working papers

Working Paper 08-01
Statistic and Econometric Series 01
January 2008

Departamento de Estadística
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34-91) 6249849

FORECASTING SPANISH INFLATION USING INFORMATION FROM DIFFERENT SECTORS AND GEOGRAPHICAL AREAS *

Juan de Dios Tena [1], Antoni Espasa [2] and Gabriel Pino[3]

Abstract

This paper evaluates different strategies to forecast Spanish inflation using information of price series for 57 products and 18 regions in Spain. We consider vector equilibrium correction (VeqC) models that include cointegration relationships between Spanish prices and prices in the regions of Valencia, Andalusia, Madrid, Catalonia and the Basque Country. This approach is consistent with economic intuition and is shown to be of tangible importance after suitable econometric evaluation. It is found that inflation forecasts can always be improved by aggregating projections from different sectors and geographical areas. Moreover, cointegration relationships between regional and national prices must be considered in order to obtain a significantly better inflation forecast.

Keywords: vector equilibrium correction models, relative prices, cointegration, disaggregation.
JEL Classification: C2, C5.

* We appreciate the comments by Geoffrey J.D. Hewings, Rebeca Albacete and participants at the 2007 EcoMod Conference on Regional and Urban Modeling. The usual quialifier applies.

[1] Corresponding author: Juan de Dios Tena, Universidad Carlos III, Departamento de Estadística, C/Madrid 126. 28903 Getafe (Madrid), España, e-mail: jtena@est-econ.uc3m.es and Universidad de Concepción, Departamento de Economía, Victoria 471 - Oficina 242 - Concepción, Chile, email: juande@udec.cl
[2] Antoni Espasa, Universidad Carlos III, Departamento de Estadística, C/ Madrid 126, 28903 Getafe (Madrid), e-mail: espasa@est-econ.uc3m.es.
[3] Gabriel Pino, Universidad de Concepción, Departamento de Economía, Victoria 471, Chile, e-mail: gapino@udec.cl.

1. Introduction

Forecasting the rate of inflation is a key activity for policy makers as monetary policy affects inflation with some delay. Identifying the likelihood of inflationary pressures is also useful in the bargaining processes involving different economic groups, such as between entrepreneurs and unions and commercial banks and borrowers.

This paper evaluates the advantages of forecasting the Spanish rate of inflation by aggregating projections from 57 different commodities in 18 Spanish regions. Our analysis is closely related to a strand of literature that considers sectoral information to improve the quality of aggregate projections; Espasa et al. (2002), Espasa and Albacete (2007), Zellner and Tobias (2000) and Hubrich (2005) amongst others. This approach can be justified as commodity prices could evolve heterogeneously because they are affected differently by economic shocks. Therefore, forecasting an aggregate variable based on separate models for each component and/or including disaggregate information in the model for the aggregate seems a reasonable strategy; see Hendry and Hubrich (2006). However, in practice, to forecast the aggregate directly can be a superior strategy when the models for the disaggregate variables are not correctly specified. Some examples of the advantages of using disaggregate information can be found in Espasa et al. (2002), Espasa and Albacete (2007) and Zellner and Tobias (2000) while Hubrich (2005) finds that aggregating projections by component does not necessarily help to forecast inflation in the Euro zone.

An important difference between the papers mentioned above and our research, and this is a main contribution of this paper, lies in the fact that we exploit the potential advantages of disaggregation by considering both sectoral and regional information in order to forecast an aggregate variable.[1] The lack of concern with the aggregation of regional prices to forecast inflation in the previous literature can be explained as sectoral price heterogeneity is, in principle, more evident than divergences in the geographical prices in a country. Thus, commodity prices could show different patterns of evolution as they can have a different degree of access to the financial markets, some of them are more affected by international market operations or simply because of the different demand price elasticities for the different products in the market. However, it is typically argued that, according to the law of one price, individual prices in the different regions of a given country should be similar otherwise these differences would be eliminated by arbitrage.

In spite of this hypothesis, at the empirical level, there is a consensus about the persistence of deviations in the law of one price in excess of what could reasonably be attributed to transportation costs; see for example Abuaf and Jorion (1990), Mac Donald (1996) and Lothian (1997). Also, a number of papers at the intranational level have found a similar result. For example, Parsley and Wei (1996) study the convergence of 51 retail prices for 48 U.S. cities during the 1975-1994 period. They find that the hypothesis of unit root for the relative prices could not be rejected at the conventional levels in a significant number of cases. Ceccheti et al. (1999) consider a century-long panel of US commodity prices for major cities and estimate a very slow rate of convergence of 9 years on average.

[1] This is the maximum level of disaggregation available at the regional level.

Our paper also analyses the long run dynamics of disaggregate regional prices, although with particular emphasis on forecasting purposes. Concretely, we forecast the Spanish rate of inflation based on a two-step procedure. In the first step, we obtain price projections in the regions of Valencia, Andalusia, Madrid, Catalonia and Basque Country by specifying vector equilibrium correction (VeqC) models in which each of the 57 sectoral prices in the aforementioned regions is allowed to work in a cointegration relationship with the national price for the same sector.[2] Our focus on these five regions can be justified because they represent 66 percent of national expenditure. Then, in a second step, we forecast Spanish inflation by aggregating the projections obtained for the 5 main regions in the previous step with those from the remaining Spanish regions based on just aggregate models.

We find that inflation forecasts are improved by aggregating projections from different sectors and geographical areas. Moreover, both levels of disaggregation are required in order to obtain a significantly better inflation forecast. We also apprise the importance of considering the potential cointegration relationship between disaggregate prices in each of the five main regional areas and Spain, finding that, consistent with Christoffersen and Diebold (1998), vector equilibrium correction (VeqC) models improve the accuracy of short run projections.

The structure of this paper is as follows. Section 2 explains the importance of considering the long run equilibrium of disaggregate regional prices. The next section presents the data in the analysis and explains some of their features. Section 4 discusses the model specification used in the different strategies. Inflation forecasts under different strategies are compared in Section 5. Some concluding remarks follow in Section 6.

2. Theoretical Motivation

The use of VeqC models in forecasting exercises has generated a burgeoned discussion in the recent literature. Thus, some authors suggest that VeqC models are not particularly useful for forecasting purposes because they are not robust to shifts in the underlying equilibrium; see for example Clements and Hendry (1998, 1999) and Hendry (2006). Others, like Espasa and Albacete (2007) and Mayo and Espasa (2006), provide evidence that support the use of VeqC models to improve the projections of economic variables over other alternatives.

