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ABSTRACT

Forecasting Economic Aggregates by Disaggregates*

We explore whether forecasting an aggregate variable using information on its disaggregate components can improve the prediction mean squared error over first forecasting the disaggregates and then aggregating those forecasts, or, alternatively, over using only lagged aggregate information in forecasting the aggregate. We show theoretically that the first method of forecasting the aggregate should outperform the alternative methods in population. We investigate whether this theoretical prediction can explain our empirical findings and analyse why forecasting the aggregate using information on its disaggregate components improves forecast accuracy of the aggregate forecast of euro area and US inflation in some situations, but not in others.

JEL Classification: C51, C53 and E31
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1 Introduction

Forecasts of macroeconomic aggregates are employed by the private sector, governmental and international institutions as well as central banks. Recently there has been renewed interest in the effect of contemporaneous aggregation in forecasting. For example, one issue has been the potential improvement in forecast accuracy delivered by forecasting the component indices and aggregating such forecasts, as against simply forecasting the aggregate itself.[1] The theoretical literature shows that aggregating component forecasts improves over directly forecasting the aggregate if the data generating process is known. If the data generating process is not known and the model has to be estimated, it depends on the unknown data generating process whether the disaggregated approach improves the accuracy of the aggregate forecast. It might be preferable to forecast the aggregate directly. Since in practice the data generating process is not known, it remains an empirical question whether aggregating forecasts of disaggregates improves forecast accuracy of the aggregate of interest. For example, the results in Hubrich (2005) indicate that aggregating forecasts by component does not necessarily help to forecast year-on-year Eurozone inflation twelve months ahead.

In this paper, we suggest an alternative use of disaggregate information to forecast the aggregate variable of interest, that is to include the disaggregate information or disaggregate variables in the model for the aggregate as opposed to forecasting the disaggregate variables separately and aggregating those forecasts.

We show that disaggregating elements of the information set $\mathcal{I}_{T-1}$ into their components cannot lower and might improve predictability of a given aggregate $\mathbf{y}_T$. We focus on disaggregation across variables (such as sub-indices of a price measure). Disaggregation may also be considered across space (e.g., regions of an economy), time (higher frequencies), or all of these. The predictability concept considered in this paper concerns a property in population of the variable of interest in relation to an information set. A related predictability concept is discussed by Diebold & Kilian (2001). Whereas that paper considers measuring predictability of different variables based on one information set, we investigate predictability of the same vari-

[1] See e.g. Espasa, Senra & Albacete (2002), Hubrich (2005) and Benalal, Diaz del Hoyo, Landau, Roma & Skudelny (2004) for forecasting euro area inflation; see also Fair & Shiller (1990) for a related analysis for US GNP). Contributions to the theoretical literature on aggregation versus disaggregation in forecasting can be found in e.g. Grunfeld & Griliches (1960), Kohn (1982), Lütkepohl (1984, 1987), Pesaran, Pierse & Kumar (1989), Van Garderen, Lee & Pesaran (2000); see also Granger (1990) for a survey on aggregation of time-series variables and Lütkepohl (2005) for a recent review on forecasting aggregated processes by VARMA models.

able based on different information sets. In contrast to predictability as a property in population, we use 'forecastability' to refer to the improvement in forecast accuracy related to the sample information given the unconditional moments of a variable. Potential misspecification of the forecast model due to model selection and estimation uncertainty as well as data measurement errors and structural breaks will affect the accuracy of the resulting forecast and help to explain why theoretical results on predictability are not confirmed in empirical applications (see also Hendry (2004) and Clements & Hendry (2004a)).

In previous work on disaggregation in forecasting all disaggregates are considered and model selection is restricted to selecting the VAR order. Our proposal of including all or a selected number of disaggregate variables in the aggregate model gives rise to a classical model selection problem, complementing previous literature on the role of model selection in disaggregation and forecasting. Although the predictability theory provides a useful guide for forecasting, we need to empirically investigate the usefulness of different methods to include disaggregate information for forecasting euro area and US inflation. Thereby we extend the results in Hubrich (2005) and relate our empirical findings to the analytical results presented in the previous sections.

The paper is organised as follows. First, Section 2 briefly reviews the notion of (un-) predictability and its properties most relevant to our subsequent analysis. Then we show that adding lagged information on disaggregates to a model of an aggregate must improve predictability. However, an improvement in predictability is a necessary, but not sufficient condition for an improvement in the forecast accuracy. In Section 4, we discuss the effect of model selection and estimation uncertainty on the forecast accuracy in a conditional model with particular reference to forecasting the aggregate when disaggregate information is included in the aggregate model. In Section 5, we investigate in a simulated out-of-sample experiment whether adding lagged values of the sub-indices of the Harmonized Index of Consumer Prices (HICP) to a model of the aggregate improves the accuracy of forecasts of that aggregate relative to forecasting the aggregate HICP only using lagged aggregate information, or aggregating forecasts of those sub-indices. Section 6 concludes.

2 Improving predictability by disaggregation

In this section the notion of predictability and its properties most relevant to our subsequent analysis are reviewed first, including the properties of predictions from a reduced information set. Then we address the issue of predictability and disaggregation.[2]

2.1 Predictability and its properties

A non-degenerate vector random variable $\boldsymbol{\nu}_t$ is unpredictable with respect to an information set $\mathcal{I}_{t-1}$ (which always includes the sigma-field generated by the past of $\boldsymbol{\nu}_t$) over a period $\mathcal{T} = \{1, \ldots, T\}$ if its conditional distribution $\mathsf{D}_{\boldsymbol{\nu}_t}(\boldsymbol{\nu}_t|\mathcal{I}_{t-1})$ equals its unconditional $\mathsf{D}_{\boldsymbol{\nu}_t}(\boldsymbol{\nu}_t)$:

$$\mathsf{D}_{\boldsymbol{\nu}_t}(\boldsymbol{\nu}_t \mid \mathcal{I}_{t-1}) = \mathsf{D}_{\boldsymbol{\nu}_t}(\boldsymbol{\nu}_t) \quad \forall t \in \mathcal{T}. \tag{1}$$

Unpredictability, therefore, is a property of $\boldsymbol{\nu}_t$ in relation to $\mathcal{I}_{t-1}$ intrinsic to $\boldsymbol{\nu}_t$. Predictability requires combinations with $\mathcal{I}_{t-1}$, as for example in:

$$\mathbf{y}_t = \boldsymbol{\phi}_t(\mathcal{I}_{t-1}, \boldsymbol{\nu}_t) \tag{2}$$

so $\mathbf{y}_t$ depends on both the information set and the innovation component. Then:

$$\mathsf{D}_{\mathbf{y}_t}(\mathbf{y}_t \mid \mathcal{I}_{t-1}) \neq \mathsf{D}_{\mathbf{y}_t}(\mathbf{y}_t) \quad \forall t \in \mathcal{T}. \tag{3}$$

The special case of (2) relevant here (after appropriate data transformations, such as logs) is predictability in mean:

$$\mathbf{y}_t = \mathbf{f}_t(\mathcal{I}_{t-1}) + \boldsymbol{\nu}_t. \tag{4}$$

Other cases of (2) which are potentially relevant are considered in Hendry (2004).

In (4), $\mathbf{y}_t$ is predictable in mean even if $\boldsymbol{\nu}_t$ is not as:

$$\mathsf{E}_t[\mathbf{y}_t \mid \mathcal{I}_{t-1}] = \mathbf{f}_t(\mathcal{I}_{t-1}) \neq \mathsf{E}_t[\mathbf{y}_t],$$

in general. Since:

$$\mathsf{V}_t[\mathbf{y}_t \mid \mathcal{I}_{t-1}] < \mathsf{V}_t[\mathbf{y}_t] \quad \text{when} \quad \mathbf{f}_t(\mathcal{I}_{t-1}) \neq \mathbf{0} \tag{5}$$

predictability ensures a variance reduction.

Predictability is obviously relative to the information used. Given an information set, $\mathcal{J}_{t-1} \subset \mathcal{I}_{t-1}$ when the process to be predicted is $\mathbf{y}_t = \mathbf{f}_t(\mathcal{I}_{t-1}) + \boldsymbol{\nu}_t$ as in (4), less accurate predictions will result, but they will remain unbiased. Since $\mathsf{E}_t[\boldsymbol{\nu}_t|\mathcal{I}_{t-1}] = \mathbf{0}$:

$$\mathsf{E}_t[\boldsymbol{\nu}_t \mid \mathcal{J}_{t-1}] = \mathbf{0},$$

[2] The theory of economic forecasting in Clements & Hendry (1998, 1999) for non-stationary processes subject to structural breaks, where the forecasting model differs from the data generating mechanism, is rooted in the properties of (un-)predictability. Hendry (2004) considers the foundations of this predictability concept in more detail.

so that:

$$\mathsf{E}_t\left[\mathbf{y}_t \mid \mathcal{J}_{t-1}\right] = \mathsf{E}_t\left[\mathbf{f}_t\left(\mathcal{I}_{t-1}\right) \mid \mathcal{J}_{t-1}\right] = \mathbf{g}_t\left(\mathcal{J}_{t-1}\right),$$

say. Let $\mathbf{e}_t = \mathbf{y}_t - \mathbf{g}_t\left(\mathcal{J}_{t-1}\right)$, then, providing $\mathcal{J}_{t-1}$ is a proper information set containing the history of the process:

$$\mathsf{E}_t\left[\mathbf{e}_t \mid \mathcal{J}_{t-1}\right] = \mathbf{0},$$

so $\mathbf{e}_t$ is a mean innovation with respect to $\mathcal{J}_{t-1}$.

