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

FORECASTING DISAGGREGATES BY SECTORS AND REGIONS. THE CASE OF INFLATION IN THE EURO AREA AND SPAIN

Gabriel Pino [1], J.D. Tena [2] and Antoni Espasa[3]

Abstract

We study the performance of different modelling strategies for 969 and 600 monthly price indexes disaggregated by sectors and geographical areas in Spain, regions, and in the EA12, countries, in order to obtain a detailed picture of inflation and relative sectoral prices through geographical areas for each economy, using the forecasts from those models. The study also provides a description of the spatial cointegration restrictions which could be useful for understanding price setting within an economy. We use spatial bi-dimensional vector equilibrium correction models, where the price indexes for each sector are allowed to be cointegrated with prices in neighbouring areas using different definitions of neighbourhood. We find that geographical disaggregation forecasts are very reliable on a regional level in Spain as they improve the forecasting accuracy of headline inflation relative to alternative methods. Geographical disaggregation forecasts are also reliable for the EA12 but only because derived headline inflation forecasting is not significantly worse than alternative forecasts. These results show that regional analysis within countries is appropriate in the euro area. These highly disaggregated forecasts can be used for competitive and other type of macro and regional analysis.

Keywords: spatial cointegration, regional and sectoral prices, regional analysis, relative prices, price setting, competitiveness.
JEL Classification: C2, C5.

1. Introduction:

[1] Gabriel Pino, Southern Illinois University, Economic Department, 1000 Faner Drive, Carbondale, IL 62901, USA, e-mail: gabriel.pino@siu.edu.
[2] Juan de Dios Tena, Universidad Carlos III, Departamento de Estadística and Instituto Flores de Lemus, C/Madrid 126. 28903 Getafe (Madrid), España, e-mail: jtena@est-econ.uc3m.es.
[3] Antoni Espasa, Universidad Carlos III, Departamento de Estadística and Instituto Flores de Lemus, C/Madrid 126. 28903 Getafe (Madrid), Spain, e-mail: antoni.espasa@uc3m.es.
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Forecasting a headline rate of inflation by considering information about sectoral disaggregates has received recently considerable attention; see, among others, Hendry and Hubrich (2011). Espasa and Mayo (2012) argue that in a variable such as inflation the aggregate and all its disaggregates matter for policy and investment decisions and they focus their attention on forecasting both aggregate and disaggregates, taking some of the common features in the latter into account. There is a large amount of information about the consumer price index of any developed economy, as Statistical Offices provide breakdowns of the respective CPIs by sector and region. A first attempt to use this double disaggregation for forecasting purposes can be found in Espasa and Albacete (2007), where the authors work with a breakdown of the euro area Harmonized Index of Consumer Prices in just two sectors and five geographical regions, using block-diagonal VEqCM. They find evidence in favour of double disaggregation. More recently, Tena et al. (2010), working with a limited geographical disaggregation for Spanish inflation, find support for the use of disaggregation by sector and region for forecasting aggregate Spanish inflation. This paper extends previous research by considering double disaggregation in two different contexts of economic integration of the geographical areas. Thus the paper studies inflation in the Euro area and Spanish economies using the most detailed information by sector and country or region, respectively. A comparison of the results of geographical breakdowns by country, euro area, with breakdowns by region, Spain, provides interesting results about the sectoral cointegration between areas and evolution of relative prices.

The vast amount of information derived from disaggregation is very useful for really understanding the evolution of inflation in a given country or economic area, particularly through the relative performance of prices indexes through sectors in different regions or members' states. Consequently, the literature on price setting and inflation persistence also recently focused on disaggregate data – initially only sectoral disaggregation- and has obtained results which significantly differ from previous ones based on aggregate data, see Clark (2006) and references therein. More recently, two contributions by Beck et al. (2009) and Beck et al. (2011) highlight the importance of considering regional factors and a combination of regional and sectoral factors, respectively, for explaining the heterogeneity of disaggregated inflation rates in the euro area. The former identifies the presence of area wide and national components that drive price dynamics in 70 European regions. However, a national factor extracted from series that ignore disaggregation by sector could represent a mixture of national-specific component and other non-national specific factors. This issue is contemplated in Beck et al. (2011), who extract aggregate, sector, country specific and regional orthogonal components from 730 inflation series, which consider a regional break down with 12 sectors in the regions of six euro area countries. They find that region-specific idiosyncratic components explain a significant part of price variations. Considering the variation of price series on regional and sectoral levels is the motivation for this paper. However, unlike the previous authors, our prime interest is to evaluate the forecasting performance of models for disaggregated price data, not only as something of interest in itself but also as the first step before proposing other economic analysis with this type of models. Two additional important differences from the previous literature are as follows. First, we consider the possible presence of cointegration between neighbouring prices instead of basing the analysis on differentiated series. The question of cointegration between regional sectoral prices could also be interesting in the study of price setting and should in any event be taken into account when modelling inflation rates. Secondly, in line with Espasa and Mayo (2012), we consider a maximum number of sectors, 50 and 57 for the euro area and Spain, respectively. The problem with using intermediate aggregates from these basic 57 and 50 sectors is that common features present between subsets of the basic sectors could disappear in a priori definitions of broader sectoral intermediate aggregates. Thus, working with basic sectors is important for avoiding the problem of aggregation bias that could result from grouping heterogeneous sectors together.

Providing forecasts of disaggregated price indexes is valuable in itself as it enables central bankers and entrepreneurs to identify how different sectors along regions are affected by different types of economic shocks, with a view to designing an efficient monetary policy, making investment decisions or receiving valuable signals about a possible lack of competitiveness. These economic agents not only need to know this detailed information from the past, but also its forecasts in individual and relative terms. In this paper we are interested in formulating a forecasting procedure for all the disaggregates of a macro-variable such as inflation at the highest level of breakdown by sector and geographical area. The procedure in itself is important because we could easily have around one thousand disaggregates to forecast.

Espasa and Albacete (2007), in a breakdown of two sectors and five areas, work with VEqCM models and Espasa and Mayo (2012) show the importance of considering not only common trends but also common cycles in forecasting inflation by a full sectoral breakdown which, in the case of US inflation involves 160 sectors. These authors forecast disaggregates by single-equation models that include restrictions derived from the existence of common features between the components. They also show that component forecasting by ARIMA models is not very accurate. The above literature implies that the consideration of restrictions between large number of components is crucial when attempting to forecast them. The main characteristic of our approach, relative to the previous papers, consists of using double criteria in the breakdown with the maximum number of components in each case. Our work represents a first attempt to forecast components at this highest disaggregated level considering some restrictions between components. In this framework, a general approach for considering restrictions would be too complex. Espasa and Mayo (2012) show the interest of restrictions as common trends from sectoral breakdowns, in this paper we limit ourselves to the study of restrictions from geographical breakdown, particularly spatial cointegration restrictions. The results obtained could identify significant or unimportant aspects to be considered in further research aimed at formulating a more complex forecasting procedure with a more general method for including restrictions between the large number of components present in this type of problem.

Forecasts of a large number of components will be useful if they are reliable. This could be tested for each component, but it does not seem to be sufficient. As the components add up to an aggregate, it has to be tested whether the forecast of the aggregate obtained by aggregating the forecasts of the components is, at least, not significantly worse than the alternative forecasts of the aggregate using the same or smaller information sets. Thus one aim of the paper is also to study different procedures for forecasting disaggregated price indexes by sector and region and to show that those forecasts are reliable because their aggregation gives a forecast of the aggregate, which at least is not worse than alternative forecasts.

As mentioned above, in this study we want to focus on cointegration restrictions in a given sector price through geographical areas. In fact, in this paper we do not focus on the national sectors' cointegration restrictions studied in Espasa and Mayo (2012) but concentrate our efforts on studying cointegration of a given sector through regions. Therefore we have a spatial cointegration issue in which there is only one neighbourhood level. However, we do not know the appropriate definition of neighbour and we need to test different definitions before choosing the definition with the best performance.

The existence of spatial cointegration could be very different when breaking down the CPI of an economic area such as the euro area by sector through country members than when applying such a breakdown to the sectors of the regions in a state economy. We therefore apply our analysis to the 12 states of Euro area 12 (EA12 henceforth) and the 17 regions of the Spanish economy.

It is widely recognized in the literature, that the question of whether a direct or indirect procedure is best for forecasting an aggregate is largely empirical. In our case, the question is whether, because of the curse of dimensionality, double breakdown by sector and geographical region performs worse than breakdowns based on a single criterion, sector or region. In the case of Spain we go from 57 price indexes for the sectors available on a national level to 969 price indexes when considering these sectors within each of the 17 Spanish regions.

This paper analyses different strategies for forecasting 600 and 969 monthly price indexes disaggregated by sector and geographical area in the EA12 and Spain, respectively. We deal with the curse of dimensionality by specifying and estimating ARIMA models as well as alternative spatial bi-dimensional vector equilibrium correction (SVeqCM) models where the price indexes for each sector in a particular geographical area is allowed to be cointegrated with the respective price in neighbouring areas using different definitions of neighbourhood based on geographical, economic and sociological considerations.

Irrespective of the empirical answer to the question in the previous paragraph, when dealing with several hundreds of time series the presentation of results and forecasts in simple way, to capture main traits, is crucial, to prevent many people from ignoring the valuable outcome of this type of exercise. Using blanks, stars and colours, for instance, we show that results related to the 600 EA12 or 969 Spanish price indexes can be presented in a friendly way.

The structure of this paper is as follows. The next section describes and analyses the main features of the time series used in the paper. Section 3 presents and discusses the different methodologies considered for forecasting inflation in Spain and the Euro Area 12, and a discussion of the forecasting results of those methodologies can be found in Section 4. Some concluding remarks follow in Section 5.

