Direct vs Indirect Forecasts of Foreign Trade Unit Value Indices*

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Abstract

This paper examines the forecasting approach of foreign trade unit value indices followed in the compilation of quarterly national accounts of Italy. Total imports and exports indices are indirectly obtained from the aggregation of ARIMA forecasts of disaggregated components, derived from the program TRAMO with automatic identification options. An out-of-sample forecasting exercise is performed to validate the automatic choices made by TRAMO and to evaluate the relative performance of a direct forecasting approach of imports and exports aggregates. The use of a crude oil price index to improve forecasting accuracy of the imports unit value index is finally assessed.

Keywords: Forecast aggregation, Foreign trade statistics, Flash estimates, Quarterly National Accounts
JEL Classification: C32, C43, C53, F17

1 Introduction

The compilation of Quarterly National Accounts (QNA) in Italy relies on a system of short-term indicators of economic activity (monthly industrial production indices, monthly foreign trade statistics, quarterly households budget survey, etc.). With the current timeliness of QNA publication, the latest observations of some indicators are often not available for the most recent quarter, generally the most interesting one for users. This is the case of foreign trade Unit Value Indices (UVIs), which are used for the deflation of imports and exports of goods and other main aggregates of

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*The opinions expressed in this paper are those of individual authors and do not necessarily reflect the official position of ISTAT.

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QNA (production, intermediate costs, gross fixed capital formation, etc.). One or two months of the current quarter can be absent: the recourse to forecasting methods is thus necessary to fill in the missing information and proceed with the subsequent steps of the estimation process.

Foreign trade UVIs are used in QNA at a detailed level of the NACE classification, more than 60 products for both imports and exports. This is justified by the fact that UVIs cannot be considered as a proxy of imports and exports prices at an aggregated level. The forecasting exercise is repeated every quarter (twice a quarter if the GDP flash estimate is considered). The program TRAMO (Gomez and Maravall, 1997) is used to obtain forecasts, that extrapolates future values of a time series on the basis of estimated ARIMA models with regression effects (the so-called REG-ARIMA model). Automatic modeling options are used, including the choice of the ARIMA order, log or level specifications and outliers. The aggregated indices for imports and exports result indirectly from a linear combination of the individual forecasts by product, with weights given by the values at current prices of NA imports and exports of goods.

Both theoretical considerations and empirical results available in the literature do not seem to suggest a clean-cut preference to a direct or an indirect forecasting approach. Results depend on the type of model used, the forecasting horizon, the kind of time series, and other determinants. For example, Benalal *et al.* (2004) investigates whether the indirect forecast of the Euro area Harmonized Index of Consumer Prices (HICP) from its components improves upon the forecast of overall HICP. The direct approach provides better results than the indirect one (especially in the long-term); however, if the HICP excluding the unprocessed food and energy is considered then the indirect approach prevails.

Through an out-of-sample forecasting exercise, this work aims at evaluating the effectiveness of the indirect forecasting approach of UVIs against several alternatives, including the direct modeling of the total imports and exports indices.

The paper is organised as follows. Section 2 gives a brief review on the theory of aggregation and disaggregation in the context of forecasting. The general principles of forecasting adopted in QNA is presented in section 3. The forecasting exercise is described in section 4, with presentation of data used, design of the experiment, and main findings. Section 5 concludes with a summary and future developments of the work.

2 Forecasting aggregates vs. aggregating forecasts: still an open issue

The problem of aggregation is a controversial and debated topic in the economic literature. An attempt to find a suitable microeconomic foundation of macroeconomics is done by Forni and Lippi (1997); other seminal works are those of Theil (1954), Grunfeld and Griliches (1960) and Zellner (1962). Behind the theoretical implications, the increasing availability of economic statistics at different detail levels makes the aggregation problem very interesting in practical applications too. A typical example is the forecast of key variables for the euro area, that influences the decisions of monetary policy makers (ECB) and operators. The choice between forecasting the euro area aggregate or aggregating forecasts of the Member states is in fact non-trivial and must be carefully analyzed (Marcellino, 2004).

A key question in this work is whether the point forecasts[1] of an aggregate (direct method) improves upon those derived from an indirect approach. Aggregation can be performed along with different dimensions; they can be classified into:

- *contemporaneous aggregation*, where the aggregation is made across variables according to a given classification (i.e. sub-indices of inflation rate[2]; the *Composite Leading Indicators* released by OECD);

- *spatial aggregation*, that regards aggregation across space (i.e. GDP for the euro area, with an example in Bacchini *et al.*, 2008);

- *temporal aggregation*, that implies the transformation of observations from higher to lower frequencies (i.e. quarterly to monthly, monthly to quarterly, etc.);

Another important aspect is the role of the aggregation rule. When several forecasts are obtained for the same variable, their combination is usually done with weights estimated according to some optimization criteria. This certainly increases uncertainty of forecasts (Timmermann, 2006). Instead, the indirect forecast of aggregates from their components does not suffer this problem, because it can be derived on the basis of pre-determined weights given by, for example, the current values of the fixed base period or the relative weights of countries.

Hendry (2004) identifies different sources of mistakes that influence the model predictability:

- model specification (choice of variables, functional form, model selection);

- estimation uncertainty;

[1] This work does not deal with interval forecasts and probability distribution forecasts, that are very important concepts in nonlinear forecast schemes (i.e. the nonparametric concept of high density region described by Hyndman (1995)).

[2] Inflation rate is often considered in practical applications; examples are Benalal *et al.* (2004), Demers and de Champlain (2005), Hubrich (2005) dealing with the forecast of the HICP index for the euro area.

- data measurement errors;
- structural breaks over the forecast horizon.

Similarly to Hendry and Hubrich (2007), we introduce the following taxonomy of the different forecasting approaches according to the kind of information set:

- $\hat{y}^a_{t+h} = f(y^a_{t+h}|\Omega_t)$, where the h-step ahead forecast of the aggregated variable is a function of its past values $\Omega_t = \{y^a_t, y^a_{t-1}, \ldots\}$, with $h = 1, 2, \ldots$;
- $\hat{y}^a_{t+h} = f(y^a_{t+h}|\Lambda^1_t, \Lambda^2_t, \ldots \Lambda^n_t)$, where Λ^i_t, for $i = 1, \ldots, n$ are the information sets of past values of components at a detailed level of disaggregation, with $\bigcup \Lambda^i_t \neq \Omega_t$;
- $\hat{y}^a_{t+h} = f(y^a_{t+h}|\Omega_t, X_{t+h})$, where X_{t+h} contains additional external variables up to period $t + h$.

Assuming a linear functional form, the minimum mean squared forecast of the (direct) aggregated variable y^a_{t+h} is the conditional expectation

$$\hat{y}^{a,d}_{t+h} = E(y^a_{t+h}|\Omega_t). \tag{1}$$

Following an indirect approach, the forecast is determined as the linear combination of forecasts of n sub-components

$$\hat{y}^{a,i}_{t+h} = \sum_{i=1}^{n} \kappa_i E(y^i_{t+h}|\Lambda^i_t) \tag{2}$$

where the weights κ_i are known and satisfy the following constraints

$$\kappa_i > 0 \qquad \sum_{i=1}^{n} \kappa_i = 1 \qquad i = 1, ..., n.$$

The debate has been enriched in the recent years by the increasing interest for nonlinear models, in particular the Switching Regime Models[3], and the potential of nonlinear forecasting[4]. The aggregation operator induces the macro-variables parameters to be intrinsically *time-varying* and therefore this suggests to use the *State-Dependent* model

$$y_t + \sum_{i=1}^{p} \phi_i(I_{t-1}) y_{t-i} = \mu(I_{t-1}) + \varepsilon_t + \sum_{j=1}^{q} \theta_j(I_{t-1}) \varepsilon_{t-j} \tag{3}$$

[3]See Granger and Tersvirta (1993) and Tong (1990) for an introductional survey on nonlinear modelization.

[4]See Stock and Watson (2001), Marcellino (2004) and most recently Granger (2008).

which consists of a set of autoregressive parameters $\phi_i(I_{t-1})$, a set of moving average parameters $\theta_j(I_{t-1})$, and a local intercept $\mu(I_{t-1})$, dependent by past information I_{t-1}. They are a generalization of linear ARIMA models, which results assuming constant coefficients[5]. Combining together the various functional forms of parameters $\mu(.)$, $\phi(.)$ and $\theta(.)$, it is possible to obtain a wide range of nonlinear models[6]. Macroeconomic aggregates might be interpreted as the parametric aggregation of two or more stochastic, or deterministic, regimes that represent "cluster" of micro-units, homogeneous in relation to their behaviors. These models are also called *piecewise* linear models because they represent linear micro-relationships that assume nonlinear framework because of the aggregation in space and time.

Despite the unequivocal limits of nonlinear models[7], one of the most promising frontier of aggregation theory in forecasting seems to be the pooling of linear and nonlinear forecasts. Stock and Watson (2001) and Marcellino (2004) use a large data set of macroeconomic variables for the US and euro area respectively, comparing three forecasting methodologies: linear, pooled linear-nonlinear and nonlinear forecasts. The results are encouraging, as pointed out by Marcellino: "*In other words, pooled forecasts, or simple* AR *models, have a stable performance over all the variables, but specific linear or non-linear models can do better for specific series.*". Similarly, Timmermann (2006) states that the combination of forecasts from linear and non-linear models with different regressors might prevail in certain circumstances.

A general opinion on aggregation problems is that the selection between direct and indirect forecasts should be done more on the basis of empirical exercises than theoretical considerations. As noted by Stock and Watson (2001): "*...time series models and forecasting methods, however appealing from a theoretical point of view, ultimately must be judged by their performance in real economic forecasting applications.*".

