economic time series*. Cambridge University Press, Cambridge.

Clements, M. and Smith, J. (1999). A Monte Carlo Study of the Forecasting Performance of Empirical SETAR models. *Journal of Applied Econometrics, 14,* 123-141.

Cooley, T. F. and Prescott, E. C. (1976). Estimation in the presence of stochastic parameter variation. *Econometrica, 44,* 167-84.

De Menil, G. and Bhalla, S. (1975). Direct measurement of popular price expectations. *American Economic Review, 65,* 169-80.

Defris, L. V. and Williams, R. A. (1979). Quantitative versus qualitative measures of price expectations. *Economics Letters, 2,* 169-73.

Diebold, F. X. and Mariano, R. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics*, *13*, 253-63.

Easaw, J. Z. and Heravi, S. M. (2004). Evaluating Consumer Sentiments as Predictors of UK Household Consumption Behavior Are They Accurate and Useful?. *International Journal of Forecasting*, *20*, 671-81.

Forsells, M. and Kenny, G. (2002). The Rationality of Consumer's Inflation Expectations: Survey-based evidence for the euro area. ECB Working Paper 163.

Garrett, T. A., Hernandez-Murillo, R. and Owyang, M. T. (2004). Does Consumer Sentiment Predict Regional Consumption?. *Federal Reserve Bank of St. Louis Review*, *87*, 123-35

Grasmann, P. and Keereman, F. (2001). An indicator-based short-term forecast for quarterly GDP in the euro area. *Economic Paper 154*¸ European Commission.

Hamilton, J. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica, 57,* 357-384.

Hamilton, J. (1990). Analysis of time series subject to changes in regime. *Journal of Econometrics, 45,* 39-70.

Hansen, B., (1997). Inference in threshold models. Unpublished manuscript.

Harvey, A. (1982). The Kalman filter and its applications in Econometrics and time series analysis. *Methods of Operational Research, 44,* 3-18.

Harvey, A. (1987). Applications of the Kalman filter in Econometrics. In Bewley, T. (ed.), *Advances in Econometrics: Fifth World Congress, Econometric Society Monograph 13.* Cambridge University Press, Cambridge.

Howrey, E. P. (2001). The predictive power of the Index of Consumer Sentiment. *Brookings Papers on Economic Activity, 1,* 205-207.

Kauppi, E., Lassila, J. and Terasvirta, T. (1996). Short-Term forecasting of industrial production with business survey data: experience from Finland's great depression 1990-1993. *International Journal of Forecasting, 12,* 373-381.

Kim, C. J. (1994). Dynamic Linear Models with Markov-Switching. *Journal of Econometrics, 60,* 1–22.

Papadia, F. (1983). Inflationary Expectations in the European Economic Communities Countries. *Empirical Economics, 8,* 187-202.

Pesaran, M. H. (1987). *The Limits to Rational Expectations*. Basil Blackwell, Oxford.

Potter, S. (1999). Nonlinear Time Series Modelling: An Introduction. Federal Reserve Bank of New York, mimeo.

Seitz, H. (1988). The estimation of inflation forecasts from business survey data. *Applied Economics, 20,* 427-438.

Sédillot, F. and Pain, N. (2003). Indicators models of real GDP growth in selected OECD countries. ECO Working Paper 364.

Souleles, N. S. (2004). Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys. *Journal of Money, Credit, and Banking*, *36*, 39-72

Theil, H. (1952). On the time shape of economic microvariables and the Munich business test. *Revue de l'Institut International de Statistique, 20,* 105-120.

Theil, H. (1955). Recent experiences with the Munich business test: an expository article. *Econometrica, 23,* 184-192.

Vuchelen, J. (2004). Consumer Sentiment and Macroeconomic Forecasts. *Journal of Economic Psychology*, *25*, 493-506

Zimmermann, K. F. (1999). Analysis of Business Surveys. In Pesaran, M. H. and Schmidt, P. (Eds.), *Handbook of Applied Econometrics. Volume II: Microeconomics*. Blackwell Publishers, Oxford.

Endnotes

[1] Data used in this paper was obtained from the European Commission DG ECFIN website http://europa.eu.int/comm/economy_finance/indicators/business_consumer_surveys/bcsseries_en.htm) in March 2006.

[2] Data used in this paper was obtained from the Eurostat website (http://europa.eu.int/comm/eurostat) and the ECB website (http://www.ecb.int) in March 2006.

[3] The Hamilton filter is an iterative procedure which provides estimates of the probability that a given state is prevailing at each point in time given its previous history. These estimates are dependent upon the parameter values given to the filter. Running the filter through the entire sample, provides a log likelihood value for the particular set of estimates used. This filter is then repeated to optimise the log likelihood to obtain the MLE estimates of the parameters. With the maximum likelihood parameters, the probability of state 0 at each point in time is calculated and these are the probabilities of recession and expansion.

[4] An alternative approach would have consisted in imposing the value of P and k instead of estimating them. These models are known as Markov Switching Autoregressive Models (MS-AR) and, in general, the values of P are 0.7 or 0.8 and the values of k, 0 or 1.

[5] We are grateful to an anonymous referee for this suggestion.

[6] This measure has been calculated using the Stata routine by Christopher F. Baum which is available at http://fmwww.bc.edu/repec/bocode/d/dmariano.ado and http://fmwww.bc.edu/repec/bocode/d/dmariano.hlp.