2. Data Description

We use both aggregate price indexes as well as information related to different sectors and geographical areas. More specifically, we consider the following series: 1) the aggregate HICP for EA12 and the Spanish Consumer Price Index; 2) price indexes for 50 sectors in the EA12 and 57 sectors in the Spanish economy; 3) aggregate price indexes for each of the 12 EA countries and the 17 Spanish regions; and 4) disaggregated sectoral price indexes for the 12 EA countries and for 17 regions in Spanish [4]. Price series for the different Spanish regions (aggregated and disaggregated by sectors) are available from the Spanish Statistical Office (http://www.ine.es). At the European level, disaggregated price series by sectors and countries were obtained from the European Commission (http://epp.eurostat.ec.europa.eu/portal/page/portal/eurostat/home). Spanish series cover the 1993:01-2009:12 period while EA12 series are available from 1996:01 to 2009:12.We use data up to 2005 to estimate the models and the remaining four years (2006:01-2009:12) to compare the forecasts obtained under different strategies.
For the EA12 Eurostat offers weights of the different countries in order to map the aggregate inflation rate in the EA12 with the national inflation series. However, for Spanish regions this information is not available from the Spanish Office for National Statistics (INE). The problem is solved using as weights each region's share of expenditure in Spanish expenditure. Indeed, the inflation series obtained by this aggregation is almost identical to the official Spanish inflation rate. Weights at the sector level, on the other hand, are available from the INE and the Eurostat. These institutions formulate the aggregate price index for each region based on a chain Laspeyres price index in both cases. During the forecasting exercise, we aggregate inflation projections by using weights computed with information up to the last available period.[5],[6]
In Tables 1 and 2 we report descriptive statistics, similar to those in Beck et al. (2011), for Spain and the EA12 respectively. In general, and consistently with Beck et al. (2011), Imbs et al. (2005) and Pesaran and Smith (1995), disaggregated inflation shows low levels of persistency which could indicate that persistence of aggregated

[4] A description of the sectors, regions, and countries can be found in the Appendix. In fact in Spain there are 18 regions since the autonomous cities of Ceuta and Melilla can be consider as another region. We have been working with these 18 regions but for the purpose of simplification only the results for the first mentioned 17 regions are reported through the paper.

[5] In the Spanish case, the aggregate for Ceuta and Melilla regions was broken down in two since 2007 and therefore it is not possible to have the complete series. Hence, given the low weight of these two autonomous cities that only represent 0.2% of the total national expenditure, in this particular case we restrict our analysis to the aggregated price index for Ceuta y Melilla in all the cases by aggregating both series since 2007 according to the share in the total Spanish expenditure.

[6] In the case of the EA12 Consumer Price Index, the only irregularities are for the series of education in Belgium and other major durables for recreation and culture in Austria that are only available from 1999:12. Therefore, in these two cases, models were specified and estimated using the information available from that date. Also, other major durables for recreation and culture in the case of Spain was only available from 2006:12 and it was dropped from the analysis and weights were rescaled for this fact.

inflation comes as a result of aggregation bias that is generated by aggregating heterogeneous price series. A second fact we observe for both Spain and the EA12 is that there is more heterogeneity across sectors than across geographical areas. Also, the last column of the tables indicate a relatively higher degree of comovement between regions for a given sector than among different sectors for a given region or country. This enhances the importance of taking into account links by sectors in different geographical areas in order to capture the dynamics of disaggregated series in an accurate way. Moreover, fairly heterogeneous values for mean and volatility for each of disaggregate series suggest the convenience of using disaggregated models by sectors and regions to have a complete picture of the Spanish and European inflation.

[INSERT TABLE 1]

[INSERT TABLE 2]

Figures of price series in levels are not shown to save space; however, their inspection reveals that most of them grow smoothly during the period under consideration. Series in first differences, on the other hand, show regular crossing points and no obvious trend. Additionally, many series, for example prices of lamb, fish, potatoes, vegetables, package holidays, accommodation services, etc. 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 Hasza 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 one by one unit roots at each of the harmonic frequencies of the seasonal cycle.

Results of the test for the disaggregate prices indicate that at the 5% confidence level the majority of the price series requires only one regular difference (and no seasonal differences) to become stationary. For example, at the 5% significant level, results of the tests indicate that for the five biggest Spanish communities, Andalusia, Catalonia, Madrid, Basque Country, and Valencia, the 77%, 77%, 75%, 72%, and 74% of their sectors can be considered integrated of order one respectively (the average of this proportion for the 17 Spanish communities is 77%). Moreover, at the same confidence level, in the EA12 countries these percentages are 88%, 80%, 84%, and 80% for Germany, Spain, France, and Italy which represent about the 80% of the weighting in the inflation of the EA12 (the average of this proportion for the 12 countries is 85%). Also, in the OCSB equation the null of not significant seasonal dummies is rejected at the 5% in 47%, 49%, 53%, 53%, and 42% of the series in Andalusia, Catalonia, Madrid, Basque Country, and Valencia respectively (the average for the 17 communities is 42%) whereas in the EA12 countries this hypothesis can be rejected in the 42%, 58%, 52%, and 46% of the cases for Germany, Spain, France, and Italy (the average for the 12 countries is 52%). As a robustness exercise, for the annual rate of inflations in each of the sectors in the different Spanish regions and countries in Europe we run the Pesaran (2006) panel unit root test that allows for cross sectional (spatial) dependence. Results of the test indicate that the null hypothesis is rejected at the 5% in all the cases for Spain and also for practically all the EA12 series with the only exception of actual rental for houses. Consistently with this analysis, we specify econometric models in the following sections by assuming that the different price series are generated by unit root processes and allowing for deterministic seasonality in the cases seasonal dummies are jointly significant. However, for robustness we also consider projections obtained under ARIMA models based on alternative hypothesis about the number of unit roots in the models.

3. Strategies to forecast regional inflation by sectors in Spain and the Euro Area

In this section we present the strategies to forecast inflation rates disaggregated by sectors and geographical areas in Spain and the EA12 for the period 2006:01-2009:12. We evaluate this forecast based on models applied to different degrees of disaggregation. More specifically, for both Spain and the EA12, we compare results obtained from a benchmark strategy, denoted by B, based on a simple ARIMA model specified for the aggregate inflation in Spain and the EA12, with those obtained from a number of alternative strategies that consider different econometric specifications and disaggregation schemes. These strategies can be split in two main groups. The first one refers to the use of ARIMA models applied to disaggregated series by sectors and geographical areas in Spain and the EA12. The second approach is based on the specification and estimation of alternative spatial vector equilibrium correction (SVeqCM) models in which the price indexes for each sector is allowed to be cointegrated with prices in neighbouring geographical areas using different definitions of neighbourhood based on geographical, economic and sociological considerations as well as alternative definitions of neighbourhood based on cointegration tests.
The different approaches correspond to different ways to deal with the curse of dimensionality. In fact, under the first strategy each of the individual time series is restricted to depend only on its own past values whereas in the second strategy besides past values we allow for the presence of a long-run equilibrium between prices in the same sector for two neighbour areas.
In all the cases, we forecast inflation by following a recursive scheme; see for example Faust et al. (2005) and West (2006). Under this approach, the size of the sample used to estimate the parameters of the different models at each forecasting base grows by one observation.
In the remaining of this section we explain the main features of the two big groups of methodologies used in this paper to forecast inflation in Spain and the EA12.

3.1. Disaggregated ARIMA models by sectors and geographical areas.

The first alternative strategy (A1 henceforth), obtains headline inflation forecasts in the EA12 and Spain from aggregating ARIMA forecasts for each of the 12 European countries and 17 Spanish regions respectively. Under the second strategy, denoted by A2, we consider sectoral disaggregation and specify ARIMA models for price indexes in 57 Spanish sectors and 50 sectors in the EA12. The third strategy (A3), considers both sectoral and geographic disaggregation. Thus inflation forecasts in each Spanish region and each European country can be obtained from the aggregation of forecasts in the different sectors of that specific geographical area and they can be aggregated again to obtain the headline inflation forecast in Spain and the EA12.
In all cases, our ARIMA models are specified using the TRAMO/SEATS automatic procedure; see Gomez and Maravall (1996).

3.2. Vector Equilibrium Correction (VeqCM) Models with Spatial Cointegration

We also consider VeqCM models to characterize the dynamic pattern for each of the sectoral regional price series. The prototype model takes the form

$$\Delta p_{i,j,t} = \gamma_{i,j} + \alpha_{i,j}[\beta_{i,j}{}' \quad \delta_{i,j}]\begin{bmatrix} p_{i,j,t-1} \\ 1 \end{bmatrix} + \Phi_{i,j}\Delta p_{i,j,t-1} + \Gamma_{i,j}D_{1t} + \Psi_{i,j}D_{2t} + \varepsilon_{i,j,t} \quad (1)$$

where $p_{i,j,t}$ is a (2x1) vector containing (logs of) price levels in sector i for a region or country j and its neighbour to be defined; $\gamma_{i,j}$ is a (2x1) vector of intercept parameters; $\alpha_{i,j}$ and β_{ij} are respectively the (2x1) adjustment and cointegration vectors; $\delta_{i,j}$ is a scalar which allows for a constant in the cointegration relationship; $\Phi_{i,j}$ is a matrix that accounts for the short-run dynamics; D_{1t} includes centered seasonal dummies and Γ_{ij} is the matrix of parameters associated to these dummies; D_{2t} are centered seasonal dummies that only takes nonzero values from 2002:01 to take into account the structural break in the seasonal pattern in many disaggregated series in Spain and the EA12 and $\Psi_{i,j}$ is the matrix of parameters associated to this second group of seasonal dummies; and ε_{ijt} is a (2x1) vector of serially uncorrelated errors.

The rationale behind this VeqCM model is very similar in nature to the Space-Time AR models proposed by Giacomini and Granger (2004). They propose a model that assumes that spatial effects take one period to become manifest and ignores dependence beyond the first temporal and spatial lag. Two important differences between that paper and our approach are: (1) we allow for a cointegration relationship with the neighbour price; and (2) we use VeqCM systems with two equations, one for the regional price in question, say P1, and another for the neighbour price, say P2, (instead of imposing neighbouring series to be exogenous as in Giacomini and Granger, 2004).These bivariate models are built for all disaggregated price indexes using with their corresponding neighbour prices. In each case the model is used to forecast P1 only.