In this section we discuss the importance of considering both VeqC models and the maximum level of disaggregation available in order to improve the forecastability of an aggregate magnitude.[3]

Let's consider P_t the aggregate price variable at time t to be forecast which consists of:

$$P_{T+1} = W_{1,T+1}P_{1,T+1} + (1 - W_{1,T+1})P_{2,T+1} \quad (2.1)$$
$$P_{1T+1} = W_{1,1,T+1}P_{1,1,T+1} + \left(1 - W_{1,1,T+1}\right)P_{1,2,T+1} \quad (2.2)$$

[2] Obviously, the process applied to these five regions can be extended to all the others.
[3] A more complete discussion on the use of cointegration to improve economic forecasting can be found in Mayo and Espasa (2006).

$$P_{2T+1} = W_{2,1,T+1}P_{2,1,T+1} + (1 - W_{2,1,T+1})P_{2,2,T+1} \text{ (2.3)}$$

where P_{iT+1} is the aggregate prices for the ith item with the weights $W_{1,T+1}$ and $W_{2,T+1} = (1 - W_{1,T+1})$.

In turn, expressions (2.2) and (2.3) indicate that P_{iT+1} is obtained from the weighted sum of prices in two geographical areas denoted by $P_{1,j,T+1}$, $j = 1,2$ with the weights $W_{i,1,T+1}$ and $W_{i,2,T+1} = (1 - W_{i,1,T+1})$.

In the following, to simplify the presentation, we assume that all the weights are constant and equal to 1. Then, expressions (2.1), (2.2) and (2.3) simplifies to:

$$P_{T+1} = P_{1,T+1} + P_{2,T+1} \text{ (2.4)}$$
$$P_{1T+1} = P_{1,1,T+1} + P_{1,2,T+1} \text{ (2.5)}$$
$$P_{2T+1} = P_{2,1,T+1} + P_{2,2,T+1}. \text{ (2.6)}$$

We also assume that there is long run equilibrium for the individual prices in the different regions that can be expressed with this simple vector equilibrium correction (VeqM) model.

$$\begin{pmatrix}\Delta P_{i,1,t}\\ \Delta P_{i,2,t}\end{pmatrix} = \begin{pmatrix}\gamma_{i,1}\\ \gamma_{i,2}\end{pmatrix} + \begin{pmatrix}\alpha_{i1}\\ \alpha_{i2}\end{pmatrix}(1 \quad -\beta_i)\begin{pmatrix}P_{i,1,t-1}\\ P_{i,2,t-1}\end{pmatrix} + \begin{pmatrix}\varepsilon_{i,1,t}\\ \varepsilon_{i,2,t}\end{pmatrix} \quad (2.7)$$

where Δ is a difference operator and $E(\varepsilon_{i,t}) = 0$, $E(\varepsilon_{i,t}\ \varepsilon_{i,t}{}') = \Omega$ and $E(\varepsilon_{i,t}\ \varepsilon_{i,s}{}') = 0$ for all $s \neq t$.

Note that expression (2.7) is consistent with the law of one price if, at least, one of these two restrictions fulfil:$\alpha_{i1} < 0$ and $\alpha_{i2} > 0$. However, cointegration is a more general assumption than this hypothesis because individual prices could be cointegrated with a deterministic trend. Indeed, deterministic components can be included in the cointegration relations in (2.7) without changing the main conclusions in the subsequent analysis.

Expression (2.7) can also be written as a vector autoregression of order one

$$\begin{pmatrix}P_{i,1,t}\\ P_{i,2,t}\end{pmatrix} = \begin{pmatrix}\gamma_{i,1}\\ \gamma_{i,2}\end{pmatrix} + \begin{pmatrix}1+\alpha_{i1} & -\beta_i\alpha_{i1}\\ \alpha_{i2} & 1-\beta_i\alpha_{i2}\end{pmatrix}\begin{pmatrix}P_{i,1,t-1}\\ P_{i,2,t-1}\end{pmatrix} + \begin{pmatrix}\varepsilon_{i,1,t}\\ \varepsilon_{i,2,t}\end{pmatrix} \quad (2.8)$$

In the following we discuss how using the model in (2.8) improves forecasting accuracy compared with two alternative cases: 1) only sectorial (but not geographical) information is included in the analysis; and 2) information on disaggregate prices is used, but without taking into account the adjustment to deviations in the long run equilibrium of individual prices in the different geographical areas. In all the cases we assume that the true generating process in known.

Note that the disaggregate forecasting model is given by expression (2.8) with (2.1), (2.2) and (2.3). Then the one-step forecast error from forecasting the disaggregate components using all the relevant information and aggregating those forecasts is

$$P_{T+1} - \widehat{P}_{T+1} = W_{1,T+1}(W_{1,1,T+1}\varepsilon_{1,1,T+1} + W_{1,2,T+1}\varepsilon_{1,2,T+1}) \quad (2.9)$$
$$+W_{2,T+1}(W_{2,1,T+1}\varepsilon_{2,1,T+1} + W_{2,2,T+1}\varepsilon_{2,2,T+1}).$$

Not surprisingly, the forecasting error in (2.9) is unpredictable regardless of whether the weights are known or not, see Hendry and Hubrich (2005).

Now consider the alternative of forecasting P_t restricting the information set to include only sectoral information. In this case, using model (2.8), the aggregate process P_t can be represented by (see Lütkepohl, 1987, Chapter 4)

$$(1 - \phi_1 L - \phi_2 L^2)P_{i,t} = c_i + (1 - b_1 L)\varepsilon_{i,1,t} + (1 - b_2 L)\varepsilon_{i,2,t} \quad (2.10)$$

where:

$$\begin{aligned}
\phi_1 &= 2 + \alpha_{i1} - \beta_i\alpha_{i2} \\
\phi_2 &= \beta_i\alpha_{i2} - \alpha_{i1} - 1 \\
b_1 &= \alpha_{i2} + 1 - \beta_i\alpha_{i2} \\
b_2 &= 1 + \alpha_{i1} + \alpha_{i2} \\
c_1 &= \gamma_1\beta_i\alpha_{i2} - \gamma_2\beta_i\alpha_{i1} \\
c_2 &= \gamma_1\alpha_{i2} - \gamma_2\alpha_{i1.}
\end{aligned}$$