However, as:

$$\mathbf{e}_t = \left(\mathbf{f}_t\left(\mathcal{I}_{t-1}\right) - \mathbf{g}_t\left(\mathcal{J}_{t-1}\right)\right) + \boldsymbol{\nu}_t = \mathbf{w}_{t-1} + \boldsymbol{\nu}_t$$

(say) where $\mathsf{E}\left[\mathbf{w}_{t-1}\boldsymbol{\nu}_t'\right] = \mathbf{0}$ then:

$$\mathsf{E}_t\left[\mathbf{e}_t \mid \mathcal{I}_{t-1}\right] = \mathbf{f}_t\left(\mathcal{I}_{t-1}\right) - \mathsf{E}_t\left[\mathbf{g}_t\left(\mathcal{J}_{t-1}\right) \mid \mathcal{I}_{t-1}\right] = \mathbf{f}_t\left(\mathcal{I}_{t-1}\right) - \mathbf{g}_t\left(\mathcal{J}_{t-1}\right) \neq \mathbf{0}.$$

As a consequence of this failure of $\mathbf{e}_t$ to be an innovation with respect to $\mathcal{I}_{t-1}$:

$$\begin{aligned}
\mathsf{E}\left[\mathbf{e}_t\mathbf{e}_t'\right] &= \mathsf{E}\left[\left(\boldsymbol{\nu}_t + \mathbf{w}_{t-1}\right)\left(\boldsymbol{\nu}_t + \mathbf{w}_{t-1}\right)'\right] \\
&= \mathsf{E}\left[\boldsymbol{\nu}_t\boldsymbol{\nu}_t'\right] + \mathsf{E}\left[\boldsymbol{\nu}_t\mathbf{w}_{t-1}'\right] + \mathsf{E}\left[\mathbf{w}_{t-1}\boldsymbol{\nu}_t'\right] + \mathsf{E}\left[\mathbf{w}_{t-1}\mathbf{w}_{t-1}'\right] \\
&= \mathsf{E}\left[\boldsymbol{\nu}_t\boldsymbol{\nu}_t'\right] + \mathsf{E}\left[\mathbf{w}_{t-1}\mathbf{w}_{t-1}'\right] \\
&\geq \mathsf{E}\left[\boldsymbol{\nu}_t\boldsymbol{\nu}_t'\right]
\end{aligned}$$

where strict equality follows unless $\mathbf{w}_{t-1} = \mathbf{0}\ \forall t$.

Nevertheless, that predictions from $\mathcal{J}_{t-1}$ remain unbiased on the reduced information set suggests that, by itself, incomplete information is not fatal to the forecasting enterprise.

In particular, disaggregating components of $\mathcal{I}_{T-1}$ into their elements cannot lower predictability of a given aggregate $\mathbf{y}_T$, where such disaggregation may be across space (e.g., regions of an economy), time (higher frequency), variables (such as sub-indices of a price measure), or all of these. These attributes suggest forecasting using general models to be a preferable strategy, and provide a formal basis for including as much information as possible, being potentially consistent with many-variable 'factor forecasting' (see e.g. Bai (2003), Bai & Ng (2002), Forni, Hallin, Lippi & Reichlin (2000, 2005), and Stock & Watson (2002a, 2002b) , and with the benefits claimed in the 'pooling of forecasts' literature (e.g., Clemen, 1989; Clements & Hendry, 2004b, for a recent theory). Although such results run counter to the common finding in forecasting competitions that 'simple models do best' (see e.g. Makridakis & Hibon, 2000; Allen & Fildes, 2001; Fildes & Ord, 2002), Clements & Hendry (2001) suggest that simplicity is confounded with robustness.

2.2 Predictability of the aggregate and disaggregation

The previous section concerns adding content to the information set $\mathcal{J}_{t-1}$ to deliver $\mathcal{I}_{T-1}$. One form of adding information is via disaggregation of the target variable $\mathbf{y}_T$ into its components $\mathbf{y}_{i,T}$ although $\mathsf{D}_{\mathbf{y}_{T+1}}(\mathbf{y}_{T+1}|\cdot)$ remains the target of interest. We consider only two components and a scalar process to illustrate the analysis, which clearly generalizes to many components and a vector process.

Consider a scalar y_t to be forecast, composed of:

$$y_{T+1} = w_{1,T+1}y_{1,T+1} + w_{2,T+1}y_{2,T+1} \tag{6}$$

with the weights $w_{1,T+1}$ and $w_{2,T+1} = (1 - w_{1,T+1})$ for each of the two components. Note that the weights are allowed to vary over time. It may be thought that, when the $y_{i,t}$ themselves depend in different ways on the general information set $\mathcal{I}_{t-1}$, which by construction includes the σ–field generated by the past of the $y_{i,t-j}$, predictability could be improved by forecasting the disaggregates and aggregating those forecasts to obtain those for y_{T+1}. However, let:

$$\mathsf{E}_{T+1}\left[y_{i,T+1} \mid \mathcal{I}_T\right] = \boldsymbol{\delta}'_{i,T+1}\mathcal{I}_T \tag{7}$$

which is the conditional expectation of each component $y_{i,T+1}$ and hence is the minimum mean-square error (MSE) predictor. Then, taking conditional expectations in (6), aggregating the two terms in (7) delivers $\mathsf{E}_{T+1}[y_{T+1}|\mathcal{I}_T]$:

$$\mathsf{E}_T\left[y_{T+1} \mid \mathcal{I}_T\right] = \sum_{i=1}^{2} w_{i,T+1}\mathsf{E}_{T+1}\left[y_{i,T+1} \mid \mathcal{I}_T\right] = \sum_{i=1}^{2} w_{i,T+1}\boldsymbol{\delta}'_{i,T+1}\mathcal{I}_T = \boldsymbol{\lambda}'_{T+1}\mathcal{I}_T \text{ (say).}$$

By way of comparison, consider predicting y_{T+1} directly from $\mathcal{I}_T$:

$$\mathsf{E}_{T+1}\left[y_{T+1} \mid \mathcal{I}_T\right] = \boldsymbol{\phi}'_{T+1}\mathcal{I}_T, \tag{8}$$

so $\boldsymbol{\phi}_{T+1} = \boldsymbol{\lambda}_{T+1}$ with a prediction error:

$$y_{T+1} - \mathsf{E}_{T+1}\left[y_{T+1} \mid \mathcal{I}_T\right] = v_{T+1} \tag{9}$$

which is unpredictable from $\mathcal{I}_T$ and hence nothing is lost predicting y_{T+1} directly instead of aggregating component predictions once the general information set $\mathcal{I}_T$ is used. In practice, if both the weights $w_{i,T+1}$ and the coefficients of the component models $\boldsymbol{\delta}'_{i,T+1}$ change more than the coefficients of the aggregate model $\boldsymbol{\lambda}_{T+1}$, forecasting the aggregate directly could well be more accurate than aggregating the component forecasts. Thus, the key issue in (say) aggregate inflation prediction is not predicting the component price changes, but including those components in the information set $\mathcal{I}_T$. This result implies that weights are not needed for aggregating component forecasts, and also saves the additional effort of specifying disaggregate models for the components.

Including the components in the information set $\mathcal{I}_T$ is quite distinct from restricting information to lags of aggregate inflation, an information set we denote by $\mathcal{J}_T$. Then:

$$\mathsf{E}_{T+1}\left[y_{T+1} \mid \mathcal{J}_T\right] = \boldsymbol{\psi}'_{T+1}\mathcal{J}_T,$$

so that using y_{T+1} from (8) and (9) gives:

$$y_{T+1} - \mathsf{E}_{T+1}\left[y_{T+1} \mid \mathcal{J}_T\right] = \boldsymbol{\phi}'_{T+1}\mathcal{I}_T - \boldsymbol{\psi}'_{T+1}\mathcal{J}_T + \upsilon_{T+1}, \tag{10}$$

which must have larger MSE than (9), since according to Section 2.1, although the predictions based on $\mathcal{I}_T$ and $\mathcal{J}_T$ are both unbiased, the prediction based on the smaller information set $\mathcal{J}_T$, here only including the lags of aggregate inflation and no disaggregate information, is less accurate, and has a larger variance than the forecast based on $\mathcal{I}_T$. If y_{T+1} was unpredictable from both information sets, i.e. $\boldsymbol{\psi}_{T+1} = \boldsymbol{\phi}_{T+1} = \mathbf{0}$, then (9) and (10) would have equal MSE.

3 Forecasting the aggregate: Does disaggregate information help?

In this section we consider forecasting the aggregate if the true data generating process (DGP) is a VAR(1) and the aggregate is a weighted average of the disaggregate components. There are three possible methods to forecast the aggregate if the information set contains the aggregate and disaggregate components: First, forecasting the disaggregates by lagged disaggregates and then aggregating those forecasts; second, forecasting the aggregate directly by the lags of the aggregate; and third we can forecast the aggregate not only by including lags of the aggregate, but also lags of the disaggregates in the aggregate model. The first and second method has been considered in previous literature on disaggregation and forecasting, whereas our paper proposes the third method to forecast the aggregate.

In the following, we elaborate on the results in the previous section by investigating whether forecasting the aggregate by disaggregates improves forecast accuracy over the other methods under the assumption that the true DGP is known or, alternatively, is not known and has to be approximated.