The number of lags in equation (1) is chosen to be equal to 1 as this is the specification that minimizes the Schwarz and Akaike criterion in almost all cases in both Spain and the Euro Area. Model (1) allows for a constant, but not a deterministic linear trend, in the cointegration relationship. This is because, a deterministic linear trend in the cointegration relationship amounts to imposing the assumption that prices in the different geographical areas diverge as the forecasting period increases. This specification is not useful to forecast as the linear deterministic trend in the cointegration equation can be interpreted as a proxy for other variables not included in the model and it is reasonable to think that they could be subject to structural shocks during the forecasting period.

Monthly inflation forecasts at the different horizons are obtained from equation (1) by iteration. Then, the annual rate of inflation are computed by adding the 12 monthly rates in the corresponding period.

In many European and Spanish series there is a structural seasonal break from the period 2002:01 that can be explained by a methodological change in the way that series were collected. This is the case, for example, of different prices for shoes and clothes in both Spain and the EA12. We account for this change in the seasonal pattern by allowing the set of seasonal dummy variables in (1) to have a different impact before and after the break period. Then, we test for each new observation using an F-statistics, whether seasonality can be captured with or without a structural break or if there is seasonality at all. In the initial estimation sample, T, and during the forecasting exercise, at each period $T+h$, a F-test for deterministic seasonality is run.

For each sectoral regional price we build model(1) for the following alternative definition of neighbours : 1) The whole area (Spain or EA12)(C1); 2) the aggregate of geographical areas with similar economic growth (C2); or 3) similar per-capita income (C3); or 4) similar macroeconomic conditions (C4); or 5) similar density of population (C5);and 6) the aggregate of geographical neighbours (C6).[7] Besides, we used two other definitions of neighbourhood. The first one (C7) is based on the cointegration test proposed by Johansen (1995) and considers that the neighbours for a price index in sector i and region j is the average of all the price indices for that sector in all the other regions for which the null of no cointegration is rejected at the 5% level. The second strategy (C8) defines neighbourhood using ADF tests applied to relative price indices for all the possible pairs of geographical areas in a given sector. Then we consider as the set of neighbours the average of all the prices for which the null of non-stationarity is rejected at the 5%.

In the case of the last two strategies, the econometric tests for cointegration and unit roots are repeated for each period during the forecasting exercise. This allows for a flexible definition of neighbours that could be different at different time periods. In the few cases where we do not find cointegration either under C7 or C8, we specify an unrestricted bivariate VAR model for variables on first differences.

Note that each one of the above definitions imposes a single concept of neighbourhood for all the price indexes across sectors. However, it could be assumed that different concepts of neighbourhood could be applied to different sectors. In order to account for this fact, a strategy (C9) is considered. In it we select at each forecasting base the model with the lowest Schwarz criterion between the strategies A3 and C1 to C8.

It is also possible that there is some combination of spatial VEqCM and ARIMA models which are not considered in the previous strategies and could improve the forecast of overall inflation. In order to explore this issue, two *ex-post* additional strategies are defined. In the first one (C10) we select for each sectoral regional price index the strategy (A3 and C1 to C9) which provides the best individual inflation forecast according to the root mean square forecast error (RMSFE henceforth) and then aggregate all of them to obtain the headline inflation forecast for Spain and EA12. The second one (C11) deals with the forecasts of the aggregate sector prices and consists on forecasting inflation in a given sector for Spain or the EA12 using the best strategy by comparing the RMSFE obtained from the aggregated ARIMA model in strategy A2 and the RMSFE obtained from the best strategy according to all the alternatives A3 and C1 to C9. Then, inflation forecasts in the different sectors are aggregated to estimate the overall rate of inflation in Spain or the EA12. Note that RMSFE under strategies C10 and C11 can only be obtained after inflation data is known. Therefore they cannot be consider as competing strategies but as a way to observe the best forecast that could be obtained if the best model was used in each case.

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[7] A description of the series contained in the different groups of neighbours for each strategy can be obtained from the authors upon request.

4. Results

4.1. Cointegration analysis and forecasting inflation and relative prices in Spanish regions.

One important problem in order to evaluate the forecast of the Spanish inflation is the high degree of volatility in the inflation rates after the economic crisis at the end of 2008. Hence, for robustness we evaluate the performance of the different forecasting strategies for both the periods 2006:01-2009:12 and 2006:01-2008:12. Table 3 shows the RMSFE of the benchmark strategy and the RMSFE of each of the alternative strategies relative to the benchmark. A RMSFE ratio smaller than one for a particular strategy indicates an improvement over the benchmark. The table also indicates whether the forecasts are significantly different using the modified Diebold and Mariano (1995) test proposed by Harvey et al. (1997).

[INSERT TABLE 3]

1.- As expected, the economic crisis has influenced negatively in the accuracy of forecasts under all the strategies. However, the main conclusions about the relative efficiency of the different methodologies are unaffected by this consideration. For these reason, the remaining of this section is based on analysis that includes 2009 in all cases. We discuss now these conclusions.

2. - It is found that the geographical consideration (A1) alone is not relevant or even disruptive while the use of the sectoral disaggregation (A2) on its own implies an improvement in forecasting accuracy which is significantly different from the baseline forecasts for short horizons.

3. - Moreover, strategy (A3) which uses double disaggregation always improves headline inflation forecast compared with the strategies which only use a single disaggregation criterion. In fact, for the whole sample, the modified DM test to compare strategies A2 and A3 takes values of 1.62 and 1.51 for 1 and 4 periods ahead indicating that they are not significantly different at the 5% level but they are at the 10% . For longer horizons, the values of these statistics surpass in many cases the critical values at the 5% significant level. For example, the values of the statistics for the 9, 10, 11 and 12 periods ahead forecast are 3.82, 3.61, 3.68 and 2.17 and the null hypothesis of forecast equality is rejected at the 5% in all these cases.[8]

4. - The results for strategies C1 to C9 using spatial cointegration indicate that the different definitions of neighbour used in this paper do not lead to significantly different accuracy results for headline inflation.

5.- About whether it is better to use an univariate ARIMA model –strategy (A3)- or a spatial bi-dimensional vector equilibrium correction (SVeqCM) model –strategies (C1) to (C9)- to forecast inflation for each of the 969 disaggregated series, Table 3 shows that the best forecasting strategy using cointegration terms is C9. In this strategy, for each sector in each region a test on which definition of neighbour leads to the best SVEqCM according to the Schwarz criterion

[8] Note that ARIMA models specified with TRAMO/SEATS assume in most cases that price series require a regular and a seasonal difference to become stationary. We also specified univariate models applied to the series with only one regular difference and, when they were significant, seasonal dummies to sectoral disaggregated price series. The results were very similar and the same conclusions were maintained. For example, for strategy A2 the RMSFE using ARIMA models with TRAMO are 0.42 and 3.10 at horizons 1 and 12 while the RMSFE using the proposed alternative ARIMA models are 0.42 and 3.08 at horizons 1 and 12. Therefore, for simplicity only the results with ARIMA models obtained from TRAMO are reported here.

is performed. In any case, as mentioned in point 4 the performance of C9 is not significantly different than the other C's strategies and in particular than C1, which considers cointegration with the corresponding Spanish sector. Therefore, for simplicity in what follows we focus the analysis in the comparison of strategies A3 and C1 with respect to A2 (in case of sector inflation forecast) and A1 (in case of geographical inflation forecast). C1 performs better than A3 at horizon one but not at the other ones. In both cases the differences are not significant.
Tables 4 and 5 show the best strategy to forecast inflation at horizons one and twelve, respectively, for each of the individual series and for the sector aggregates (last column). Table 6 summarizes the main results by sectors and regions.

6.- For the one-step ahead forecast, it can be observed that the best forecast for the aggregate of a region is always obtained under strategy C1. Also, the majority of the 969 inflation series are better forecast by considering cointegration relationships with Spain instead of using ARIMA models. For longer horizons, see Table 6, the opposite is true. This is consistent with Christoffersen and Diebold (1998) who find that vector equilibrium correction (VeqCM) models are particularly useful to forecast in the short run as it identifies situations of disequilibrium and indicates the dynamic of the variables in the model to return to equilibrium in the subsequent periods. In fact, Table 3 shows that for horizon one the best procedure to forecast headline inflation is C1.
7.- On the other hand, if the purpose of the analysis is to predict inflation in each of the 57 national sectors, the best strategy in more cases (24 over 57) is A2, which uses an ARIMA model for the aggregate national series of each sector. But still for the forecasting of the overall inflation, see Table 3, the best procedure is C1. For longer horizons, see Table 6, the best strategy in more cases is C1 closely followed by A3, being A3 the one which shows better accuracy for the overall aggregate, Table 3.