3 The practice of forecasting in QNA

In Italy, QNA are compiled through an indirect approach: quarterly time series of NA aggregates are derived from temporal disaggregation of annual data by means of short-term indicator series. Indicators are chosen according to well-founded statistical and economic relationships with aggregates (see Marini and Fimiani, 2006). For example, quarterly production (and value

[5]Any nonlinear model can be approximated by linear time-varying parameters model, as demonstrated by the White theorem; see Granger (2008).

[6]For example bilinear models, threshold models, Markov-chain models, autoregressive with smooth transition, autoregressive with neural networks, etc.

[7]As is stressed in Granger (2008): "*...most nonlinear models are difficult to use to form point forecasts more than one step ahead and forecast confidence intervals are also typically difficult to obtain.*"

added) of manufacturing sectors are based upon econometric relationships between annual NA data and industrial production indices; quarterly imports of goods are derived on the basis of monthly imports from external trade statistics; etc.

When yearly data are known, temporal disaggregation ensures their values are distributed across the quarters according to the movements of the chosen indicator series: long-term trends of NA variables and intra-year variations of short-term indicators are thus mixed together in QNA time series. When the annual figure is not yet available (normally the most recent year), short-term information are also employed to extrapolate the quarterly behavior of QNA aggregates during the year. This probably constitutes the most delicate and crucial task in the compilation of QNA, considering the prominent role of GDP and its components for purposes of economic analysis, decision-taking and policy-making.

Timeliness of indicators is of key importance in QNA. The preliminary estimate of GDP (the so-called flash estimate) is released by ISTAT after 45 days the end of the reference quarter; the complete set of production, expenditure and income accounts are published at 70 days. The acquisition of monthly and quarterly indicators carries on until the last moment in both cases, in order to exploit as much as possible the information set available for the current quarter. Nevertheless, the latest observations of some indicators are still missing due to collection and processing problems encountered by the producer. For monthly indicators, this generally implies that only one or two months of the quarter are known: the remaining information are usually predicted by using time series forecasting models.

The program TRAMO (Gomez and Maravall, 1997) is used to this purpose. It is a natural choice for ISTAT researchers, being TRAMO employed, along with the companion program SEATS, for seasonal and calendar adjustment of QNA indicators. TRAMO computes forecasts according to Reg-ARIMA models, which is a convenient way to model a time series with both deterministic and stochastic effects. A pure automatic modeling strategy is normally followed when the target is the prediction of missing information (instead, manual intervention of the user is preferred in seasonal adjustment processes): the order of ARIMA models, the type and number of outliers, level or log-level specifications are all chosen by the automatic routines available in TRAMO. Despite the reduced control this automatism implies, this practice allows to obtain reliable and prompt time series forecasts of the missing months in a very short time. Clearly, the recourse to forecasting is more frequent in flash estimates of GDP: this is the reason why preliminary estimates are affected by more uncertainty than the data subsequently published.

Unit value indices (UVIs) of foreign trade statistics represent a typical information in QNA which needs to be forecasted. These indices are used in Italy to deflate current values estimates of imports and exports of goods, considered as a proxy of import and export prices. Moreover, they contribute to the construction of the system of input and output prices (along with domestic prices), afterward used for the deflation of production and intermediate costs. On average, UVIs are published by ISTAT after 50 days the end of the month. This implies that only one month of UVIs is available for GDP flash estimates and two months for the complete estimation of quarterly accounts. One and two-step ahead forecasts are thus calculated to complete the information of the current quarter.

A description of UVIs (and their use in QNA) is provided in section 4.1. Here it is worth remarking the importance of such information in QNA. As stated above, the estimate of imports and exports in volume are obtained by applying UVIs to the current values' estimates. Poor forecasts of UVIs lead to bad volume estimates of external components of GDP, and thus of GDP itself. Moreover, forecasting errors of UVIs have a negative impact on the GDP deflator through the system of input and output prices. From our past experience it is possible to state that monthly UVIs are very difficult to predict: they are volatile, affected by structural breaks and outliers and sometimes present a highly unstable seasonal component.

These properties are particularly evident when indices are considered at the 3-digit NACE classification, that is currently used in the estimation of NA. At this detail, around 60 products (or sectors) are traded between Italy and foreign countries. Disaggregated UVIs are therefore taken into account in the deflation process: total imports and exports (of goods) in volume are indirectly derived by aggregating the volume estimates of such sectors.

Generally, disaggregated time series are less predictable than aggregated data. This seems confirmed in UVIs: the total UVI of imports and exports show certainly smoother movements than their components by sector. Therefore, the practice of forecasting disaggregated information when the primary target is the aggregate variable (in this case exports and imports in volume) might be questionable. In such cases, a direct forecasting model to predict total UVIs of imports and exports might outperform the indirect approach.

The use of time series models guarantees point forecasts in accordance with past movements of the individual series; no information is considered on the periods to be predicted. If available, gain accuracy can be achieved by considering exogenous information through appropriate specifications of regression models (possibly with a dynamic structure). Despite some attempts in the past[8], forecasting models with exogenous information have never been used in the production process. Usually, the main difficulty is just connected with the lack of ready-to-use information on the missing months. However, the situation for UVIs of imports and exports is now different. For exam-

[8]Forecasting models with qualitative variables extracted from business and consumer surveys (available within a month) have been fitted to some indicators of production and expenditure components, generally with unsatisfactory results.

ple, imports prices are likely to depend on world index prices of primary commodities, such as crude oil or steel, which are very rapidly available on international data warehouses (such as those of IMF or Eurostat); exports prices can be somehow related to domestic prices of manufactured goods (released by after 30 days) or, even better, to producer prices indices on foreign markets, recently made available by ISTAT.

Through a real-time forecasting exercise this work aims at assessing the current practice adopted in QNA to forecast foreign trade UVIs along different directions, summarized in the following questions:

- do the automatic routines in TRAMO guarantee a satisfactory out-of-sample performance?
- does a direct approach to forecasting total UVIs of imports and exports improve upon the results of an indirect approach?
- when available, can the use of additional information be effective to increase the forecasting accuracy of UVIs?

The results of the experiment presented in the next section provide useful information to answer each of these questions.

4 The real-time forecasting exercise

4.1 The data

Imports and exports UVIs are published every month by ISTAT. The calculation of UVIs have been recently revised (ISTAT, 2008), in order to comply with new international standards and introduce important methodological improvements. UVIs are now derived from a very detailed level of product disaggregation, which generates more than 220,000 elementary indices. The aggregation process of the elementary indices is done through the use of trimmed means, that smoothes the high volatility of the original flows.

UVIs in Italy are Fisher-type indices, namely they are obtained as the geometric mean of Laspeyres and Paasche indices. The base of the index shifts every year, with weights given by the current values of imports and exports in the previous year. Chain-linked time series are derived using the annual overlap technique. Total imports and exports UVIs are shown in figures 1 and 2. Both series exhibit an upward long-term trend, with cyclical fluctuation (not exactly synchronized) and many spikes throughout the period. Taking the logarithms of the data and applying the first difference operator, non-stationarity is removed from both series (according to the Augmented Dickey Fuller test not shown in this paper). A seasonal component is not clearly identified. From an exploratory analysis with TRAMO, it is found that the most suited model for imports is the classical Airline model (0,1,1)(0,1,1); instead, the exports series is well represented by the non-seasonal ARIMA model with order (0,1,1).

As said before, UVIs are considered at the three-digit level of the NACE classification. This is presented in table 1, reporting codes and descriptions of each sector of economic activity. This is part of the broader classification used by national accountants in Italy, composed of 101 branches. Clearly, disaggregated UVI time series at this detail level present common features and idiosyncratic movements: the relative shares vary according to the type of product.

Table 2 presents the current values (and their percentages over the total) of imports and exports by product in year 2005. Imports of crude petroleum and natural gas (product 6) has the largest share (about 13%), followed by products 51 (motor vehicles, 11.4%), 37 (iron, steel and ferrous materials, 8.9%), and 27 (chemicals, 6.4%). Concerning exports, the largest contribute is by far the one of production of machine and mechanical tools (16.9%); exports' shares of products 51 (7.9%) and 37 (5.8%) are also notable.

The sample used in the exercise covers monthly data from 1996:1 to 2007:12. The data are not seasonally adjusted, but seasonality is present in UVIs for some products: seasonal ARIMA models are occasionally identified by TRAMO. There are 62 imported products in the chosen classification, and 61 for exports (crude oil is not available in Italy).

The aggregate UVIs cannot be indirectly derived from the disaggregate UVIs. This happens because the indices are chain-linked, and so they suffer the additivity problem. This represents a problem in our exercise, because aggregate forecasts cannot be immediately derived from disaggregate forecasts. To overcome such problem, aggregation of forecasts is done by means of the transformed indices having the previous year as the base period (the inverse process of annual overlap chain-linking). Next, these indices are applied to deflate monthly levels of imports and exports at current prices (independently estimated for the same products): the resulting figures expressed at prices of the previous year, can be added to achieve the aggregate imports and exports in volume (but with a shifting base year). Finally, the aggregate chain-linked UVIs are obtained by applying the annual overlap technique.

4.2 The experimental design

An out-of-sample exercise is used to evaluate the accuracy of ARIMA forecasts resulting from the following two strategies:

- identify each time the order of the ARIMA model according to the automatic model identification implemented in TRAMO (strategy AMI), that corresponds to the current practice adopted in QNA;
- use the standard ARIMA model (0,1,1)(0,1,1) in all the experiments

(strategy AIR), a model chosen because it fits generally well to many economic time series.