[7] We have carried out similar analysis for different periods and results have been similar. For example, using information up to 2000.12 or 2000.IV for estimating the model and forecasts until 2001.12 or 2001.IV, in 12 out of 19 cases there is no significant difference between forecasts including survey information or not. However, in seven cases the difference is significant and in five of them, this difference is in favour of models with survey information.

[8] To our knowledge, no other study covers such a high number of macroeconomic variables and indicators (attention has been usually paid to industrial production, inflation and GDP). The number of econometric methods and models applied is also considerable higher than in previous research.

[9] Among others, it is worth mentioning the works by Easaw and Heravi (2004), Garret et al. (2004), Souleles (2004), Vuchelen (2004) for consumption, Kauppi et al. (1996) and Bodo et al. (2000) for industrial production, Howrey (2001) and Forsells and Kenny (2002) for inflation, Sédillot and Pain (2003) for GDP and the more broad works by the European Commission (the BUSY and BUSY II models or the approach by Grasmann and Keereman, 2001) or by the European Central Bank .

Table 1. List of business and consumer surveys indicators for the euro area (continues next page)

	Description	Freq.	Sample		Obs.	Categories						
v1	**Economic Sentiment Indicator**	month	jan-85	dec-05	252							
v2	**Industrial Confidence Indicator (v7+v4-v6)/3**	month	jan-85	dec-05	252							
v3	Production trend observed in recent months	month	jan-85	dec-05	252	P	E	M				B
v4	Assessment of order-book levels	month	jan-85	dec-05	252	P	E	M				B
v5	Assessment of export order-book levels	month	jan-85	dec-05	252	P	E	M				B
v6	Assessment of stocks of finished products	month	jan-85	dec-05	252	P	E	M				B
v7	Production expectations for the months ahead	month	jan-85	dec-05	252	P	E	M				B
v8	Selling price expectations for the months ahead	month	jan-85	dec-05	252	P	E	M				B
v9	Employment expectations for the months ahead	month	jan-85	dec-05	252	P	E	M				B
v10	New orders in recent months	quarter	1985-I	2005-IV	84	P	E	M				B
v11	Export expectations for the months ahead	quarter	1985-I	2005-IV	84	P	E	M				B
v12	**Consumer Confidence Indicator (v14+v16-v19+v23)/4**	month	jan-85	dec-05	252							
v13	Financial situation over last 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v14	Financial situation over next 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v15	General economic situation over last 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v16	General economic situation over next 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v17	Price trends over last 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v18	Price trends over next 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v19	Unemployment expectations over next 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v20	Major purchases at present	month	jan-85	dec-05	252	PP	E	MM	N			B
v21	Major purchases over next 12 months	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v22	Savings at present	month	jan-85	dec-05	252	PP	P	M	MM	N		B
v23	Savings over next 12 months	month	jan-85	dec-05	252	PP	P	M	MM	N		B
v24	Statement on financial situation of household	month	jan-85	dec-05	252	PP	P	E	M	MM	N	B
v25	Intention to buy a car within the next 2 years	quarter	1990-I	2005-IV	64	PP	P	M	MM	N		B
v26	Purchase or build a home within the next 2 years	quarter	1990-I	2005-IV	64	PP	P	M	MM	N		B
v27	Home improvements over the next 12 months	quarter	1990-I	2005-IV	64	PP	P	M	MM	N		B

Table 1. List of business and consumer surveys indicators for the euro area (continuation)

	Description	Freq.	Sample		Obs	Categories			
v28	**Construction Confidence Indicator (v30+v31)/2**	month	jan-85	dec-05	252				
v29	Trend of activity compared with preceding months	month	jan-85	dec-05	252	P	E	M	B
v30	Assessment of order books	month	jan-85	dec-05	252	P	E	M	B
v31	Employment expectations for the months ahead	month	jan-85	dec-05	252	P	E	M	B
v32	Price expectations for the months ahead	month	jan-85	dec-05	252	P	E	M	B
v33	**Retail Trade Confidence Indicator (v34-v35+v37)/3**	month	jan-86	dec-05	240				
v34	Present business situation	month	jan-85	dec-05	252	P	E	M	B
v35	Assessment of stocks	month	jan-85	dec-05	252	P	E	M	B
v36	Orders placed with suppliers	month	feb-85	dec-05	251	P	E	M	B
v37	Expected business situation	month	jan-86	dec-05	240	P	E	M	B
v38	Employment	month	abr-85	dec-05	249	P	E	M	B
v39	**Services Confidence Indicator (v40+v41+v42)/3**	month	abr-95	dec-05	129				
v40	Assessment of business climate	month	abr-95	dec-05	129	P	E	M	B
v41	Evolution of demand in recent months	month	abr-95	dec-05	129	P	E	M	B
v42	Evolution of demand expected in the months ahead	month	abr-95	dec-05	129	P	E	M	B
v43	Evolution of employment in recent months	month	abr-95	dec-05	129	P	E	M	B
v44	Evolution of employment expected in the months ahead	month	jan-97	dec-05	108	P	E	M	B

The letters refer to positive answers (pp and p), neutral answers (e), negative answers (mm and m), non answers (n), balance (b) and composite indicators (i).