Note that one solution to the characteristic equation $1 - \phi_1 x - \phi_2 x^2 = 0$ is x=1. Also, it can be shown following Lütkepohl (1987) that the right hand side of (2.10) can be represented as a MA(1) process. Therefore, expression (2.10) can be written as

$$(1 - \lambda L)\Delta P_{i,t} = c_i + (1 - \theta L)u_t \quad (2.11).$$

If we ignore the disaggregate information provided by the different geographical areas when we forecast the price level for the ith item, the forecast error is given by

$$\begin{aligned}
\hat{u}_{i,T+1/T} &= P_{i,T+1} - \widehat{P}_{i,T+1} \quad (2.12) \\
&= (\alpha_{i1} + \beta_i\alpha_{i2})P_{i,1,T} - (\beta_i\alpha_{i2} - \alpha_{i1} - 1)P_{i,1,T-1} \\
&+ (1 + \alpha_{i1} - \beta_i\alpha_{i2})P_{i,2,T} + (1 + \alpha_{i1} - \beta_i\alpha_{i2})P_{i,2,T-1} \\
&+ b_1\varepsilon_{i,1,T} + b_2\varepsilon_{i,2,T}.
\end{aligned}$$

In general, this is not going to be unpredictable unless some parameter restrictions are fulfilled.

Now we address the importance of considering the long run equilibrium about individual prices in different geographic areas by assuming that the individual prices $P_{i,j,t}$ are forecasted ignoring the information provided by the cointegration relationships. More specifically, we approximate model (2.8) with the following vector autoregressive model

$$\begin{pmatrix} P_{i,1,t} \\ P_{i,2,t} \end{pmatrix} = \begin{pmatrix} \gamma_{i,1} \\ \gamma_{i,2} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} P_{i,1,t-1} \\ P_{i,2,t-1} \end{pmatrix} + \begin{pmatrix} u_{i,1,t} \\ u_{i,2,t} \end{pmatrix} \quad (2.13)$$

According to this, we forecast individual prices as

$$\begin{pmatrix} \widehat{P}_{i,1,t} \\ \widehat{P}_{i,2,t} \end{pmatrix} = \begin{pmatrix} \gamma_{i,1} \\ \gamma_{i,2} \end{pmatrix} + \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} P_{i,1,t-1} \\ P_{i,2,t-1} \end{pmatrix}, \quad (2.14)$$

and the forecast error is given by

$$\begin{aligned}
\hat{u}_{i,T+1/T} &= P_{i,T+1} - \widehat{P}_{i,T+1} \quad (2.15) \\
&= (\alpha_{i1} + \alpha_{i2})(P_{i,1,T} - \beta_i P_{i,2,T})
\end{aligned}$$

$$+b_1\varepsilon_{i,1,T} + b_2\varepsilon_{i,2,T},$$

that is not going to be unpredictable unless the system is already in the long run equilibrium.

Christoffersen and Diebold (1998) provide an interpretation for this result. According to these authors, vector equilibrium correction (VeqC) models are useful for forecasting but only with short run horizons because they describe the adjustment process of each variable to return to the long run equilibrium.

At the empirical level, the advantage of using information about (1) sectorial and regional disaggregation and (2) cointegration relationships is not clear as disaggregate series could be more erratic than the aggregate counterpart, making model specification difficult. Moreover, the use of cointegration can also be misguided because although one may think that econometric models including inertial dynamics should have smaller prediction errors than purely extrapolative devices, however, ignoring cointegration but analyzing differences could improve forecasting accuracy if the cointegration relations are not constant; see Hendry (2006) and references therein. Therefore, a key aspect in order to judge the accuracy of VeqC models is to appraise the likelihood of shifts in the underlying equilibrium during the forecasting period. In this context, cointegration relations between geographic prices within a given country are usually stable through time and, in principle, can be considered useful devices to explore the advantages of VeqC models in forecasting.

3. Data Description

This section describes the features of the individual price series included in the analysis. We use both aggregate information as well as information related to different sectors and geographical areas. Concretely, we consider the following series: 1) the aggregate Spanish Consumer Price Index; 2) price series for 57 different commodities in the Spanish economy; 3) aggregate price series for each of the 18 Spanish regions; and 4) price series for 57 different commodities in the Spanish regions of Valencia, Andalusia, Madrid, Catalonia and the Basque Country.[4]

The series are available from the Spanish Office for National Statistics at the following URL: http://www.ine.es. Also, all the series are in natural logarithm and cover the 1993:01-2006:12 period. However, given that forecasting evaluation is the main purpose of this paper, in the econometric analysis we only use information for 1993:01-2002:10 in order to compare the projections obtained under different strategies for 2002:11-2006:12.

Two points can be highlighted at this stage. First, some of the series show a break in their seasonal evolution in 2002 because of a methodological change in the way that series were collected. We discuss this issue more explicitly in Section 5. The second point is that we study 57 commodities as this is the highest disaggregate level that can be considered at the regional level. However, an interesting intermediate alternative would be to focus our analysis on five groups of products for the Spanish economy: 1) processed food, 2) non-energy industrial goods, 3) services, 4) unprocessed

[4] A description of the sectors and regions is found in the Appendix.

food, and 5) energy; see Espasa et al. (1987). Here, we could not use this set-up because, at the moment, these five series are only available from 2002:01 at the regional level.

Figures of the series are not shown to save space, however the inspection reveals that practically all of them grow smoothly during the period under consideration.[5]Two exceptions to this general pattern are the price of mail and communications, which grows until the end of the 90s and then decreases, and the price of recreational objects, which remains stable until 2001 and then shows a negative trend. However, even these two series cannot be considered as stationary as they show little tendency to return to the mean.

Series in first differences, on the other hand, show regular crossing points and no obvious trend. Additionally, some series such as meat, transport and tourism exhibit a clear seasonal behaviour.

For a formal test on the number of unit roots in the series we employed the methodology proposed by Osborn et al. (1988) (OCSB henceforth) who extended the procedure of Hazsa and Fuller (1982) to seasonal time series for monthly data. Although we are aware of other more sophisticated procedures to investigate the presence of seasonal unit roots such as the tests proposed by Franses (1991) and Beaulieu and Miron (1993), we choose the OCSB test because of simplicity enables us to determine whether or not to take seasonal differences instead of testing for unit roots one by one at each of the harmonic frequencies of the seasonal cycle.