For each of these strategies two experiments are conducted to mimic the actual situations encountered in the estimation of QNA. In the former experiment the last two months of the quarter are considered as missing and need to be forecasted. To complete the quarterly information, it is thus necessary to calculate one-step and two-step ahead ARIMA projections. The quarters from 2002 to 2007 is used to evaluate the forecasting performance. The exercise starts with the forecasts of 2002:2 and 2002:3, on the basis of the sample 1996:1-2002:1. After that, the complete information for quarter 2002:Q1 can be calculated by averaging the actual value for the first month and the forecasts for the remaining ones. Next, the forecasts of 2002:5 and 2002:6 are calculated, shifting one quarter ahead the in-sample period (1996:1-2002:4). The sample is then extended sequentially by three months until 2007:10, from which the forecasts of 2007:11 and 2007:12 are derived. The parameters of the models are re-estimated each time; moreover, the order of the ARIMA model is chosen each time in the strategy AMI.

In the second experiment two months of the quarter are considered as known, with the last month to be predicted: then, the exercise begins with the prediction of 2002:3 on the basis of the in-sample period 1996:1-2002:2, then the prediction of 2002:6 with 1996:1-2002:5, and so on. In this case, only a one-step ahead forecast is necessary: this is in fact the problem actually faced at 70 days for the complete estimation of QNA. Overall, we compute 48 forecasts (one-step and two-step ahead) in the first exercise, 24 in the second one (only one-step ahead).

Forecasts are evaluated with standard measures of accuracy: the Root Mean Squared Forecast Error (RMSFE) and the Mean Forecast Error (MFE). They are both calculated on the year-on-year growth rates. It is useful to introduce a formal notation to define both measures properly. Denoting with h the forecast horizon, the forecast error is defined as follows

$$e_{t+h|t} = y_{t+h} - \hat{y}_{t+h|t} \qquad\qquad h = 1, 2$$

where y_{t+h} is the annual growth rate (in %) calculated from monthly data m_t as

$$y_{t+h} = \frac{x_{t+h} - x_{t+h-12}}{x_{t+h-12}} * 100$$

and $\hat{y}_{t+h|t}$ is the same rate obtained with the actual value x_{t+h} replaced by its forecast $\hat{x}_{t+h|t}$.

The MFE is calculated as

$$\text{MFE} = \frac{1}{TH} \sum_{t=1}^{T} \sum_{h=1}^{H} e_{t+h|t}$$

with the index t denoting all the months in the forecasting period and H equals to 1 or 2. This measure is useful to verify the presence of a forecast bias. The RMSFE is derived according to the following formula

$$\text{RMSFE} = \left[\frac{1}{TH} \sum_{t=1}^{T} \sum_{h=1}^{H} e_{t+h|t}^2 \right]^{1/2}$$

that measures the average size of error, irrespective of their signs.

The same exercise is done for aggregated and disaggregated UVIs (imports and exports). Aggregate forecasts are also derived indirectly from the disaggregated forecasts, using the procedure described in the previous section.

A final remark concerns the software used in this work. We have already cited TRAMO: the Linux version of December 2005 has been used, available in the software Modeleasy+. The program *R* (version 2.8.0[9]) has been used for data processing, the famous open-source environment that offers both a high-level programming language and a wide collection of statistical and mathematical libraries. Finally, the software *Gretl* has also been employed: it is a very good and user friendly open-source econometric software, developed by Allin Cottrell and Jack Lucchetti [10] .

4.3 Results

Table 3 compares the out-of-sample results in terms of RMSFE and MFE of the approaches AMI and AIR. The two exercises (2 months missing and only one month missing) are considered apart. The table shows the number of times the approaches AMI and AIR obtains the minimum statistics. Considering the first exercise, the minimum RMSFE is achieved in 40 out of 61/62 cases for imports/exports. Instead, the MFE statistic does not show any significant difference. As far as the second exercise is concerned, AMI shows again a better performance relative to AIR for 35 products.

For completeness, table 4 and 5 present all RMSFE and MFE statistics for imports and exports UVIs by product. They are presented for both approaches AMI and AIR. The first four columns refers to the exercise with two months predicted for each quarter, the last four columns to the exercise with only one month missing. Large RMSFE statistics are found for several products, but the most important ones are those relative to products with a high weight. Concerning imports, the RMSFE is very large for products 6 (around 7% in the first exercise), 26 (10.9%) and 60 (9.6%): prices of these products are strictly connected with the world energy market and therefore are subject to a higher price volatility. This certainly makes imports UVIs

[9]URL http://www.R-project.org.

[10]Both softwares are released under GNU General Public License.

less predictable than exports; in fact, the RMSFE are often higher than that of the corresponding exports UVIs.

Overall, the AMI approach yields satisfactory results: this confirms the good properties of TRAMO as a pure forecasting tool. To evaluate the stability of the selection process, we verify the sequence of ARIMA models sequentially chosen for each product. Table 6 and 7 shows the number of times in which selected ARIMA models are identified in the series. For imports, the order (0,1,1) is identified in about 40% of the cases: therefore, most of the series do not present a seasonal component. Considering the nature of the data, this result is quite reasonable. However, the classical Airline model is found in 22%: for products 17, 41, and 43 it is even the most frequent model. Regarding exports, the model (0,1,1) is again the most selected one but with a smaller percentage than imports (less than 27%). The Airline model is confirmed in the second position (24.4%).

The same forecasting experiment is replicated for the aggregate imports and exports UVIs (those shown in figures 1 and 2). The first row of tables 6-7 present the ARIMA orders chosen by the AMI approach. For imports the most selected model is (0,1,1) (37 out of 48 cases); two seasonal models are instead identified for exports (the Airline and the model (0,1,0)(0,1,1)). At an aggregate level, seasonality is thus more visible in exports than imports UVI series. Table 8 compares the RMSFE and MFE statistics of the direct forecasts with those derived indirectly from the disaggregated forecasts. For imports, the indirect approach clearly prevails against the direct approach: 1.079% against 1.237% in the first exercise, and even 0.863% against 1.475% in the second exercise (the AMI and AIR approaches gives approximately the same results). The MFE is also lower following an indirect approach: in the second exercise, it drops from -0.22% to -0.02%. On the contrary, the two approaches provides very similar results for exports: it is worth noting that the direct approach provides the minimum RMSFE in the first exercise (0.709% against 0.727%).

Actual and predicted values from the direct and indirect approaches are plotted in figures 3 and 4. The 48 forecast errors of the first exercise (two months missing) are displayed in figures 5 and 6.

4.4 Forecasting with exogenous information: an example for imports UVI of crude oil

As a final experiment, a dynamic regression model is used to forecast the imports UVI of crude oil and natural gas (product 6). A world index price of crude oil (petroleum) is available from the IMF website (Primary Commodity Prices section). The index is calculated as a simple average of three spot prices: UK Brent, West Texas Intermediate, and the Dubai Fateh. It is published within a month from the reference period, so it might be used to forecast the missing information of the UVI. Since the prices are expressed in \$ per barrels, the index must be first transformed in € before putting it into relationship with UVI. The euro-dollar exchange rate series is used to this end.

The crude oil price index (COPI) and the imports UVI are compared in figure 7 (both in logs). The two series show very similar movements: the imports UVI of petroleum products is strictly connected with COPI. Since the latter can be considered an exogenous information, it is useful to analyze its contemporaneous and delayed effects on the UVI. In fact, a change in the price index might not affect immediately the imports in Italy, but with a certain delay. Figure 8 shows the cross-correlogram of the stationary transformation (first-differences of log-levels) of UVI with leads and lags of COPI. Positive values in the x-axis indicate lags of COPI, whereas negative values indicate leads. The cross-correlogram is computed up to lag/lead 13. It is shown that COPI is a fairly coincident index relative to UVI, with large and positive correlation at lags 0 and 1 (0.59 and 0.68, respectively). Apart from lags 8 and 13, the correlation coefficients at other lags are also positive (even if not significant). Considering the dynamic relationship, an Autoregressive model with Distributed Lags (ADL) model is used to derive forecasts on the basis of COPI.

To simplify notation, we denote by y_t the imports UVI of product 6 and by x_t the crude oil price index. We start by fitting the general ADL model of order 13

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{13} \alpha_i \Delta y_{t-i} + \sum_{j=0}^{13} \gamma_j \Delta x_{t-j} + \varepsilon_t$$

with the usual IID normal assumption for ε_t (the shortened sample 1996:1-2002:1 is used). Then, the model is simplified by omitting the non statistically significant lags, following a general-to-specific approach (Hendry, 2004). The sequential strategy implemented in the software *Gretl* is followed: the dependent variable with the highest p-value is omitted at each step, until all the remaining variables show p-values less than 0.10 per cent. The selection process yields the specific model presented in table 9: the contemporaneous and 7 lagged terms of COPI enter the final equation. The first three autoregressive components are also retained, all with negative coefficients. The goodness of fit of the model is satisfactory ($R^2 = 0.85$) and standard diagnostics on residuals are acceptable.

The equation model in table 9 is used throughout the out-of-sample period (2002:1-2007:12). The model parameters are estimated each time with additional observations: the values of the coefficients and the statistical properties of the model do not vary across the period, therefore the model can be considered sufficiently robust. The same forecasting exercises described in the previous section are performed, with prediction of two months of the quarter (one- and two-step ahead forecasts) and one month (one-step ahead forecast). Table 10 compares RMSE and ME statistics obtained from this ADL model with the ARIMA forecasts (with the AMI approach). The RMSE value is reduced from almost 7% to 4% in the first exercise, from 5.5% to 3.2% in the second exercise. Overall, the reduction of RMSE for total imports UVI is strong, around 0.2% when two months are predicted (from 1.08% to 0.88%).

5 Conclusion

The aim of this paper is to assess the current practice of forecasting foreign trade UVIs adopted in QNA of Italy. The program TRAMO with automatic options is used to obtain one-step and two-step ahead forecasts of imports and exports UVIs disaggregated according to the NACE classification. Forecasts of total imports and exports UVIs are obtained from the aggregation of the disaggregated forecasts.

