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Forecasting aggregates and disaggregates with common features

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Abstract

This paper focuses on providing consistent forecasts for an aggregate economic indicator, such as a consumer price index, and all its components. The procedure developed is a disaggregated approach based on single-equation models for the components, which take into account the stable features as common trend and common serial correlation that some components share. Our procedure starts by classifying a large number of components based on restrictions from common features. The result of this classification is a disaggregation map, which may also be useful in applying dynamic factors, defining intermediate aggregates or formulating models with unobserved components. We apply the procedure to forecast inflation in the Euro Area, the UK and the US. Our forecasts are significantly more accurate than a direct forecast of the aggregate and other indirect forecasts.

Key Words: Common trends; Common serial correlation; Inflation; Euro area; UK; US; Cointegration; Single-equation econometric models; Disaggregation maps

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1. Introduction.

The demand for macroeconomic forecasts has increased considerably in the last twenty years and with it the requests for quicker and more detailed releases of official data. In this context, one important phenomenon is the steadily growing flow of information available to forecasters; in particular, data are increasingly becoming available at a higher degree of disaggregation—at the regional, temporal and sector levels. Therefore, the traditional debate about forecasting an aggregate variable directly or indirectly by aggregating the forecasts of its components has recently received considerable attention. Usually, this discussion concentrates only on the forecasting accuracy of the aggregate. By contrast, the starting point of this paper is that all data—aggregate and components—are relevant, both for a full understanding of the aggregate and for the formulation of useful economic policies. The focus of this paper is on inflation, but the question of the usefulness of disaggregated information for econometric modelling and forecasting is relevant for many other macroeconomic variables to which the proposals in this paper could therefore be applied.

Behind an aggregate lies a great amount of data that should not be ignored when generating the forecasting results that economic agents need for designing economic policy measures, making investment decisions and related activities. For instance, in analysing all the price components of a Consumer Price Index (CPI), a frequent observation is that several prices share features such as common trends or common serial correlation, whereas others do not, perhaps because they are affected by technological changes in a particular way or because they are affected differently by changes in preferences. Similar remarks apply when considering the specific sectorial industrial production indexes of a national industrial production index, or the individual components of aggregates such as exports and imports. In examples such as these, a valid hypothesis is that a certain subset of components of the aggregate share a common feature but others do not. Consequently, it seems convenient to use disaggregated information and exploit the restrictions existing between the components in econometric modelling in order to provide decision makers with forecasts that refer to the aggregate and its components. For example, a forecast of 2.2% for headline inflation next year with a large percentage of price components forecast to grow at around the same rate is quite different from the same forecast in which the rate of growth of energy prices is forecast at 15% and many other prices are forecast to grow at very small percentage. We advocate consideration of all, say n components of an aggregate, which we call basic components. We aim to provide joint consistent forecasts for the aggregate and its basic components as well as for useful intermediate aggregates. A validation of our proposal would involve showing that the indirect forecast of the aggregate is at least as accurate as the direct one, and then clearly disaggregation is useful.

The literature in this area of research considers mainly three time-series forecasting procedures: (F1) the direct approach, which works with a scalar model for the time series of the aggregate; (F2) the disaggregated procedure based on univariate models for each of the basic components; and (F3) the multivariate disaggregated approach, which works with a vector model for the time series of all the basic components. A fourth alternative (F4), developed in this paper, is a disaggregated approach based on single-equation models for the basic components that include restrictions between them. In the applications in Section 5, we extend this alternative considering three possibilities denoted as FP2, FP3 and FP4.

Theory shows that when the data generation process (DGP) is known, the forecasting accuracy of F3 is at least as good as that of the other procedures. Nevertheless, if the number of components is large, as is usually the case when working with basic components—numbering 160 in the US CPI in this study, for example—then F3 is not feasible; in any case, it would be subject to a great deal of estimation uncertainty, on which we comment below. On the other hand, F2 can be better or worse than F1 depending on the properties of the data. As will become clear, the existence of restrictions between the components is one of the main reasons why the disaggregated approach could be useful. In this paper, we develop an intermediate—in relation to F1, F2 and F3—approach, called F4, which is based on single-equation models that take into account important restrictions between the components arising from the fact that some share common features. We keep this approach simple by using bivariate methods to identify a unique common feature in a subset of components and by using single-equation models to forecast each basic component. Furthermore, the basic components that do not share common features are aggregated into an intermediate aggregate, which is forecasted directly. Our procedure differs from that used in the dynamic factor literature because we consider the possibility of common features in analysing the behaviour of each variable in relation to the others—the basic components of an aggregate—and we only estimate common features between the basic components that truly share them—the estimation restriction. Then, each factor is used only in modelling and forecasting the basic components that have the corresponding common features—the forecasting restriction. At the same time, the procedure requires that the presence of common features be stable. In the dynamic factor literature applied to a large number of series, as it is our case, all elements are considered to incorporate a common factor without the above estimation restriction, which leaves the estimation process to determine which components enter with zero weight. If application of the estimation restriction is appropriate, the common factors (features) in our procedure could be estimated more precisely in small samples and may also have a more direct economic interpretation.

Recently, Hendry & Hubrich (2006, 2010), hereafter HH, proposed a procedure for forecasting an aggregate by using a model for that aggregate that includes as regressors its own lags as well as lags of the components. They use autometrics (see Doornik, 2009), and follow the general-to-specific approach to build the model. Our procedure differs from the HH procedure in two main respects. The first arises because our procedure incorporates specific identified and tested restrictions between the basic components in forecasting the aggregate. Because their model does not include all the components in the equation for the aggregate, HH implicitly incorporate unknown restrictions between the components. However, as shown by Clark (2000), specific restrictions, such as cointegration restrictions should also be taken into account. The second difference is that our procedure naturally provides forecasts for the basic components, which are considered of interest because they could be necessary for policy decision makers. HH only provide results for the aggregate because, the forecasts at different horizons are made using a horizon-specific estimated models, where the dependent variable is the multi-period ahead value being forecasted, and so, they only need observed values of the independent variables.

The remainder of the paper is structured as follows. In Section 2, in relation to forecasting an aggregate, we comment on theoretical efficiency, estimation uncertainty and the relevant restrictions. In Section 3, we describe the data, the intermediate aggregation schemes with basic components and the tests for positive and seasonal unit

roots. In Section 4, we present our forecasting approach and the classification of the basic components in a disaggregation map which take account of some common features between them. In Section 5, we apply our procedure to forecast inflation in the US, the Euro Area (EA) and the UK, and we compare these results with those obtained from a direct forecast, an indirect forecast based on univariate models and an indirect forecast based on models with a stationary dynamic factor. In Section 6, we draw conclusions and propose extensions for future works. The applications in this paper include a large amount of results which cannot be reported here, but the interested reader will find more details about them on the first author's website³.

2. Theoretical efficiency, estimation uncertainty and relevant restrictions.

Theoretical results for stationary variables—for details, see Rose (1977), Tiao & Guttman (1980), Wei & Abraham (1981), Kohn (1982) and Lütkepohl (1984) among others—have shown that, in general, procedure F3 will provide more accurate forecasts of the aggregate. It is only if the data satisfy special conditions—conditions for efficiency of the direct forecast (CEDFs)—that the direct approach is efficient; see Kohn (1982). In the case of one aggregate and n basic components, these conditions require that when applying the vector of aggregating weights to the polynomial matrix of the vector moving average (VMA) representation of the components, one obtains a vector in which all of its n elements are simply the dynamic polynomial of the MA representation of the aggregate. Similarly, the condition can also be formulated for VAR processes.