[INSERT TABLE 4]
[INSERT TABLE 5]
[INSERT TABLE 6]

A series of robust exercises were also run but not explicitly reported here for the sake of brevity[9]. First, we have also estimated dynamic common factors by principal components that explain most of the variability of annual inflation series in each one of the aggregated sectors. The baseline model is given by

$$\Delta_{12} \mathrm{p}_{i,j,t} = \mathrm{c}_{i,j} + \sum_{r=1}^{p} \beta_r f_{r,t} + e_{i,j,t} \quad (2)$$

where $\mathrm{c}_{i,j}$ is a constant parameter, $\mathrm{f}_{r,t}$ is a common factor for that sector in all the Spanish regions, β_r is a factor loading coefficient and $e_{i,j,t}$ is the idiosyncratic component. We have estimated models for p=1, 2, 4 and 8 common factors by principal components for each of the 57 sectors. Then we have used the approaches described by Boivin and Ng (2006) and Schumacher and Breitung (2008) to forecast the 969 series, using four different dynamic factor models in each case.
8.- The results show that the forecasting strategies based on dynamic factors do not improve the forecast of the headline inflation is most cases. The headline inflation forecasts under dynamic factors were significantly worse than the ones obtained under strategies A3 and A2 at horizons one to four and they were not significantly better than

[9] Results of these experiments are available from the authors upon request.

these forecasts at horizons five to twelve. For robustness we also specified dynamic factor models for the monthly rate of inflation including in these models one or two sets of seasonal dummy variables in the same way that we did for the vector equilibrium correction (VeqCM) models. Then, these models were used to forecast the annual rate of inflation. The RMSFE under the best forecast with dynamic factors were 0.47, 1.54, 2.39 and 2.96 at the one, four, eight and twelve horizons respectively. This does not change the main conclusion of our analysis.
9.- The robustifying procedure proposed by Hendry (2006) has been applied to all the strategies using bivariate models SVeqCM, but no important differences with the previous results were obtained.
10.- In a final set of experiments, for each of the 969 disaggregated prices we specify single-equation models in which we allow the dependent variable to react to several price differences between the region in question and the corresponding price of each one of the other regions, in a spirit similar to Aron and Muelbauer (2012). However, this specification did not improve inflation forecast in most cases.

The analysis developed in this section is not only useful to forecast inflation but also to get a better insight about cointegration links. Thus it is particularly helpful to identify the sectors and areas prone to be affected by problems of competitiveness. Table 7 classifies Spanish regions according to their number of cointegrated sectoral prices with Spain and with other regions, but not clear pattern emerges from this table. Table 8 specifies the sectors which show the greatest and lowest number of cointegration relationships with the corresponding sectors in all the other regions and in Spain. The results are classified for the groups of prices corresponding to food, industrial goods and services. The presence of long-run relationships in food is more common in fish, cereal and alcoholic drinks; in other goods appears more often in clothes and footwear; and in services in medical services, some education items, publications, some repairing services, rental apartments and recreational objects.
The above results show that the forecasts of all sectoral regional prices are reliable because their aggregation leads to a forecast for the headline inflation that is better, even when not in a significant way, than forecasts from the alternative methods considered in this paper. But at this high disaggregation level it is important to use the above results to generate forecasts of the relative prices in a particular sector of a given region with the corresponding prices in Spain and in all the other regions. Table 9 presents the forecasts of changes between 2008:12 and the base forecast 2007:12 in the relative price of each sectoral regional price with respect the corresponding one in Spain. The table points out those changes which are significant with respect the sample standard deviation. The table shows that for the considered period the sectors with less expected significant changes in relative prices are clothes and footwear in general. On the other hand, the sectors with more significant expected changes are beef, bird, eggs, fresh fruit, bread, preserved fruit, vegetables, milk, primary school, other expenditures in education, public urban transportation, publications, secondary school, and mail and communications.

[INSERT TABLE 7]
[INSERT TABLE 8]
[INSERT TABLE 9]

4.2. Cointegration analysis and forecasting inflation and relative prices in the EA12.

In the same vein that the Spanish inflation case, Table 10 shows the RMSFE for the benchmark strategy and the relative mean square forecast errors (RMSFE) obtained under different strategies. For simplicity, we omit in this table results from strategies C2 to C11 given that they are very similar to the ones obtained under C1. Table 11 reports a comparative evaluation of strategies A2, A3 and C1 following Harvey et al. (1997).The main conclusions are as follows.

1.- Unlike the Spanish case, the strategy based on disaggregation by geographical regions and sectors is not the best one in order to forecast EA12 headline inflation, but it does not performs significantly worse than A2. Strategy A2 provides lower, although not significantly different, RMSFE for all forecast horizons than the alternative disaggregated methodologies, except at horizon 12 in the evaluation period 2006:01 to 2008:12. This implies that the reliability of the disaggregated forecasts for the 600 country sectors is not rejected and could be use for basing on them forecasts of the relative sectoral prices between countries. This difference in the importance of the geographical dimension in the analysis of Spanish and AE12 inflation data could reflect that spatial links are stronger between the regions of a country than in the countries of an economic union.

[INSERT TABLE 10]

[INSERT TABLE 11]

2.- The procedures in this paper allow to generate inflation forecasts by countries, by sectors or both.

When the purpose is to forecast the headline inflation for a particular country, strategies A3 and C1, which breakdown prices by sectors, provide a better performance than the aggregated strategy A1. This has no exceptions in all cases for the one-step ahead forecasts. This superiority of disaggregate models to forecast inflation by countries is also evident at longer horizons. For example, for the 12 step-ahead forecasts, strategies A3 and C1 outperform A1 in 8 out of 12 countries.

3.- Table 12 shows the relative performance of strategies A2, A3 and C1 in order to forecast inflation in each of the EA12 sectors. At horizon one, A2 is clearly the best strategy in 44 out of 50 sectors from which they are significant at 5% in 32 cases. Inflation forecast could only be significantly improved by considering either A3 or C1 in 3 sectors.

[INSERT TABLE 12]

4.- It is also of interest to compare strategies A3 and C1.In forecasting the overall inflation in the EA12, C1 performs better than A3, see Table 10, but not in a significant way, see Table 11. In forecasting inflation in each of the 50 sectors of the 12 countries we have that for the 1 step-ahead forecast, cointegration improves inflation forecast compared to simple extrapolative devices in at least 8 out of 12 countries for sectors: s1: bread and cereals, s3: fish and seafood, s5: oils and fat, s14: beer, s38: major appliances and s48: recreational objects. Note that all of them correspond to tradable goods whose prices, due to the possibility of arbitrage, are not expected to diverge through countries.

5.- Cointegration results for countries and sectors are shown in Tables 13 and 14 respectively. We do not observe important differences by countries. In all of them there are at least 40 sectors cointegrated with the corresponding sector in EA12. Regarding cointegration by sectors, the main features are broadly consistent with those obtained at the regional level for Spain. Specifically, perishable food products and local services do not cointegrate much while long run relationships are stronger in homogeneous and durable tradable goods.

[INSERT TABLE 13]
[INSERT TABLE 14]
Table 15 presents the forecasts of changes between 2008:12 and the base forecast point 2007:12 in the relative price of each country sectoral price with respect the corresponding one in EA12. The table points out those changes which are significant with respect the sample standard deviation. In this case it is more informative to fix the attention on the countries for which more significant negative changes are expected and those countries are Spain, Italy, Greece and Belgium. For the contrary the countries with significant positive changes are Netherland, Germany and France.

[INSERT TABLE 15]

5. Concluding remarks.

In this paper we have studied the performance of different strategies to forecast 969 and 600 monthly price indexes disaggregated by sectors and geographical areas in Spain and the EA12 respectively. We have dealt with the curse of dimensionality problem avoiding modelling with vectors of dimension higher than two. Thus we specify and estimate ARIMA models as well as alternative spatial bi-dimensional vector equilibrium correction (SVeqCM) models where the price index for each sector is allowed to be cointegrated with price indexes in neighbouring geographical areas using different definitions of neighbourhood based on geographical proximity, economic and sociological considerations. The results for both economies show that disaggregating by just one criterion, sector or region, the former is more relevant than the latter in forecasting the corresponding headline inflation. These results confirm the ones given in Espasa and Albacete (2007), who use much more reduced disaggregation levels, ten sectoral country sectors in the EA compared with the 600 in this paper.

The relevance of the use of the double disaggregation criteria based on sectors and geographical areas seems to depend on the level of economic integration between the areas. Thus the sectoral breakdown by regions within a country like Spain improves the headline inflation forecasting accuracy, but this is not the case when breaking down the sectors by countries in the EA12. These results suggest that it could be useful to breakdown sectoral European data in regions corresponding to the different country members. This approach is proposed by Beck et al. (2011) in the context of price setting. In any case, the implementation of the double-disaggregation criterion is aimed to make use of the models and forecasts at the level of sectors within a geographical area. In order to show that in both cases, Spain and EA12, these highly disaggregated forecasts are trustworthy we have shown that the accuracy of the resulting headline inflation forecast is not significantly worse than the accuracy in the other forecasts based on simpler breakdowns analysed in the paper. This is relevant because it points out that passing from dealing with 57/50 aggregated-sector series to work with 969/600 sectors through all the geographical areas, we do not get worse aggregated results and we can provide a much wider forecasting information through sectors within areas. This is of special interest when putting the results for the highly disaggregated series in relative terms with respect to global economy under study or to the other geographical areas. Using different colours, Tables 9 and 15, with 969 and 600 cells respectively, provide a friendly summary of the results for one-year ahead forecast of the relative sectoral prices.

Espasa and Albacete(2007) and Espasa and Mayo (2012) show that when analysing disaggregated data it is important to consider restrictions between the disaggregates coming from the presence of common features

between them. In this paper we have studied the relevance of spatial cointegration. On the question of how to define neighbourhood, the paper provides evidence that the different definitions do not lead to significantly different results and that considering the whole area under study as neighbour is as good as any other definition based on specific geographical areas. This can simplify considerably the treatment of spatial cointegration in these contexts.
Including spatial cointegration restrictions does not help to improve significantly the aggregate forecast, but it pays a useful role in forecasting inflation in the aggregated sectors. In this sense the paper provides evidence, see Tables 8 and 14, of which are the sectors that can be considered with high cointegration levels. These results could be very interesting when dealing with price-setting questions.

Regarding modelling and forecasting inflation at the sectoral regional level we have dealt with many questions and have shown that the results are reliable and therefore they can be useful for policy makers, investors and agencies watching competitiveness. But more applications seem interesting, for example, to find how this approach can be used in big countries like the US, where the economic integration of the states could be something in between the member countries in the EA12 and the regions in Spain. Also, the study if in the Euro Area the breakdown of sectors within regions in the different country members turns to be really useful. Another questions for the future is to study cointegration through sectors as in Espasa and Mayo (2012) and spatial cointegration together, and the consideration of other common features besides common trends. Finally the application to other economic indicators as industrial production seems also promising. .