Through an out-of-sample exercise, this practice is assessed along three different directions. Firstly, the automatic selection strategy of TRAMO is evaluated in comparison with a standard ARIMA model (the Airline model). Then, a direct forecasting approach is experimented. Finally, the use of exogenous information to improve the forecasting accuracy is investigated.

The main findings shown in the paper suggest that:

- the automatic selection process of the ARIMA model carried out by TRAMO provides acceptable forecasts, on average better than those from the classical Airline model. In this way, we have certified the good properties of TRAMO as a pure forecasting tool;

- the indirect forecasting approach outperforms the direct approach in the case of total imports UVI; for exports, the two approaches give approximately the same results. This is probably connected with the higher volatility of imports UVIs of certain products (i.e. crude oil and gas), that worsen the predictability of the aggregate series. Therefore, a direct approach does not ensure any gain in accuracy with these data;

- the RMSFE is markedly reduced with a simple ADL model for imports UVI of petroleum products with the IMF crude oil price index.

The last finding seems very interesting and promising for the future. For example, imports UVIs (but also exports) disaggregated by product can be put into relationships with other primary commodity prices (steel, iron, agricultural products, etc.). This practice would be simple to implement and maintain, fruitful and even feasible considering time and resource constraints of a data producer. We believe that this practice is likely to improve forecasting accuracy of UVIs and, more generally, the accuracy of QNA.

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Table 1: NACE-rev.1.1 classification used in National Accounts

Codes	Description
1	Growing of crops; market gardening; horticulture; agricultural and animal husbandry service activities, except veterinary services
2	Farming of animals; hunting, trapping and game propagation; growing of crops combined with farming of animals; related service activities
3	Forestry, logging and related service activities
4	Fishing, operation of fish hatcheries and fish farms; service activities incidental to fishing
5	Mining and agglomeration of coal, lignite and peat
6	Extraction of crude petroleum and natural gas; mining of uranium and thorium ores; incidental service activities
7	Mining of iron ores; mining of non-ferrous metal ores, except uranium and thorium ores
8	Quarrying of stone, gravel, sand and clay and other quarried minerals; production of salt
9	Mining of chemical and fertilizer minerals
10	Production, processing and preserving of meat and meat products
11	Processing and preserving of fish and fish products; manufacture of vegetable and animal oils and fats; manufacture of other food products
12	Processing and preserving of fruit and vegetables
13	Manufacture of dairy products
14	Manufacture of grain mill products, starches and starch products
15	Manufacture of prepared animal feeds
16	Manufacture of tobacco products
17	Manufacture of beverages
18	Preparation and spinning of textile fibres; textile weaving; finishing of textiles
19	Manufacture of made-up textile articles; manufacture of knitted and crocheted fabrics; manufacture of knitted and crocheted articles
20	Manufacture of wearing apparel; dressing and dyeing of fur
21	Tanning and dressing of leather; manufacture of leather products
22	Manufacture of footwear
23	Sawmilling and planing of wood; impregnation of wood; manufacture of builders' carpentry and joinery; wooden containers; panels and boards; plywood; carpentry and joinery
24	Manufacture of pulp, paper and paper products
25	Publishing, printing and reproduction of recorded media; related activities
26	Manufacture of coke oven products; manufacture of refined petroleum products; processing of nuclear fuel
27	Manufacture of basic chemicals
28	Manufacture of chemical products for agriculture, building, printing and various other uses
29	Manufacture of pharmaceuticals, medicinal chemicals and botanical products; manufacture of soap and detergents, toilet preparations
30	Manufacture of man-made fibres
31	Manufacture of rubber products
32	Manufacture of plastic products
33	Manufacture of glass products
34	Manufacture of ceramic products
35	Manufacture of cement, lime and plaster; manufacture of articles of concrete, plaster and cement
36	Manufacture of other non-metallic mineral products; cutting, shaping and finishing of stone
37	Production of iron, steel and ferro-alloys (ECSC); manufacture of basic precious and non-ferrous metals first processing
38	Manufacture of structural metal products
39	Forging, pressing, stamping and roll forming of metal; treatment and coating of metals; manufacture of various metal tools
40	Manufacture, installation, repair and maintenance of machine tools and machinery for the production and use of mechanical power, manufacture of weapons and ammunition
41	Manufacture of agricultural and forestry machinery
42	Manufacture of domestic appliances
43	Manufacture of office machinery and computers
44	Manufacture of electric motors, generators and transformers
45	Manufacture of electricity distribution and control apparatus, accumulators, primary cells and primary batteries, and lamps and lighting fittings
46	Manufacture of electronic valves and tubes and other electronic components
47	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
48	Manufacture of television and radio receivers, sound or video recording apparatus
49	Manufacture of medical and surgical equipment and orthopaedic appliances; manufacture of instruments and appliances for measuring, checking, testing, navigating and the like
50	Manufacture of optical instruments and photographic equipment; manufacture of watches and clocks
51	Manufacture of motor vehicles, trailers and semi-trailers, including coachwork, parts and accessories
52	Manufacture of motorcycles, bicycles and other transport equipment
53	Building and repairing of ships and boats
54	Manufacture of locomotives and rolling stock
55	Manufacture of aircraft and spacecraft
56	Manufacture of furniture and musical instruments
57	Manufacture of jewellery and related articles
58	Manufacture of sports goods, games and videogames; miscellaneous manufacturing n.e.c.
60	Production and distribution of electricity, steam and hot water
88	Computer and related activities
90	Professional and business activities
99	Recreational and cultural activities

Table 2: Imports and exports of goods by product in 2005. Current values in billions of €.

Sector	Imports billion €	Imports %	Exports billion €	Exports %	sector	Imports billion €	Imports %	Exports billion €	Exports %
1	6206	2.004	3944	1.317	34	814	0.263	4241	1.417
2	2268	0.732	100	0.034	35	416	0.134	482	0.161
3	562	0.182	109	0.036	36	702	0.227	2356	0.787
4	846	0.273	207	0.069	37	27626	8.922	17430	5.822
5	1791	0.578	6	0.002	38	839	0.271	2879	0.961
6	39473	12.749	0	0.000	39	4218	1.362	10545	3.522
7	1379	0.445	74	0.025	40	19570	6.321	50640	16.914
8	1119	0.361	440	0.147	41	607	0.196	2987	0.998
9	130	0.042	61	0.020	42	1952	0.630	7167	2.394
10	4977	1.607	1749	0.584	43	8222	2.655	2111	0.705
11	7674	2.478	6521	2.178	44	2265	0.731	3122	1.043
12	1255	0.405	1959	0.654	45	6124	1.978	8051	2.689
13	2972	0.960	1506	0.503	46	3368	1.088	3066	1.024
14	502	0.162	809	0.270	47	5876	1.898	2792	0.933
15	596	0.193	206	0.069	48	4517	1.459	1476	0.493
16	1781	0.575	20	0.007	49	6730	2.174	4684	1.565
17	1334	0.431	4228	1.412	50	2040	0.659	2750	0.918
18	3581	1.157	7850	2.622	51	35438	11.446	23841	7.963
19	3790	1.224	6539	2.184	52	1634	0.528	2130	0.711
20	8418	2.719	12421	4.149	53	1030	0.333	2972	0.993
21	2962	0.957	5649	1.887	54	361	0.116	481	0.161
22	3696	1.194	7370	2.462	55	2102	0.679	2396	0.800
23	3885	1.255	1444	0.482	56	1647	0.532	8949	2.989
24	5909	1.908	4887	1.632	57	1012	0.327	4145	1.384
25	957	0.309	1653	0.552	58	3037	0.981	2644	0.883
26	6211	2.006	10153	3.391	60	2187	0.706	64	0.021
27	19843	6.409	10181	3.401	88	916	0.296	93	0.031
28	6087	1.966	4965	1.658	90	6	0.002	18	0.006
29	14636	4.727	14503	4.844	99	96	0.031	273	0.091
30	1424	0.460	1104	0.369	100	3	0.001	4	0.001
31	2474	0.799	3087	1.031	Total	309616	100.000	298892	100.000
32	4107	1.327	8368	2.795					
33	1419	0.458	1991	0.665					

Table 3: AMI versus Airline model: number of times with the minimum RMSFE and MFE

	2 months missing		1 month missing	
Index	AMI	AIR	AMI	AIR
import				
RMSFE	40	22	35	27
MFE	29	33	28	34
export				
RMSFE	40	21	35	26
MFE	31	30	30	31