Table 2. List of considered macroeconomic variables

Endogenous variables

	Description	Freq.	sample		Obs
qv1	Harmonized consumer price index	Monthly	jan-90	dec-05	192
qv2	Construction - number of persons employed index	Monthly	jan-91	dec-05	180
qv3	Building permits index - New residential buildings	Monthly	jan-85	nov-05	251
qv4	Industry Production index	Monthly	jan-85	dec-05	252
qv5	Industry Producer price index	Monthly	jan-85	dec-05	252
qv6	Number of new car registrations	Monthly	jan-85	dec-05	252
qv7	Retail Deflated turnover index	Monthly	jan-94	dec-05	144
qv8	Unemployment rate	Monthly	jan-93	dec-05	156
qv9	Industry Gross value added	Quarterly	1991-I	2005-IV	60
qv10	Construction Gross value added	Quarterly	1991-I	2005-IV	60
qv11	Wholesale and retail trade & other Gross value added	Quarterly	1991-I	2005-IV	60
qv12	Financial intermediation Gross value added	Quarterly	1991-I	2005-IV	60
qv13	Savings rate	Quarterly	1991-I	2005-III	59
qv14	Gross domestic product	Quarterly	1991-I	2005-IV	60
qv15	Gross fixed capital formation: construction work - other constructions	Quarterly	1991-I	2005-III	59
qv16	Gross fixed capital formation: metal products and machinery	Quarterly	1991-I	2005-III	59
qv17	Exports of goods	Quarterly	1991-I	2005-IV	60
qv18	Final consumption expenditure: household and NPISH	Quarterly	1991-I	2005-IV	60
qv19	Gross fixed capital formation: construction work - housing	Quarterly	1991-I	2005-III	69

Exogenous variables

	Description	Freq.	Sample		Obs
qv20	Interest rate	Quarterly	1990-I	2005-IV	64
qv21	Exchange rate	Quarterly	1993-I	2005-IV	52

Table 3 Correspondence between business and consumer surveys indicators and the selected macroeconomic variables (continues)

	Description				
v1	**Economic Sentiment Indicator**	qv13			
v2	**Industrial Confidence Indicator (v7+v4-v6)/3**				
v3	Production trend observed in recent months	qv4	qv8	qv13	
v4	Assessment of order-book levels	qv4	qv8	qv13	
v5	Assessment of export order-book levels	qv4	qv8	qv13	qv16
v6	Assessment of stocks of finished products	qv4	qv8	qv13	
v7	Production expectations for the months ahead	qv4	qv8	qv13	
v8	Selling price expectations for the months ahead	qv1	qv5		
v9	Employment expectations for the months ahead	qv4	qv8	qv13	qv19
v10	New orders in recent months	qv4	qv8	qv15	
v11	Export expectations for the months ahead	qv4	qv8	qv13	qv16
v12	**Consumer Confidence Indicator (v14+v16-v19+v23)/4**	qv13	qv17		
v13	Financial situation over last 12 months	qv6	qv13	qv17	
v14	Financial situation over next 12 months	qv6	qv13	qv17	
v15	General economic situation over last 12 months	qv6	qv13	qv17	
v16	General economic situation over next 12 months	qv6	qv13	qv17	
v17	Price trends over last 12 months	qv1			
v18	Price trends over next 12 months	qv1			
v19	Unemployment expectations over next 12 months	qv13	qv17	qv19	
v20	Major purchases at present	qv13	qv17		
v21	Major purchases over next 12 months	qv13	qv17		
v22	Savings at present	qv12			
v23	Savings over next 12 months	qv12			
v24	Statement on financial situation of household	qv12			
v25	Intention to buy a car within the next 2 years	qv6			
v26	Purchase or build a home within the next 2 years	qv18			
v27	Home improvements over the next 12 months	qv18			

Table 3 Correspondence between business and consumer surveys indicators and the selected macroeconomic variables (continuation)

	Description					
v28	**Construction Confidence Indicator (v30+v31)/2**	qv3	qv10	qv14	qv15	qv19
v29	Trend of activitiy compared with preceding months	qv3	qv10	qv14	qv15	qv19
v30	Assessment of order books	qv3	qv10	qv14	qv15	qv19
v31	Employment expectations for the months ahead	qv2	qv8			
v32	Price expectations for the months ahead	qv1				
v33	**Retail Trade Confidence Indicator (v34-v35+v37)/3**	qv11	qv14			
v34	Present business situation	qv11	qv14			
v35	Assessment of stocks	qv11				
v36	Orders placed with suppliers	qv11				
v37	Expected business situation	qv11	qv14			
v38	Employment	qv8				
v39	**Services Confidence Indicator (v40+v41+v42)/3**	qv11	qv12	qv14		
v40	Assessment of business climate	qv11	qv12	qv14		
v41	Evolution of demand in recent months	qv11	qv12	qv14		
v42	Evolution of demand expected in the months ahead	qv11	qv12	qv14		
v43	Evolution of employment in recent months	qv8				
v44	Evolution of employment expected in the months ahead	qv8				

Table 4. VAR models specification

VAR model	Considered quantitative variables
Total of the economy	Harmonized consumer price index Gross domestic product Unemployment rate
Supply	Industry Gross value added Construction Gross value added Wholesale and retail trade & other Gross value added Financial intermediation Gross value added
Industry (a)	Industry Production index Industry Producer price index
Industry (b)	Industry Production index Industry Producer price index Gross fixed capital formation: metal products and machinery
Building	Construction - number of persons employed index Building permits index - New residential buildings Gross fixed capital formation: construction work - other constructions Gross fixed capital formation: construction work – housing Interest rates
Exports	Gross domestic product Exports of goods Exchange rates
Consumption	Harmonized consumer price index Gross domestic product Final consumption expenditure: household and NPISH Unemployment rate Interest rates
Savings	Harmonized consumer price index Savings rate Gross domestic product Interest rates