A CEDF is a very restrictive condition and when it is not satisfied, the use of the direct forecasting approach implies that invalid restrictions are imposed on the DGP, defined as the set of all the basic components. To avoid imposing invalid restrictions in this sense, one can work from the basic components. This is because if we break down the aggregate into a smaller number of components, which we term intermediate aggregates, these intermediate aggregates will be aggregates of basic components; then, when modelling these intermediate aggregates, one could find that invalid restrictions are being imposed on the basic components included in them. If this is the case, we can use a wider disaggregation to improve the modelling and forecasting of these intermediate aggregates and thereby forecast the overall aggregate more accurately. There is another, perhaps more important, reason for considering the basic components. Assume that a subset of basic components share a common feature. Our procedure reduces the variance of the forecasting errors of the aggregate by taking these restrictions into account. However, intermediate aggregates based on official or ad hoc breakdowns include, in general, a subset of basic components which are cointegrated plus other components which are not. Therefore when testing a pair of intermediate aggregates for cointegration, it is often found that they are not cointegrated. For

³ Detailed results for all these tests can be obtained from the first author's website: <http://halweb.uc3m.es/esp/Personal/personas/espasa/esp/publications/ExtendedResults.html>

instance, Espasa and Albacete (2007) show that in breakdowns of the CPI's of different Euro Area countries into two components, Core CPI and the rest, these components are not cointegrated. In these cases, the cointegration present in the basic components cannot be exploited working with intermediate aggregates.

Lütkepohl (1987) shows that CEDFs hold, for instance, when the components are uncorrelated and have identical stochastic structures. This can be taken as an indication that when components have different distributions—for instance when some have conditional heteroskedasticity or have a conditional mean with a nonlinear structure—or when there are cross-restrictions between them, disaggregation could be important. In this paper, we limit ourselves to considering the case in which there are restrictions between the components. This does not mean that distributional differences are unimportant; it merely allows us to study the problem in a way that is easier to solve in a general framework.

Recent consideration has been given to the case in which the components are nonstationary and cointegrated. Our approach is inspired by the results of Clark (2000), who shows that, when the model is known, the indirect forecast from a vector equilibrium correction model (VEqCM) for the components is more accurate than the direct forecast. Again, it is only under very specific conditions that the two forecasts are equivalent. These conditions include ones similar to those specified by Kohn (1982) for the transitory dynamics of the VEqCM as well as a requirement that the aggregation of the matrix of equilibrium correction coefficients is a vector of zeros, in which case aggregation does not cause the loss of relevant information on the aggregate. Clark (2000) shows the importance, in general, of taking into consideration the cointegration restrictions when forecasting the aggregate and proposes testing for cointegration and then testing the CEDFs. For the latter, we need to include in the model for the aggregate lags of all but one of the components and the error correction terms, and test the null hypothesis that the corresponding coefficients are zero. The problem is that when the number of components is large, one cannot perform even the initial cointegration tests. Thus, in this paper, we consider only what we call full cointegration, meaning that in a vector of n variables, there is only one common trend, that is, $(n - 1)$ cointegration restrictions. In this case, one can test for the presence of a unique common trend by using bivariate cointegration tests between all possible pairs of elements in the vector. The tests are implemented by following the Engle & Granger (1987) approach. Thus, if in a vector of n elements there is a subset of n_1 elements such that all possible pairs formed with its elements are cointegrated, then in this subset there is only one common trend. Therefore, in order to develop a simple procedure to capture common trends, we restrict ourselves to finding subsets of basic elements that are fully cointegrated. Our application refers to inflation. In Section 3 we test for positive and seasonal unit roots in CPI components and conclude that most of them have a positive unit root—so they are $I(1)$ - and that some of them have deterministic seasonality. Consequently all cointegration tests in this paper are applied, including the appropriate seasonal dummies in the equation proposed by Engle and Granger (1987).

In this paper, by following an approach similar to that of Engle & Kozicki (1993), we also consider common serial correlation as another possible common feature in the data. The number of studies of comovements among stationary time series has increased considerably since the 1990s, and the different common features that have been defined

and proposed include codependence (Gourieroux et al., 1991) and polynomial serial correlation (Cubadda & Hecq, 2001). Most of these features can be encompassed in the notion of the weak form of polynomial serial correlation proposed by Cubadda (2007). In this paper, we restrict our attention to the concept of common serial correlation as defined by Engle & Kozicki (1993). That is, two stationary time series have common serial correlation if each series exhibits serial correlation and there is a linear combination of them that is white noise. The coefficients of the linear combination define the cofeature vector. For the general case of a vector of n stationary variables, y_t , the presence of common serial correlation implies reduced rank in the matrix of coefficients, Γ , on the variables that are used to capture the common feature, lags of y_t . This matrix will have rank $(n - r)$ if there are r linear combinations that are white noise, and consequently, there will be $(n - r)$ common serial correlation factors. Thus, testing for common serial correlation involves testing the rank of Γ .

As proposed for common trends, we restrict ourselves to the case in which there is just one common serial correlation factor (CSCF) in a vector of n_2 components; this means that there are $(n_2 - 1)$ linear combinations that are white noise. This can be tested by applying the canonical correlation test proposed by Engle & Kozicki (1993) to all possible pairs of components in the vector. If, for each possible pair, we do not reject the hypothesis of one zero canonical correlation (one CSCF), each component will have one CSCF with any one of the other components, which will be common to all components of the vector. Suppose that n_2 is three and that in all possible pairs of the three elements there is a CSCF, then each element can be expressed by two different equations in terms of a CSCF plus a white noise. This implies that there is just one linearly independent CSCF.

CPI components could have cointegration restrictions between them. In this case, as shown by Vahid & Engle (1993), the test for common serial correlation in the stationary transformation of the original data should also consider the lags of the cointegration restrictions. This implies that all cointegration restrictions and not only those derived from full-cointegration, must be taken into consideration but, as mentioned above, this is not feasible for vectors with a large number of basic components. Our procedure could incorporate full-cointegration restrictions when testing for CSCF in small dimension subsets, which it is not the case of subsets N in this paper. Consequently, we apply the Engle & Kozicki (1993) method in the following way. We look for non-overlapping subsets of basic components with a common trend and a CSCF, respectively. Thus, for a vector of n basic price index components, we first test for the largest subset of (n_1) basic components having just one common trend, subset N , and then we test for common serial correlation in the first differences of the remaining $(n - n_1)$ basic components in which this common trend is absent. We also include appropriate seasonal dummies in these tests.

Other cointegration restrictions, such as those potentially present in the second largest subset of basic elements with only a single common trend—which could be identified by using bivariate methods—are very few in our applications and have dimensions much smaller than those of subset N , as shown on the website cited at end of the introduction. In particular for the US CPI, where subset N contains 30 elements, there is only one additional subset with a stable common trend and it has only four elements; for UK and the EA we find one additional subset of dimension two for the former and none for the latter. Thus, in this paper we considered only the largest subset of basic components with a common trend. Ignoring other subsets with a common trend

means that we lose information, but it does not seem very important for the applications in this paper since there are just a few subsets of this type and their dimensions are very small. In this first formulation of our procedure we intend to show that it works. Succeeding, while ignoring some potentially useful information only increases the procedure's interest. It could be widened to include the ignored information on other subsets with one common trend and the consideration of overlapping subsets of small dimensions with common features, but these are not the only possible extensions, or even the most important ones, they will be better covered by another paper defining a more general procedure.

Hence, our approach, of first finding the largest subset of basic components with a common trend and then looking for CSCFs in the remaining basic components (based on the work of Engle & Kozicki, 1993), represents a simple and appropriate procedure for identifying relevant restrictions when working with the basic components of an aggregate. As we explain below, this approach is also consistent with that of Giacomini & Granger (2004).

When dealing with aggregated macroeconomic variables, for exploiting the possible advantages of disaggregation, it is generally necessary to work with a large number of components since these variables typically comprise many basic components. The theoretical results relating to the advantages of aggregating component forecasts from a multivariate model over forecasting the aggregate directly apply when the DGP is known. Because this is rarely the case in practice, the mean squared error (MSE) of the forecasts includes an additional factor, which is $1/T$ times a term that depends on the number of parameters to be estimated; see Giacomini & Granger (2004) and the references therein. Then, as it is widely recognized in the literature, the question of which is the best procedure for forecasting the aggregate is mainly empirical. However, results from the literature also shed light on this issue. The Giacomini & Granger (2004) results for space-time models argue on the existence of a trade-off between the efficiency gain achieved from specifying the fully disaggregated system and the loss in efficiency that arises from parameter estimation errors. In this context, Giacomini & Granger (2004) also consider four forecasting procedures, F1 to F4, which can be related to the time-series procedures considered in our paper. The F1 procedure is equivalent to a direct forecast of the aggregate; F2 is equivalent to an indirect forecast of the aggregate using ARIMA models for the components; F3 is equivalent to an indirect forecast based on a multivariate model for the components; and F4 is related to the forecasting procedure, which we propose in this paper.