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Table 1. *Descriptive statistics: Spanish inflation, disaggregation by sectors and regions*

	Level		Volatility		Persistence		Disp	Corr(xi,x)
	Mean	Std	Mean	Std	Mean	Std		
Overall Inflation	2.93	0.15	14.77	1.89	0.20	0.03	17.44	0.20
				Autonomous Communities				
Andalusia	2.81	1.53	14.43	16.39	0.23	0.18	17.35	0.20
Aragon	2.92	1.57	16.37	15.44	0.18	0.19	19.34	0.20
Asturias	2.90	1.57	16.75	18.05	0.17	0.17	20.13	0.16
Balearic Island	3.04	1.59	14.47	10.61	0.14	0.21	16.01	0.23
Canary Island	2.69	1.57	13.10	11.05	0.19	0.17	14.65	0.25
Cantabria	2.84	1.46	16.05	14.00	0.16	0.19	18.95	0.21
Castilla y Leon	2.87	1.54	14.79	15.23	0.25	0.17	18.18	0.20
Castilla la Mancha	2.88	1.48	15.84	16.74	0.22	0.17	19.10	0.21
Catalunya	3.17	1.45	14.56	14.92	0.20	0.19	17.11	0.19
C. Valenciana	2.87	1.50	14.57	15.38	0.19	0.18	17.25	0.21
Extremadura	2.72	1.60	16.33	16.19	0.15	0.19	19.05	0.20
Galicia	2.92	1.41	15.58	16.11	0.23	0.17	17.82	0.21
Madrid	2.83	1.58	13.49	12.59	0.17	0.19	15.89	0.20
Murcia	3.14	1.49	17.70	18.67	0.15	0.20	20.86	0.21
Navarra	3.15	1.47	17.79	15.50	0.15	0.21	20.24	0.18
Basque Country	3.08	1.57	14.92	15.43	0.18	0.17	17.87	0.18
Rioja	3.22	1.44	19.71	22.30	0.16	0.17	23.02	0.14
				Sectors				
s1	2.16	0.32	6.54	1.40	0.07	0.13	5.04	0.64
s2	4.15	0.66	10.49	2.81	0.23	0.15	7.22	0.64
s3	3.29	0.54	12.43	3.18	0.27	0.13	9.08	0.68
s4	3.80	0.67	55.78	9.49	0.46	0.07	23.51	0.89
s5	1.85	0.44	28.97	6.18	0.34	0.06	11.86	0.90
s6	2.40	0.36	49.93	11.45	0.10	0.06	18.42	0.91
s7	1.95	0.37	6.59	1.56	0.18	0.14	5.00	0.67
s8	2.21	0.37	42.32	11.36	-0.08	0.06	18.63	0.88
s9	3.26	0.52	12.75	3.16	0.03	0.09	10.06	0.61
s10	2.76	0.65	20.27	5.62	0.27	0.13	13.46	0.76
s11	2.51	0.28	14.97	1.35	0.53	0.09	5.92	0.90
s12	2.10	0.26	9.34	1.68	0.13	0.10	6.05	0.77
s13	3.13	0.20	30.31	2.30	0.57	0.06	10.33	0.92
s14	4.41	0.49	10.62	1.96	0.69	0.04	3.98	0.93
s15	3.70	0.43	10.49	2.67	0.29	0.17	7.96	0.66
s16	4.63	0.35	13.09	1.72	0.57	0.04	4.93	0.92
s17	2.20	0.32	8.62	1.88	0.12	0.15	6.83	0.62
s18	5.10	0.83	86.71	19.70	0.43	0.07	41.26	0.85
s19	2.83	0.37	17.36	2.65	0.49	0.13	9.37	0.82
s20	0.73	0.53	9.37	2.57	0.16	0.18	6.80	0.66
s21	2.39	0.22	4.90	1.26	0.11	0.09	4.08	0.60
s22	1.53	0.51	10.43	2.37	-0.03	0.12	7.87	0.61
s23	2.82	0.36	7.65	2.84	0.20	0.14	5.54	0.66
s24	6.79	0.13	22.04	1.13	-0.01	0.08	2.85	0.96
s25	1.91	0.42	47.06	6.33	0.28	0.04	7.67	0.98
s26	1.82	0.58	59.67	6.70	0.23	0.03	8.74	0.98
s27	1.81	0.80	69.31	11.60	0.16	0.04	10.87	0.98
s28	2.66	0.35	33.58	7.45	0.20	0.06	9.57	0.94
s29	2.56	0.53	34.35	7.12	0.24	0.03	9.32	0.95
s30	2.73	0.70	48.03	5.86	0.21	0.04	10.17	0.96
s31	2.36	0.67	45.85	10.46	0.22	0.04	12.58	0.95
s32	4.30	0.31	6.68	1.79	0.10	0.08	5.17	0.57
s33	4.50	0.36	3.71	1.10	0.33	0.13	2.74	0.62
s34	2.86	0.41	11.96	2.31	0.15	0.08	4.60	0.90
s35	4.12	0.23	5.52	1.71	0.14	0.08	4.39	0.52
s36	2.95	0.45	6.72	2.72	0.17	0.06	3.80	0.76
s37	2.22	0.40	16.78	3.72	0.12	0.05	5.82	0.93
s38	0.21	0.31	3.63	0.92	0.10	0.07	2.86	0.54
s39	2.87	0.26	5.38	1.22	0.11	0.06	4.16	0.60
s40	1.54	0.27	6.70	1.50	0.09	0.10	5.62	0.55
s41	4.36	0.38	6.23	1.21	0.13	0.08	4.30	0.65
s42	3.96	0.39	6.48	1.49	0.12	0.06	3.12	0.82
s43	0.18	0.23	9.42	0.68	-0.04	0.05	2.83	0.95
s44	3.01	0.09	10.71	0.64	0.43	0.01	1.45	0.99
s45	4.83	0.45	12.36	2.91	0.03	0.12	6.91	0.62
s46	4.41	0.46	9.76	2.85	0.20	0.07	4.23	0.87
s47	0.37	0.14	14.08	0.64	0.01	0.00	0.35	1.00
s48	-2.31	0.59	5.69	0.94	0.20	0.13	3.91	0.72
s49	2.75	0.18	5.37	0.41	0.18	0.05	1.71	0.88
s50	2.89	0.48	10.93	4.79	-0.18	0.15	9.60	0.39
s51	4.71	0.98	12.76	1.95	0.03	0.09	6.12	0.64
s52	4.55	0.64	13.69	4.70	0.06	0.08	4.42	0.81
s53	4.80	0.02	17.48	0.25	-0.07	0.00	0.13	1.00
s54	3.12	0.41	4.73	1.39	0.07	0.10	3.76	0.53
s55	2.85	0.32	4.24	0.76	0.16	0.09	3.31	0.62
s56	4.13	0.21	10.24	2.09	0.11	0.05	3.43	0.95
s57	3.55	0.25	5.36	0.78	0.10	0.07	2.90	0.78

This table reports descriptive statistics for monthly inflation rates disaggregated by sectors and regions. The reported statistics include the weighted mean and the standard deviation (std) of the time-series means of all inflation series included in a given group (level), the weighted mean and the standard deviation (std) of the time series standard deviation of all inflation series included in a given group (volatility), the weighted mean and the standard deviation (std) of the persistence measures of all inflation series included in a given group, the average over time of the cross-sectional dispersion of all inflation series included in a given group and the weighted mean of the correlation of all inflation series included in a given group with the group aggregate inflation rate. The measure for persistence is based on the weighted mean of the first order autocorrelation for all the series.

Table 2. Descriptive statistics: EA12 inflation, disaggregation by sectors and countries