Table 5. Specification of “augmented” VAR models

	Macroeconomic variables	Indicators
Total	*qv1 qv14 qv8*	*v1*
Supply	*qv9 qv10 qv11 qv12*	*v1*
Industry (a)	*qv4 qv5*	*v7b v8b*
Industry (b)	*qv4 qv5 qv16*	*v2*
Building (a)	*qv2 qv3 qv15 qv19 qv20*	*v28*
Building (b)	*qv2 qv3 qv15 qv19 qv20*	*v31b v32b*
Exports	*qv14 qv17 qv21*	*v5b*
Consumption (a)	*qv1 qv8 qv14 qv18 qv20*	*v12*
Consumption (b)	*qv1 qv8 qv14 qv18 qv20*	*v14b v16v v18b v19b*
Savings	*qv1 qv13 qv14 qv20*	*v23b v24b*

Table 6. Summary of the results of the Kruskal Wallis test

	Rejection of the Null	Non-rejection of the Null	TOTAL
Month	9	30	39
Quarter	1	4	5
TOTAL	10	34	44

	Rejection of the Null	Non-rejection of the Null	TOTAL
Month	23.08%	76.92%	100.00%
Quarter	20.00%	80.00%	100.00%
TOTAL	22.73%	77.27%	100.00%

Null hypothesis: Non-seasonal pattern in the considered serie

Table 7. Summary of the results from the forecasting competition

Monthly models

		1 month	2 months	3 months	6 months	12 months
Non-survey	AR	qv1, qv3, qv5, qv6, qv7, qv8	qv1, qv3, qv5, qv7, qv8	qv1, qv3, qv5, qv6, qv7, qv8	qv1, qv6, qv7	qv1
	ARIMA					
	TAR					
	MK-TAR					
	VAR					
Survey	AR	qv4	qv4	qv4	qv4	qv7, qv8
	MK-TAR					
	VAR					qv4
	Leading indicator	qv2	qv2, qv6	qv2	qv2, qv3, qv5, qv8	qv2, qv3, qv5, qv6

Quarterly models

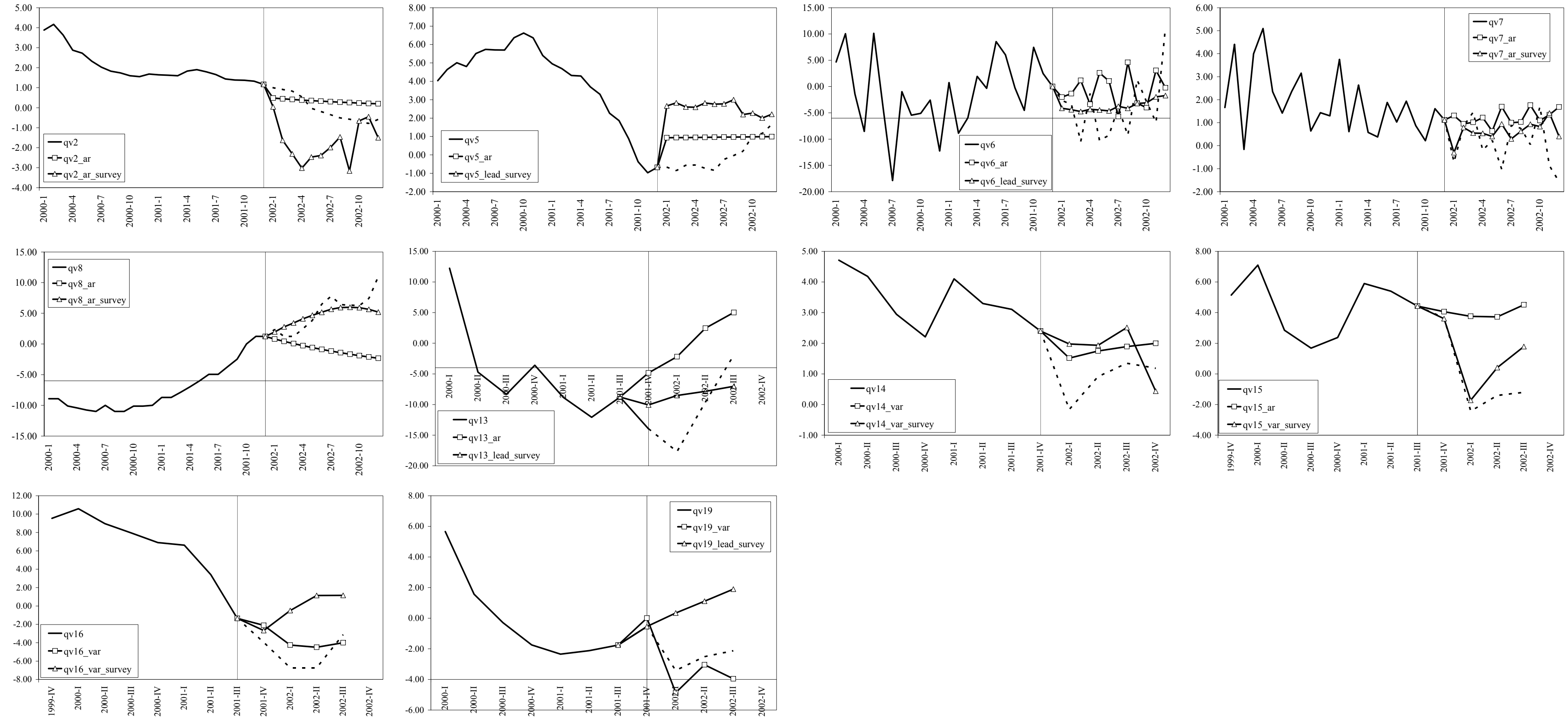
		1 quarter	2 quarters	4 quarters
Non-survey	AR	qv10	qv10	
	ARIMA			
	TAR			
	MK-TAR			qv9
	VAR	qv14, qv15, qv16, qv19	qv15	qv14, qv18
Survey	AR		qv16	qv10, qv17
	MK-TAR	qv9	qv9	
	Leading indicator	qv11, qv13, qv17, qv18, qv19	qv13, qv14, qv17, qv18, qv19	qv12, qv13
	VAR	qv12	qv11, qv12	qv11, qv15, qv16