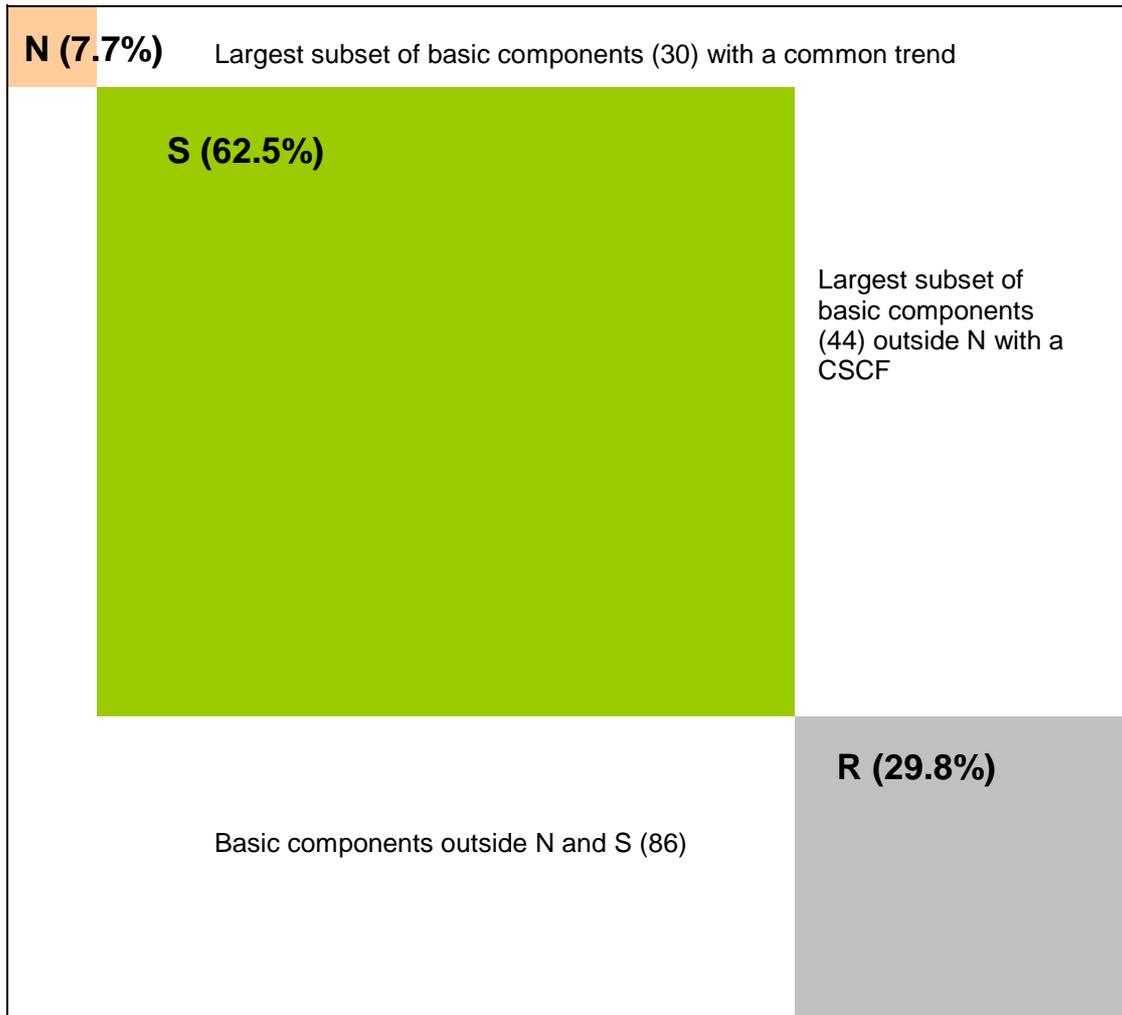
Giacomini & Granger (2004) show that imposing constraints in the fully disaggregated model improves the forecasts. One way to impose constraints is to use their F4 procedure instead of the theoretically optimal F3. Our proposed forecasting procedures, denoted FP2, FP3 and FP4 below, are also ways of imposing a large number of constraints in the vector model of the basic components. Note that the purpose of this paper is not to obtain new theoretical results but to formulate a procedure that is useful in practice, and one that deals with specification and estimation issues. Thus, the contributions of this paper are as follows. First, as already argued the advantages of disaggregation must be explored from the most disaggregated level, in order to ensure that one is making a proper and efficient use of all the available information and considering important restrictions between components. This approach facilitates the definition of possible useful intermediate aggregates and points out that their formulation is an endogenous question that must be investigated based on the properties of the basic components.

In this paper, we limit our attention to restrictions arising from the fact that non-overlapping subsets of basic components share a common trend (subset N) or a CSCF (subset S). Used in conjunction with bivariate methods, this procedure generates a disaggregation map in which the basic components are classified into subsets N, S and R. The disaggregation map obtained from our results can be represented as a squared $n \times n$ matrix, M , the elements of which are arranged in such a way that the upper left corner of the matrix collects the n_1 basic components with a common trend, followed by the n_2 basic components with a CSCF. In Figure 1, we report the results for the US. Detailed results for the disaggregation maps of EA and UK are given in the mentioned website.

Our work represents a first attempt to build disaggregation maps for the basic components of an aggregate. The results could be useful for several purposes other than forecasting, such as the application of dynamic factors, the formulation of models with unobserved components and the design of economic policies. Indeed, in this paper we apply stationary dynamic factors to the elements in S and the applications will show that we thus obtain better forecasting accuracy for the aggregate than by just applying stationary dynamic factors to the whole set of basic components, ignoring the results of the disaggregation map as is standard practice. The disaggregation map can be extended by including overlapping subsets of basic components with common features and by incorporating, for example, additional common-trend restrictions, the types of common cyclical features identified by Cubadda (2007), common seasonality, co-breaks, common non-linearity, common volatility, etc.

Figure 1

Disaggregation map for the basic components in the US CPI.^a



^a The percentages in parentheses refer to the weight in the US CPI of all the basic components in the corresponding subset.

The second and our most important contribution is to develop, along the lines of Giacomini & Granger (2004), a simple indirect forecasting procedure based on single-equation models that departs from the use of vector models, that imposes important restrictions on those models, and that can in practice produce improved forecasts, as we will see in Section 5. At the same time, our procedure improves on direct forecasting by including additional relevant information, so that it more than compensates for the greater cost arising from estimation errors in more complex models. We expect this procedure to be widely applicable because it works with the basic components that share selected common features. Moreover, having tested for these restrictions, the basic components that do not share the common features specified in the procedure—subset R—are aggregated⁴, using the official weights, into an intermediate aggregate r_t , which is forecast by using a scalar model.

We also show that the procedure works when forecasting inflation in three big economies, the US, the EA and the UK. In this context, our work is intended to provide

⁴ The aggregation methodology is explained in Section 3.2

not only better forecasts of an aggregate, but also forecasts of the basic components and of any intermediate aggregates which one could require. The basic elements in R can be forecast by using $ARI(p,1)$ models under the restriction that the aggregation of those forecasts gives the direct forecast of the intermediate aggregate r_t . This could be done following Guerrero and Peña (2000).