Let the DGP be a vector autoregression of order one in the components $y_{i,t}$:

$$\begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \end{pmatrix} + \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix} \tag{11}$$

where $\mathsf{E}[\mathbf{v}_t] = \mathbf{0}$, $\mathsf{E}[\mathbf{v}_t \mathbf{v}_t'] = \mathbf{\Sigma}_v$ and $\mathsf{E}[\mathbf{v}_t \mathbf{v}_s'] = \mathbf{0}$ for all $s \neq t$. Furthermore, $y_t = w_{1,t} y_{1,t} + (1 - w_{1,t})\, y_{2,t}$, as in a price index, where weights shift with value shares, leading to:

$$\begin{aligned} y_t &= w_{1,t} \left[(\pi_{11} - \pi_{21})\, y_{1,t-1} + (\pi_{12} - \pi_{22})\, y_{2,t-1} \right] + \pi_{21} y_{1,t-1} + \pi_{22} y_{2,t-1} \\ &\quad + w_{1,t} v_{1,t} + (1 - w_{1,t})\, v_{2,t}. \end{aligned} \tag{12}$$

3.1 Disaggregate forecasting model: True disaggregate process known

The disaggregate forecasting model for known parameters is:

$$\begin{pmatrix} \widehat{y}_{1,T+1|T} \\ \widehat{y}_{2,T+1|T} \end{pmatrix} = \begin{pmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{pmatrix} \begin{pmatrix} y_{1,T} \\ y_{2,T} \end{pmatrix},$$

with:

$$\widehat{y}_{T+1|T} = w_{1,T+1} \widehat{y}_{1,T+1|T} + w_{2,T+1} \widehat{y}_{2,T+1|T}.$$

Thus, the forecast error from forecasting the disaggregate components and aggregating those forecasts is:

$$\begin{aligned} y_{T+1} - \widehat{y}_{T+1|T} &= w_{1,T+1} \left(y_{1,T+1} - \widehat{y}_{1,T+1|T} \right) + w_{2,T+1} \left(y_{2,T+1} - \widehat{y}_{2,T+1|T} \right) \\ &= w_{1,T+1} v_{1,T+1} + w_{2,T+1} v_{2,T+1} \end{aligned} \tag{13}$$

which is unpredictable, independent of whether the weights are known or not known.

3.2 Aggregate forecasting model with known disaggregate process parameters

In contrast to the first example where the disaggregate forecasting model is fitted to the process, consider restricting the information set underlying the forecasting model to lags of y_t alone, with no disaggregates used. Furthermore, the true aggregate process is assumed known so that the true parameters of the aggregate forecasting model are known to the forecaster. In the following, to simplify the presentation, it is assumed that $w_{1,t} = w_{2,t} = 1$,[3] so that $y_t = y_{1,t}+y_{2,t}$. Then the aggregate y_t based on the true disaggregate process (11) can be represented by an ARMA(2,1) process (for a proof see e.g. Lütkepohl, 1987, Ch.4,1984a).

The VAR in (11) can be written as $\mathbf{\Pi}(L)\mathbf{y}_t = \mathbf{v}_t$:

$$\begin{pmatrix} 1-\pi_{11}L & -\pi_{12}L \\ -\pi_{21}L & 1-\pi_{22}L \end{pmatrix} \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix}. \tag{14}$$

Multiplying (14) by the adjoint $\mathbf{\Pi}(L)^*$ of the VAR operator $\mathbf{\Pi}(L)$ gives:

$$\begin{pmatrix} 1-a_1-a_2L^2 & 0 \\ 0 & 1-a_1-a_2L^2 \end{pmatrix} \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix} = \begin{pmatrix} 1-\pi_{22}L & \pi_{12}L \\ \pi_{21}L & 1-\pi_{11}L \end{pmatrix} \begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix}. \tag{15}$$

Furthermore, multiplying (15) by the vector of weights $F = (1, 1)$ of the disaggregate components entails:

$$(1-a_1L-a_2L^2)y_t = (1-b_1L)v_{1,t} + (1-b_2L)v_{2,t} \tag{16}$$

with $a_1 = \pi_{11}+\pi_{22}$, $a_2 = \pi_{12}\pi_{21}-\pi_{11}\pi_{22}$, $b_1 = \pi_{21}+\pi_{22}$ and $b_2 = \pi_{12}+\pi_{11}$. It can be shown that the right-hand side of expression (16) is a process with an MA(1) representation, so that the aggregate process has an ARMA(2,1) representation: $(1-a_1L-a_2L^2)y_t = (1-\gamma L)u_t$.[4]

The model in (16) is used as a forecasting model based on the information set restricted to the aggregate:

$$\hat{y}_{T+1} = a_1y_T + a_2y_{T-1} + v_{1,T+1} - b_1v_{1,T} + v_{2,T+1} - b_2v_{2,T} \tag{17}$$

To derive the forecast error made, recall that the aggregate is $y_t = y_{1,t} + y_{2,t}$. Then (16) entails:

$$\begin{aligned} y_t \;=\;& a_1y_{1,t-1} + a_2y_{1,t-2} + a_1y_{2,t-1} + a_2y_{2,t-2} \\ & + v_{1,t} - b_1v_{1,t-1} + v_{2,t} - b_2v_{2,t-1} \end{aligned} \tag{18}$$

Since in this section, we have assumed that $w_{1,t} = w_{2,t} = 1$ for ease of exposition, the disaggregate process in (11) simplifies to

$$y_t = (\pi_{11}+\pi_{21})\, y_{1,t-1} + (\pi_{12}+\pi_{22})\, y_{2,t-1} + v_{1,t} + v_{2,t}. \tag{19}$$

[3] Results are easily extended to the case of different and time-varying component weigths.

[4] More generally, it has been shown in the literature that, if the disaggregate process follows a VARMA(p,q), the aggregate process follows an ARMA(p^*,q^*) process with $p^* \leq (n-m)+1\times p$ and $q^* \leq (n-m)\times p+q$ with n being the number of variables in the system and m being the rank of the matrix of aggregation weights (see e.g. Lütkepohl, 1987, Ch.4).

Then the forecast error of the disaggregate process is given by the difference between (19) and (18):

$$
\begin{aligned}
\widehat{u}_{T+1|T} &= y_{T+1} - \widehat{y}_{T+1|T} \\
&= (\pi_{11} + \pi_{21})\, y_{1,T} - a_1 y_{1,T} - a_2 y_{1,T-1} \\
&\quad + (\pi_{12} + \pi_{22})\, y_{2,T} - a_1 y_{2,T} - a_2 y_{2,T-1} \\
&\quad + v_{1,T+1} + v_{2,T+1} - v_{1,T+1} + b_1 v_{1,T} - v_{2,T+1} + b_2 v_{2,T} \\
&= (\pi_{11} - \pi_{22})\, y_{1,T} - a_2 y_{1,T-1} + (\pi_{12} - \pi_{11})\, y_{2,T} - a_2 y_{2,T-1} \\
&\quad + b_1 v_{1,T} + b_2 v_{2,T}
\end{aligned}
$$

which will not be unpredictable in general. The entailed restrictions are of the following form[5]:

$$
\begin{aligned}
\pi_{21} - \pi_{22} &= 0 \\
\pi_{12} - \pi_{11} &= 0 \\
a_2 &= -\pi_{11}\pi_{22} - \pi_{12}\pi_{21} = 0
\end{aligned}
$$

These restrictions will usually not be fulfilled simultaneously, so u_t will be predictable from $y_{1,t-i}$ and/or $y_{2,t-i}$ $(i = 1, 2)$.

3.3 Aggregate forecasting model with unknown disaggregate process parameters

Again, consider restricting the information set to lags of y_t with no disaggregates used. However, in contrast to the example in Section 3.2, the true disaggregate process is not known. Consequently, the aggregate process has to be approximated. We assume that the aggregate is a weighted average of the two disaggregates where the weights are allowed to vary across components and change over time.

We approximate (11) by an autoregression of the form:

$$y_t = \rho y_{t-1} + u_t \tag{20}$$

where:

$$\widehat{y}_{T+1|T} = \widehat{\rho} y_T.$$

Since $y_t = w_{1,t} y_{1,t} + (1 - w_{1,t})\, y_{2,t}$, (20) entails that:

$$y_t = \rho w_{1,t-1} y_{1,t-1} + \rho\,(1 - w_{1,t-1})\, y_{2,t-1} + u_t. \tag{21}$$

[5](See e.g., Lütkepohl, 1984, for the implied restrictions for equality of the aggregate and the disaggregate forecast model for a more general DGP).

Thus, the forecast error $\widehat{u}_{T+1|T}$ from forecasting the true disaggregate process (11) with an estimated AR(1) model is given by (12) minus (21):

$$\begin{aligned}
\widehat{u}_{T+1|T} &= y_{T+1} - \widehat{y}_{T+1|T} \\
&= \left(w_{1,T+1}\left[\pi_{11} - \pi_{21}\right] + \pi_{21} - \widehat{\rho} w_{1,T}\right) y_{1,T} \\
&\quad + \left(w_{1,T+1}\left[\pi_{12} - \pi_{22}\right] + \pi_{22} - \widehat{\rho}\left(1 - w_{1,T}\right)\right) y_{2,T} \\
&\quad + w_{1,T+1} v_{1,T+1} + \left(1 - w_{1,T+1}\right) v_{2,T+1},
\end{aligned} \tag{22}$$

which will not be unpredictable in general. Even for constant weights, the entailed restrictions are well known to be of the form:

$$\begin{aligned}
w_1\left(\pi_{11} - \pi_{21} - \widehat{\rho}\right) + \pi_{21} &= 0 \\
w_1\left(\pi_{12} - \pi_{22} + \widehat{\rho}\right) + \left(\pi_{22} - \widehat{\rho}\right) &= 0
\end{aligned}$$

There is no reason to anticipate that $\widehat{\rho}$ can simultaneously satisfy both requirements (even less so with time-varying weights), so u_{T+1} will be predictable from $y_{1,T}$ and $y_{2,T}$, as in the previous example where the true aggregate process was known.