Table 8. Results of the Diebold-Mariano test

Monthly data: 2002m1-2002m12		Quarterly data: 2002q1-2002q4	
qv1	-1.26	qv9	-0.12
qv2	-2.24*	qv10	-1.92
qv3	0.29	qv11	-0.01
qv4	-1.72	qv12	1.02
qv5	-3.81*	qv13	**3.84***
qv6	**3.81***	qv14	-2.18*
qv7	**2.97***	qv15	**3.14***
qv8	**2.64***	qv16	-2.45*
		qv17	-1.49
		qv18	-1.67
		qv19	-10.88*

Null hypothesis: The difference between the two competing series is non-significant.
A positive sign of the statistic implies that the RMSE associated to the forecast from the model with survey information is lower while a negative sign implies the opposite.
* significant at the 5% level.

Figure 1. Comparison of actual values and significantly different competing forecasts according to the Diebold-Mariano test



Appendix A.

Table A.1. Detailed results of the Kruskal-Wallis test

Variable	KW-statistic	P-value	
v1	6.04	0.87	Non RH0
v2	8.26	0.69	Non RH0
v3b	29.23	0.00	RH0
v4b	1.84	1.00	Non RH0
v5b	1.59	1.00	Non RH0
v6b	4.74	0.94	Non RH0
v7b	73.50	0.00	RH0
v8b	25.06	0.01	RH0
v9b	5.16	0.92	Non RH0
v10b	14.06	0.00	RH0
v11b	5.67	0.13	Non RH0
v12	5.85	0.88	Non RH0
v13b	1.53	1.00	Non RH0
v14b	4.25	0.96	Non RH0
v15b	1.27	1.00	Non RH0
v16b	8.13	0.70	Non RH0
v17b	0.43	1.00	Non RH0
v18b	2.46	1.00	Non RH0
v19b	7.34	0.77	Non RH0
v20b	4.11	0.97	Non RH0
v21b	1.10	1.00	Non RH0
v22b	1.06	1.00	Non RH0
v23b	4.73	0.94	Non RH0
v24b	2.10	1.00	Non RH0
v25b	0.88	0.83	Non RH0
v26b	0.27	0.97	Non RH0
v27b	0.38	0.94	Non RH0
v28	27.01	0.00	RH0
v29b	150.68	0.00	RH0
v30b	14.52	0.21	Non RH0
v31b	70.02	0.00	RH0
v32b	9.81	0.55	Non RH0
v33	7.45	0.76	Non RH0
v34b	1.91	1.00	Non RH0
v35b	48.11	0.00	RH0
v36b	21.40	0.03	RH0
v37b	9.42	0.58	Non RH0
v38b	34.70	0.00	RH0
v39	0.88	1.00	Non RH0
v40b	0.39	1.00	Non RH0
v41b	7.94	0.72	Non RH0
v42b	7.53	0.75	Non RH0
v43b	3.90	0.97	Non RH0
v44b	14.62	0.20	Non RH0

H0: Non-seasonality / HA: seasonality

Appendix B.

Table B.1

qv1: HCPI. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*0.20**	*0.26**	*0.30**	*0.30**	*0.28**
ARIMA	1.55	1.85	2.18	2.32	2.53
TAR	2.04	3.12	3.91	6.03	13.13

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v18b)	**0.20**	**0.26**	0.33	0.41	0.58
AR (+v18 quantified)	**0.20**	0.27	0.34	0.41	0.57
Leading indicators model 1	0.56	0.55	0.66	0.43	0.52
Leading indicators model 2	0.42	0.37	0.43	0.53	0.82

v18: Price trends over next 12 months

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.2

qv2. Construction - number of persons employed index: Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*0.78*	*0.95*	*1.10*	*1.32*	*1.38*
ARIMA	6.19	7.93	8.75	10.14	10.66
TAR	25.89	26.49	52.13	230.52	1102.48
MK-TAR	0.99	1.35	9.25	52.58	10.76