Table 4: Out-of-sample performances of disaggregated Imports UVIs

	2 months missing				1 month missing			
Sector	RMSFE		MFE		RMSFE		MFE	
	AMI	AIR	AMI	AIR	AMI	AIR	AMI	AIR
1	2.946	2.644	0.459	0.273	1.477	1.368	0.091	-0.058
2	2.717	2.708	0.406	0.627	2.508	2.466	-0.027	0.073
3	2.170	2.356	0.399	-0.074	2.065	2.004	0.683	-0.010
4	1.843	1.834	0.291	0.432	1.954	1.967	0.644	0.780
5	10.160	10.081	1.629	0.471	6.773	6.107	2.187	1.244
6	6.962	7.820	1.103	-0.939	5.532	5.987	-0.309	-0.738
7	7.026	8.061	-0.137	-1.969	5.433	5.863	-1.303	-0.809
8	2.167	2.279	-0.619	-0.653	2.022	2.069	0.003	-0.261
9	4.670	5.097	1.352	-0.411	4.315	4.319	0.955	-0.203
10	3.094	2.807	1.170	0.411	1.957	1.775	1.025	0.271
11	1.819	1.869	0.278	-0.047	1.650	1.650	0.037	-0.130
12	1.964	2.197	0.822	0.427	1.713	1.950	0.130	-0.126
13	1.183	1.557	0.360	0.267	1.050	1.088	-0.038	0.144
14	1.728	1.790	0.139	0.064	1.272	1.239	0.075	-0.307
15	2.155	2.246	0.169	-0.207	2.407	2.359	0.918	0.222
16	4.733	3.894	0.300	-0.387	3.584	3.957	-0.414	-0.642
17	2.982	2.900	0.237	-0.314	2.981	2.987	-0.393	-0.733
18	1.159	1.300	-0.060	-0.248	0.896	0.795	0.016	0.129
19	1.656	1.716	0.109	-0.147	1.359	1.159	0.120	-0.071
20	2.020	2.005	-0.128	-0.087	1.784	1.834	0.201	0.164
21	4.986	4.680	0.509	0.346	2.836	3.094	0.569	0.518
22	2.930	2.608	0.545	0.029	2.866	2.516	0.108	-0.072
23	1.520	1.059	0.362	0.162	1.214	0.789	-0.072	0.024
24	1.390	1.670	-0.140	-0.285	1.295	1.226	-0.441	-0.291
25	5.821	6.015	1.211	0.872	5.563	5.672	1.647	1.455
26	10.930	12.397	-0.989	-1.128	6.212	6.484	-0.427	-0.503
27	2.638	2.435	0.117	-0.068	1.715	1.304	0.110	-0.272
28	2.176	2.161	-0.083	-0.436	2.333	2.289	0.157	-0.007
29	4.558	4.333	0.744	-0.790	3.778	3.444	-0.202	-1.410
30	1.476	1.549	0.145	-0.055	1.785	1.741	-0.490	-0.519
31	1.650	1.699	0.490	-0.083	1.763	1.644	0.470	0.111
32	1.044	1.304	0.244	-0.085	0.956	1.217	-0.083	-0.473
33	1.473	1.582	0.136	-0.485	1.704	1.809	-0.145	-0.290
34	2.440	2.340	0.859	0.669	2.188	2.258	0.382	0.216
35	3.087	3.318	0.323	-0.225	2.196	2.740	-0.353	-0.365
36	2.073	2.228	0.096	0.304	2.016	2.181	0.150	0.302
37	2.364	2.711	0.309	-0.695	2.024	2.266	-0.037	-0.475
38	3.055	3.376	0.046	-0.930	2.295	2.551	0.585	0.238
39	1.612	1.638	0.154	0.048	1.368	1.442	0.284	0.192
40	2.233	2.339	-0.100	-0.375	2.139	1.748	0.262	-0.056
41	2.849	2.925	-0.341	-0.241	2.653	2.822	-0.504	-0.334
42	2.597	2.854	0.035	-0.430	2.135	2.371	0.634	0.170
43	4.062	4.110	-0.397	-0.413	3.889	3.878	-1.704	-1.735
44	3.672	3.984	0.753	-0.256	3.101	3.593	-0.216	-1.191
45	1.836	1.900	0.234	0.029	1.585	1.706	0.347	0.431
46	4.235	4.685	-1.535	-1.077	2.695	3.093	-0.785	-0.132
47	7.725	8.306	-0.865	-1.419	8.454	8.298	-2.108	-1.996
48	2.657	2.587	-1.185	-0.541	2.424	2.427	-0.885	-0.204
49	3.016	3.008	-0.870	-0.514	2.500	2.832	0.686	0.335
50	4.222	5.195	-0.054	-0.987	4.074	3.915	1.181	0.134
51	1.282	1.173	-0.203	-0.250	1.077	1.054	0.243	0.073
52	2.310	2.332	-0.058	-0.044	2.213	2.209	0.503	0.476
53	13.795	13.781	2.146	3.000	12.329	12.287	0.164	3.266
54	11.010	10.701	1.838	2.133	11.796	11.699	1.396	-0.125
55	11.085	11.983	1.565	4.595	10.581	10.084	0.429	2.601
56	1.942	1.992	-0.160	-0.585	1.513	1.661	0.259	-0.279
57	10.709	10.060	1.345	1.073	10.560	8.993	-1.269	-0.301
58	2.977	3.180	-0.494	-0.519	2.926	2.931	0.098	0.068
60	9.628	10.938	1.192	0.847	10.616	12.520	1.221	-1.702
88	18.174	19.206	-2.529	2.306	17.760	20.311	4.082	6.522
90	23.852	25.089	1.421	-4.563	23.381	23.546	3.790	0.888
99	23.580	23.418	-2.307	-1.596	16.547	16.581	0.483	1.446

Table 5: Out-of-sample performances of disaggregated Exports UVIs

Sector	2 months missing				1 month missing			
	RMSFE		MFE		RMSFE		MFE	
	AMI	AIR	AMI	AIR	AMI	AIR	AMI	AIR
1	4.077	3.213	0.225	-0.087	3.333	3.051	-0.490	-0.079
2	5.853	6.826	0.066	-1.690	6.043	6.174	1.623	0.224
3	2.250	2.517	0.208	-0.052	2.682	2.597	-0.011	-0.157
4	8.007	8.590	0.264	-1.756	6.399	7.152	-1.542	-2.669
5	73.855	71.615	28.936	23.188	49.350	42.918	21.201	13.273
7	12.551	11.713	-0.312	-1.900	10.639	11.360	3.049	0.469
8	3.227	3.364	0.675	-0.675	3.313	3.027	0.859	-0.218
9	4.342	5.098	-0.329	-1.526	3.828	4.348	0.719	-0.272
10	0.924	1.125	0.116	0.039	0.918	1.178	-0.005	-0.321
11	1.244	1.140	0.223	-0.265	0.975	0.976	0.261	-0.095
12	1.082	1.327	0.075	-0.131	0.865	0.964	-0.045	-0.278
13	1.101	1.140	0.223	-0.236	1.001	1.203	-0.262	-0.559
14	1.805	2.136	0.522	-0.169	1.139	1.476	-0.189	-0.520
15	1.969	2.159	0.470	-0.625	1.784	1.900	0.206	-0.105
16	5.653	6.034	-0.165	-1.100	4.687	4.939	1.201	-0.528
17	1.131	1.145	0.161	0.154	1.221	1.219	-0.039	-0.048
18	1.001	1.091	0.062	-0.026	1.205	1.168	0.111	0.138
19	1.635	1.470	0.632	0.270	1.276	1.576	0.080	-0.109
20	1.732	2.007	-0.100	-0.312	1.498	1.599	0.321	0.146
21	3.502	3.264	1.217	0.461	2.360	2.244	0.426	0.018
22	2.333	2.386	-0.167	-0.321	1.776	1.756	0.156	-0.017
23	2.222	1.775	0.670	0.363	2.348	1.967	-0.246	-0.356
24	0.942	1.149	-0.317	-0.530	0.696	0.659	-0.073	-0.110
25	2.637	2.630	0.242	0.281	2.532	2.402	-0.364	-0.175
26	9.265	8.263	2.421	0.615	9.901	9.284	-0.271	-2.037
27	1.927	1.840	-0.065	-0.263	1.517	1.365	-0.006	-0.077
28	1.449	1.608	-0.058	0.000	1.188	1.251	-0.044	-0.338
29	3.343	3.248	0.256	0.298	3.055	2.810	-0.036	-0.106
30	1.623	1.724	0.420	0.250	1.601	1.713	-0.133	-0.474
31	1.489	1.496	-0.044	0.091	1.124	1.128	0.274	0.376
32	1.114	1.177	0.019	-0.070	1.208	1.235	0.402	0.092
33	1.309	1.274	0.355	0.093	0.949	1.050	0.010	-0.342
34	1.143	1.159	-0.048	-0.269	0.939	0.984	-0.151	-0.339
35	1.812	1.865	0.190	-0.233	1.640	1.606	0.523	-0.314
36	1.299	1.302	-0.007	-0.035	1.214	1.200	0.132	0.117
37	2.049	2.148	-0.029	-0.195	1.739	1.734	0.292	-0.238
38	2.618	2.530	-0.124	-0.096	2.251	2.513	-0.151	-0.126
39	1.398	1.011	0.503	0.023	1.098	0.997	0.261	-0.005
40	1.461	1.706	0.095	0.350	1.552	1.650	0.446	0.491
41	1.820	1.671	-0.038	-0.021	1.516	1.374	-0.519	-0.527
42	1.280	1.201	0.180	0.038	1.136	1.088	0.511	0.169
43	6.881	6.933	-0.329	-0.084	5.777	6.503	0.873	1.830
44	3.815	3.433	1.337	0.545	4.732	4.238	1.833	1.205
45	1.715	1.733	0.201	-0.089	2.065	1.850	0.481	0.326
46	6.069	6.480	-1.388	-0.806	6.716	6.726	-0.896	-0.206
47	6.394	6.782	-0.898	0.111	6.208	6.611	-1.569	-0.600
48	6.074	6.789	-0.484	1.857	5.982	6.274	-1.412	0.953
49	2.196	2.402	0.089	0.475	2.076	2.250	-0.373	0.073
50	2.827	2.981	0.394	-0.235	3.245	2.973	-0.026	-0.901
51	0.958	0.970	-0.014	-0.213	0.790	0.783	-0.019	-0.187
52	1.960	2.176	0.013	0.194	1.847	2.058	-0.043	0.054
53	9.458	10.942	0.061	2.037	8.755	9.936	0.705	2.054
54	6.993	7.005	1.352	1.000	8.175	8.276	0.947	0.553
55	6.990	7.663	-0.330	1.890	7.856	7.927	0.079	2.141
56	1.274	1.222	0.144	-0.060	1.378	1.411	0.133	-0.005
57	7.288	7.143	0.003	-0.450	6.833	6.913	2.130	2.068
58	1.450	1.362	0.121	-0.097	1.214	1.171	0.100	-0.165
60	17.746	19.815	5.358	1.794	16.626	17.182	1.665	2.302
88	18.428	19.685	5.455	5.656	14.033	13.387	7.756	5.727
90	12.796	13.484	4.440	-0.436	12.205	12.604	4.520	1.000
99	13.814	12.814	-2.469	-1.775	10.455	11.872	-4.235	-5.602