These results indicate that it should improve forecast accuracy to include disaggregate information in the aggregate forecasting model. The additional difficulties in an actual forecast exercise of the choice of the information set, estimation of unknown parameters, unmodeled breaks, forecasting the weights, and data measurement errors that the forecaster faces, however, may be sufficiently large to offset the potential benefits. In the next section the influence of changes that potentially influence the model selection when considering the disaggregate information set are presented analytically. Section 5 presents an empirical analysis for forecasting euro-area inflation.

4 Adding disaggregates to forecast aggregates

In this section we illustrate how different types of changes, that occur in the real world forecasting environment affect the forecast accuracy of the aggregate.

Let $\mathbf{y}_t$ denote the vector of n disaggregate prices with elements $y_{i,t}$ where we illustrate using:

$$\mathbf{y}_t = \mathbf{\Gamma}\mathbf{y}_{t-1} + \mathbf{e}_t \tag{23}$$

as the DGP for the disaggregates. Let $y_t = \boldsymbol{\omega}_t'\mathbf{y}_t$ be the aggregate price index with weights $\boldsymbol{\omega}_t$.

Then pre-multiplying (23) by $\boldsymbol{\omega}_t'$:

$$\begin{aligned} y_t &= \boldsymbol{\omega}_t'\boldsymbol{\Gamma}\mathbf{y}_{t-1} + \boldsymbol{\omega}_t'\mathbf{e}_t = \kappa\boldsymbol{\omega}_{t-1}'\mathbf{y}_{t-1} + \left(\boldsymbol{\omega}_t'\boldsymbol{\Gamma} - \kappa\boldsymbol{\omega}_{t-1}'\right)\mathbf{y}_{t-1} + \boldsymbol{\omega}_t'\mathbf{e}_t \\ &= \kappa y_{t-1} + \left(\boldsymbol{\phi}_t - \kappa\boldsymbol{\omega}_{t-1}\right)'\mathbf{y}_{t-1} + \nu_t \end{aligned} \tag{24}$$

where $\boldsymbol{\phi}_t = \boldsymbol{\Gamma}\boldsymbol{\omega}_t$ are the parameters of the disaggregates in the aggregate model. In (24) the aggregate y_t depends on lags of the aggregate, y_{t-1}, and the lagged disaggregates $\mathbf{y}_{t-1}$. Thus, even if the DGP is (23) at the level of the components, an aggregate model will be systematically improved by adding disaggregates only to the extent that $\boldsymbol{\phi}_t - \kappa\boldsymbol{\omega}_{t-1} = \boldsymbol{\pi}$, i.e. the coefficients of the disaggregates, are constant, and the elements contribute substantively to the explanation. The additional role of disaggregate information over just including the lagged aggregate in the aggregate model (24) is represented by the extent to which $\phi_{i,t} \neq \kappa\omega_{i,t-1}$ for each variable i.

Four distinct types of change can be distinguished in (24) that will affect the forecasting accuracy forecasting the aggregate by lags of the aggregate and disaggregates:

a) changes in the price index weights $\boldsymbol{\omega}_{t-1}$ can be due to changes in expenditure shares with constant correlations between the disaggregates;

b) changes in the second-moment matrix of the disaggregates $\mathbf{y}_{t-1}$ (i.e., in the regressor correlation structure) can change collinearity, affecting the trade-off between the cost of estimation and the cost of omission that is central to forecast model selection;

c) changes in the parameters $\boldsymbol{\phi}_t$ of the disaggregates, so the role of the disaggregate regressors is non-constant; and

d) changes in the autoregressive parameter κ.

All four potential shifts influence the decision of whether or not to include (or model) the disaggregates, and might hamper possible improvements in the forecast of the aggregate y_t from adding disaggregate variables $x_{i,t}$ to a model with lags of the aggregate. The first three of these shifts favour an aggregate model as a more robust forecasting device, and could do so even if κ is not constant. The selection issue in this context, concerns omitting or retaining the disaggregates, where changing collinearity over the forecast period affects the trade-off is between increasing estimation uncertainty by including irrelevant variables on the one hand and the misspecification costs of omitting relevant regressors on the other hand. Therefore, the choice of including some or all disaggregates in the aggregate model relates to a classical model selection problem. In the empirical analysis we consider a broad range of forecast models and model selection procedures.

5 Forecasting euro area and US inflation

In this section, we analyze empirically the relative forecast accuracy of the three methods to forecast the aggregate investigated analytically in the previous sections. We aim to answer the following questions: First, does including the disaggregate variables in the aggregate model improve the direct forecast of the aggregate? Second, is including disaggregate information in the aggregate model better in terms of forecast accuracy than forecasting disaggregate variables and aggregating those forecasts? Third, does it improve the indirect forecast of the aggregate to include aggregate information in the component models? We relate the findings to our theoretical results.

5.1 Data

The euro area data employed in this study include aggregated overall HICP for the euro area as well as its breakdown into five subcomponents: unprocessed food (p^{uf}), processed food (p^{pf}), industrial goods (p^{i}), energy (p^{e}) and services prices (p^{s}).

This particular breakdown into subcomponents has been chosen in accordance with the data published and analyzed in the ECB Monthly Bulletin.

The data employed are of monthly frequency, starting in 1992(1) until 2001(12). We also employ an extended data set until 2004(12). The relatively short sample is determined by the availability of subcomponent data for the euro area and has to be split for the out-of-sample forecast experiment. Seasonally adjusted data have been chosen[6] because of the changing seasonal pattern in some of the HICP subcomponents for some countries due to a measurement change.[7]

The euro area month-on-month inflation rates (in decimals) and the year-on-year inflation rates (in %) of the indices are displayed in Figures 1 and 2, respectively.

We have carried out Augmented Dickey Fuller (ADF) tests for all HICP (sub-) indices (in logarithms), since Diebold & Kilian (2000) show for univariate models that testing for a unit root can be useful for selecting forecasting models. The tests are based on the sample from 1992(1) to 2000(12). This is the longest of the recursively estimated samples in the simulated out-of-sample forecast experiment in Section 5.3. The tests do not reject non-stationarity for

[6] Except for interest rates, producer prices and HICP energy that do not exhibit a seasonal pattern.

[7] The data used in this study are taken from the ECB and Eurostat. The seasonal adjustment procedure is based on Census X-12-ARIMA.

the levels of all (sub-) indices over the whole period.[8] Non-stationarity is rejected for the first differences of all series except the aggregate HICP and HICP services. For the first differences of the latter two series, however, non-stationarity is rejected for all shorter recursive estimation samples up to 2000(8) and 2000(7), respectively. Therefore and because of the low power of the ADF test HICP (sub-)indices are assumed to be integrated of order one in the analysis and modeled accordingly in the VAR based forecast comparison.

We compare our results for the euro area with forecasts for the US consumer price index (CPI; source: Bureau of Labor Statistics). The US all items CPI can be divided into 4 components: food, industrial goods, services and energy prices. For comparability with the euro area results, we also employ seasonally adjusted data for the US.[9] For the US we consider sample periods from 1990 to 2004 and 1980 to 2004, respectively. Figure 3 depicts aggregate year-on-year inflation for the US.

5.2 Forecast methods and model selection

Different forecasting methods using different model selection procedures are employed for both direct and indirect forecast methods, i.e., forecasting HICP inflation directly versus aggregating subcomponent forecasts. We employ simple autoregressive (AR) models where the lag length is selected by the Schwarz (SIC) and the Akaike (AIC) criterion respectively (see e.g. Inoue & Kilian, 2005). We include a subcomponent vector autoregressive model (VAR^{subc}) to indirectly forecast the aggregate by aggregating subcomponent forecasts. We use a VAR including the aggregate and the components, VAR^{agg,sub}, to investigate the hypothesis from Section 2 that including component information in the aggregate forecast model improves the forecast of the aggregate. The lag length of the VAR is selected on the basis of the SIC, the AIC and an F-test.[10] We include a VAR where the lags of the aggregate and the components are automatically chosen using *PcGets*, VAR$^{agg,sub}_{Gets}$ (see Hendry & Krolzig, 2003).

We also include results for factor models where factors are estimated from disaggregate price information by Maximum Likelihood (see Lawley & Maxwell (1971)) using an EM al-

[8]The ADF test specification includes a constant and a linear trend for the levels and first differences. The number of lags included is chosen according to the largest significant lag on a 5% significance level.

[9]Seasonal adjustment is based on X12-ARIMA, as in the euro area.