Models with survey information	1 month	2 month	3 month	6 months	12 months
AR (+v31b)	**0.77**	**0.93**	**1.05**	**1.24**	**1.15**
AR (+v31b quantified)	**0.77**	**0.93**	**1.06**	**1.27**	**1.22**
Leading indicators model 1	**0.42***	**0.37***	**0.43***	**0.53***	**0.82***
Leading indicators model 2	1.55	2.01	**1.04**	2.39	3.82

v31: Employment expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.3

qv3: Building permits index. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from December 2001 to November 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*5.55**	*5.92**	*6.19**	*7.04*	*6.48*
ARIMA	39.87	43.83	47.42	53.18	56.89
TAR	68.87	97.78	125.16	172.36	261.11
MK-TAR	6.47	7.98	8.98	10.20	7.83

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v29b)	6.47	6.93	6.96	7.71	7.07
AR (+v30b)	6.14	6.39	6.49	7.23	6.96
AR (+v29b+v30b)	5.87	6.57	6.61	7.38	6.46
AR (+v29b quantified)	6.24	6.49	6.64	7.44	7.13
AR (+v30b quantified)	5.87	6.57	6.59	7.34	6.40
Leading indicators model 1	6.46	6.19	6.38	**6.37**	**5.85***
Leading indicators model 2	6.83	7.00	8.35	**6.08***	**7.65**

v29: Trend of activity compared with preceding months

v30: Assessment of order books

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.4

qv4: Industry Production Index. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*1.47*	1.57	1.69	2.35	3.06
ARIMA	10.06	10.64	10.86	14.36	15.71
TAR	14.86	16.29	22.51	33.58	52.52
VAR industry (a)	1.53	*1.53*	*1.40*	*1.64*	*1.57*

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v7b)	**1.37***	**1.39***	**1.39***	**1.55***	**1.66**
AR (+v7b quantified)	1.48	**1.49**	**1.46**	**1.59**	**1.60**
Leading indicators model 1	**1.45**	**1.53**	**1.44**	**1.96**	**1.38**
Leading indicators model 2	1.49	**1.33**	1.73	**1.95**	**2.80**
VAR-industry (a) (+v7b quantified+v8b quantified)	1.48	1.58	**1.54**	**1.61**	**1.56***

v7: Production expectations for the months ahead

v8: Selling price expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.5

qv5: Industry Producer Price Index. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*0.42**	*0.68**	*0.88**	*1.37*	*2.04*
ARIMA	2.93	4.94	6.48	10.04	15.08
TAR	4.88	6.76	8.57	15.01	23.74
VAR industry (a)	0.44	0.70	0.90	1.42	2.15

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v8b)	0.44	0.70	0.91	1.42	2.15
AR (+v8b quantified)	0.43	0.69	0.89	1.39	2.10
Leading indicators model 1	1.56	1.49	1.44	**1.28***	**1.84***
Leading indicators model 2	1.95	1.55	1.66	3.13	4.63
VAR-industry (a) (+v7b quantified+v8b quantified)	0.44	0.71	0.92	1.41	2.12

v7: Production expectations for the onths ahead

v8: Selling price expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.6

qv6: Number of new car registrations. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*4.95**	*5.09*	*5.37**	*5.33**	*5.19*
ARIMA	40.81	42.26	43.82	38.38	40.65
TAR	77.25	79.33	78.06	81.21	116.51

Models with survey information	1 month	2 months	3 months	6 months	12 months
Leading indicators model 1	5.46	**4.61***	5.85	6.31	**5.14***
Leading indicators model 2	5.76	6.78	6.95	6.01	8.16

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.7

qv7: Retail Deflated turnover index : Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*1.11**	*1.12**	*1.13**	*1.26**	*1.42*
ARIMA	8.79	8.48	7.92	8.62	9.13
TAR	14.20	14.24	14.34	17.04	19.53
MK-TAR	1.89	3.14	2.48	2.27	7.15

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v34b)	1.25	1.24	1.22	1.31	**1.39***
AR (+v35b)	1.31	1.28	1.25	1.44	1.59
AR (+v36b)	1.42	1.37	1.34	1.48	1.46
AR (+v37b)	1.31	1.29	1.28	1.37	1.47
AR (+v34b +v35b +v36b +v37b)	2.27	2.58	2.64	2.68	2.64
AR (+v34b quantified)	1.23	1.22	1.22	1.32	1.49
AR (+v35b quantified)	1.33	1.29	1.25	1.38	1.47
AR (+v36b quantified)	1.40	1.36	1.33	1.52	1.62
AR (+v37b quantified)	1.32	1.29	1.24	1.35	1.47
Leading indicators model 1	1.22	1.19	1.28	1.71	1.91
Leading indicators model 2	1.24	1.17	1.21	1.42	1.59

v34: Present business situation
v35: Assessment of stocks
b: balance
v36: Orders placed with suppliers
v37: Expected business situation

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.8

qv8: Unemployment rate. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from January 2002 to December 2005

Models without survey information	1 month	2 months	3 months	6 months	12 months
AR	*2.44**	*2.73**	*2.94**	*3.83*	*4.63*
ARIMA	20.31	21.27	22.81	29.29	47.49
TAR	21.54	26.82	32.74	58.39	135.12

Models with survey information	1 month	2 months	3 months	6 months	12 months
AR (+v19b)	2.47	2.85	3.15	4.20	**4.56***
AR (+v19b quantified)	2.48	2.80	3.03	3.98	4.98
MK-TAR(+v19b)	2.51	5.72	8.63	13.06	28.89
Leading indicators model 1	3.81	3.85	3.67	3.66	7.16
Leading indicators model 2	5.00	4.85	4.24	**3.56***	8.95

v19: Unemployment expectations over next 12 months

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.9

qv9: Industry Gross value added. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*1.79*	*1.98*	2.11
ARIMA	8.00	9.95	10.34
TAR	16.97	16.46	15.54
MK-TAR	2.61	3.27	*2.09**
VAR- supply	2.27	2.96	2.94