	Level		Volatility		Persistence		Disp	Corr(xi,x)
	Mean	Std	Mean	Std	Mean	Std		
Overall Inflation	1.99	0.48	14.09	9.17	0.12	0.07	20.64	0.15
				Countries				
Germany	1.62	1.83	14.47	27.11	0.08	0.23	24.85	0.06
Austria	1.70	1.49	14.19	15.94	0.08	0.19	19.54	0.12
Belgium	1.89	1.52	21.56	38.79	0.11	0.29	34.00	0.14
Spain	2.69	1.81	14.27	19.03	0.29	0.20	20.17	0.16
Finland	1.70	1.80	15.22	15.83	-0.02	0.16	19.84	0.20
France	1.54	1.86	10.88	14.18	0.12	0.25	16.14	0.18
Greece	3.31	1.94	28.26	30.85	0.06	0.21	34.72	0.26
Netherland	1.97	2.18	18.13	23.71	0.05	0.15	26.13	0.17
Ireland	2.45	2.71	15.62	17.81	0.13	0.23	19.13	0.24
Italy	2.26	1.31	11.63	14.97	0.11	0.26	14.19	0.19
Luxembourg	2.32	1.65	14.92	14.28	-0.10	0.24	16.57	0.26
Portugal	2.52	1.65	13.81	15.88	0.14	0.19	18.06	0.13
				Sectors				
s1	2.11	0.67	3.76	1.33	0.57	0.16	2.47	0.75
s2	1.87	0.56	5.77	2.78	0.42	0.19	4.82	0.65
s3	2.61	0.47	12.56	5.14	-0.11	0.19	10.43	0.56
s4	1.54	0.61	7.18	2.74	0.55	0.11	3.93	0.72
s5	1.42	0.69	13.55	8.10	0.50	0.19	10.05	0.46
s6	2.26	0.81	37.62	25.83	0.36	0.21	33.17	0.59
s7	1.52	1.42	44.06	22.12	0.29	0.21	32.44	0.75
s8	1.64	0.52	3.98	1.37	0.31	0.22	3.28	0.54
s9	1.61	0.49	3.52	1.84	0.32	0.15	3.45	0.45
s10	0.69	0.53	8.70	5.26	0.44	0.21	7.37	0.67
s11	1.32	0.57	4.68	2.62	0.17	0.11	4.50	0.50
s12	1.41	0.93	5.11	5.89	0.10	0.21	5.17	0.37
s13	1.86	0.78	4.31	2.21	0.18	0.20	3.94	0.51
s14	1.90	0.76	5.50	3.24	0.12	0.18	5.02	0.36
s15	5.23	0.84	17.25	3.00	0.05	0.14	10.33	0.46
s16	0.96	1.24	49.65	33.15	0.06	0.19	36.98	0.83
s17	1.47	1.20	42.81	25.00	0.10	0.17	29.88	0.83
s18	2.54	1.07	3.18	2.65	0.12	0.31	3.42	0.33
s19	2.51	0.77	4.40	1.34	0.10	0.27	3.41	0.48
s20	3.21	0.94	7.26	17.32	0.09	0.16	6.42	0.56
s21	3.15	1.04	15.35	6.07	0.15	0.07	10.33	0.71
s22	1.58	0.73	5.68	4.17	-0.08	0.20	5.40	0.53
s23	1.05	0.99	16.98	14.61	0.02	0.15	16.05	0.62
s24	-0.63	0.74	5.15	8.15	-0.04	0.16	6.64	0.43
s25	2.70	0.50	5.55	2.34	0.06	0.22	4.17	0.40
s26	1.78	0.66	6.67	13.52	0.03	0.13	10.97	0.52
s27	1.23	0.79	3.08	1.94	-0.12	0.18	3.08	0.40
s28	1.05	0.78	3.28	2.16	0.33	0.17	3.42	0.47
s29	2.81	1.16	6.88	3.46	-0.02	0.15	5.44	0.30
s30	2.24	0.68	8.72	3.74	-0.01	0.06	4.55	0.48
s31	0.82	0.62	5.56	2.91	-0.04	0.18	4.58	0.43
s32	0.74	0.56	5.72	3.39	0.03	0.11	5.14	0.42
s33	1.14	0.45	3.87	1.74	0.10	0.12	3.33	0.41
s34	3.31	0.56	31.51	4.55	0.29	0.14	12.08	0.91
s35	3.29	0.90	4.34	1.81	0.10	0.29	3.65	0.56
s36	2.45	1.15	8.26	7.35	-0.13	0.15	6.54	0.46
s37	2.94	1.06	17.57	7.96	-0.16	0.13	13.22	0.60
s38	2.56	1.66	19.21	19.47	-0.03	0.11	13.81	0.38
s39	-2.60	0.90	10.86	2.29	0.05	0.07	7.59	0.44
s40	-6.13	1.55	7.06	3.98	0.21	0.29	6.41	0.53
s41	1.43	0.71	6.45	4.44	-0.02	0.10	4.51	0.34
s42	0.88	0.52	8.56	4.03	0.09	0.23	7.02	0.64
s43	2.40	0.54	11.03	21.33	-0.09	0.13	7.83	0.36
s44	2.19	0.55	4.40	2.89	0.02	0.10	4.25	0.41
s45	3.58	1.43	86.36	39.08	-0.23	0.26	58.44	0.58
s46	3.14	0.94	12.31	7.09	0.06	0.12	5.42	0.50
s47	2.56	0.84	2.95	3.13	0.18	0.15	3.07	0.58
s48	2.49	1.03	5.44	2.90	-0.01	0.16	4.07	0.50
s49	3.10	0.63	56.82	32.61	0.00	0.25	41.22	0.65
s50	2.23	0.61	3.31	1.40	0.07	0.13	2.81	0.55

This table reports descriptive statistics for monthly inflation rates disaggregated by sectors and countries. The reported statistics include the weighted mean and the standard deviation (std) of the time-series weighted means of all inflation series included in a given group (level), the weighted mean and the standard deviation (std) of the time series standard deviation of all inflation series included in a given group (volatility), the weighted mean and the standard deviation (std) of the persistence measures of all inflation series included in a given group, the average over time of the cross-sectional dispersion of all inflation series included in a given group and the weighted mean of the correlation of all inflation series included in a given group with the group aggregate inflation rate. The measure for persistence is based on the weighted mean of the first order autocorrelation for all the series.. The measure for persistence is the first order autocorrelation.

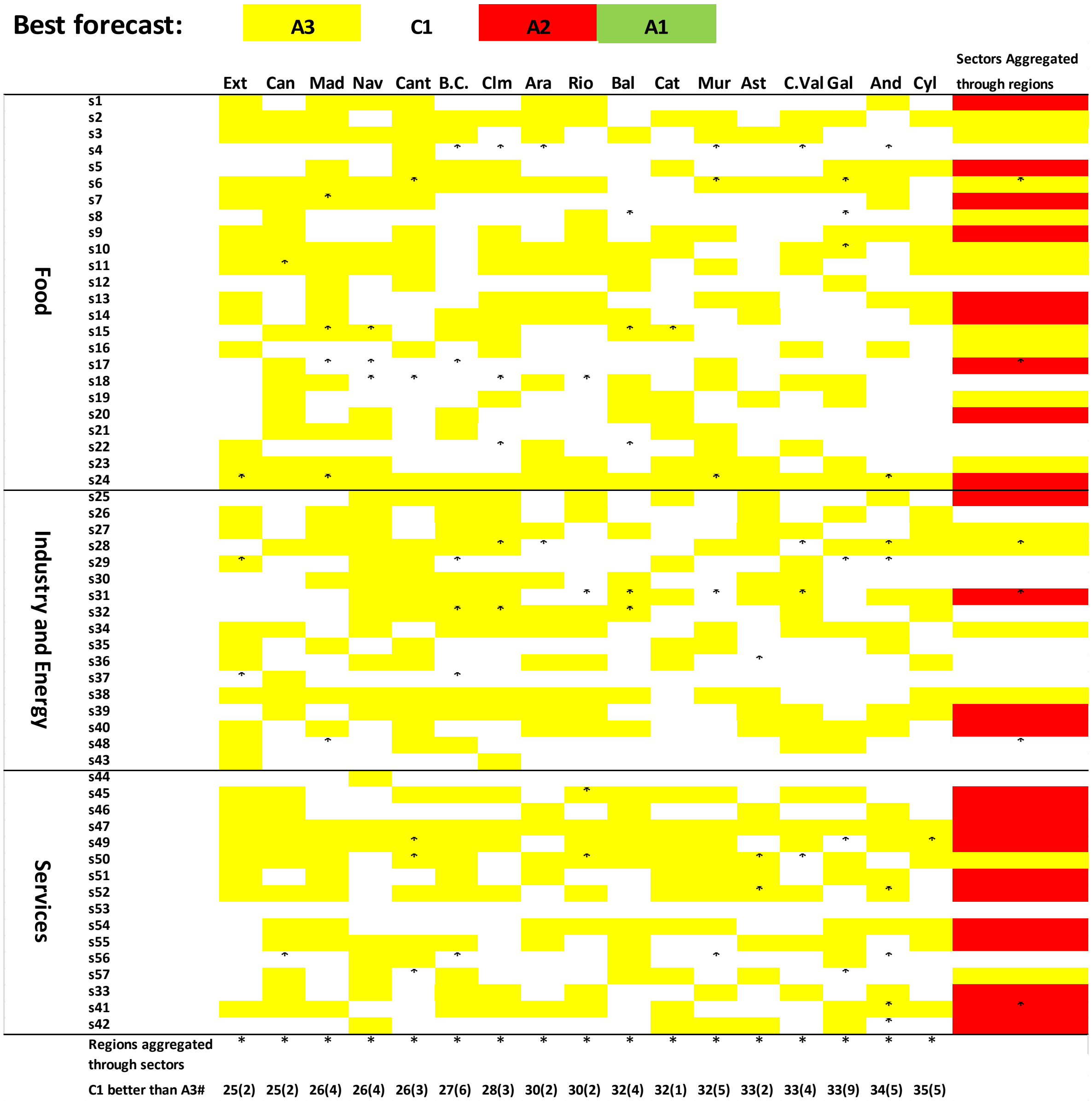
Table 3. *RMSFE for the Spanish headline inflation of the Benchmark strategy and relative RMSFEs with respect to Benchmark under alternative strategies.*

	Period 2006:01-2009:12				**Period 2006:01-2008:12**			
	1P	**4P**	**8P**	**12P**	**1P**	**4P**	**8P**	**12P**
B	0.66	1.97	2.93	3.65	0.56	1.51	1.85	2.14
A1	0.91(*)	0.99	1.03	1.07	0.89 (*)	1.04	1.04	1.10
A2	0.63(**)	0.71(*)	0.80	0.84	0.66 (**)	0.77	0.75	0.83
A3	0.62(**)	0.69(*)	0.77(*)	0.82	0.64 (**)	0.75	0.71	0.79
C1	0.60(**)	0.70(*)	0.82(*)	0.87	0.64 (**)	0.77 (*)	0.74 (*)	0.82
C2	0.60(**)	0.70(*)	0.82(*)	0.89	0.64 (**)	0.77 (*)	0.76 (*)	0.85
C3	0.60(**)	0.70(**)	0.83(*)	0.90	0.64 (**)	0.77 (*)	0.76 (*)	0.86
C4	0.60(**)	0.71(*)	0.82(*)	0.88	0.64 (**)	0.77 (*)	0.75 (*)	0.83
C5	0.60(**)	0.70(*)	0.81(*)	0.88	0.64 (**)	0.77 (*)	0.75 (*)	0.85
C6	0.63(**)	0.72(*)	0.83(*)	0.89	0.68 (**)	0.79 (*)	0.77 (*)	0.86
C7	0.60(**)	0.70(**)	0.82(*)	0.89	0.64 (**)	0.77 (*)	0.74 (*)	0.84
C8	0.60(**)	0.71(*)	0.82(*)	0.88	0.64 (**)	0.77 (*)	0.73 (*)	0.83
C9	0.62(**)	0.70(*)	0.79(*)	0.85	0.64 (**)	0.76	0.72	0.80
C10	0.59(**)	0.68(*)	0.77(*)	0.82	0.61 (**)	0.75 (*)	0.70 (*)	0.80
C11	0.57(**)	0.68(*)	0.76(*)	0.82	0.61 (**)	0.74 (*)	0.70 (*)	0.78

B: ARIMA model for the aggregate series; A1: ARIMA models applied to regions; A2: ARIMA models applied to sectors; A3: ARIMA models applied to sectors and regions; C1: SVeqCM with the whole area; C2: SVeqCM with similar economic growth; C3: SVeqCM with similar per-capita income; C4:SVeqCM wiht similar macroeconomic conditions; C5: VeqCM with similar density of population; C6: VeqCM with geographical contiguity; C7: SVeqCM with cointegrated regions using Johansen (1995); C8: SVeqCM with regions with stationary relative prices; C9: SVeqCM with neighbours selected according to the Schwarz criterium; C10: SVeqCM with the smallest RMSFE for each individual series; C11: SVeqCM with the smallest RMSFE for a given sector.