3. The data.

3.1 Data sets and aggregation procedure.

We apply our procedure to the US CPI and the harmonized EA and UK CPIs. These economies were selected because they represent almost 50% of the world GDP and because most econometric applications relate to at least one of these economies. For the US, we use monthly CPI data for all urban consumers, CPI-U, seasonally unadjusted, published by the Bureau of Labor Statistics. The sample goes from January 1999 to December 2010. The aggregate is broken down into 160 basic components. For the EA and UK, we use monthly Harmonised Index of Consumer Prices data (HICP), seasonally unadjusted, published by Eurostat. The samples used for the EA and the UK start in January 1995 and finish in December 2010 and the breakdowns of the aggregates have 79 and 70 elements, respectively⁵. One of the study's outputs is a disaggregation map based on estimated common features of the basic components. Some intermediate aggregates are formulated from the basic components in the paper, using the official weights and normalizing the sum of the weights of all the basic components in an intermediate aggregate to 100 and applying the normalizing factor to the weight of each basic component in this intermediate aggregate.

3.2. Trend and seasonal factors.

The basic components have trends and some of them seasonal oscillations; therefore we need to test for the presence of positive and seasonal unit roots in the data. To implement these tests to a large number of series we have developed a standard procedure which could automatically be applied to each series. This almost prevents the possibility of considering the presence of outliers when performing these tests and we have ignored the correction for outliers in them. The tests were performed using the log transformation of the data and their results can be found on the website cited in the introduction. We applied the Osborn et al. (1988) tests, hereafter OCSB, and Hylleberg et al. (1990) test as extended in Beaulieu and Miron (1993), hereafter HEGY. Using the terminology employed in the first paper, $I(r,s)$ -where r and s can take values one or zero- means that the data needs r regular differences and s annual differences in order to be stationary. Following both references, we can test whether a particular series is $I(1,1)$, $I(1,0)$, $I(0,1)$ or $I(0,0)$ and in the second and fourth cases if seasonal dummies are significant. All tests are performed at the 1% significance level and the critical values are taken from Rodrigues and Osborn (1997). Following OCSB test, hypothesis $I(1,1)$ is rejected in all cases except for 4, 9 and 3 basic elements in the EA, US and UK,

⁵ In all cases the data correspond to the existing published versions in 15th March 2011.

respectively. Hypothesis $I(0,1)$ is also rejected in most cases, with just 1, 8 and 2 exceptions in the above economic areas. Finally, null hypothesis $I(1,0)$ is only rejected in two cases, one in the UK and another in the US. In the latter hypothesis, the set of seasonal dummies can be appropriate and this can be tested by an F test. In many cases – 24 in the EA, 17 in US and 14 in UK- the presence of seasonal dummies is not rejected. Thus, based on these results, for the purpose of this paper we consider that all the basic components are integrated of order one and some of them exhibit deterministic seasonality. To corroborate this conclusion we apply the HEGY test. This test refers to the twelve π_i coefficients following in the notation of Beaulieu and Miron (1993) and the critical values were also taken from Rodrigues and Osborne (1997). At the above mentioned significance level, we get similar results than the ones obtained with OCSB: the need for seasonal differencing is strongly rejected (by an $F_{1,12}$ test on the null: $\pi_i, i=1,\dots,12$, are zero), but regular differencing is required in all the cases (by a t-test on the null that π_1 is zero). In particular, the null $I(0,1)$ is rejected for all series except one in the EA. The null for a positive unit root is not rejected in any case and the null for eleven seasonal unit roots (by an $F_{2,12}$ test on the null that $\pi_i, i=2,\dots,12$, are zero) is rejected in all cases but five, four in the basic components of US and one in the EA data. Since $I(1,0)$ has not been rejected, in these last cases there is a contradiction with the results with the $F_{1,12}$, but this is something that can occur in finite samples. In sum, the $I(1,0)$ hypothesis with possible deterministic seasonality seems quite acceptable for the data.

Additionally, applying the ADF test to the differences of the basic components, the null of $I(2)$ for the basic components is rejected in all cases at the 1% significance level. The critical values are taken from McKinnon (1991) for the case in which a constant is included. This result is as expected, because otherwise innovations in the distant past would have a greater impact on the contemporaneous value of a price index than recent innovations.

In the EA, seasonality in the harmonized index of consumer prices (HICP) has a break at the beginning of 2001 because of a change in Eurostat's data collection methodology. Thus, in all the tests and models for the EA, following Espasa & Albacete (2007), we always include two sets of seasonal dummies, one of which applies up to December 2000 with the other operating from January 2001. Given the initial 1995–2003 sample, seasonal change is estimated with few degrees of freedom, so this could be seen as a necessary correction for outliers. With the use of recursive samples – samples in which the initial observations remain fixed but which are enlarged at the end each time that the base of the forecast moves forward- in the forecasting process, seasonal change is ultimately estimated more precisely.

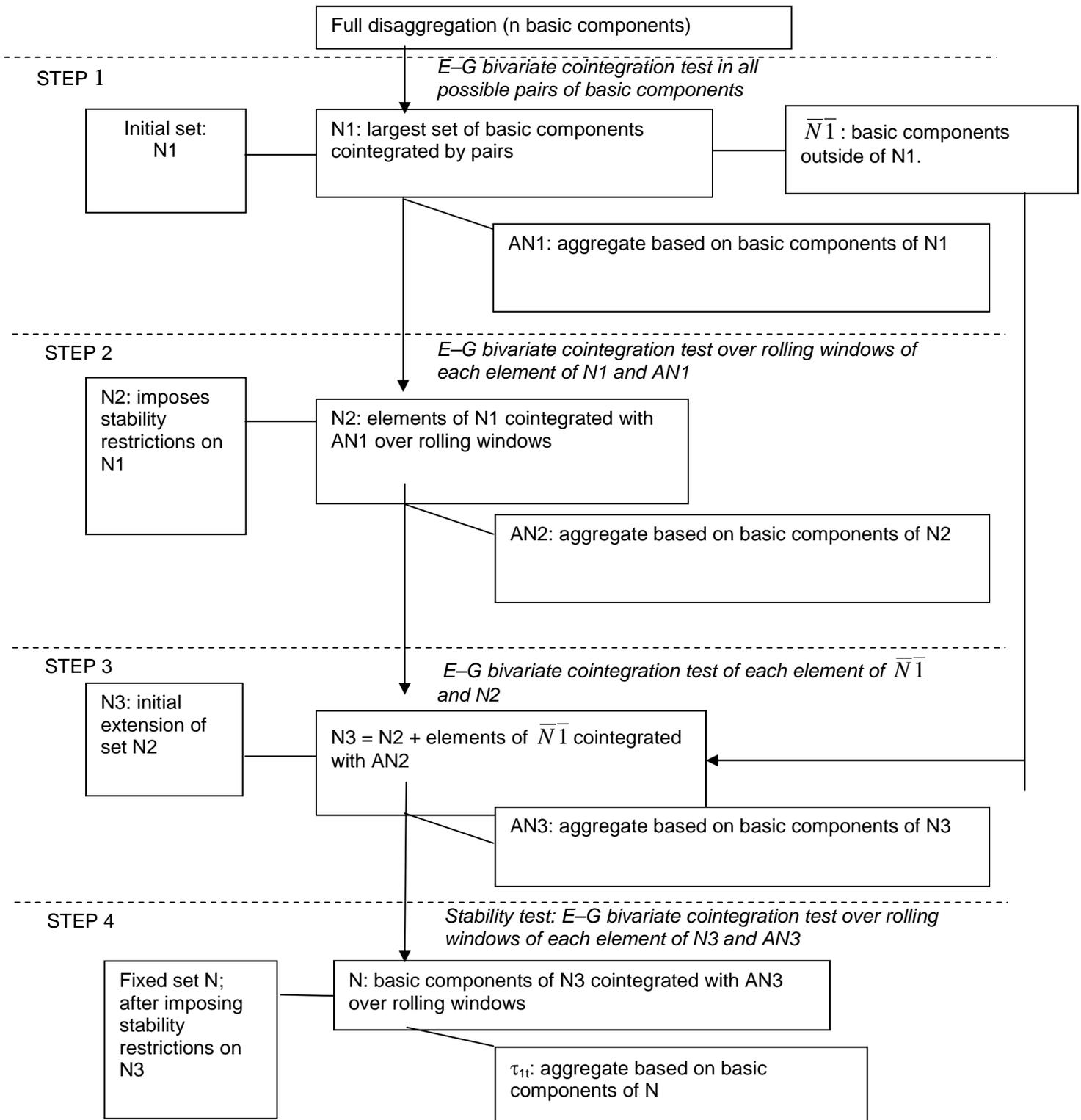
All the models estimated in the following Section, even when denoted as ARI, include the appropriate sets of seasonal dummies when required.