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+ICI)	2.61	3.06	3.39
MK-TAR(+ICI)	2.34	2.57	2.25
Leading indicators model 1	**1.57***	**1.95***	3.44
Leading indicators model 2	**1.69**	2.55	3.16
VAR- supply (+ESI)	1.95	2.15	2.15

VAR-supply: Industry Gross value added + Construction + Wholesale and retail trade + Financial intermediation

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.10

qv10: Construction Gross value added. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*1.58**	*1.74**	*1.99*
ARIMA	8.03	9.08	11.12
TAR	12.14	15.24	19.55
MK-TAR	1.81	3.11	4.13
VAR- supply	2.28	2.96	2.94

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+CCI)	2.24	2.29	**1.55***
Leading indicators model 1	1.72	1.79	3.29
Leading indicators model 2	2.48	2.67	3.65
VAR- supply (+ESI)	1.99	1.96	**1.73**

VAR-supply: Industry Gross value added + Construction + Wholesale and retail trade + Financial intermediation

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.11

qv11: Wholesale and retail trade & other Gross value added. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*1.20*	1.22	*1.19*
ARIMA	5.41	5.57	5.22
TAR	8.37	7.93	9.70
VAR- supply	1.24	*1.16*	1.42

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v34b)	**1.17**	**0.99**	**1.08**
AR (+v34b quantified)	**1.16**	**1.00**	**0.99**
Leading indicators model 1	**0.91***	**1.08**	1.64
Leading indicators model 2	**1.04**	**1.03**	1.51
VAR- supply (+ESI)	**1.14**	**0.94***	**0.82***

VAR-supply: Industry Gross value added + Construction + Wholesale and retail trade + Financial intermediation

v34: Present business situation

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.12

qv12: Financial intermediation Gross value added. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*1.05*	*1.49*	*1.87*
ARIMA	4.28	5.99	7.73
TAR	8.25	9.69	13.36
VAR- supply	1.07	1.57	2.04

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v13b)	11.64	13.76	22.66
AR (+v14b)	13.62	15.47	19.29
AR (+v13b +v14b)	1.05	1.58	2.23
AR (+v13b quantified)	11.65	13.77	22.67
AR (+v14b quantified)	13.62	15.47	19.29
Leading indicators model 1	1.45	1.69	**1.71***
Leading indicators model 2	1.10	1.64	**1.78**
VAR- supply (+ESI)	**1.00***	**1.42***	**1.86**

VAR-supply: Industry Gross value added + Construction + Wholesale and retail trade + Financial intermediation

v13: Financial situation over last 12 months

v14: Financial situation over next 12 months

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.13

qv13: Savings rate. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 4th quarter 2001 to 3rd quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*7.94*	9.70	*8.27*
ARIMA	32.27	42.92	50.93
TAR	53.88	58.98	62.78
VAR- savings	9.27	*9.14*	12.45

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v22b)	11.65	13.77	22.67
AR (+v23b)	13.62	15.47	19.29
AR (+v22 +v23b)	17.45	17.99	22.62
AR (+v22b quantified)	11.64	13.76	22.66
AR (+v23b quantified)	13.62	14.47	19.30
Leading indicators model 1	**6.73***	**7.24***	**7.72***
Leading indicators model 2	8.86	**8.55**	9.55
VAR- savings (+v23b+v24b)	8.72	9.24	10.14

VAR-savings: HCPI + Savings rate + GDP + Interests rates

v22: Savings at present

v23: Savings over next 12 months

b: balance

v24: Statement on financial situation of household

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.14

qv14: Gross Domestic Product. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	0.94	1.02	1.11
ARIMA	4.15	4.80	4.69
TAR	7.93	10.49	14.16
MK-TAR	1.10	1.86	2.29
VAR-total	*0.70**	*0.67*	*0.76**
VAR-consumption	0.89	1.10	1.57
VAR-savings	1.28	1.67	1.88
VAR-exports	0.94	1.24	2.53

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+ESI)	0.87	0.89	0.91
AR (+v15b)	0.90	0.90	0.94
AR (+v16b)	0.80	0.85	0.86
AR (+ESI+v15b+v16b)	1.11	1.41	1.39
AR (+v15 quantified)	0.94	1.00	1.09
AR (+v16 quantified)	0.94	1.00	1.11
MK-TAR (+v1)	1.19	1.17	1.59
Leading indicators model 1	0.96	**0.64***	2.14
Leading indicators model 2	1.04	1.66	1.89
VAR-total (+ ESI)	0.99	0.93	0.88
VAR-exports (+v5b)	1.01	1.13	1.82
VAR-consumption (+ CCI)	0.98	1.07	0.97
VAR-consumption (+v14b+v16b+v18b+v19b)	1.18	1.09	0.85
VAR-savings (+v23b+v24b)	1.68	1.66	1.44

v14: Financial situation over next 12 months

v15: General economic situation over last 12 months

v16: General economic situation over next 12 months

v18: Price trends over next 12 months

v19: Unemployment expectations over next 12 months

v23: Savings over next 12 months

v24: Statement on financial situation of household

b: balance

VAR-total: HCPI+ GDP + Unemployment

VAR-consumption: Consumption + HCPI + GDP + Unemployment + Interest rates

VAR-savings: Savings rate + GDP + HCPI + Interest rates

VAR-exports: GDP + Exports of goods + Exchange rate

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.15

qv15: Gross fixed capital formation: construction work - other constructions. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 4th quarter 2001 to 3rd quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	2.55	2.93	*2.69*
ARIMA	11.96	12.82	13.49
TAR	21.37	21.41	21.61
MK-TAR	2.75	3.55	3.73
VAR- building	*2.06**	*1.43**	3.22