** (*) denotes rejection at the 0.01 (0.05) significance level relative to the benchmark strategy by using the modified Diebold and Mariano (1995) test as proposed by Harvey et al. (1997).

Table 4. *Best forecasting strategy according to RMSFE. One period ahead.*



Note: * denotes rejection at the 0.05 significance level by using the modified Diebold and Mariano (1995) test as proposed by Harvey et al. (1997). This test has been run by comparing strategies A3 and C1 for each individual series, and A2 (A1) with respect to the best of A3 and C1 for aggregated regions (aggregated sectors).

≠ Between brackets the number of cases significant at the 5% level.

Table 5. *Best forecasting strategy according to RMSFE. Twelve period ahead.*

Best forecast:	**A3**

		Bal	Cat	Cant	Cyl	C.Val	Mad	And	Ast	Can	Clm	Ara	Gal	Mur	Nav	Ext	B.C.	Rio	Sectors aggregated through regions
Food	s1											*						*	
	s2																		
	s3																		
	s4	*								*									*
	s5																		
	s6			*					*			*							
	s7																	*	*
	s8						*				*		*						
	s9												*				*	*	
	s10					*											*		
	s11		*					*	*				*				*		
	s12												*						
	s13																		
	s14							*						*				*	
	s15	*	*			*			*	*									
	s16								*										
	s17										*	*							
	s18																		
	s19						*		*										*
	s20				*							*	*						
	s21		*					*					*	*	*				
	s22		*		*				*					*					*
	s23				*														
	s24								*		*								
Industry and Energy	s25																		
	s26			*					*			*		*	*			*	
	s27		*				*			*									
	s28					*													
	s29				*			*									*		
	s30	*																	*
	s31	*	*										*						
	s32			*							*								*
	s34			*													*		
	s35	*		*													*		*
	s36																		
	s37						*				*	*		*					*
	s38										*		*						*
	s39																		
	s40	*													*	*	*	*	
	s48	*					*		*	*	*				*			*	
	s43	*	*		*	*	*	*		*			*	*	*	*	*	*	*
Services	s44																		
	s45														*				
	s46																		
	s47			*								*					*		
	s49															*			*
	s50				*		*	*											
	s51		*	*									*	*					*
	s52		*									*							
	s53																		*
	s54		*								*								
	s55													*					
	s56								*										*
	s57			*									*				*		
	s33				*								*				*	*	*
	s41		*											*					
	s42														*	*		*	
	Regions aggregated through sectors																		
	C1 better than A3#	23(6)	24(6)	26(3)	26(5)	26(4)	26(3)	27(3)	27(6)	27(2)	27(6)	28(4)	28(8)	28(4)	28(4)	29(1)	29(7)	32(6)	

Note: * denotes rejection at the 0.05 significance level by using the modified Diebold and Mariano (1995) test as proposed by Harvey et al. (1997). This test has been run by comparing strategies A3 and C1 for each individual series, and A2 (A1) with respect to the best of A3 and C1 for aggregated regions (aggregated sectors).

≠ Between brackets the number of cases significant at the 5% level.

Table 6. Number of cases that the different strategies A2,A3 and C1 show the best forecasting performance in the EA12 and in Spain.

	Spain			Euro Area		
	Sectors	Regions	Disaggregated	Sectors	Countries	Disaggregated
			1 step-ahead forecast			
A2	24(8)			42(32)		
A3	16(4)	0(0)	462(78)	2(1)	2(2)	336(56)
C1	17(3)	17(17)	507(57)	6(2)	10(6)	264(42)
			4 step-ahead forecast			
A2	13(5)			34(20)		
A3	21(5)	9(9)	507(99)	10(1)	3(1)	324(69)
C1	23(0)	8(8)	462(67)	6(0)	9(3)	276(31)
			8 step-ahead forecast			
A2	17(0)			28(9)		
A3	19(1)	15(6)	522(79)	16(2)	3(0)	363(80)
C1	21(2)	2(2)	447(65)	6(0)	8(0)	237(41)
			12 step-ahead forecast			
A2	17(1)			22(4)		
A3	19(2)	15(0)	508(65)	18(3)	3(1)	368(44)
C1	21(4)	2(0)	461(74)	10(1)	5(0)	232(30)

The number of cases in which the strategy is significantly better at the 5% than the second best strategy is shown between brackets.

Table 7. *Cointegration by Spanish regions*

Region	Cointegration with Spain (I)	Cointegration with other regions (II)
Val	50	30
PV	48	32
Ast	48	32
Ara	48	27
Nav	47	35
Rio	47	30
Gal	46	27
Can	45	31
CYL	45	25
Cat	45	25
I.Can	44	39
And	43	32
Bal	43	30
Ext	43	28
CLM	42	29
Mad	41	25
Mur	35	25

All the estimation use the sample 1993:01-2009:12 and use a confident level of 5% to decide about cointegration.

(I) Number of sectors in each region that are cointegrated with the corresponding sector in Spain. (II) Number of sectors which are cointegrated with the corresponding sector in at least in 14 of the 19 regions.

Table 8. ***Spain.*** *Cointegration by Sectors*

Highly cointegrated sectors	Low cointegrated sectors
Food	
Highly cointegrated sectors	**Low cointegrated sectors**
Potatoes, Lamb, Preserved fruits, Fish, Crustaceans, molluscs and processed fish, Cereals, Bread, Alcoholic drinks, sugar.	Tobacco, Fresh fruit, Coffee, cacao and infusions, Vegetables, Milk, Pork and Eggs.
Industry and energy	
Highly cointegrated sectors	**Low cointegrated sectors**
Men's clothes, Women's clothes, Clothes for babies and children, Men's footwear.	Textile and home accessories, Major appliances, Non durable household items.
Service	
Highly cointegrated sectors	**Low cointegrated sectors**
Rented apartments, Recreational objects, Publications, Repair of footwear, Primary School, Complements and repair, medical services, secondary school, other expenses in education	Personal transportation, mail and communication.

Highly cointegrated sectors are those for which the corresponding regional series cointegrate with Spain in at least 15 regions and cointegrate with other regions in at least 14 cases.
Low cointegrated sectors are those which cointegrate with Spain in 10 to 14 regions and with other regions in 9 to 13 cases.

Table 9. Spain. Expected variation of the relative regional prices with respect to Spain in 2008.(I)(II)

Expected fluctuation of relative prices in 2008 is significantly positive	No significant fluctuation of relative prices in 2008	Expected fluctuation of relative prices in 2008 is significantly negative

		Clm	Cat	Cyl	Bal	Can	Mad	Mur	C.Val	B.C.	Gal	Rio	Ast	And	Nav	Cant	Ext	Ara	Total Positive	Total Negative
Food	s8																		2	1
	s18																		1	2
	s22																		1	3
	s1																		1	5
	s4																		5	1
	s5																		2	4
	s19																		3	3
	s21																		2	4
	s13																		2	5
	s17																		4	3
	s20																		4	3
	s24																		7	0
	s7																		4	4
	s12																		4	4
	s9																		4	5
	s23																		5	4
	s3																		5	5
	s6																		4	6
	s10																		3	7
	s14																		4	6
	s2																		6	6
	s15																		7	6
	s16																		4	9
	s11																		1	16
Industry and Energy	s28																		0	0
	s30																		0	0
	s31																		0	0
	s25																		1	0
	s29																		0	1
	s26																		1	1
	s27																		0	2
	s43																		1	4
	s32																		2	3
	s37																		4	1
	s36																		2	4
	s34																		4	3
	s35																		2	5
	s38																		5	2
	s48																		4	5
	s39																		4	6
	s40																		4	6
Services	s46																		0	0
	s56																		1	4
	s57																		2	3
	s50																		3	3
	s53																		0	6
	s44																		4	3
	s33																		3	4
	s55																		4	4
	s41																		3	5
	s42																		5	3
	s51																		4	5
	s54																		3	6
	s45																		8	2
	s49																		3	7
	s52																		2	10
	s47																		8	6
Total positive		6	15	10	8	7	5	15	8	6	8	13	12	8	14	12	12	13		
Total negative		11	4	10	13	14	16	6	14	16	16	11	13	18	12	16	16	20		

(I) The variation of the relative prices is computed as the percentage change of expected relative price in 2008:12 with respect to the pbserved relative price in 2007:12 using information up to 2007:12.

(II) The variations are considered significant when they are outside the interval ±1.96 times the standard error of the annual variations of the corresponding relative prices. This variance is computed from the observed historical values.