Table 6: Frequency table of SARIMA models identified by TRAMO: Import

Sector	(1,1,1) (0,0,0)	(1,1,0) (0,0,0)	(0,1,1) (0,0,0)	(1,0,0) (0,0,0)	(1,0,1) (0,0,0)	(1,0,0) (0,0,1)	(0,1,1) (0,1,1)	(0,1,1) (1,0,0)	(0,1,1) (0,0,1)	(0,1,0) (0,1,1)	others
Agg dir	-	37	-	-	-	-	4	-	-	-	7
1	-	-	-	-	-	-	16	7	-	5	20
2	-	5	42	-	-	-	-	-	-	-	1
3	-	-	-	-	6	29	-	-	8	-	5
4	-	-	-	-	-	-	41	-	-	3	4
5	-	9	37	-	-	-	-	-	-	2	-
6	-	-	48	-	-	-	-	-	-	-	-
7	-	19	26	-	-	-	1	-	-	2	-
8	-	-	-	-	-	-	1	-	-	-	47
9	-	-	45	-	-	-	3	-	-	-	-
10	-	-	9	18	13	-	-	-	-	5	3
11	-	3	9	-	24	-	9	-	-	3	-
12	-	-	48	-	-	-	-	-	-	-	-
13	-	5	-	-	-	-	4	-	-	-	39
14	-	-	37	-	-	-	11	-	-	-	-
15	-	-	38	-	-	-	7	-	-	-	3
16	-	-	30	-	-	-	6	-	-	-	12
17	-	-	-	-	-	-	45	2	-	-	1
18	-	5	-	-	-	-	13	-	-	12	18
19	-	-	-	-	-	-	5	43	-	-	-
20	-	-	-	-	-	-	34	-	-	13	1
21	-	-	7	-	-	-	11	-	-	14	16
22	8	-	21	-	-	-	12	2	-	-	5
23	-	-	33	-	-	-	11	-	4	-	-
24	-	19	-	-	-	-	-	-	-	-	29
25	-	2	36	-	3	-	1	-	-	-	6
26	-	-	32	-	-	-	16	-	-	-	-
27	-	10	2	-	-	-	4	-	-	-	32
28	-	-	12	-	-	-	36	-	-	-	-
29	-	-	25	-	-	-	3	10	1	-	9
30	-	31	-	-	14	-	-	-	-	1	2
31	-	-	40	-	-	-	-	-	-	-	8
32	-	-	48	-	-	-	-	-	-	-	-
33	-	16	25	-	-	-	7	-	-	-	-
34	4	-	40	-	-	-	4	-	-	-	-
35	-	-	-	-	-	-	4	19	-	-	25
36	-	-	38	-	-	-	-	10	-	-	-
37	-	30	-	-	-	-	2	-	-	-	16
38	-	-	24	-	-	-	15	9	-	-	-
39	-	-	42	-	-	-	6	-	-	-	-
40	-	2	-	-	-	-	18	21	-	-	7
41	-	-	-	-	-	-	44	-	-	-	4
42	-	-	24	-	-	-	6	1	3	-	14
43	-	-	-	-	-	-	45	-	-	2	1
44	-	-	42	4	-	-	2	-	-	-	-
45	-	-	48	-	-	-	-	-	-	-	-
46	-	-	19	-	-	-	-	24	5	-	-
47	-	-	42	2	-	-	3	-	-	-	1
48	-	-	39	-	-	-	9	-	-	-	-
49	-	-	8	-	-	-	12	28	-	-	-
50	-	-	-	-	-	-	-	34	-	-	14
51	-	-	46	-	-	-	2	-	-	-	-
52	-	-	35	-	-	-	13	-	-	-	-
53	-	-	13	-	-	-	13	4	1	-	17
54	11	-	23	-	-	-	12	-	-	-	2
55	-	-	18	-	-	-	29	-	-	-	1
56	-	-	6	-	-	-	30	-	-	-	12
57	-	-	-	-	-	-	42	-	-	-	6
58	-	24	8	-	-	-	-	-	-	-	16
60	-	-	15	-	-	-	3	4	-	-	26
88	1	-	5	-	-	-	-	-	6	-	36
90	-	-	8	-	-	-	19	6	14	-	1
99	-	-	5	-	-	-	37	5	-	-	1
Sum	24	180	1198	24	60	29	667	229	42	62	461
%	0.81	6.05	40.26	0.81	2.02	0.97	22.41	7.69	1.41	2.08	15.49

Table 7: Frequency table of SARIMA models identified by TRAMO: Export

Sector	(1,1,1) (0,0,0)	(1,1,0) (0,0,0)	(0,1,1) (0,0,0)	(1,0,0) (0,0,0)	(1,0,1) (0,0,0)	(2,1,0) (0,0,0)	(0,1,1) (0,1,1)	(0,1,1) (1,0,0)	(0,1,1) (0,0,1)	(0,1,0) (0,1,1)	others
Agg dir	-	-	-	-	-	-	26	-	-	21	1
1	-	-	10	-	-	-	-	-	-	7	31
2	-	-	43	-	-	-	1	-	-	-	4
3	-	-	-	-	-	-	32	3	-	-	13
4	-	-	-	2	-	-	13	5	-	-	28
5	7	-	10	-	4	-	1	-	-	-	26
7	-	8	1	-	-	-	23	-	-	-	16
8	-	-	2	-	-	34	3	-	-	-	9
9	-	36	2	-	-	-	-	-	-	-	10
10	24	4	-	-	-	-	-	-	-	3	17
11	-	-	27	-	1	-	7	1	-	-	12
12	-	38	-	-	10	-	-	-	-	-	-
13	-	1	28	-	-	-	-	-	-	-	19
14	-	7	-	-	-	7	4	-	-	2	28
15	-	-	20	1	-	-	23	-	-	-	4
16	5	-	28	-	-	-	1	-	-	-	14
17	-	-	-	-	-	-	48	-	-	-	-
18	-	-	-	-	-	-	9	-	-	13	26
19	-	-	-	-	-	-	-	-	-	-	48
20	-	-	-	-	-	-	-	-	-	-	48
21	-	-	-	-	-	-	17	-	-	-	31
22	-	-	-	-	-	-	47	-	-	-	1
23	-	-	10	18	-	-	10	-	-	-	10
24	1	-	-	-	-	12	-	-	-	-	35
25	-	-	-	-	-	-	41	-	-	-	7
26	-	-	34	-	-	-	4	-	-	-	10
27	-	2	16	-	-	-	-	1	7	-	22
28	-	-	37	-	-	-	11	-	-	-	-
29	-	-	20	-	21	-	1	-	-	-	6
30	-	24	7	-	-	-	17	-	-	-	-
31	-	-	33	-	-	-	4	-	-	-	11
32	-	-	2	-	-	-	-	43	-	3	-
33	-	-	11	-	-	-	37	-	-	-	-
34	-	-	-	-	-	-	43	-	-	1	4
35	7	-	19	-	-	-	4	6	2	-	10
36	-	-	-	-	-	-	40	-	-	-	8
37	16	-	-	-	-	8	-	-	-	-	24
38	-	-	20	6	17	-	5	-	-	-	-
39	-	2	38	-	-	-	3	5	-	-	-
40	-	-	30	-	-	-	5	12	-	-	1
41	2	-	-	-	-	-	6	15	9	-	16
42	8	-	13	-	11	-	10	-	-	-	6
43	-	-	16	2	-	-	22	-	-	-	8
44	-	-	9	-	-	-	12	27	-	-	-
45	-	2	22	-	-	-	21	-	-	-	3
46	-	-	48	-	-	-	-	-	-	-	-
47	-	-	17	-	-	-	4	-	27	-	-
48	-	-	15	19	10	-	3	-	-	-	1
49	-	-	20	13	12	-	3	-	-	-	-
50	-	-	-	-	-	-	19	13	-	-	16
51	-	-	-	-	-	-	30	-	-	-	18
52	4	-	2	-	-	-	31	1	-	-	10
53	3	-	33	-	-	-	-	-	-	-	12
54	-	-	35	-	-	-	8	-	-	-	5
55	-	-	44	-	-	-	4	-	-	-	-
56	-	-	-	-	-	-	38	10	-	-	-
57	7	-	1	-	-	-	22	12	-	-	6
58	-	-	-	-	-	3	1	12	-	-	32
60	-	-	17	-	22	-	3	-	-	1	5
88	-	-	37	-	-	-	1	-	-	-	10
90	-	-	2	-	17	-	-	-	-	-	29
99	-	-	-	-	-	-	24	-	-	-	24
Sum	84	124	779	61	125	64	716	166	45	30	734
%	2.87	4.23	26.61	2.08	4.27	2.19	24.45	5.67	1.54	1.02	25.07

Table 8: Out-of-sample performance of aggregated UVIs: direct and indirect approaches

	2 months missing				1 month missing			
Approach	RMSFE		MFE		RMSFE		MFE	
	AMI	AIR	AMI	AIR	AMI	AIR	AMI	AIR
Imports								
direct	1.237	1.294	0.268	-0.266	1.475	1.494	-0.220	-0.298
indirect	1.079	1.300	0.159	-0.269	0.863	0.875	-0.021	-0.223
Exports								
direct	0.709	0.706	0.059	-0.046	0.635	0.633	0.112	0.073
indirect	0.727	0.734	0.112	0.030	0.606	0.603	0.140	0.045

Table 9: OLS estimates using the 62 observations 1996:12–2002:01 Dependent variable: Δy_t