Following OCSB, our test regression for a given y_t variable takes the form:

$$\Delta\Delta_{12} y_t = c + \sum_{s=1}^{11} \delta_s D_{st} + \beta_1 \Delta_{12} y_{t-1} + \beta_2 \Delta y_{t-12} + \sum_{i=1}^{p} \phi_i \Delta\Delta_{12} y_{t-i} + \varepsilon_t \qquad (3.1)$$

where c is a constant term; D_{st} is a centred seasonal dummy variable for the s*th* month; Δ and Δ_{12} denote respectively the regular and seasonal difference operator; p is the number of augmentation lags that in our case is chosen using the sequential approach by Ng and Perron (1995); and $\varepsilon_t \sim \mathbf{iid(0,}\sigma^{\mathbf{2}}\mathbf{)}$ is the disturbance term.

If y_t is non stationary but $\Delta\Delta_{12} y_t$ is a stationary invertible process then, following OCSB, y_t is denoted as being I(1,1). The I(1,1) null hypothesis, $\beta_1 = \beta_2 = 0$, can be tested by using a F-type statistic.

One alternative to the I(1,1) null hypothesis is that stationarity is obtained after first differences. This alternative hypothesis, denoted as I(1,0), can be represented in equation (2.1) by $\beta_1 = 0$ and $\beta_2 < 0$. A second alternative is that the process requires annual differencing to be stationary. This alternative hypothesis I(0,1) is captured in equation (3.1) by $\beta_1 < 0$ and $\beta_2 = 0$. Following OCSB, separate t-type statistics for $\beta_1 = 0$ and $\beta_2 = 0$ can be used to distinguish between the two possible alternatives.

[5] All the information not explicitly reported in this paper can be obtained from the authors upon request.

Results of the test for the disaggregate commodities indicate that we can consider as I(1,0) at the 5% level the majority of the price series; 54% in Andalusia, 63% in Catalonia, 65% in Madrid, 70% in Valencia and 68% in the Basque Country. The hypothesis, I(1,1) can be accepted at the 5% level in only a few cases; 21% in Andalusia, 14% in Catalonia, 12% in Madrid, 14% in Valencia and 12% in the Basque Country. Also, the I(0,0) hypothesis was only accepted in a few number of cases: 25% in Andalusia, 18% in Catalonia, 18% in Madrid, 12% in Valencia and 16% in the Basque Country.

Seasonal dummies are jointly significant at 5% for some series; this is the case, for example, for the different types of meat, potatoes, home and medical services, transport and secondary school. We include seasonal dummies in 42% of the cases for Andalusia, 49% for Catalonia, 40% for C. Madrid, 46% for the Basque Country and 44% for Valencia.

When the test is applied to the aggregate series we find that the null cannot be rejected at the 5% level. This is a surprising result, given that the null hypothesis is rejected in the vast majority of cases at the disaggregate level. This also happens with the aggregate series of the different regions with the only exception of Madrid. The result suggests the convenience of using a disaggregate approach for analysing the properties of the time series as these features could be masked in the aggregate counterpart.

4. Testing the Law of One Price.

In this section, we test the hypothesis of price convergence in the five largest Spanish regions for each of the 57 disaggregate price indices considered in our analysis. This is useful both to have a better understanding about whether or not there is price convergence in Spanish prices and in order to improve the forecast of the aggregate rate of inflation.

According to the Balassa (1964)-Samuelson (1964) hypothesis, we should not observe long run differences among individual prices in the different geographic areas. The explanation is that poor regions are expected to experience faster productivity growth compared to wealthier, high-price regions. A rise in productivity raises output and wages in the traded sector, which in turn push up wages and hence price in the non-traded sector. As a result of this, we should expect a higher rate of inflation in poor compared to wealthier regions.

However, the process of relative price adjustment within a country could be delayed or even impeded by some of the following reasons:[6]

- Transport cost.
- Economic policies of regional scope, including the bureaucratic difficulties of setting big markets or foreign distribution systems for traded goods.
- Local monopolies exercising price discrimination in segmented markets.

[6] Some of the reasons mentioned here can be also found in Cecchetti et al. (1999).

- Local features such as weather, habits, land layout, etc., which could affect the utility of consuming different commodities.

An additional argument against the law of one price in this particular context is in the fact that, as in Cecchetti et al. (1999), we are not considering individual prices but disaggregate price indices because we are interested in having a broad coverage of goods and services sold in various locations in order to obtain measures of aggregate inflation. These indices could evolve differently because of different regional tastes for the items in the basket of consumption.

Given the previous discussion, we focus our analysis on testing conditional convergence between the price of each of the 57 commodities in the five large regions and the same commodity for the whole country. We do this in two ways. First, the hypothesis of unit root in relative prices is tested following Parsley and Wei (1996) by using the panel unit root test proposed by Levin et al. (2002). More precisely, for each of the disaggregate price index in the five largest Spanish regions, the basic regression specification is

$$\Delta R_{i,k,t} = \mathrm{c}_i + \sum_{s=1}^{11} \delta_s D_{st} + \beta R_{i,k,t-1} + \sum_{i=1}^{p} \gamma_i \, \Delta R_{i,k,t-1} + \varepsilon_{i,k,t} \qquad (4.1)$$

where $R_{i,k,t}$ is the log-difference in the *kth* price in the region *i* relative to Spain at time *t* and c_i is a regional specific effect.
According to Levin et al. (2002), the critical values for T=100 and N=5 (that is, approximately our panel size) at 1, 5 and 10 percent are -4.85, -4.30 and -4.01, respectively. The results of this test are shown on Table 1. The unit root hypothesis is rejected in only 6 out of the 57 disaggregate prices at the 5% level; tobacco, oil and fats, alcoholic drinks, fresh fruits, publications and university. This result is consistent with Parsley and Wei (1996) who also found that the null hypothesis could not be rejected in most cases in a fixed effect regression.

[INSERT TABLE 1]

Different arguments can be considered to explain price convergence in the aforementioned sectors. For example, tobacco and university prices are highly regulated by national policies. Also, in the case of alcoholic drinks, the law of one price may be met because of the important role of value added taxes on these products that are decided at the national level. Oil and fats are very open to international trade.[7] Publication goods can be easily traded as they are non-perishable and information about their features is generally available for customers. It is more difficult to find an argument to explain price convergence in fresh fruit. One possible explanation comes from the fact that, compared to other agricultural products, trade of fresh fruits products has been standardized, see www.infoagro.com.

[7] Concretely, according to the Instituto Español de Comercio Exterior (http://www.icex.es), exports of oil and fats to other countries were valued at 2,102,435 euros in 2006. This magnitude is relatively similar, for example, to the export value of all types of meat products, 2,401,301 euros.