[10]It should be noted that due to the large number of parameters in the high-dimensional VARs the maximum lag order was chosen on the basis of a rough rule such that the total number of parameters in the system would not exceed half the sample size.

gorithm (see e.g. Dempster, Laird & Rubin (1977)).[11] Since the cross-sectional dimension of our information set of disaggregate price components is small, principal component analysis and dynamic principal component analysis as in Bai (2003), Bai & Ng (2002), Forni et al. (2000, 2005), and Stock & Watson (2002a, 2002b) would not provide consistent estimators of the factors.[12]

5.3 Simulated out-of-sample forecast comparison

5.3.1 The experiment

A simulated out-of-sample forecast experiment is carried out to evaluate the relative forecast accuracy of alternative methods to forecast aggregate euro area and US inflation using information on its disaggregate components as opposed to aggregating the forecasts of subcomponent models or forecasting the aggregate only using aggregate information. One to twelve step ahead forecasts are performed based on different linear time series models estimated on recursive samples. The main criterion for the comparison of the forecasts employed in this study, as in a large part of the literature on forecasting, is the root mean square forecast error (RMSFE).

5.3.2 Aggregate and disaggregate information in VARs

Table 1 presents the comparison of the relative forecast accuracy measured in terms of RMSFE of year-on-year (headline) euro area inflation of the direct forecast of aggregate inflation ($\Delta_{12}\widehat{p}^{agg}$) and the indirect forecast of aggregate inflation, i.e. the aggregated forecasts of the sub-indices ($\Delta_{12}\widehat{p}^{agg}_{sub}$). Various model selection procedures are applied to AR and VAR models. Multi-step forecasts in this section are derived in an iterative procedure. The results for 1-,6- and 12-months ahead forecasts are presented.

First we compare methods only based on aggregate information as opposed to forecast methods for the aggregate including disaggregate variables in addition (see Table 1, column for direct forecast for each forecast horizon). Within the framework of the general theory of prediction we have shown that including disaggregate variables in the aggregate model does improve predictability of a variable (see Section 2). We find that the direct forecast using a VAR including

[11] We thank Dominico Giannone for providing the Matlab code for this algorithm.

[12] For treatments of classical factor models when the cross-sectional dimension n is small, see e.g. Anderson (1984), Geweke (1977), Sargent & Sims (1977); see Doz, Giannone & Reichlin (2005) for maximum likelihood estimation of factor models with large n.

the aggregate and subcomponents where the variables are selected by PcGets, $\text{VAR}^{agg,sub}_{Gets}$, performs slightly better in RMSFE terms 1 month ahead than directly forecasting the aggregate with an AR model only including lagged aggregate information with the lag length determined by the SIC criterion. Thus, our RMSFE results for the $\text{VAR}^{agg,sub}_{Gets}$ for $h = 1$ confirm this predictability result in a forecast experiment. However, the model including the aggregate and all subcomponents, $\text{VAR}^{agg,sub}_{(1)}$ does not provide a more accurate forecast of the aggregate than the autoregressive models AR^{SIC} and AR^{AIC}.

Furthermore, we investigate the accuracy of forecasting the aggregate directly including disaggregate variables relative to the forecast accuracy of indirectly forecasting the aggregate by aggregating component forecasts based on an AR model or a subcomponent VAR, VAR^{sub}, (Table 1), i.e., the way previous literature has taken disaggregate variables into account (see e.g. Lütkepohl (1984, 1987), Hubrich (2005)). The VAR model that outperforms the other direct forecast methods of the aggregate, $\text{VAR}^{agg,sub}_{Gets}$, also exhibits higher forecast accuracy for the indirect forecast than all other methods for $h = 1$. Thus, including aggregate variables in the disaggregate model improves forecast performance for short horizons. The $\text{VAR}^{agg,sub}_{Gets}$ does also outperform the $\text{VAR}^{agg,sub}_{(1)}$, where the variables and lag length are the same across the aggregate and components, for $h = 1$. Therefore, selection pays at short horizons in this context.

Overall, the direct forecast including the aggregate and subcomponents is best for 1 month ahead forecasts. That confirms within a forecasting set-up the results derived with respect to predictability in Section 2, i.e. that forecasting the aggregate directly including disaggregate information in the aggregate model might perform better than aggregating component forecasts. Figure 4 (upper two panels) shows that the one month ahead forecasts from the different direct and indirect methods that perform either best or worst in RMSFE terms are very close to actual year-on-year inflation. The differences between the different methods for one month ahead forecasts appear to be quite small. The six months ahead forecasts of year-on-year inflation (Figure 4, lower two panels) do generally relatively well. The graphs show that the differences in RMSFE terms between some of the forecasts are relevant to be considered when choosing the forecasting model.

More important from a monetary policy point of view is the 12 months ahead forecast. Here we find that the direct forecast including disaggregate information ($\text{VAR}^{agg,sub}_{(1)}$) is clearly better than the indirect forecast based on AR or VAR models of the components. The low forecast accuracy of aggregating subcomponent models is analyzed in Hubrich (2005), and it is found that this can be related to unexpected shocks that occur in the forecast period and affect some or all components in the same direction so that forecast errors do not cancel. Furthermore, predictability in the sense we have defined in Section 2.1 is low for some component series and their unconditional variance is large. Consequently they are very difficult to forecast. This leads to low forecast accuracy of the indirect forecast of the aggregate. Hubrich (2005) investigates whether forecast combination of different methods improves forecast accuracy of the components and hence the indirect forecast of the aggregate and finds that this is not the case. However, directly forecasting the aggregate using $\text{VAR}_{(1)}^{agg,sub}$ is very similar in terms of forecast accuracy to using the same model, i.e. including all disaggregate variables and the aggregate, for the indirect forecast. Including the aggregate in the component models seems to improve forecast accuracy of the aggregate.[13] We find that the indirect forecast based on a VAR including subcomponents with no lags as chosen by the SIC exhibits higher forecast accuracy than all other indirect forecast methods. This model represents a random walk with drift for prices for each of the components and for the aggregate and is selected by the SIC for the VAR^{sub}, the $VAR^{agg,sub}$ and the VAR^{int}. However, the direct forecast using a simple AR model does lead to the highest forecast accuracy 12 months ahead overall.

For a 12 months ahead horizon the $\text{VAR}_{(1)}^{agg,sub}$ outperforms the $\text{VAR}_{Gets}^{agg,sub}$ in contrast to the one-month ahead result. Furthermore, note that the AR^{SIC} performs better than the AR^{AIC} for one and twelve months ahead forecasts.[14]

Although perfect collinearity between aggregate and components does not pose a problem due to annually changing weights in price indices, we present additional results where different subsets of price components are selected. Comparing forecast accuracy of the $\text{VAR}^{agg,i,s,pf}$, the $\text{VAR}^{agg,e,uf,pf}$ and the $\text{VAR}^{agg,e,uf}$ we find that selection from disaggregate variables seems to improve the forecast accuracy. When we exclude processed food inflation from the $\text{VAR}^{agg,e,uf,pf}$, the lower dimensional $\text{VAR}^{agg,e,uf}$ does perform worse than the $\text{VAR}^{agg,e,uf,pf}$, in particular for $h = 12$. Therefore, the decline in collinearity of the excluded variable and the variables in the system does matter for the forecast accuracy of the method.

Figure 5 shows the relevance of the differences in the forecasts for h=12 discussed above from a monetary policy viewpoint, i.e., a difference between 0.2 up to almost 2 percentage points for some methods in some periods of the forecast period is clearly relevant in this context. Tests to compare the significance of the difference in forecast accuracy are not carried out

[13]This result is based on the lag length of 2 suggested by the F-test.

[14]See e.g.Inoue & Kilian (2005) for a comparison of the SIC and the AIC with respect to forecast model selection.

due to their poor size (and power) properties in small forecast samples as considered here (for simulation evidence see e.g. Harvey, Leybourne & Newbold (1997) and Clark (1999)).

Change in component weights and correlation structure In Section 4 we have analysed theoretically the effects of different types of changes influencing forecast accuracy of the aggregate model including disaggregate components. We now analyse two of those changes in the context of forecasting euro area inflation: a change in component weights and a change in collinearity of disaggregate regressors.

There is some change in (consumer spending) weights of euro area price components: Weights decline between -3.9 % and -1.3 % annually on average over the previous year over the forecast evaluation period for unprocessed food, processed food and industrial goods prices, where in one year for example the decline is almost -9% for unprocessed food. For energy prices weights decline by -6.5% in 1999 and then increase by 3.4% and 5.6 %, respectively. Service price weights increase by 3% on average per year over the forecast evaluation period. These changes in weights mean that the relevance of the changes of, say, unprocessed food prices for the aggregate declines over the forecast evaluation period so that positive shocks to unprocessed food prices does affect the aggregate less, whereas the positive shocks to energy prices will affect the aggregate more in the future. [15]

Second, we analyse the change in the correlation structure between the aggregate and the components over the forecast evaluation period. Table 2 presents the correlation matrix, where the upper triangle represents the correlation for the first estimation sample until 1998(1) and the lower triangle represents the correlation for the last forecast sample up to 2001(12). Most of the time correlations between aggregate and components, particularly large declines are observed between Δp^{agg} and Δp^{s}. Overall, correlations between the aggregate and the components decline. Including the respective component(s) in the forecast model might then lower forecast accuracy by increasing estimation uncertainty. This might help explaining that selection pays according to the results in Table 1 where the $\text{VAR}^{agg,sub}_{Gets}$ outperforms all other models one month ahead. Furthermore, correlation among disaggregate components included in the models decline, i.e. collinearity is lower between the regressors. This will affect forecast accuracy. A particularly large decline in correlation can be found in Δp^{uf} and Δp^{pf} as well as Δp^{i} and Δp^{s}. In some cases even the sign switches: Δp^{uf} and Δp^{pf}, Δp^{uf} and Δp^{i} as well as Δp^{e} and Δp^{s},

[15] The indirect forecast of the aggregate by aggregating the component forecasts is also affected since the weights are used for aggregation.

with low negative correlation between those components for the longest sample. This increases the costs of omission of the respective components, as is apparent in the lower forecast accuracy of the more parsimonious model $\text{VAR}_{(1)}^{agg,e,uf}$ in comparison with $\text{VAR}_{(1)}^{agg,e,uf,pf}$.