	Coefficient	Std. Error	t-ratio	p-value
c	-0.0003	0.0036	-0.0779	0.9382
Δy_{t-1}	-0.3435	0.1286	-2.6710	0.0102
Δy_{t-2}	-0.2427	0.1205	-2.0147	0.0493
Δy_{t-3}	-0.2929	0.1438	-2.0376	0.0469
Δx_t	0.2963	0.0404	7.3320	0.0001
Δx_{t-1}	0.5429	0.0558	9.7246	0.0001
Δx_{t-2}	0.1476	0.0851	1.7350	0.0889
Δx_{t-3}	0.3442	0.0915	3.7618	0.0004
Δx_{t-4}	0.2151	0.0844	2.5472	0.0140
Δx_{t-6}	0.0836	0.0463	1.8050	0.0771
Δx_{t-7}	0.0805	0.0421	1.9143	0.0613
Δx_{t-10}	0.0892	0.0434	2.0535	0.0453

Mean of dependent variable	0.00426820
S.D. of dependent variable	0.0652780
Sum of squared residuals	0.0378795
Standard error of the regression ($\hat{\sigma}$)	0.0275244
Unadjusted R^2	0.854273
Adjusted $\bar{R}^2$	0.822213
$F(11, 50)$	26.6460
Durbin–Watson statistic	2.07904
First-order autocorrelation coeff.	-0.0439446

Table 10: Improvements of forecasting accuracy using the crude oil price index

	two months missing		one month missing	
	RMSE	ME	RMSE	ME
Product 6 (ARIMA)	6.962	1.103	5.532	0.309
Total Imports UV index	1.079	0.159	0.863	-0.021
Product 6 (ADL with BRENT)	4.037	0.508	3.200	0.445
Total Imports UV index	0.883	0.083	0.817	-0.018

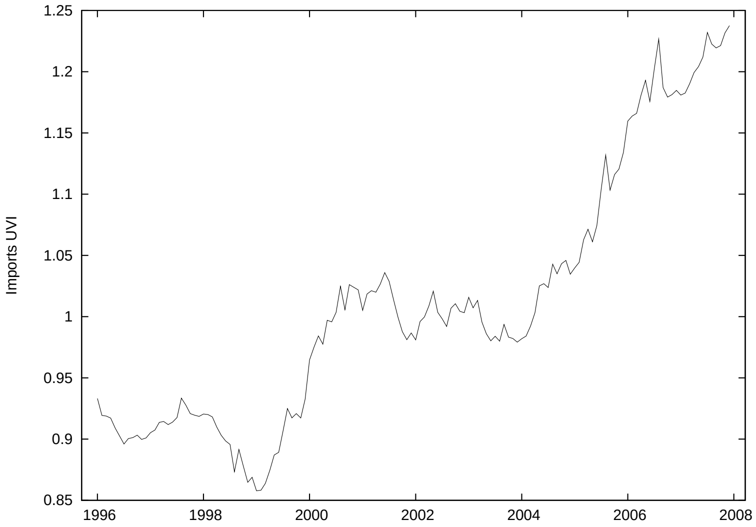

Figure 1: Monthly UVI of imports. Period: 1996:01-2007:12.

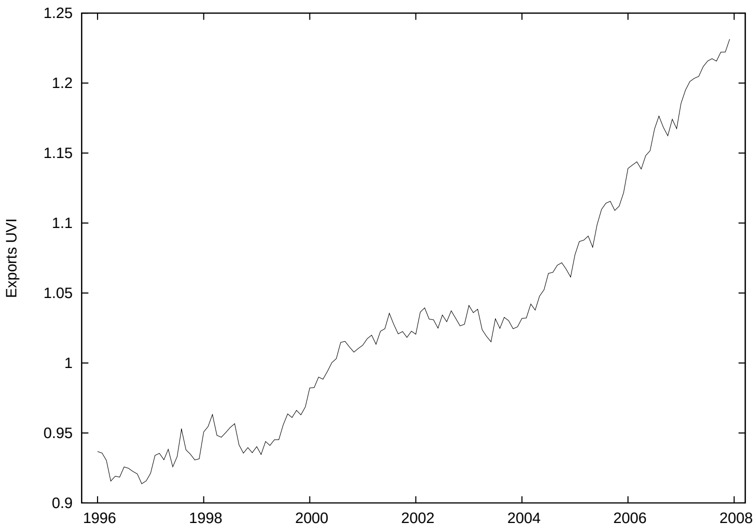

Figure 2: Monthly UVI of exports. Period: 1996:01-2007:12.

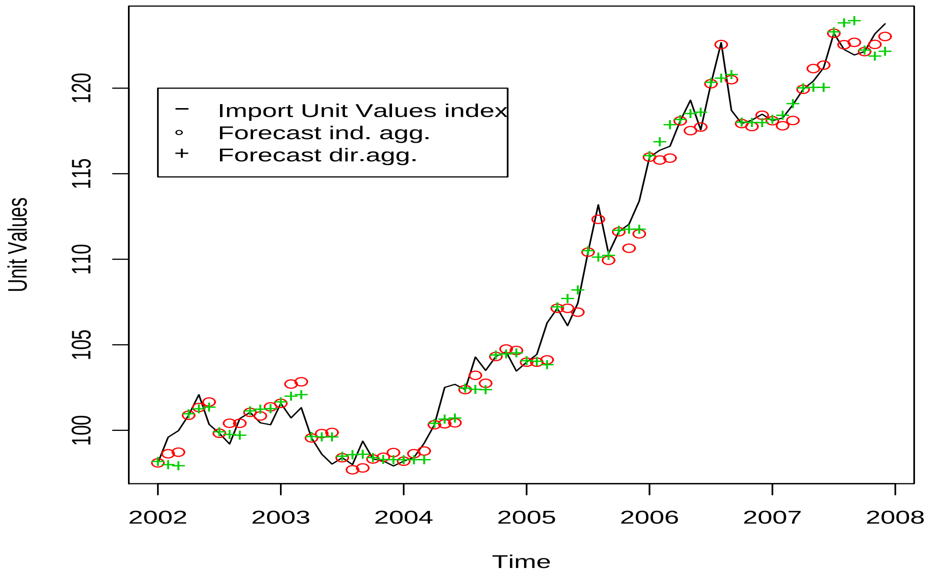

Figure 3: Observed series and forecasts for total imports UVI. Period: 2002:1-2007:12

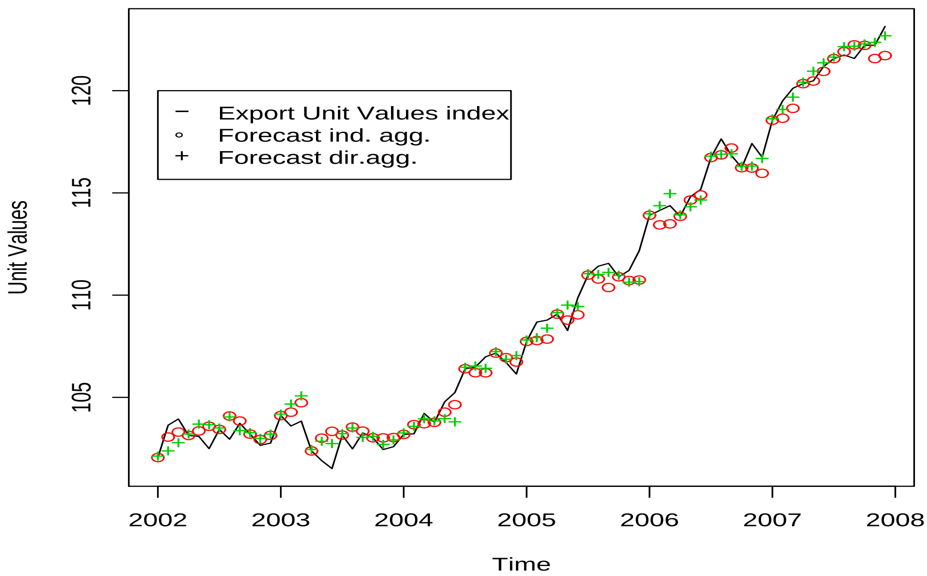

Figure 4: Observed series and forecasts for total exports UVI. Period: 2002:1-2007:12