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v29b)	2.81	2.82	3.32
AR (+v30b)	2.56	2.44	**2.55**
AR (+v29b +v30b)	4.80	4.93	7.00
AR (+v29b quantified)	2.76	3.33	3.29
AR (+v30b quantified)	2.57	2.66	2.74
Leading indicators model 1	2.74	2.71	2.90
Leading indicators model 2	2.88	2.88	3.84
VAR-building (a) (+CCI)	5.17	3.74	**2.45***
VAR-building (b) (+v31b+v32b)	4.76	3.05	3.85

VAR-building: construction + Building permits index + construction work (other constructions) + construction work (housing)

v29: Trend of activity compared with preceding months

v30: Assessment of order books

v31: Employment expectations for the months ahead

v32: Price expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.16

qv16: Gross fixed capital formation: metal products and machinery. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 4th quarter 2001 to 3rd quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	2.15	3.44	4.81
ARIMA	8.41	14.31	17.32
TAR	21.73	34.09	57.61
VAR- industry (b)	*1.67**	*2.91*	*3.94*

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v3b)	1.90	**2.76***	4.21
AR (+v7b)	2.89	3.77	6.63
AR (+v3b +v7b)	5.59	9.03	37.16
AR (+v3b quantified)	1.94	2.78	4.18
AR (+v7b quantified)	3.23	3.98	5.04
MK-TAR(+v7b)	2.89	5.37	6.75
Leading indicators model 1	1.72	3.23	4.01
Leading indicators model 2	2.44	4.56	7.95
VAR-industry (b) (+ICI)	2.26	3.15	**2.34***

VAR-industry (b): Industry production index + Industry producer price index + metal products and machinery

v3: Production trend observed in recent months

v7: Production expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.17

qv17: Exports of goods. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*3.38*	*5.22*	*6.12*
ARIMA	5.62	5.68	6.61
TAR	22.23	30.80	44.41
VAR- exports	3.39	5.76	9.80

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+11b)	4.63	6.02	**5.13**
AR (+v5b)	4.15	5.75	**4.39***
AR (+v11b +v5b)	4.62	6.73	7.77
AR (+v11b quantified)	4.39	7.25	8.74
AR (+v5b quantified)	3.86	6.71	8.83
MK-TAR(+v11b)	**3.01**	5.65	6.92
Leading indicators model 1	**2.98**	**1.90***	**6.42**
Leading indicators model 2	**2.39***	**2.68**	**6.58**
VAR-exports (+v5b)	3.54	**4.47**	**4.41**

VAR-exports: GDP + Exports of goods + Exchange rate

v5: Assessment of export order-book levels

v11: Export expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.18

qv18: Consumption. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 1st quarter 2002 to 4th quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	*1.16*	*1.03*	0.87
ARIMA	5.62	5.67	6.60
TAR	7.65	7.15	6.42
MK-TAR	1.31	1.41	7.52
VAR- consumption	1.27	1.19	*0.80**

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v20b)	**1.14**	**1.01**	0.92
AR (+v20b quantified)	1.19	1.06	0.86
Leading indicators model 1	**1.04***	**0.95***	0.84
Leading indicators model 2	**1.11**	1.38	1.89
VAR-consumption (a) (+ CCI)	1.33	1.29	0.83
VAR-consumption (b) (+v14b+v16b+v18b+v19b)	1.43	1.18	0.99

VAR-consumption: Consumption + HCPI + GDP + Unemployment + Interest rates

v14: Financial situation over next 12 months

v16: General economic situation over next 12 months

v18: Price trends over next 12 months

v19: Unemployment expectations over next 12 months

v20: Major purchases at present

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model

Table B.19

qv19: Gross fixed capital formation: construction work – housing. Year-on-year growth rates of raw data

Average RMSE - Recursive forecasts from 4th quarter 2001 to 3rd quarter 2005

Models without survey information	1 quarter	2 quarters	4 quarters
AR	2.86	3.31	3.14
ARIMA	13.31	14.72	19.81
TAR	16.98	18.92	21.21
VAR- building	*2.78**	*3.27*	*2.51*

Models with survey information	1 quarter	2 quarters	4 quarters
AR (+v26b)	4.85	5.29	5.70
AR (+v26b quantified)	4.61	4.42	4.92
Leading indicators model 1	2.85	**2.69***	**2.45***
Leading indicators model 2	3.64	4.86	5.78
VAR-building (a) (+CCI)	5.09	3.91	3.57
VAR-building (b) (+v31b+v32b)	4.71	4.07	5.22

VAR-building: construction + Building permits index + construction work (other constructions) + construction work (housing)

v26: Purchase or build a home within the next 2 years

v31: Employment expectations for the months ahead

v32: Price expectations for the months ahead

b: balance

Italics: best model without survey information

Bold: Better forecast performance than best model without survey information

* Best model