One advantage of the previous test is that, as Levin et al. (2002) show, the panel data test can significantly increase the power of the unit root test. However, in our particular context, an important drawback of this procedure is that auto-regressive parameters in equation (4.1) are imposed to have the same values in the different regions. Moreover, stationarity of relative price series is a very vague measure of the adjustment to equilibrium of regional prices. A more sophisticated analysis requires considering separately the dynamics of disaggregate regional and national prices. It should then be possible to distinguish whether regional or national prices (or both) react to deviations in the long run equilibrium.

For this reason, we also test for cointegration between disaggregate price in the different regions and Spain. Our initial specification takes the following form:

$$\Delta y_{ijt} = \gamma_{ij} + \alpha_{ij}\left[\beta_{ij}^{'}, \delta_{ij}, \theta_{ij}\right]\begin{bmatrix} y_{ijt-1} \\ 1 \\ t \end{bmatrix} + \Phi_{ij}\Delta y_{ijt-1} + \Gamma_{ij} D_t + \varepsilon_{ijt} \qquad (4.2)$$

where y_{ijt} is a (2x1) vector containing price levels in the ith product of the jth region and the price for the same product in Spain; α_{ij} and β_{ij} are respectively the (2x1) adjustment and cointegration vectors; Φ_{ij} is a (2x2) matrix of parameters; γ_{ij} is a (2x1) vector of intercept parameters; δ_{ij} and θ_{ij} are scalars; D_t includes intervention and seasonal dummies and Γ_{ij} is the matrix of parameters associated to the interventions; and ε_{ijt} is a (2x1) vector of serially uncorrelated errors.

It is important to note that cointegration implies a weaker assumption than price convergence. This is because regional prices can be cointegrated once we include deterministic components in the cointegration relationships. More specifically, the law of one price is met in expression (4.2) when $\beta_{ij}' = (1 \quad -1)$, $\delta_{ij} = 0$ and $\theta_{ij} = 0$.

Thus, expression (4.2) is a general specification as it allows for two deterministic intercepts, one of them belong to the α_{ij} space (δ_{ij}) and the other to the orthogonal space (γ_{ij}). However, the trend component is forced to belong only to the α_{ij} space (θ_{ij}) as imposing a quadratic deterministic trend in y_{ijt} is an implausible assumption; see for example Johansen (1995).

In practice, there are four possible cases of interest: 1) $\delta_{ij} = \gamma_{ij} = \theta_{ij} = 0$; 2) $\delta_{ij} \neq 0$, $\gamma_{ij} = \theta_{ij} = 0$; 3) $\delta_{ij} \neq 0$, $\gamma_{ij} \neq 0$ and $\theta_{ij} = 0$; and 4) $\delta_{ij} \neq 0$, $\gamma_{ij} \neq 0$ and $\theta_{ij} \neq 0$. Notice that only the last two cases allows for deterministic linear trend in y_{ijt}.

We specify VeqCM models, selecting for each of the 57 models in each of the 5 largest Spanish regions the case which minimizes the Akaike information criterion. We also include seasonal deterministic components when they are jointly significant at a 5% level in at least one of the equations. In most of the cases, we select cases 3 and 4 that allow for linear trend in the variables, which is consistent with the results found in the previous section. Also, the trace test indicates that the null of no cointegration can be rejected at the 5% significance level in 34 cases for Valencia, 30 for Madrid, 26 for

Catalonia, 24 for Andalusia and 24 for the Basque Country. Moreover, in most of the cases where the null was not rejected, the trace test statistic is close to the critical values for rejection. According to this result, the vector equilibrium correction (VeqC) models in (4.2) seem a plausible strategy for obtaining forecast values of disaggregate regional prices.

However, we do not find strong evidence for price convergence. Concretely, for the cases when cointegration was accepted at the 5% level, a deterministic trend in the long run relationship has to be included in 54% of the cases for Andalusia, 65% for Catalonia, 63% for Madrid, 68% for the Basque Country and 67% for Valencia.

An important point to mention is that results in the previous section suggest that some of the series could need one regular and one seasonal difference to become stationary. However, when we test cointegration for that series in differences instead of levels, we find that the null of cero and one cointegration relationship can be rejected in all the cases at the conventional levels. This is an indication that series in annual differences could be considered as stationary and therefore it is accurate to consider all the series in levels for the cointegration tests.

5. Forecast Evaluation

We consider in this section different approaches to forecasting Spanish inflation for the 2002:11-2006:12 period. More specifically, we compare the projections obtained under our benchmark specification: a simple ARIMA model for the aggregate series, with those obtained under four alternative strategies.

The first alternative strategy (A1), relates to the sectoral disaggregation level and considers 57 ARIMA models for each disaggregate Spanish sector. Our second strategy (A2), is based on the projections obtained from ARIMA models for each of the 18 Spanish regions. The third strategy (A3), considers both sectoral and geographic disaggregation. More specifically, we estimate vector equilibrium correction (VeqC) models that consider potential cointegration relationships between each of the commodities in the different 5 large regions with the same product in Spain. Using this approach, we forecast inflation in the 5 aforementioned regions by aggregating the projections obtained for each of the products. We compute forecasting values in the remaining Spanish regions in a similar way to the second alternative strategy. Then, we aggregate all the regional prices to forecast the Spanish rate of inflation. Finally, our fourth alternative strategy (A4), is similar to the former but using ARIMA models for the sectoral price indices in each of the 5 large regions instead of vector equilibrium correction (VeqC) models.

An important point to mention at this stage is that the Spanish Office for National Statistics (INE) does not offer weights in order to obtain the aggregate price index from the regional series. However, we solve this problem using as weights the share of expenditure of each region in the Spanish expenditure. Proceeding in this way, we obtain an aggregate series that shows a very similar pattern to the Spanish Consumer Price Index.

In all cases, our ARIMA models are specified using the TRAMO/SEATS automatic procedure as it is completely aseptic and not affected by the subjective analyst criterion. Although our ARIMA specifications are not explicitly reported for the sake of brevity, in most cases, the growth pattern of the series is either captured by including a regular and a seasonal difference in the model or by specifying a model with a regular difference and a constant term. This is in contradiction with the unit root tests results shown in Section 3 that suggest the presence of only one unit root in most cases. In fact, there is an open debate in the literature on whether inflation is stationary or generated by a unit root process; see for example Culver and Papell (1997) for a discussion on this issue. Assuming that there is not an equilibrium rate for inflation is a quite strong hypothesis. But, it is also true that the inflation level is typically affected by different breaks on the levels of the series and therefore, for empirical purposes, it is reasonable to capture these changes with a unit root. However, there are no material changes in the results when we base the analysis on ARIMA models specified considering the results about the integration order of the series in Section 3 and based on the interpretation of figures and correlograms using the methodology proposed by Box and Jenkins; see Box et al. (1994).