4. Our procedure.

In our procedure, we distinguish between the following three phases: (1) selection of the relevant common features, which in our case are a stable single common trend and a stable single CSCF; (2) the construction of a disaggregation map, with the largest non-overlapping subsets of basic components sharing one of the above common features; and (3) the construction of single-equation forecasting models for the elements of the disaggregation map.

Figure 2

Identification of the largest subset of basic components with just one common trend⁶.



⁶ This procedure can also be used to look for the second largest subset with a common trend, applying it to the basic components outside N.

4.1 Construction of the disaggregation maps.

Figure 2 summarizes the process followed to identify the elements in N , the largest subset of basic components with just one common trend. This is done by using cointegration tests based on the Engle–Granger (EG) procedure, although the Johansen test could also be used. Since we have rejected the $I(2)$ hypothesis for the data, the EG tests are performed including a constant and seasonal dummies in the models and the critical values are obtained by simulation following MacKinnon (1991) for sample size of 60 and 108 depending on the economic region at the 10% significance level⁷. In the initial step, we apply the cointegration test to all possible pairs of basic components and select the largest subset, say N_1 , of n_0 basic components in which all pairs are cointegrated. The tests are performed using a restrictive approach for ending up with the presence of bivariate cointegration. Thus, we conclude that two basic components are cointegrated when the hypothesis is not rejected after applying the EG test in both directions.

The second step involves testing whether the bivariate cointegration relationships found in the previous step are stable over time, in the sense that they are evident in shorter subsamples. For this purpose, an intermediate aggregate, AN_1 , with all the elements of N_1 is constructed. Each element of N_1 must be cointegrated with AN_1 and the stability of this restriction is investigated by estimating and testing for cointegration across the sample by using a rolling window. The elements of N_1 that do not pass this “stability test” are removed from N_1 , and the resulting subset is denoted by N_2 .

A third step is used to check whether it is possible to enlarge N_2 . Thus, we consider the basic elements outside of N_1 as potential candidates and perform a bivariate cointegration test between each of them and the intermediate aggregate AN_2 . Any elements that are cointegrated with this AN_2 are added to N_2 to form a new subset at the end of step 3, termed N_3 , and the corresponding intermediate aggregate AN_3 is constructed.

The final step tests for stability in the bivariate cointegration relationships of the elements of N_3 , proceeding as in the second step but relating each element of N_3 to AN_3 . Removing from N_3 the basic components that do not pass the test results in the final subset N , which is taken as the largest subset of basic components with only a single (stable) common trend. With the elements of N , the intermediate aggregate τ_{1t} is formed as it is described in Figure 2, and τ_{1t} can be seen as a proxy for the common trend in the basic components of N .

To apply the procedure proposed by Engle & Kozicki (1993), we look for the largest subset of basic components outside N with just a single CSCF, subset S . The elements of S can be identified by using a four-step procedure similar to that used to identify a common trend, but now testing for a CSCF. With the elements of S , the intermediate aggregate τ_{2t} is formed. In this case, the CSCF can be approximated by the univariate fit of $\Delta\tau_{2t}$, as we did for the purpose of the disaggregation map in this paper, or by applying the dynamic factor analysis to the components of S .

The procedure could be extended to identify other subsets of basic components with other types of common trends or CSCFs. For example, one could consider the subset of

⁷ The simulated critical values are -3.15 for US, -3.13 for UK and EA, with a unique set of dummies, and -3.33 for EA with two sets of dummies. All critical values are at the 0.1 significance level.

basic components outside N in which all its elements share two common trends with the elements of N. In addition, the disaggregation map could consider the type of cyclical features identified by Cubadda (2007) as well as other common features such as seasonality, cobreaks, common non-linearities and volatility.

4.2. The final disaggregation maps

The US data used correspond to a breakdown of the US CPI into 160 basic components (listed on the website referred to above). A useful sectorial breakdown of the CPI includes the following sectors: energy (ENE); nonprocessed food (NPF); processed food (PF); non-energy industrial goods (MAN); and services (SERV). We use these “broad CPI categories” to present the disaggregation maps for the basic CPI components. Note, however, that the correspondence is not perfect because a basic component could include prices belonging to two broad categories.

According to Table 1, for the US, the subset N contains 30 basic components that account for 7.66% of the CPI, and belong mainly to MAN (2.90 percentage points (pp)) and SERV (2.15 pp); see Table 2. The number of basic components in subset S—basic components with a CSCF—is 44 and they account for 62.5% of the CPI. The elements of S are more widely distributed among the broad CPI categories; see Table 2. This subset of the disaggregation map has the most weight in the CPI and includes the prices of food, fuels, heat energy, transport and tourism services, nondurable household goods, sporting equipment, and goods related to new technologies. The subset R has 86 elements and they contribute 29.81% to the CPI.

Table 1
Composition of the largest subsets of basic components sharing a common trend (N) or a CSCF (S) and the subset of the remaining basic components (R) in the US, the EA and the UK.

US CPI	Subset N	Subset S	Subset R	Total
Number of basic components	30	44	86	160
Weight in the CPI	7.66%	62.53%	29.81%	100%
EA HICP	Subset N	Subset S	Subset R	Total
Number of basic components	26	23	30	79
Weight in the HICP	39.51%	22.08%	38.41%	100%
UK HICP	Subset N	Subset S	Subset R	Total
Number of basic components	26	19	25	70
Weight in the HICP	39.30%	30.40%	30.30%	100%

Table 2

Classification by broad categories in the US CPI of the basic components belonging to the subsets N, S and R.^a

Basic components in subset N (one common trend)	Number of basic components	Weights of basic components in subset N	Weights of basic components in the corresponding broad category	Weights of basic components in CPI
NPF	5	6.96%	16.21%	0.53%
ENE	2	17.56%	18.12%	1.35%
PF	4	9.49%	10.88%	0.73%
MAN	15	37.91%	12.67%	2.90%
SERV	4	28.08%	3.60%	2.15%
TOTAL	30	100.00%		7.70%

Basic components in subset S (one CSCF)	Number of basic components	Weights of basic components in subset N	Weights of basic components in the corresponding broad category	Weights of basic components in CPI
NPF	5	1.40%	26.70%	0.88%
ENE	3	9.72%	81.88%	6.08%
PF	11	4.15%	38.89%	2.60%
MAN	13	18.80%	51.31%	11.76%
SERV	12	65.92%	69.03%	41.23%
TOTAL	44	100.00%		62.50%