Table 10. *RMSFE of the Benchmark strategy and relative RMSFE with respect to Benchmark under alternative strategies (Euro Area 12).*

	Period 2006:01-2009:12				**Period 2006:01-2008:12**			
	1P	**4P**	**8P**	**12P**	**1P**	**4P**	**8P**	**12P**
B	0.37	1.05	1.73	2.30	0.33	0.83	0.99	1.25
A1	1.12	1.13	1.10	1.08	1.06 (*)	1.07	1.10	1.06
A2	0.77(**)	0.81(*)	0.84	0.95	0.70 (**)	0.88	0.89	1.00
A3	0.81(**)	0.93	0.98	0.99	0.79 (**)	0.93	0.97	0.94
C1	0.78(**)	0.87(*)	0.90	0.95	0.73 (**)	0.89	0.90	0.93

B: ARIMA model for the aggregate series; A1: ARIMA models applied to regions; A2: ARIMA models applied to sectors; A3: ARIMA models applied to sectors and regions; C1: SVeqCM with the whole area.
** (*) denotes rejection at the 0.01 (0.05) significance level relative to the benchmark strategy by using the modified Diebold and Mariano (1995) test as proposed by Harvey et al. (1997).

Table 11. *Comparison of strategies A2, A3 and C1.*

	One period ahead			*Twelve periods ahead*	
	C1	*A3*		*C1*	*A3*
A2	*-0.24*	*-1.51*	*A2*	*0.08*	*-0.40*
C1		*-0.84*	*C1*		*-0.93*

** (*) denotes rejection at the 0.01 (0.05) significance level relative to the benchmark strategy by using the modified Diebold and Mariano (1995) test as proposed by Harvey et al. (1997).

Table 12. *Best forecasting strategy according to the RMSFE, one and twelve periods ahead.*

Best forecast: A3 C1 A2

	One period-ahead	Twelve periods-ahead
s1	A2 *	A3
s2	A2 *	A2
s3	A2 *	A2
s4	A2	A3
s5	A2 *	A2
s6	A2	A3
s7	C1 *	A3
s8	A2	A3
s9	A2 *	A3 *
s10	A2	A3
s11	C1	A3
s12	A2 *	A3
s13	A2 *	A3
s14	A2 *	A3
s15	A2	C1
s16	A2 *	A2
s17	A3 *	A3 *
s18	A2 *	A2 *
s19	A2	A3
s20	A2 *	A2
s21	A3	A2
s22	A2 *	A3
s23	A2	C1
s24	A2 *	A2
s25	A2 *	A2 *
s26	A2 *	A2
s27	A2 *	A3 *
s28	A2 *	A2 *
s29	A2 *	A2
s30	A2	C1
s31	A2 *	A3
s32	A2 *	A2
s33	A2 *	A2
s34	C1	C1
s35	A2 *	C1
s36	A2 *	A3
s37	A2	A2
s38	A2 *	A2
s39	A2	C1 *
s40	A2 *	C1
s41	A2 *	A2 *
s42	C1 *	A3
s43	A2 *	A2
s44	A2	A2
s45	A2 *	A2
s46	C1	C1
s47	A2 *	C1
s48	A2 *	C1
s49	A2 *	A2
s50	A2 *	A2

Table 13 *Cointegration by EA12 countries*

Country	Cointegration with the EA12 (I)	Cointegration with other EA12 countries (II)
Spa	44	24
Por	44	21
Bel	43	25
Ger	43	24
Fra	42	31
Ita	42	31
Gre	41	25
Irl	41	24
Aus	41	21
Lux	40	23
Hol	40	22
Fin	40	19

All the estimation use the sample 1993:01-2009:12 and use a confident level of 5% to decide about cointegration.

(I) Number of sectors in each country that are cointegrated with the corresponding sector in the EA12 using a sample 1993:01-2009:12. (II) Number of sectors which are cointegrated with a similar sector in more than 6 countries.

Table 14. EA12 *Cointegration by Sectors*

Food	
Highly cointegrated sectors	*Low cointegrated sectors*
Fruit, vegetables; foot products nec; spirits; wine and beer.	*Oil and fat; coffee, tea and cocoa.*
Industry and energy	
Highly cointegrated sectors	*Low cointegrated sectors*
Clothing; footwear including repair; furniture and furnishing, carpets and other floor covering; households textiles; glassware; tools and equipment for house and garden; motor cars; spare parts and accessories for personal transport equipment; audiovisual, photographic and information processing equipment; other major durables for recreation and culture; newspapers, books and stationery.	*Fuels and lubricants for personal transport equipment*
Service	
Highly cointegrated sectors	*Low cointegrated sectors*
Maintenance and repair of personal transport equipment; maintenance and repair of personal transport equipment; actual rentals for housing; maintenance and repair of the dwelling; water supply and miscellaneous services relating to the dwelling; domestic services and household services; health; other services in respect of personal transport equipment; postal services; recreational and cultural services; package holidays; education; restaurants, cafés and the like; canteens; accommodation services; miscellaneous of goods and services	

Highly cointegrated sectors are those for which the corresponding country series cointegrate with the EA12 at least 8 countries and cointegrate with other countries in at least 8 cases.

Low cointegrated sectors are those which cointegrate with the EA12 in less than 6 cases and with other countries in less than 6 cases.

Table 15. EA12. Expected variation of the relative regional sectoral prices with respect to EA12 in 2008. (I) (II)

Expected fluctuation of relat
is significantly po

		Ire	Spa	Gre	Ita	Por	Fra	Bel	Ger	Aus	Fin	Net	Lux	Total Positive	Total Negative
Food	s7													1	1
	s6													1	4
	s10													2	4
	s11													3	3
	s13													4	3
	s2													3	4
	s4													3	5
	s14													1	7
	s1													4	5
	s3													2	7
	s8													3	6
	s9													5	4
	s12													4	6
	s5													3	9
	s15													4	8
Industry & Energy	s16													3	2
	s34													3	2
	s17													3	2
	s21													3	3
	s42													3	4
	s22													4	3
	s23													2	5
	s26													4	3
	s44													2	6
	s30													5	4
	s27													5	5
	s28													5	5
	s31													6	4
	s32													5	5
	s33													9	2
	s40													6	5
	s41													7	4
	s24													5	7
Services	s49													1	1
	s37													4	3
	s36													2	5
	s19													5	2
	s46													7	1
	s29													5	3
	s38													2	7
	s43													2	7
	s47													6	3
	s25													3	6
	s18													2	7
	s20													3	6
	s48													2	8
	s39													3	8
	s45													10	1
	s50													3	8
	s35													6	6
Total positive		21	8	9	12	18	23	16	25	11	12	27	7		
Total negative		16	31	28	30	14	13	26	16	13	14	8	20		

(I) The variation of the relative prices is computed as the percentage change of expected relative price in 2007:12 compared to the expected relative price in 2008:01 using information up to 2007:12.

(II) The variations are considered as significant when they are outside the interval ±1.96 times the standard error of the relative price fluctuations. This variance is computed from the observed historical values.

Appendix

Time Series

We use time series for the following disaggregate products in the case of Spain: S1: Cereals; S2: Bread; S3: Beef; S4: Lamb; S5: Pork; S6: Bird; S7: Other meat; S8: Fish; S9: Crustaceans, molluscs and processed fish; S10: Eggs; S11: Milk; S12: Milk products; S13: Oil and fats; S14: Fresh fruit; S15: Preserved fruit; S16: Vegetables; S17: Preserved vegetables; S18: Potatoes; S19: Coffee, cacao and infusions; S20: Sugar; S21: Other food products; S22: Non-alcoholic drinks; S23: Alcoholic drinks; S24: Tobacco; S25: Men's clothes; S26: Women's clothes; S27: Clothes for babies and children; S28: Complements and Repairs; S29: Men's footwear; S30: Women's footwear; S31: Footwear for babies and children; S32: Repair of footwear; S33: Rented apartments; S34: Heating, lighting and water distribution; S35: Own apartments; S36: Furniture and floor coverings; S37: Textile and home accessories; S38: Major appliances; S39: Household items; S40: Non durable household items; S41: Home services; S42: Medical services; S43: Medicines and other chemical products; S44: Personal transportation; S45: Public urban transportation; S46: Public intercity transportation; S47: Mail and communications; S48: Recreational objects; S49: Publications; S50: Recreation; S51: Primary school; S52: Secondary school; S53: University; S54: Other expenditures in education; S55: Personal items; S56: Tourism and hotels; and S57: Other goods and services.

We use time series for the following disaggregate products in the case of EA12: S1: Bread and cereals; S2: Meat; S3: Fish and seafood; S4: Milk, cheese and eggs; S5: Oils and fats; S6: Fruit; S7: Vegetables; S8: Sugar, jam, honey, chocolate and confectionery; S9: Food products n.e.c; S10: Coffee, tea and cocoa; S11: Mineral waters, soft drinks, fruit and vegetable juices; S12: Spirits; S13: Wine; S14: Beer; S15: Tobacco; S16: Clothing; S17: Footwear including repair; S18: Actual rentals for housing; S19: Maintenance and repair of the dwelling; S20: Water supply and miscellaneous services relating to the dwelling; S21: Electricity, gas and other fuels; S22: Furniture and furnishings, carpets and other floor coverings; S23: Household textiles; S24: Major household appliances whether electric or not and small electric household appliances; S25: Repair of household appliances; S26: Glassware, tableware and household utensils; S27: Tools and equipment for house and garden; S28: Non-durable household goods; S29: Domestic services and household services; S30: Health; S31: Motor cars; S32: Motor cycles, bicycles and animal drawn vehicles; S33: Spares parts and accessories for personal transport equipment; S34: Fuels and lubricants for personal transport equipment; S35: Maintenance and repair of personal transport equipment; S36: Other services in respect of personal transport equipment; S37: Transport services; S38: Postal services; S39: Telephone and telefax equipment and services; S40: Audio-visual, photographic and information processing equipment; S41: Other major durables for recreation and culture; S42: Other recreational items and equipment, gardens and pets; S43: Recreational and cultural services; S44: Newspapers, books and stationery; S45: Package holidays; S46: Education; S47: Restaurants, cafés and the like; S48: Canteens; S49: Accommodation services; S50: Miscellaneous goods and services.