In our analysis, we consider both static and dynamic forecasts. The former assumes that for a forecasting horizon k, the practitioner knows all the information at $t+h-1$ ($h \leq k$) in order to forecast the value of the relevant variable at $t+h$. Dynamic forecasting, on the other hand, assumes that values of the variables are not updated with the new information during the forecasting horizon. Static forecasting is especially consistent with forecasting activity as the analyst has to adjust the predictions after the new information arrives while dynamic forecasting is a good indicator of how successful the different strategies are to predict the evolution in the medium and long run.

The different strategies are compared by using the root of the mean square, the mean absolute and the percentage absolute mean of the forecasting errors. We test how significantly different the projections obtained are under the different strategies using the standard test proposed by Diebold and Mariano (1995) (DM). This is an asymptotic test to compare the forecasts obtained under different strategies. It is based on the difference of the estimated loss function under two alternative strategies denoted by $d_t = p(e_{jt}) - p(e_{it})$, where $p(e_{jt})$ and $p(e_{it})$ are the loss functions computed for alternatives *j* and *i* respectively.

Based on these definitions, DM consider the $\bar{d}$ statistic which denotes the sample mean of d_t, $t = 1,...,T$, $\bar{d} = T^{-1}\sum_{t=1}^{T} d_t$ and show that

$$ST = \frac{\bar{d}}{\sqrt{T^{-1}2\pi\hat{f}_d(0)}} \qquad (5.1)$$

converges to a normal distribution when $T \to \infty$, where $\hat{f}_d(0)$ is a consistent estimator of the spectral density of d_t at the zero frequency.

The results, shown in Table 2, highlight the advantages of using a disaggregate approach regardless of the loss function considered in both the static and dynamic evaluation. Concretely, when we consider static forecasting, projections of the aggregate rate of inflation based on either sectorial or geographic disaggregate models significantly outperform the forecasts obtained from the benchmark specification. Moreover, using two disaggregation levels we can further improve the forecast of the aggregate variable compared to strategies A1 and A2. A similar conclusion can be drawn for dynamic forecasts. In this case, considering both levels of disaggregation, by sectors and geographical areas, is also useful to forecast aggregate inflation. Also, in this case, forecasting inflation based solely on sectorial models is a worse strategy than the benchmark case. In light of this result, it seems that it is necessary to consider both disaggregation levels.

[INSERT TABLE 2]

Another interesting point lies in the use of cointegration in this analysis. Here, we find that projections based on vector equilibrium correction (VeqCM) models outperform those from simple univariate models at the same disaggregation level. This is an indication that it is useful to exploit the long run relationships between regional and national price series.

Notice that our vector equilibrium correction (VeqC) model specifies the long run adjustment for both disaggregate regional and national series. In fact, one can assume that these models are especially useful for forecasting purposes when the regional series is endogenous to the cointegration relationship. Following this argument, we forecast the aggregate rate of inflation using a strategy that is a mix of A3 and A4. Concretely, we forecast disaggregate prices in the 5 large regions using vector equilibrium correction (VeqC) models when disaggregate prices in that region can be considered as endogenous at the conventional levels and we forecast regional prices using ARIMA models otherwise. However, the root of the mean square errors for this strategy are 0.31 and 0.72 for the static and dynamic cases, respectively, and projections obtained under this procedure do not improve significantly our results.

One special feature of the series in our analysis lies in the fact that there is a clear structural break in the seasonal behaviour of many series that can be explained by a methodological change in the way that series were collected in 2002:01. It was known beforehand when they were to happen and that they would cause a structural break in the evolution of prices. Therefore, we follow Espasa and Albacete (2007) and the forecasting exercises are performed assuming that these effects are known by the inclusion of seasonal dummies in each model when they are jointly significant at a 5% level with coefficients estimated using the whole sample.

We follow Hubrich (2005) and compare forecasting performance for different forecasting horizons: one, four, eight, twelve and twenty-four periods ahead. Table 3 shows the main results of this analysis. Notice first that, based on the root of the mean square, the mean absolute and the percentage absolute mean of the forecasting errors, our forecast one period ahead for all the strategies clearly outperforms the previous static forecast analysis that did not consider the change in the seasonal pattern of some of the series.

[INSERT TABLE 3]

Comparing the different alternative strategies for different forecasting horizons, it is found that that in order to improve the forecast of the aggregate rate of inflation we need to consider both levels of disaggregation, geographic and sectorial, as well as the long run relationships of the regional and national price series. Therefore, using disaggregate models does not necessarily improve the forecast of the aggregate variables. In order to achieve that, it is necessary to consider accurate models that describe price movements under the appropriate level of disaggregation.

6. Concluding remarks

Our analysis deals with the use of both regional and sectoral disaggregate information in order to forecast the aggregate rate of inflation. We consider different strategies to forecast Spanish inflation using different disaggregation levels (by sectors and geographic areas) as well as two basic statistical specifications: univariate ARIMA models and vector equilibrium correction (VeqC) models. The results indicate that forecasts of the Spanish rate of inflation can be significantly improved by using disaggregate models by regions and sectors which consider cointegration relationships between regional and national prices.

In spite of this result, we find no evidence of price convergence and a deterministic trend has to be included in most of the cases in the cointegration relationship.

Future lines of research are suggested by this work. First, given that there are important differences in the disaggregate price levels of different regions, an interesting economic analysis would be to explain these divergences based on a number of variables such as wages, income, market structure, the type of markets where the different commodities are sold to customers, transportation costs, etc. Obtaining a plausible explanation for the persistent differences in the price level of different products within a given country can be helpful for improving the forecasts of individual prices and it could be a potentially interesting contribution to the ongoing debate on intranational price convergence; see Parsley and Wei (1996) and Ceccheti et al. (2000) among others. The second suggestion relates to the use of spatial correlations among different regions to improve the forecast of the aggregate variable. Following this, the approach proposed by Giaccomini and Granger (2004) can be seen as an interesting line of research to be considered in our particular context for future contributions.

Bibliography

Abuaf, N. and Jorion, Ph., (1990), "Purchasing power parity in the long run", Journal of Finance, 45, 157-174.