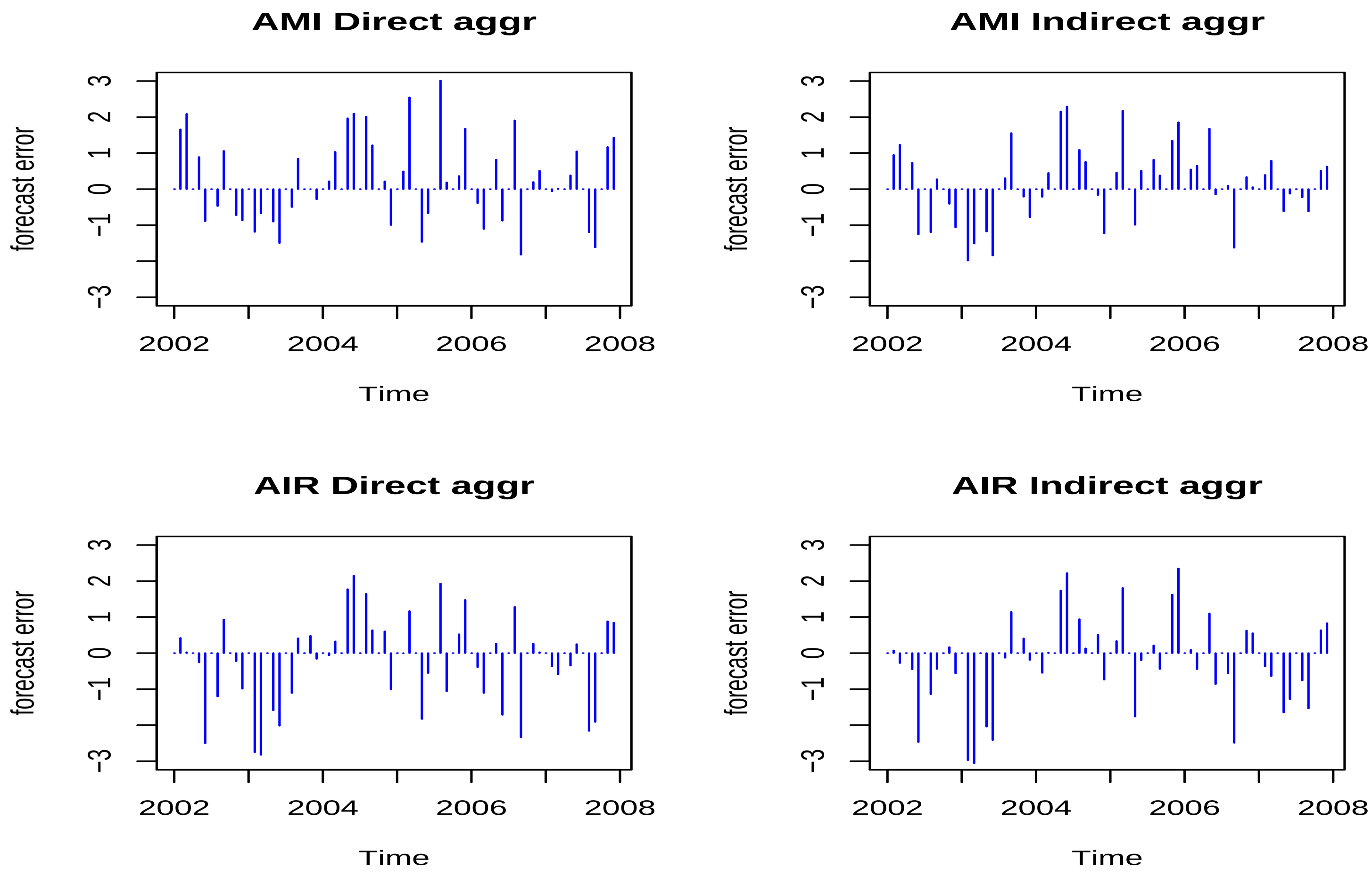

Figure 5: Forecast errors of total imports UVI (two months missing)

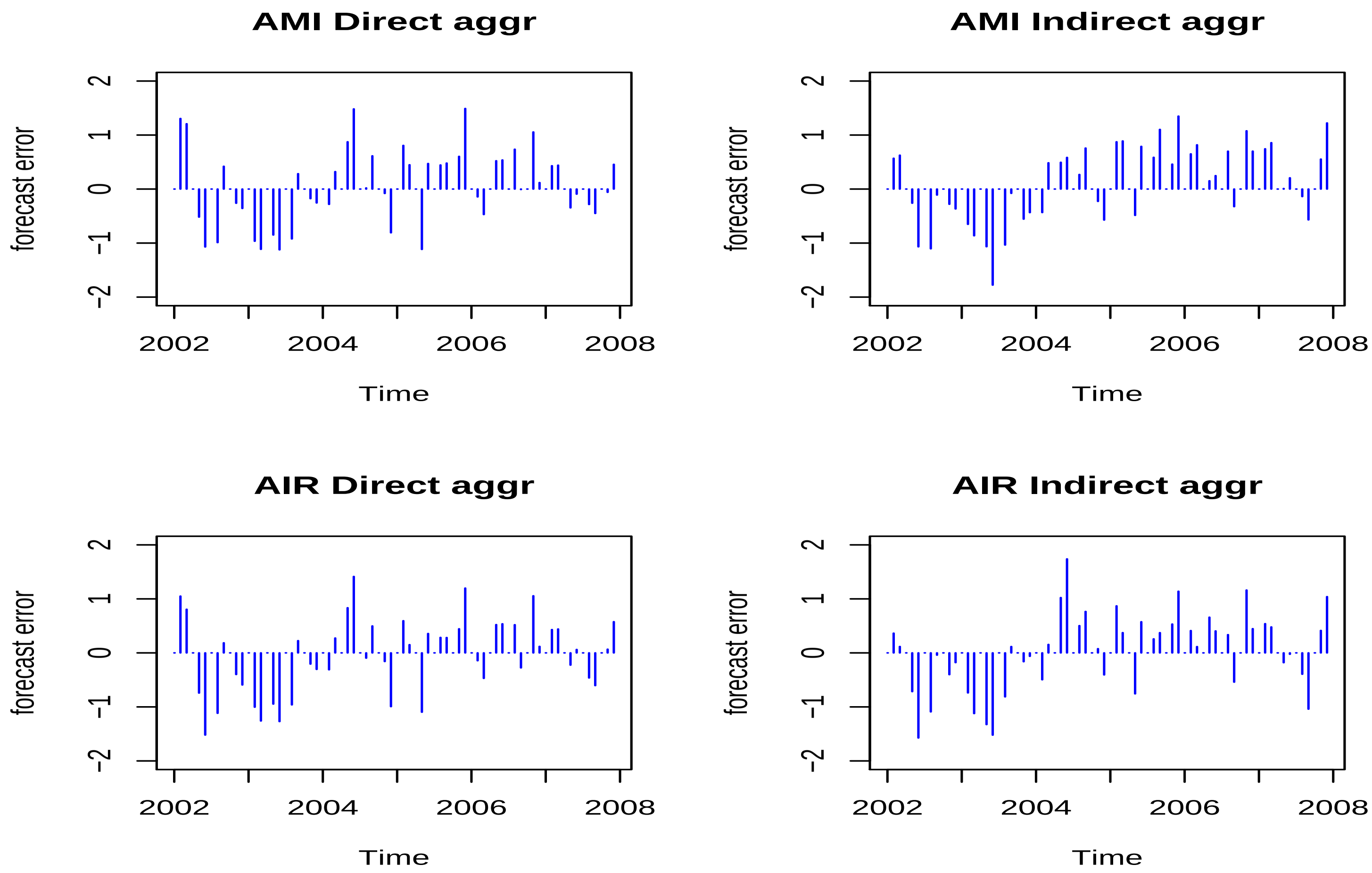

Figure 6: Forecast errors of total exports UVI (two months missing)

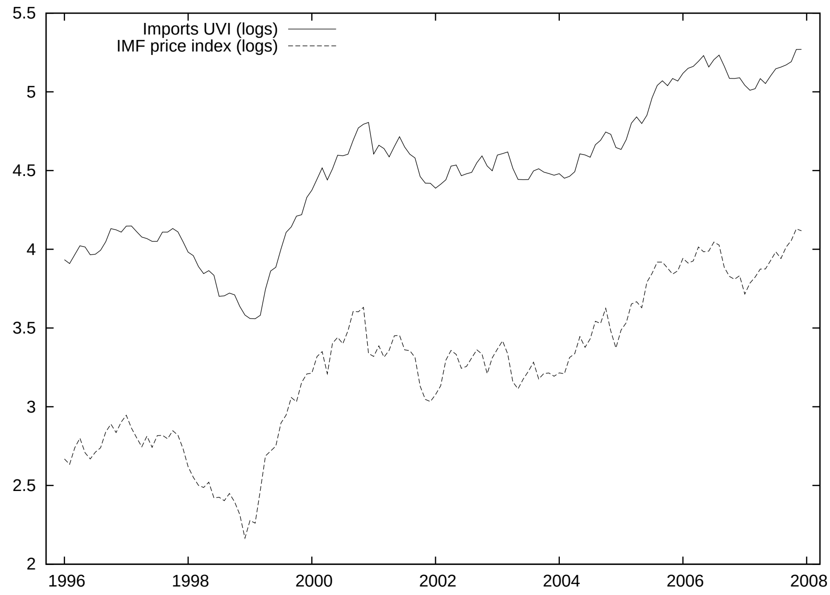

Figure 7: Imports UVI and crude oil price index. Period: 1996:1-2007:12.

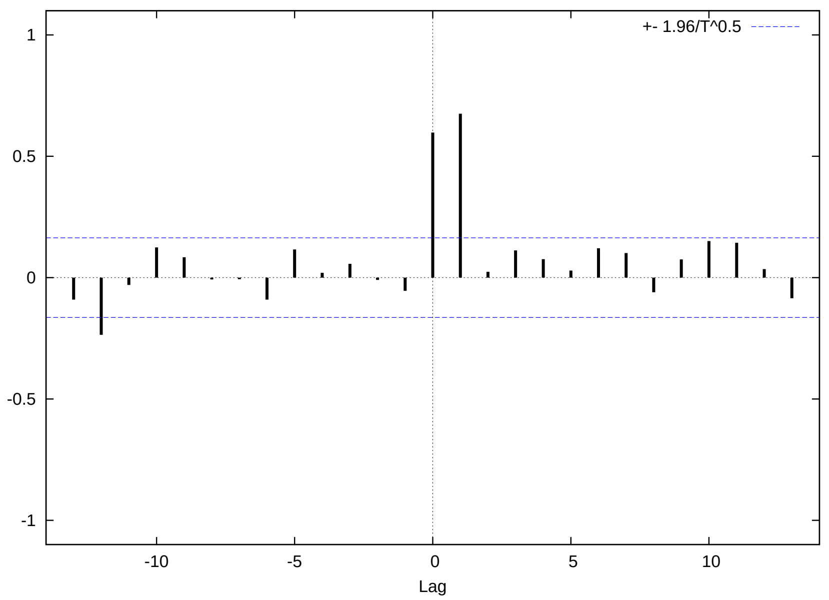

Figure 8: Correlation of imports UVI and lags of crude oil price index