The above effects favour an aggregate model, in particular for longer forecast horizons like a year, in the sense that an aggregate only including lags of the aggregate might be a more robust forecasting device when the effect of changing weights and collinearity on the trade-off between the costs of estimation and those of omission in forecast model selection is unknown a priori.

5.3.3 Disaggregate information in dynamic factor models

We also employ factor models averaging away idiosyncratic variation in the disaggregate series, then including the factors in the aggregate model. Little is known so far how the size and the composition of the data affect the factor estimates. Some results indicating that more data are not always better for factor analysis can be found in Boivin & Ng (2005). In this paper we are concerned with how factors from disaggregate information affect forecast accuracy of the aggregate economic variable. As discussed in 5.2 we estimate the factors by maximum likelihood. The following sections present the forecast accuracy comparison for euro area and US inflation in terms of RMSFE ratio over the AR^{SIC} of different factor models based on disaggregate prices for the euro area as well as regression models with one disaggregate component as a predictor, respectively. Please note that these results are not directly comparable across all horizons with the previous table since here direct multi-step ahead forecasts are carried out and forecast accuracy is evaluated for annualised inflation (instead of year on year inflation as in the previous tables).[16] We compute the direct h-step DFM forecasts as

$$\pi_{t+h|t}^{h} = \hat{\alpha} + \sum_{i=1}^{p} \hat{\phi}_i \pi_{t-i} + \sum_{j=1}^{q} \hat{\theta}_j \hat{F}_{t-j+1}$$

where $\pi_{t+h|t}^{h}$ denotes the rate of inflation over the period t to $t+h$, $\hat{F}_t$ are the estimated factors, and the direct forecasts based on a single predictor Z_t as

$$\pi_{t+h|t}^{h} = \hat{\alpha} + \sum_{i=1}^{p} \hat{\phi}_i \pi_{t-i} + \sum_{k=1}^{l} \hat{\theta}_k Z_{t-k+1}$$

We also consider forecast combination of all single predictor models based on the respective disaggregate component with equal weights.

[16] See e.g. Stock & Watson (1999).

Euro area inflation Table 3 presents the forecast accuracy comparison in terms of RMSFE ratio over the AR^{SIC} for euro area inflation. A result to note for the 1 month ahead forecast is that the difference between the RMSFE based on the AR(SIC) model presented in Table 3 (RMSFE 0.183) and the results in Table 1 (RMSFE 0.137) is due to the annualised representation of the underlying model. The forecast model based on annualised inflation seems to perform worse than the month on month forecast evaluated on the basis of the year-on-year transformation of the forecast. A further result of interest is that the direct multi-step ahead forecast of aggregate euro area inflation 12 months ahead (see Table 3), where it is comparable in terms of the underlying transformation with the iterative procedure, is somewhat worse than the iterative 12 months ahead forecast based on the AR(SIC) model (see Table 1). This result suggests that in the context of forecasting euro area inflation the loss of efficiency by not using all information available in direct multi-step ahead forecasts is dominating the potentially higher bias due to mis-specification in the iterative procedure.[17]

Only some models improve over the AR^{SIC} at 1 to 12 months horizons and only the regression model with unprocessed food, p^{uf}, as a predictor outperforms the AR^{SIC} over all horizons. A simple average combination of the five model forecasts based on one disaggregate component, respectively, does not improve over the AR model.

Table 4 presents the forecast accuracy of the different models relative to the AR model for an extended sample period up to 2004(12). For the extended sample period disaggregate information is even less useful. Hardly any of the models outperform the AR model on that sample. The respective graphs of realisation and forecasts for $h = 12$ are depicted in Figures 6 and 7. They show that the different models do perform similarly in forecasting aggregate euro area inflation. They all miss the upturn in inflation in 1999 and do better from 2001 onwards.

To summarise the results for the euro area, we find that disaggregate information might help in forecasting euro area aggregate year-on-year inflation, in particular one month ahead using VARs or for all horizons using a regression model with unprocessed food as a predictor.

US inflation The results for US year-on-year inflation are presented in Tables 5 and 6. The results for the same short sample period as for the euro area, i.e. starting in 1990(1) and evaluating the forecast accuracy over the years 1998 to 2004, do confirm the euro area findings that disaggregate information might help in forecasting the aggregate in some situations. For

[17] The issue of multi-step horizon forecasts is investigated in more detail in e.g. Chevillon & Hendry (2004) and Marcellino, Stock & Watson (2005).

this sample, disaggregate information does help forecasting aggregate US inflation one month ahead, but not for higher horizons. However, if we extend the estimation sample backwards starting in 1980(1), we find that disaggregate information does also help for 12 months ahead forecasts. Notably, for this longer horizon all factor models and single predictor models do improve over the AR model. The longer estimation sample including the eighties does contain more information on the disaggregates that is useful for forecasting aggregate inflation. Comparing the forecasts in Figures 9 and 10 shows that the forecasts of all models based on the longer estimation sample starting in 1980 do capture the increase in US inflation in 1999 better than the same models estimated on the shorter sample. These results suggest that the longer estimation sample contains information on disaggregate components that is relevant for forecasting the aggregate and therefore improve forecast accuracy.

To investigate this issue, we examine the correlation of the components with the aggregate and how much of the variability in the data is explained by the estimated factors.

The correlations of the CPI components with the aggregate in terms of year-on-year changes are higher for the US for the longer sample from 1980 onwards, in particular for industrial goods CPI, indicating in-sample perdictive content of the disaggregates for the aggregate.

For the sample 1980 to 2004 the first factor of the year-on-year changes in CPI components explains 75% of the variability in the data, the second factor explains 15% and third factor 6%. For the sample starting in 1990 the first three factors explain 57, 26, 13 % of the variation in the data, respectively, and therefore much less than in the longer sample. For the euro area sample 1992-2004 the first, second and third factor explain 52, 24 and 16 % of the variability in the data, similar to the US for the comparable sample. Less of the variation in the data can be explained by disaggregate based factors for the shorter sample.

To analyse the robustness of our forecast results, we extend the sample backward as far as data are available, i.e. starting the sample in 1967(1). The result that disaggregate information improves the forecast of the aggregate does not change qualitatively. The results do not change substantially either when extending the forecast evaluation period from 6 to 10 years.

Comparing the forecast accuracy in RMSFE terms of the AR model for aggregate annualised inflation for different horizons, we find that the AR forecast accuracy is similar for different length of the estimation samples for one month horizons, but is more accurate based on the shorter estimation sample when forecasting 12 months ahead. Comparing the absolute RMSFE of the AR model, factor models and regression models for forecasting 12 months ahead, we find that disaggregate information in factor models and regression models improves forecast accuracy for the longer sample in comparison with the aggregate model only including lags of the aggregate. However, all models provide more accurate predictions based on the shorter sample. A characteristic to note of the shorter sample is that the variance of the aggregate is considerably lower than for the longer sample. Therefore, there is less variability to be explained by disaggregates.

6 Conclusions

In this paper, we show theoretically that a forecasting model including both aggregate and disaggregate variables in the predictor set should lower the prediction mean squared error in population relative to a model that includes only lags of the aggregate or to first forecasting the disaggregates and then aggregating those forecasts. However, we find that it does not always do so when forecasting euro area and US inflation and analyse reasons for this discrepancy between theoretical predictions and the empirical results.

There are many steps between predictability in population and 'forecastability'. Predictability need not translate into forecastability in finite samples when the forecast model differs from the data generation process. The predictability concept that we consider in this paper refers to a property of the variable of interest in relation to the information set considered. In contrast, forecastability refers to the improvement in forecast accuracy given the unconditional moments of a variable. The predictive value of disaggregate information can be off-set by estimation uncertainty, model selection uncertainty, changing collinearity, structural breaks and measurement errors.

In the context of forecasting euro area inflation, we find that changing weights in the price index and changing collinearity between disaggregate prices undermine the performance of disaggregate-based models. The following conclusions can be drawn from our empirical analysis: Overall, we find that there is little cost or benefit from model selection in VAR models including disaggregate components at short horizons, although the model chosen by *PcGets* is best at a forecast horizon of $h = 1$. More stringent selection pays as h grows when comparing AR models based on the SIC versus AIC. Indirect forecasts, i.e., forecasting the disaggregates and aggregating those forecasts, usually perform worst, although the selection procedure does play a role. Furthermore, including aggregates as robust predictors in the disaggregate models might pay, again depending on the lag order selection procedure applied. Dynamic factor forecasts, where the factors are derived based on disaggregate price variables only, improve over the AR model only in some cases when forecasting euro area inflation.

All methods perform quite similar at forecast horizons of one month. At the forecast horizon of one year, differences between the forecasts from the different methods are larger and are relevant from a monetary policy perspective.

The theoretical prediction that disaggregate information should increase forecast accuracy, is not strongly supported for forecasting euro area inflation, where only a short sample can be considered due to data availability. We find that including disaggregate variables in the aggregate model does rarely improve forecasts of the euro area aggregate, in particular at longer forecast horizons. The forecasting model based on lags of the aggregate seems to be a more robust forecasting device in this context.