Balassa, B., (1964), "The purchasing power parity doctrine: A re-appraisal", Journal of Political Economy, 72, 584-596.

Beaulieu, J.J. and Miron, J.A. (1993), "Seasonal unit roots in aggregate U.S data", Journal of Econometrics, 55, 305-328.

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C., (1994), Time Series Analysis: Forecasting and Control, (Third Edition), Englewood Cliffs, HJ: Prentice Hall.

Cecchetti, S., Mark, N., and Sonora, R., (1999), "Price level convergence among United States cities: lessons for the European Central Bank", Ohio State University, mimeo.

Christoffersen, P.F. and Diebold, F.X., (1998), "Cointegration and Long-Horizon Forecasting," Journal of Business and Economic Statistics, 16, 450-458.

Clements , M.P. and Hendry, D.F., (1998), Forecasting Economic Time Series, Cambridge: Cambridge University Press.

Clements , M.P. and Hendry, D.F., (1999), Forecasting Non-stationary Economic Time Series, Cambridge, Mass.:MIT Press.

Crucini, M.J, and Shintani, M., (2002). "Persistence in Law-Of-One-Price Deviations: Evidence from Micro-Data," Working Papers 0222, Department of Economics, Vanderbilt University, revised Jul 2004.

Culver, S.E. and Papell, D.H,, (1997), "Is there a unit root in the inflation rate? Evidence from sequential break and panel data models, Journal of Applied Econometrics, 12, 436-44.

Dickey D.A. and Fuller, W.A., (1979), "Distribution of the estimators for autoregressive time series with a unit root", Journal of the American Statistical Association, 74, 427-431.

Diebold, F. and Mariano, R., (1995), "Comparing predictive accuracy", Journal of Business and Economic Statistics, 13, 253-265. Published again in Journal of Business and Economic Statistics, 20(1), 135-145, January 2002.

Espasa, A. and Albacete, R., (2007), "Econometric Modelling for Short-Term Inflation Forecasting in the EMU", Journal of Forecasting, 26, 303-316.

Espasa, A., Matea, M. L., Manzano, M. C. & Catasus, V. (1987), "La inflación subyacente en la economía española: estimación y metodología", Boletín Económico del Banco de España, marzo, 32-51.

Espasa, A., Senra, E., and Albacete, R., (2002), "Forecasting inflation in the European Monetary Union: a disaggregate approach by countries and by sectors", European Journal of Finance, 8, 402-421.

Franses, P.H., (1991), "Seasonality, nonstationarity and the forecasting of monthly time series", International Journal of Forecasting, 199-208.

Giacomini, R., Granger, C.W.J., (2004) , "Aggregation of space-time processes", Journal of Econometrics, 118, 7-26.

Hasza, D.P. and W.A. Fuller, (1982), "Testing for Nonstationary Parameter Specifications in Seasonal Time Series Models", The Annals of Statistics, 10, 1209-1216.

Hendry, D.F., (2006), "Robustifying forecasts from equilibrium-correction systems", Journal of Econometrics, 135, 399-426.

Hendry, D.F. and Hubrich, K., (2005), "Forecasting aggregates by disaggregates", manuscript.

Hubrich, K., (2005), "Forecasting euro area inflation: does aggregating forecasts by HICP components improve forecasts accuracy?", International Journal of Forecasting, 21, 119-136.

Johansen, S., (1995), <u>Likelihood-based inference in cointegrated vector autoregressive models</u>, Oxford University Press.

Levin, A., Lin, Ch. and James Chu, Ch., (2002), "Unit root tests in panel data: asymptotic and finite-sample properties," Journal of Econometrics, 108, 1-24.

Lothian, J.,(1997), "Multi-Country Evidence on the Behavior of Purchasing Power Parity Under the Current Float", Journal of International Money and Finance, 16, 19-35.

Lütkepohl, H., (1987), <u>Forecasting Aggregated Vector ARMA Processes</u>, Springer-Verlag.

MacDonald, R., (1996), "Panel unit root tests and real exchange rates", Economic Letters, 50, 7-11.

Mayo, I., and Espasa, A., (2007), "Forecasting an aggregate which includes components with common trends and comovements", manuscript.

Ng, S. and Perron, P., (1995), "Unit root tests in ARMA models with data dependent methods for selection of the truncation lag", Journal of the American Statistical Association.

Osborn, D.R., Chui, A.P.L., Smith, J.P. and Birchenhall, C.R., (1988), "Seasonality and the order of integration for consumption", Oxford Bulletin of Economics and Statistics, 50, 361-377.

Parsley, D. and Wei, S-J., (1996), "Convergence to the Law of One Price without Trade Barriers of Currency Fluctuations", Quarterly Journal of Economics, 111, 1211-1236.

Samuelson, P., (1964), "Theoretical notes on trade problems", Review of Economics and Statistics, 64, 145-154.

Zellner, A. and Tobias, J., (2000), "A note on aggregation, disaggregation and forecasting performance", Journal of Forecasting, 19, 457-469.

Appendix
Time Series

The time series considered in the analyses can be freely obtained from the INE (Instituto Nacional de Estadística). We use time series for the following disaggregate products:

Food Products

R1: Cereals.
R2: Bread.
R3: Beef.
R4: Lamb.
R5: Pork.
R6: Bird.
R7: Other meat.
R8: Fish.
R9: Crustaceans, molluscs and processed fish.
R10: Eggs.
R11: Milk.
R12: Milk products.
R13: Oil and fats.
R14: Fresh fruit.
R15: Preserved fruit.
R16: Vegetables.
R17: Preserved vegetables.
R18: Potatoes.
R19: Coffee, cacao and infusions.
R20: Sugar.
R21: Other food products.
R22: Non alcoholic drinks.
R23: Alcoholic drinks.
R24: Tobacco.

Industrial products

R25: Men's clothes.
R26: Women's clothes.
R27: Clothes for babies and children.
R28: Complements and Repairs.
R29: Men's footwear.
R30: Women's footwear.
R31: Footwear for babies and children.
R32: Repair of footwear.
R33: Rented apartments.
R34: Heating, lighting and water distribution.
R35: Own apartments.
R36: Furniture and floor coverings.
R37: Textile and home accessories.
R38: Major appliances.
R39: Household items.
R40: Non durable household items.

R43: Medicines and other chemical products.