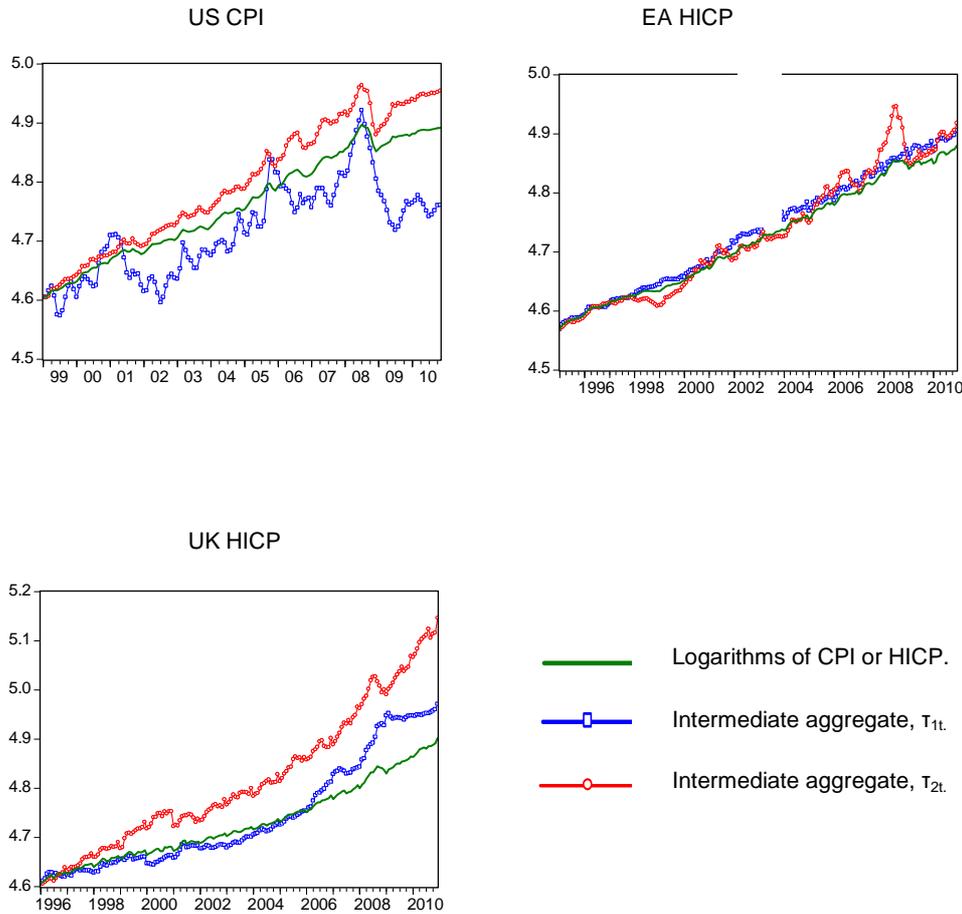
Basic components in subset R	Number of basic components	Weights of basic components in subset N	Weights of basic components in the corresponding broad category	Weights of basic components in CPI
NPF	15	6.29%	57.10%	1.88%
ENE	0	0.00%	0.00%	0.00%
PF	16	11.25%	50.23%	3.36%
MAN	32	27.67%	36.02%	8.25%
SERV	23	54.79%	27.37%	16.35%
TOTAL	86	100.00%		29.80%

^a The broad categories are: non-processed food (NPF); energy (ENE); processed food (PF); other goods (MAN); and other services (SERV).

Table 1 also presents results for the EA and the UK. Although they differ from the US results, an important source of this difference is that the US CPI includes (in S) the “owner’s equivalent rent of primary residence” (with a weight in the CPI of around 24%), which the HICPs in the EA and the UK do not include. Nevertheless, correcting for this divergence in CPI composition methods, the basic components with a common trend carry less weight in the US than in the EA and the UK, whereas the basic components with a CSCF carry relatively more weight. In any case, a result that emerges from these applications is that the characteristics of the intermediate aggregates τ_{1t} , τ_{2t} and r_t differ greatly between countries. This is illustrated in Figure 3. In our sample period, τ_{1t} and τ_{2t} have been diverging considerably in the US and the UK but not so much in the EA.

Figure 3

Logarithms of CPI and HICP and logarithms of the intermediate aggregates τ_{1t} and τ_{2t} , for the US, the EA and the UK.



5. Forecasting results for inflation in the US, the EA and the UK

In this Section, we apply our procedure to forecast inflation in the US, the EA and the UK⁸.

5.1. Forecasting procedures

We examine the forecasting results for the year-on-year inflation rates, approximated by the annual differences of the logarithmic transformation of the price indexes. The data are monthly and the samples range from 1995:01 or 1999:01 to 2010:12. The data till December 2003 are used for specification and initial estimation of the models and the remaining data are employed to evaluate the forecasts of the different methods. To do so, we replicate real-time forecasting by using recursive windows for the different

⁸ Additional results for all three regions referred to the procedure FP3 estimating the CSCF by the fit of $\Delta\tau_{2t}$ can be obtained from the above mentioned website.

forecasting procedures and employing at each step all the available disaggregated information and forecasting up to 12 periods ahead. This means that, by starting with information up to December 2003, we forecast up to December 2004. Then, by extending the sample to January 2004, we test again for the number of lags, check for outliers, re-estimate the models and forecast from February 2004 up to January 2005, and so on. In the forecasting procedures we include dummies for additive outliers.

The forecasting accuracy of each formulation is evaluated by using the root mean squared forecast errors (RMSFEs) at any given forecast horizon. The Diebold & Mariano (1995) test is implemented to test for significant differences between pairs of RMSFEs. In addition, we use the version of the Diebold–Mariano test proposed by Capistran (2006) based on a multivariate loss function to test jointly the forecast accuracy between two procedures over the 12 horizons.

The following forecasting exercise compares the performance of alternative formulations of the indirect procedures proposed in the paper, and an indirect procedure that uses stationary dynamic factors, against the performance of the direct procedure using an ARI(p,1) for the aggregate variable, called Y_t . The direct procedure models the aggregate variable as a constant, the corresponding deterministic dummies and the own past. All the models include dummies for additive outliers (AO). This is our benchmark model. Stock & Watson (2004, 2007) argue that it is difficult to improve on the results from a simple univariate model with gradually evolving relevant parameters.

$$\begin{aligned}
 \Delta \log Y_t = & \alpha + \sum_{j=1}^m \delta_j D_j^{AO} + \sum_{j=1}^{11} \gamma_j D_j & \text{(I) constant, dummies for additive} \\
 & & \text{outliers (AO) and seasonal dummies} \\
 & + \sum_{j=1}^s \omega_j \Delta \log Y_{t-j} & \text{(II) own lags} \\
 & + \varepsilon_t & \text{(III) residual term}
 \end{aligned} \tag{1}$$

Table 3

Summary of forecasting approaches.

The models refer to the first differences of the log transformation of the variables.

I) Direct approach

FP1) Forecast the aggregate data by an AR(p) model.

II) Indirect approaches based on the disaggregation map proposed in this paper

FP2) Procedure using a common-trend restriction.

Forecast each basic component of N and the intermediate aggregate formed with the remaining basic components.

FP3) Procedure using a CSCF restriction.

Forecast each basic component of S and the intermediate aggregate formed with the remaining basic components.

FP4) Procedure using a common-trend and a CSCF restrictions.

Forecast each basic component of N and S and the intermediate aggregate formed with the remaining basic components.

III) Indirect approach based on factor-augmented models for the full disaggregation

FP5) Procedure using a stationary dynamic factor.

Forecast each basic component by including a stationary dynamic factor.

IV) Indirect approaches based on AR(p) models

FP6) Forecast each basic component by an AR(p) model.

The forecasting approaches applied in this paper, denoted as FP, could be classified into four groups, see Table 3. The first, approach FP1, is the direct procedure, which uses the simplest information set and, therefore, a univariate model for the first differences of the aggregate price index. It corresponds to approach F1 in the Introduction. The model used is given above in equation (1). The second group, comprising approaches FP2 to FP4, includes indirect procedures based on the disaggregation map proposed in this paper. They represent different alternatives of approach F4 in the introduction. These procedures use different subsets of restricted basic components—N in approach FP2, S in approach FP3 and N and S in approach FP4—and in each case, a specific residual intermediate aggregate is formed from the remaining basic components. Consequently, the residual intermediate aggregates are different under procedures FP2, FP3 and FP4; specifically, it is only under approach FP4 that the residual subset is the subset R, as illustrated in Figure 1. Then, all the basic components selected in each approach are forecast by using the appropriate specification of the general model presented below in equation (3), and the corresponding residual intermediate aggregate is forecast by using an ARI(p,1) model like equation (1). In the final step, these forecasts are aggregated.

Approach FP3 can be run in two different options corresponding to two approaches for estimating CSCF. One is the fit of $\Delta\tau_{2t}$ and the other is by applying the dynamic factor analysis to the components of S. Thus the results with FP3 could be compared with those from an application of dynamic factors to all basic components, i.e., ignoring the results from the disaggregation map, as it is done in FP5 below.