However, the theoretical result on predictability that disaggregate information does help is supported for forecasting US inflation, in particular for a longer sample period from 1980 to 2004. We find that for the US CPI inflation and its components, disaggregates clearly help forecasting the aggregate at short horizons for a sample excluding the 1980s. Based on a longer, more informative estimation sample including the 1980s disaggregates help forecasting the aggregate at all horizons.

We find that the differences between the theoretical results on predictability and the empirical results for different forecasting methods, countries and sample periods can be attributed to changes in collinearity between disaggregate price components that affect the bias-variance trade-off in forecast model selection, to changes in the extent that the variance of disaggregate price components can be explained by factors, as well as changes in the unconditional moments of the aggregate. Estimation samples with sufficient variability in the aggregate and the components are necessary for disaggregate variables to improve forecast accuracy of the aggregate. Our results suggest that model selection does play an important role in whether disaggregate information helps in forecasting. More research is necessary on how to select a good forecasting model, in particular in the presence of changing collinearity that affects the bias-variance trade-off in model selection.

We conclude that disaggregate information might help for forecasting the aggregate in line with our theoretical results on predictability in population, but the scope of such an improvement has to be assessed depending on the particular forecasting situation.

References

Allen, P. G. & Fildes, R. A. (2001). Econometric forecasting strategies and techniques, *in* J. S. Armstrong (ed.), *Principles of Forecasting*, Kluwer Academic Publishers, Boston, pp. 303–362.

Anderson, T. W. (1984). *An Introduction to Multivariate Statistical Analysis*, 2nd edn, Wiley, New York.

Bai, J. (2003). Inference on factor models of large dimensions, *Econometrica* **71**(1): 135–172.

Bai, J. & Ng, S. (2002). Determining the number of factors in approximate factor models, *Econometrica* **70**(1): 191–221.

Benalal, N., Diaz del Hoyo, J. L., Landau, B., Roma, M. & Skudelny, F. (2004). To aggregate or not to aggregate? euro area inflation forecasting, *Working Paper 374*, European Central Bank.

Boivin, J. & Ng, S. (2005). Are more data always better for factor analysis?, *Journal of Econometrics, forthcoming*.

Chevillon, G. & Hendry, D. F. (2004). Direct multi-step estimation for forecasting economic processes, *International Journal of Forecasting* pp. –. Forthcoming.

Clark, T. E. (1999). Finite sample properties of tests for equal forecast accuracy, *Journal of Forecasting* **18**: 489–504.

Clemen, R. T. (1989). Combining forecasts: A review and annotated bibliography, *International Journal of Forecasting* **5**: 559–583.

Clements, M. P. & Hendry, D. F. (1998). *Forecasting Economic Time Series*, Cambridge University Press, Cambridge, UK.

Clements, M. P. & Hendry, D. F. (1999). *Forecasting Non-stationary Economic Time Series*, MIT Press, Cambridge,Massechusetts.

Clements, M. P. & Hendry, D. F. (2001). Explaining the results of the M3 forecasting competition, *International Journal of Forecasting* **17**: 550–554.

Clements, M. P. & Hendry, D. F. (2004a). Forecasting with breaks, *in* G. Elliott, C. W. J. Granger & A. Timmermann (eds), *Handbook of Economic Forecasting, forthcoming*, Elsevier.

Clements, M. P. & Hendry, D. F. (2004b). Pooling forecasts, *Econometrics Journal*, *forthcoming*.

Dempster, A., Laird, N. & Rubin, D. (1977). Maximum likelihood from incomplete data via the em algorithm, *Journal of the Royal Statistical Society, Series B* **39**(1): 1–38.

Diebold, F. X. & Kilian, L. (2000). Unit-root tests are useful for selecting forecasting models, *Journal of Business & Economic Statistics* **18**(3): 265–272.

Diebold, F. X. & Kilian, L. (2001). Measuring predictability: Theory and macroeconomic applications, *Journal of Applied Econometrics* **16**: 657–669.

Doz, C., Giannone, D. & Reichlin, L. (2005). A maximum likelihood approach for large approximate dynamic factor models, mimeo.

Espasa, A., Senra, E. & Albacete, R. (2002). Forecasting inflation in the European Monetary Union: A disaggregated approach by countries and by sectors, *European Journal of Finance* **8**(4): 402–421.

Fair, R. C. & Shiller, J. (1990). Comparing information in forecasts from econometric models, *The American Economic Review* **80**(3): 375–389.

Fildes, R. & Ord, K. (2002). Forecasting competitions - their role in improving forecasting practice and research, *in* M. P. Clements & D. F. Hendry (eds), *A Companion to Economic Forecasting*, Blackwell, Oxford, pp. 322–253.

Forni, M., Hallin, M., Lippi, M. & Reichlin, L. (2000). The generalized factor model: Identification and estimation, *Review of Economics and Statistics* **82**: 540–554.

Forni, M., Hallin, M., Lippi, M. & Reichlin, L. (2005). The generalized facotr model: One-sided estimation and forecasting, mimeo, *Journal of the American Statistical Association*, *forthcoming*.

Geweke, J. F. (1977). The dynamic factor analysis of economic time series, *in* D. J. Aigner & A. S. Goldberger (eds), *Latent Variables in Socio-Economic Models*, North-Holland, Amsterdam.

Granger, C. W. J. (1990). Aggregation of time-series variables: A survey, *in* T. Barker & M. H. Pesaran (eds), *Disaggregation in econometric modelling*, Routledge, London and New York, pp. 17–34.

Grunfeld, Y. & Griliches, Z. (1960). Is aggregation necessarily bad?, *The Review of Economics and Statistics* **XLII**(1): 1–13.

Harvey, D., Leybourne, S. & Newbold, P. (1997). Testing the equality of prediction mean squared errors, *International Journal of Forecasting* **13**: 281–291.

Hendry, D. F. (2004). Unpredictability and the foundations of economic forecasting, *Working paper*, Economics Department, Oxford University.

Hendry, D. F. & Krolzig, H.-M. (2001). *Automatic Econometric Model Selection Using PcGets 1.0*, Timberlake Consultants Ltd., London, UK.

Hendry, D. F. & Krolzig, H.-M. (2003). New developments in automatic general-to-specific modelling, *in* B. P. Stigum (ed.), *Econometrics and the Philosophy of Economics*, Princeton University Press, Princeton, pp. 379–419.

Hubrich, K. (2005). Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?, *International Journal of Forecasting* **21**(1): 119–136.

Inoue, A. & Kilian, L. (2005). On the selection of forecasting models, *Journal of Econometrics, forthcoming*.

Kohn, R. (1982). When is an aggregate of a time series efficiently forecast by its past?, *Journal of Econometrics* (18): 337–349.

Lawley, D. N. & Maxwell, A. E. (1971). *Factor Analysis as a Statistical Method.*, Butterworth & Co., London.

Lütkepohl, H. (1984). Forecasting contemporaneously aggregated vector ARMA processes, *Journal of Business & Economic Statistics* **2**(3): 201–214.

Lütkepohl, H. (1987). *Forecasting Aggregated Vector ARMA Processes*, Springer-Verlag.

Lütkepohl, H. (2005). Forecasting with VARMA processes, *in* G. Elliott, C. W. J. Granger & A. Timmermann (eds), *Handbook of Economic Forecasting, forthcoming*, Elsevier.

Makridakis, S. & Hibon, M. (2000). the M3-competition: Results, conclusions and implications, *International Journal of Forecasting* **16**: 451–476.

Marcellino, M., Stock, J. H. & Watson, M. W. (2005). A comparison of direct and iterated multistep ar methods for forecasting macroeconomic time series, *Journal of Econometrics, forthcoming*.

Pesaran, M. H., Pierse, R. G. & Kumar, M. S. (1989). Econometric analysis of aggregation in the context of linear prediction models, *Econometrica* **57**: 861–888.

Sargent, T. J. & Sims, C. A. (1977). Business cycle modeling without pretending to have too much a-priori theory, *in* C. Sims (ed.), *New Methods in Business Cycle Research*, Federal Reserve Bank of Minneapolis, Minneapolis.

Stock, J. H. & Watson, M. W. (1999). Forecasting inflation, *Journal of Monetary Economics* **44**: 293–335.

Stock, J. H. & Watson, M. W. (2002a). Forecasting using principal components from a large number of predictors, *Journal of the American Statistical Association* **97**: 1167–1179.

Stock, J. H. & Watson, M. W. (2002b). Macroeconomic forecasting using diffusion indices, *Journal of Business and Economic Statistics* **20**(2): 147–162.

Van Garderen, K. J., Lee, K. & Pesaran, M. H. (2000). Cross-sectional aggregation of non-linear models, *Journal of Econometrics* **95**: 285–331.