Services

R41: Home services.
R42: Medical services.
R44: Personal transportation.
R45: Public urban transportation.
R46: Public intercity transportation.
R47: Mail and communications.
R48: Recreational objects.
R49: Publications.
R50: Recreation.
R51: Primary school.
R52: Secondary school.
R53: University.
R54: Other expenditures in education.
R55: Personal items.
R56: Tourism and hotels.
R57: Other goods and services.

Also, the Spanish regions considered and their respective weights are:

Andalusia	*153.10*
Aragón	*32.12*
Asturias	*25.26*
Balearic Islands	*24.15*
Canary Islands	*39.89*
Cantabria	*12.46*
Castilla y león	*55.08*
Castilla la Mancha	*36.08*
Catalonia	*173.79*
Valencia	*105.41*
Extremadura	*16.34*
Galicia	*55.97*
Madrid	*162.66*
Murcia	*26.03*
Navarre	*13.84*
Basque Country	*58.19*
Rioja	*6.92*
Ceuta y Melilla	*2.71*

All the series are in monthly basis and cover the period 1993:01-2006:10.

Table 1. Panel unit root test.

Sector(I)	t-statistic	Sector	t-statistic
R1	-1.97	R30	-1.75
R2	-3.55	R31	-3.03
R3	-2.15	R32	-2.55
R4	0.35	R33	2.10
R5	-3.73	R34	-3.89
R6	-2.08	R35	-3.16
R7	-1.87	R36	0.29
R8	-2.20	R37	-4.21
R9	-2.98	R38	0.36
R10	-3.00	R39	-1.59
R11	-2.30	R40	-2.41
R12	-2.46	R41	-2.30
R13	-4.93 (**)	R42	-2.62
R14	-4.35(*)	R43	-1.66
R15	-2.17	R44	-0.15
R16	-2.62	R45	-3.55
R17	-2.92	R46	-2.03
R18	-2.99	R47	2.38
R19	-2.47	R48	0.06
R20	-3.57	R49	-4.45(*)
R21	-0.60	R50	-2.91
R22	-3.84	R51	-0.87
R23	-5.01(**)	R52	-2.65
R24	-5.10(**)	R53	-4.72(*)
R25	-2.21	R54	-1.11
R26	-1.63	R55	-1.79
R27	0.00	R56	-3.65
R28	-1.84	R57	-3.21
R29	-1.08		

(I) The different industrial sectors are defined in the appendix.
*(**) indicates rejection of the null hypothesis at the 0.05 (0.01) significance level.

Table 2. Inflation Forecasting under Alternative Strategies

					Static Forecast					Dynamic Forecast
	B	***A1***	***A2***	***A3***	***A4***	***B***	***A1***	***A2***	***A3***	***A4***
RMSF(I)	0.348	0.341	0.323	0.291	0.304	0.743	0.949	0.652	0.565	1.39
MAF(II)	0.27	0.273	0.25	0.23	0.241	0.598	0.828	0.524	0.442	1.17
PAM(III)	0.242	0.246	0.224	0.206	0.215	0.541	0.735	0.472	0.395	1.031
DM test using RMSF						DM test using RMSF				
B	-	0.24	3.84(**)	2.53(*)	3.00(**)	-	1.11	1.98	1.79	2.11(*)
A1	0.24	-	0.57	1.81	1.09	1.11	-	1.86	2.8(*)	1.49
A2	3.84(**)	0.57	-	1.47	1.49	1.98	1.86	-	1.53	2.38(*)
A3	2.53(*)	1.81	1.47	-	0.72	1.79	2.8(*)	1.53	-	2.56(*)
A4	3.00(**)	1.09	1.49	0.72	-	2.11(*)	1.49	2.38(*)	2.56(*)	-
DM test using MAF						DM test using MAF				
B	-	0.1	2.61(*)	1.98	1.96	-	1.29	2.17(*)	1.91	2.68(*)
A1	0.1	-	0.85	1.92	1.11	1.29	-	2.0(*)	3.26(**)	1.47
A2	2.61(*)	0.85	-	1.07	0.65	2.17(*)	2.0(*)	-	1.59	3.3(**)
A3	1.98	1.92	1.07	-	0.84	1.91	3.26(**)	1.59	-	3.9(**)
A4	1.96	1.11	0.65	0.84	-	2.68(*)	1.47	3.3(**)	3.9(**)	-
DM test using PAM						DM test using PAM				
B	-	0.17	2.56(*)	1.95(*)	1.97(*)	-	1.21	2.22(*)	1.95	2.65(*)
A1	0.17	-	0.89	1.93(*)	1.16	1.21	-	1.94	3.21(**)	1.47
A2	2.56(*)	0.89	-	1.05	0.69	2.22(*)	1.94	-	1.63	3.34(**)
A3	1.95(*)	1.93(*)	1.05	-	0.76	1.95	3.21(**)	1.63	-	4.06(**)
A4	1.97(*)	1.16	0.69	0.76	-	2.65(*)	1.47	3.34(**)	4.06(**)	-

(I) RMSF is the root of the mean square forecast error; (II) MAF is the mean absolute forecast error; and (III) PAM is the percentage absolute mean error.
* (**) denotes rejection at the 0.05 (0.01) significance level using the DM test.

Table 3. Inflation forecasting for different horizons

Strategies	Root of the Mean Square Forecast Error					Mean Absolute Forecast Error					Percentage Absolute Mean				
	Forecast Horizon					Forecast Horizon					Forecast Horizon				
	1	**4**	**8**	**12**	**24**	**1**	**4**	**8**	**12**	**24**	**1**	**4**	**8**	**12**	**24**
A1	0.29	0.67	0.75 (*)	0.82	1.14	0.23	0.48	0.57 (*)	0.69	0.98	0.2	0.43	0.5 (*)	0.61	0.85
A2	0.32	0.72	0.89	0.92	1.37	0.24	0.54	0.74	0.78	1.1	0.21	0.48	0.66	0.69	0.95
A3	0.26	0.57 (**)	0.69 (**)	0.68 (**)	0.9 (*)	0.21	0.43 (*)	0.56 (*)	0.56 (**)	0.77	0.19	0.38 (*)	0.49 (*)	0.51 (*)	0.67
A4	0.29	0.64	0.66 (**)	0.82	1.16 (*)	0.23	0.45	0.55 (**)	0.69	0.93	0.2	0.4	0.48 (**)	0.61	0.8

(I) A1, A2, A3 and A4 are strategies 1, 2, 3 and 4 respectively.
** (**) denotes that, compared to the benchmark specification, the forecast is significantly better at the 0.05 (0.01) significance level using the DM test.*