The third group, approach FP5, collects indirect procedures based on factor-augmented models, as proposed by Bernanke et al. (2005) and Stock & Watson (2005), for each basic component. Each model is an ARI(p,1) model with stationary dynamic factors as regressors. The dynamic factor is estimated over all basic components by

applying the procedure described by Stock & Watson (1998, 2002). We obtained the best forecasting results with just one dynamic factor, as did Duarte & Rua (2007). We denote the dynamic factor by F_t . We also found that when using the dynamic factors, a better forecast of the aggregate is obtained by aggregating the forecasts of the basic components than by forecasting it directly. The general forecasting model used in FP5 for each basic component, $x_{i,t}$, is as follows:

$$\begin{aligned}
 \Delta \log x_{i,t} = & \alpha_i + \sum_{j=1}^m \delta_j D_j^{AO} + \sum_{j=1}^{11} \gamma_{i,j} D_j & \text{(I) constant, dummies for additive} \\
 & & \text{outliers (AO) and seasonal dummies} \\
 & + \sum_{j=1}^k \lambda_j F_{t-j} & \text{(IIa) lags of the stationary factor } F_t \\
 & + \sum_{j=1}^s \omega_{i,j} \Delta \log x_{i,t-j} & \text{(III) own lags} \\
 & + \varepsilon_{i,t} & \text{(IV) residual term}
 \end{aligned} \tag{2}$$

The last group, approach FP6, is an indirect procedure based on a univariate ARI(p,1) model for each basic component, similar to the equation (1) for the direct procedure. It corresponds to approach F2 in the Introduction

We are interested in comparing the procedure FP3 proposed in this paper with an indirect procedure that also uses a common factor but that is extracted automatically from the whole set of basic components without having to test for restrictions between these basic components; this is approach FP5. This is the approach that would be followed by those working with dynamic factors from the set of basic components. It is thus interesting to compare it with FP3 where we also use a dynamic factor, but estimated only from the elements in S .

This is important because, as mentioned in the introduction, our procedure incorporates an estimation restriction when calculating the common factors and incorporates a forecasting restriction when forecasting the basic components. In addition, because our procedure allows isolation of the basic components that do not share the common features identified by the analysis, it can directly forecast the intermediate aggregate formed from those (residual) basic components.

The indirect forecasting approaches, FP2 to FP5, require some additional steps in the forecasting process. This is because forecasting the dependent variables requires forecasts of the explanatory variables: common trends, the CSCF and the dynamic factor. For this forecasting exercise, at each forecast horizon, h (> 1) of a given base period n , we need forecasts of those explanatory variables for the time periods $n + h - 1$. These are calculated by weighting the forecasts of the corresponding basic components obtained for previous horizons. For the common trend and the CSCF, we use official weights as explained above. We use the loading vector for the dynamic factor. Approach FP3 was used in the two different options mentioned above. The option that estimates CSCF by applying dynamic factors to the elements of S gives better results and is the only FP3 option for which we publish the results here. The comparison of

procedures FP3 and FP5 shows the usefulness of applying dynamic factors in the context of a disaggregation map such as that proposed in this paper.

5.2 Single-equation forecasting models.

From the disaggregation map, we need to build single-equation forecasting models for the basic components in N and S and for the intermediate aggregate r_t . Then, by aggregating these forecasts using the normalized official weights of the corresponding CPI as explained in Section 3.1, we obtain the headline inflation rate forecast.

The general structure of the forecasting model of the $x_{i,t}$ basic component in N or S is as follows:

$$\Delta \log x_{i,t} = \alpha_i + \sum_{j=1}^m \delta_j D_j^{AO} + \sum_{j=1}^{11} \gamma_{i,j} D_j \quad \text{(I) } \Delta \log x_{i,t} \text{ denote the first differences (3)}$$

of the log of i -th basic component. The model include constant, dummies for additive outliers (AO) and seasonal dummies

$$+ \delta_i (\log x_{i,t} - \beta_{1,i} \log \tau_{1,t}) \quad \text{(IIa) cointegration relationship of basic component } i \text{ of N with the intermediate aggregate } \tau_{1,t}$$

$$+ \theta_i \left(\sum_{j=1}^S \lambda_j CSCF_{t-j} \right) \quad \text{(IIb) the estimate of the CSCF in S}$$

$$+ \sum_{j=1}^k \delta_{i,j} \Delta \log \tau_{1,t-j} \quad \text{(IIIa) lags of } \Delta \log \tau_{1,t}$$

$$+ \sum_{j=1}^q \varphi_{i,j} \Delta \log r_{t-j} \quad \text{(IIIb) lags of } \Delta \log r_t$$

$$+ \sum_{j=1}^s \omega_{i,j} \Delta \log x_{i,t-j} \quad \text{(IIIc) own lags}$$

$$+ \varepsilon_{i,t} \quad \text{(IV) residual term}$$

The number of lags is selected based on the Akaike information criterion (AIC). Because we have not tested whether the basic components in N have the same CSCF as that found for the basic components in S, we can now include in the models for the basic components in N the estimated CSCF for S, if this is significant. This is an indirect way of identifying the basic components that share not only the common trend of N but also the CSCF of S. Thus, the models for the basic components in N could include all the terms of the above general structure.

However, because we rejected the hypothesis that the basic components in S have the common trend that is present in N, the models for these components can include all the terms of the general structure equation (3) except for (IIa).

For the basic elements of R, we proceed, as mentioned above, by forecasting the intermediate aggregate r_t directly using a model like equation (1). We do so because in all the applications described in Section 5.3, forecasting r_t directly generates greater accuracy than does aggregating the individual forecasts of the basic components in R.

5.3. Forecasting exercise.

The forecasting results are summarized in Table 4, which in column FP1 reports the root mean squared error (RMSE) of the direct procedure, which is our benchmark. The other columns report the ratios between the RMSEs of the corresponding specific forecasting approaches and the RMSE of FP1. Values below unity indicate an improvement in forecast accuracy with respect to the benchmark model. In this table, a single asterisk (*) indicates that the difference in RMSFEs is significant at the 5% significance level based on the Diebold–Mariano test and (**) indicates that the difference is significant at the 1% level. In Table 5, we report the Diebold–Mariano test results based on the multivariate loss function proposed by Capistran (2006) to test jointly the forecast accuracy between two procedures over 12 horizons. Tables 6, 7, 8 and 9 reports similar results for EA and the UK.

Table 4
RMSE (in percentage terms) of the direct approach FP1 and RMSE ratio for each approach to FP1.
US, year-on-year inflation rate

Prediction horizon (months)	Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper			Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
	FP1	FP2	FP3	FP4	FP5	FP6
1	0.42	1.04	0.96	0.95	1.05	0.98
2	0.83	0.93*	0.92*	0.90*	0.93	1.00
3	1.11	0.94	0.93	0.91*	0.91*	1.01
4	1.32	0.94	0.93	0.90*	0.91*	1.01
5	1.48	0.94*	0.93	0.90*	0.91*	1.01
6	1.59	0.93*	0.93	0.89*	0.92*	1.01
7	1.67	0.93	0.91	0.88*	0.93	1.01
8	1.76	0.93	0.87*	0.85*	0.92	1.01
9	1.85	0.92	0.84*	0.81**	0.91	1.00
10	1.94	0.91	0.81**	0.78**	0.89*	1.00
11	2.04	0.90	0.78**	0.76**	0.87*	1.00
12	2.15	0.91*	0.78**	0.75**	0.86**	1.01

Forecast sample: 2004/01–2010/12

* Significantly different at 5% significance level using the Diebold and Mariano test

** Significantly different at 1% significance level using the Diebold and Mariano test

The base periods of the forecasts go from 2003/12 to 2010/11. For horizons 1 and 12, we have 84 and 72 forecasting errors, respectively.

Table 5
Diebold–Mariano test results based on multivariate loss function for the path forecast between two approaches (Capistran 2006)

US results.					
Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper			Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
FP1	FP2	FP3	FP4	FP5	FP6
FP1	**	**	**	**	
FP2		*	**		
FP3			*		
FP4				*	
FP5					**
FP6	**	**	**	**	

* Means that the procedure appearing in the column performs significantly better than the procedure appearing in the row at 5% significance level

** the same but at 1% significance level

Table 6
RMSE (in percentage terms) of the direct approach FP1 and RMSE ratio for each approach to FP1.
EA, year-on-year inflation rate

Prediction horizon (months)	Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper			Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
	FP1	FP2	FP3	FP4	FP5	FP6
1	0.21	0.94*	0.88**	0.85**	0.90*	0.90
2	0.31	0.96*	0.91*	0.91*	0.94	1.27
3	0.41	0.97*	0.92*	0.91*	0.96	1.34
4	0.49	0.99	0.90**	0.89**	0.95	1.32
5	0.58	0.99	0.89**	0.88**	0.93	1.29
6	0.65	1.01	0.89**	0.89**	0.94	1.29
7	0.73	1.01	0.87**	0.87**	0.92	1.21
8	0.81	1.01	0.86**	0.86**	0.91	1.14
9	0.88	1.01	0.87**	0.87**	0.91*	1.09
10	0.94	1.01	0.90**	0.90**	0.92*	1.07
11	1.00	1.01	0.91**	0.90**	0.93*	1.05
12	1.05	1.02	0.93**	0.92**	0.95	1.04

Forecast sample: 2004/01–2010/12

* Significantly different at 5% significance level using the Diebold and Mariano test

** Significantly different at 1% significance level using the Diebold and Mariano test

The base periods of the forecasts go from 2003/12 to 2010/11. For horizons 1 and 12, we have 84 and 72 forecasting errors, respectively.

Table 7

Diebold–Mariano test results based on multivariate loss function for the path forecast between two approaches (Capistran 2006): Euro Area results

EA results						
Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper				Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
	FP1	FP2	FP3	FP4	FP5	FP6
FP1			**	**	**	
FP2			*	**	**	
FP3						
FP4						
FP5			*	**		
FP6			**	**	**	

* Means that the procedure appearing in the column performs significantly better than the procedure appearing in the row at 5% significance level

** the same but at 1% significance level

Table 8

RMSE (in percentage terms) of the direct approach FP1 and RMSE ratio for each approach to FP1.

UK, year-on-year inflation rate						
	Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper			Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
Prediction horizon (months)	FP1	FP2	FP3	FP4	FP5	FP6
1	0.27	0.99	0.98	0.98	1.05	0.92
2	0.39	0.97	0.93	0.99	0.98	1.07
3	0.51	0.96	0.91**	0.90*	0.97	1.53
4	0.63	0.94	0.88**	0.84**	0.96	1.38
5	0.75	0.91*	0.86**	0.78**	0.92*	1.24
6	0.86	0.90**	0.85**	0.75**	0.93**	1.19
7	0.97	0.91*	0.84**	0.72**	0.93**	1.16
8	1.08	0.91**	0.82**	0.70**	0.93**	1.14
9	1.19	0.90**	0.80**	0.69**	0.92**	1.12

10	1.30	0.89**	0.79**	0.68**	0.92**	1.11
11	1.39	0.89**	0.79**	0.67**	0.92**	1.11
12	1.49	0.88**	0.79**	0.66**	0.92**	1.11

Forecast sample: 2004/01–2010/12

* Significantly different at 5% significance level using the Diebold and Mariano test

** Significantly different at 1% significance level using the Diebold and Mariano test

The base periods of the forecasts go from 2003/12 to 2010/11. For horizons 1 and 12, we have 84 and 72 forecasting errors, respectively.

Table 9

Diebold–Mariano test results based on multivariate loss function for the path forecast between two approaches (Capistran 2006)

UK results						
Direct procedure	Indirect procedures based on intermediate disaggregations considered in the paper				Indirect procedure based on factor-augmented models	Indirect procedure based on AR models
	FP1	FP2	FP3	FP4	FP5	FP6
FP1			**	**		
FP2			*	**		
FP3				**		
FP4						
FP5			*	**		
FP6	**	**	**	**	**	

* Means that the procedure appearing in the column performs significantly better than the procedure appearing in the row at 5% significance level

** the same but at 1% significance level

6. Conclusions and proposed extensions.

6.1 Conclusions.

These results, based on CPI data for economic regions that cover about 50% of world GDP, were obtained with a sample of seven years of forecasting errors. Therefore, the results are informative and generate interesting conclusions. The indirect forecast based on using ARI(p,1) models for all the basic components (FP6) is not better than the direct forecast. In fact, for the US, the forecasting performance of FP6 is similar to that of the direct approach for all horizons. In the EA and the UK, FP6 performs relatively poorly for most horizons. Therefore, disaggregation in itself without considering relationships between components does not improve the aggregate forecast in these cases.

In contrast, for the US, the indirect approaches that incorporate information about common features (FP2 to FP4) or about stationary dynamic factors (FP5) perform significantly better than the direct approach for several horizons –all horizons but the first in FP4- (Table 4) and as a whole for the entire forecasting path (Table 5). Similar results are obtained for the EA, except for FP2. For the UK, only approaches FP3 and FP4, which incorporate information about a CSCF, and CSCF and the common trend based on the disaggregation map, significantly outperform the direct approach for the entire forecasting path. Moreover, for all three areas and for all horizons, all the indirect approaches, FP2 to FP5 (except FP2 for the EA), have RMSEs below that of the direct method, except in some cases for the one-period-ahead horizon. In addition, in the cases of US and UK the relatively superior performance of these indirect methods improves with the length of the horizon.

Procedures FP3 and FP5 are similar in the sense that both only include one stationary dynamic factor extracted from the basic components, the former making use of the disaggregation map and the latter ignoring it. FP3 is significantly better than FP5 for the whole forecasting path for the EA and UK, but not for the US. Therefore, in this experiment, overall, FP3 performs better than FP5, showing that dynamic factor analysis is more important when used in connection with a disaggregation map.

The relevance of our approach becomes more apparent when we consider the indirect procedure, FP4, which exploits the full disaggregation map by incorporating a subset of basic components that share a common trend or a CSCF. For all three areas, this approach gives the best forecasting results, in the sense that are significantly better than those from all other approaches for the forecasting path as a whole, except in the comparison with FP3 in the EA. Clearly, this is the preferred approach. In this exercise, for 12-period-ahead forecasts, relative to the direct method, using this approach reduces the RMSE by 8% for the EA, by 25% for the US and by 34% for the UK.

The above comments show that there is evidence that distinguishing basic components with a common trend or a CSCF from the rest matters. Also, tables 5, 7 and 9 show that CSCF (FP3) is significantly more useful than a subset with a common trend (FP2). Our results show that in a comparison between a direct forecasting procedure and the theoretically efficient one based on a vector model for all the basic components—which is usually not feasible and often unreliably estimated—the indirect procedure based on single-equation models for the basic elements that share some common features is an intermediate alternative that can successfully forecast inflation in three different economies. The key point seems to be that the procedure incorporates important restrictions between the basic components. This suggests that when using disaggregated information to forecast an aggregate, one should consider any relevant restrictions present in the disaggregated information.

6.2 Proposed extensions.

To apply our procedure, one must classify a large number of basic components based on their shared features -conveyed by our disaggregation map- which we have shown can be obtained simply by using bivariate methods. The disaggregation map may be useful in other respects, such as in the application of dynamic factors –as it was illustrated in the above comparison between FP3 and FP5–, the definition of useful intermediate aggregates and the formulation of models with unobserved components. In

this paper, we have concentrated on exploiting the restrictions in non-overlapping subsets, the largest subset of basic components with a common trend (N), and on the largest subset with a common serial correlation factor (S), but the disaggregation map could be more sophisticated as described in Section 2. An extension of the forecasting procedure presented here using a disaggregation map which considers common trends, CSCFs, common seasonality, common non-linearity, co-breaks and common volatility seems promising.

Because the current version of our indirect forecasting approach does not incorporate variables outside the whole information set of consumer prices, it cannot be used to explain the economic determinants of inflation. Nevertheless, the forecasts of the basic components generated by our procedure may shed light on what economic factors constitute the main drivers of inflation. In any case, our procedure can easily be extended to include exogenous variables in the models for the basic components or in the model for the intermediate residual aggregate, r_t , which could be done by applying autometrics (see Doornik, 2009).

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