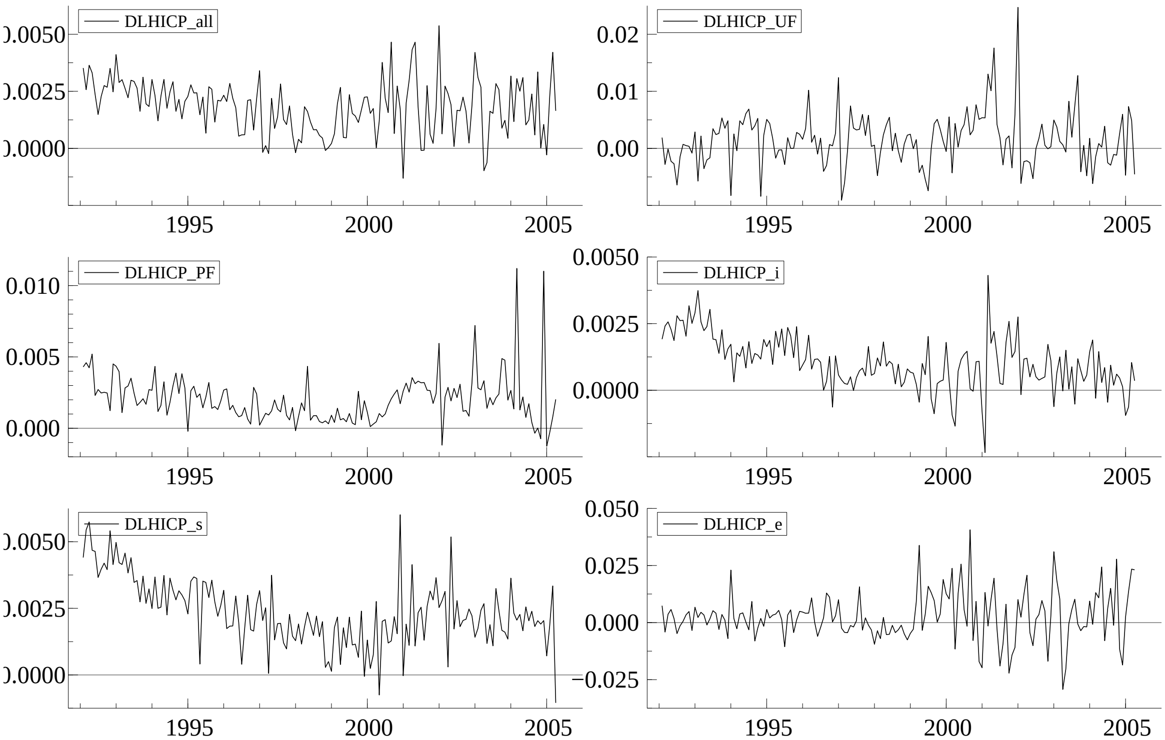

Figure 1: First differences of euro area HICP (sub-)indices (in logarithm)

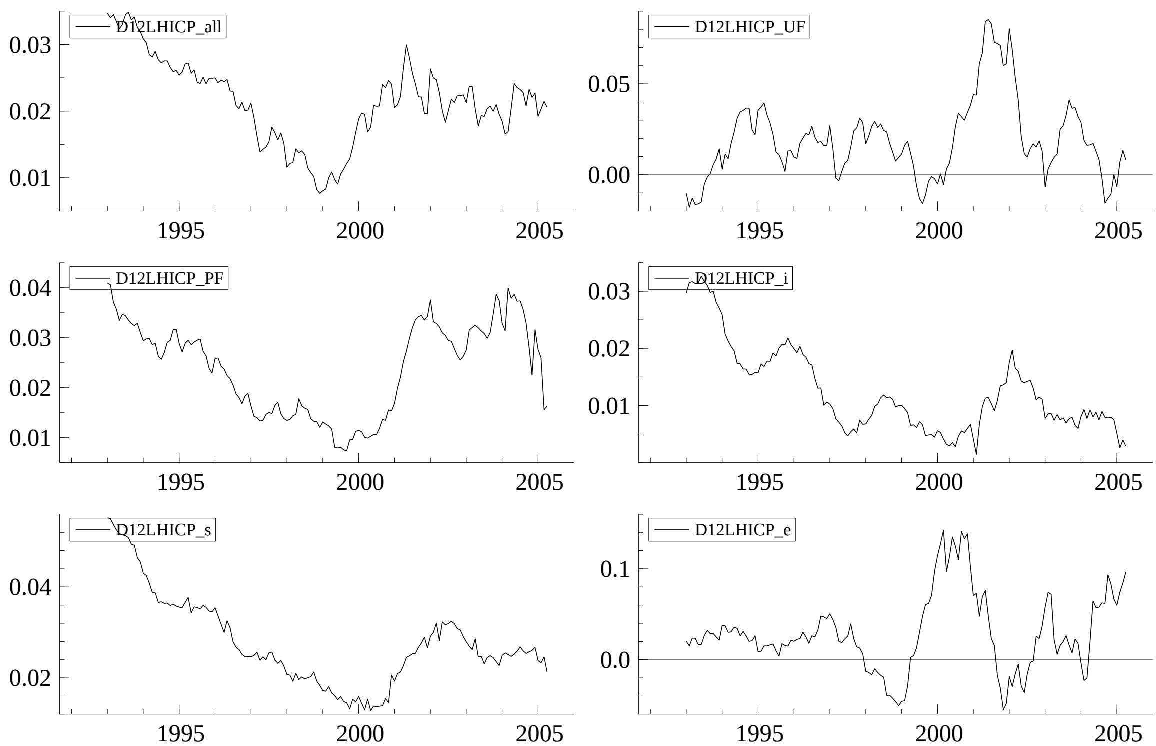

Figure 2: Euro area year-on-year HICP inflation (in %), aggregate and subindices

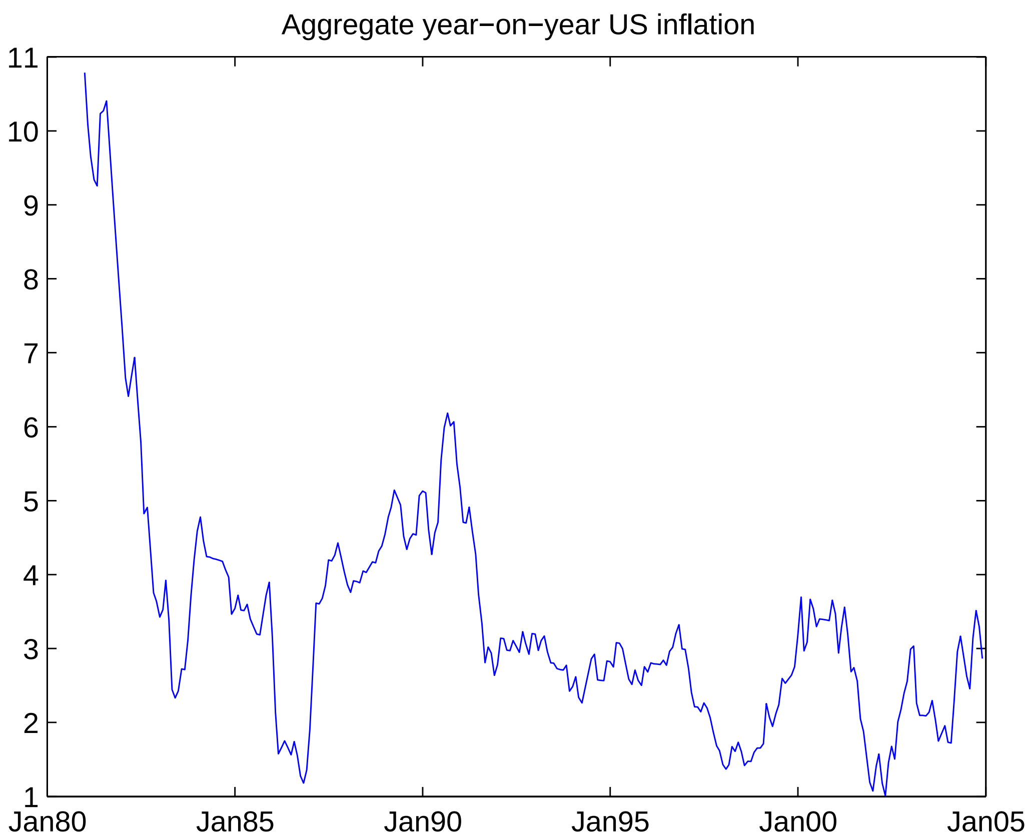

Figure 3: US year-on-year CPI aggregate inflation (in %)

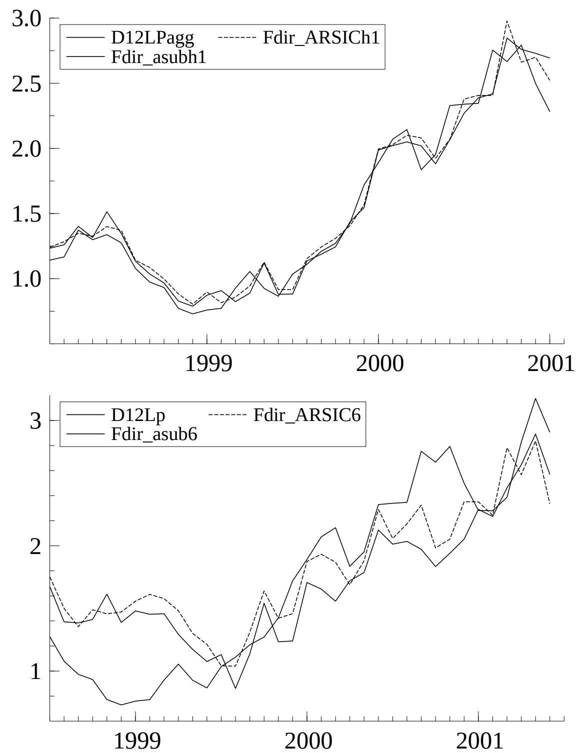

Figure 4: Euro area year-on-year inflation rate and forecasts in %, upper panels: 1 month ahead, lower panels: 6 months ahead, solid line: actual, Fdir: direct forecast of aggregate, Find: indirect forecast of aggregate

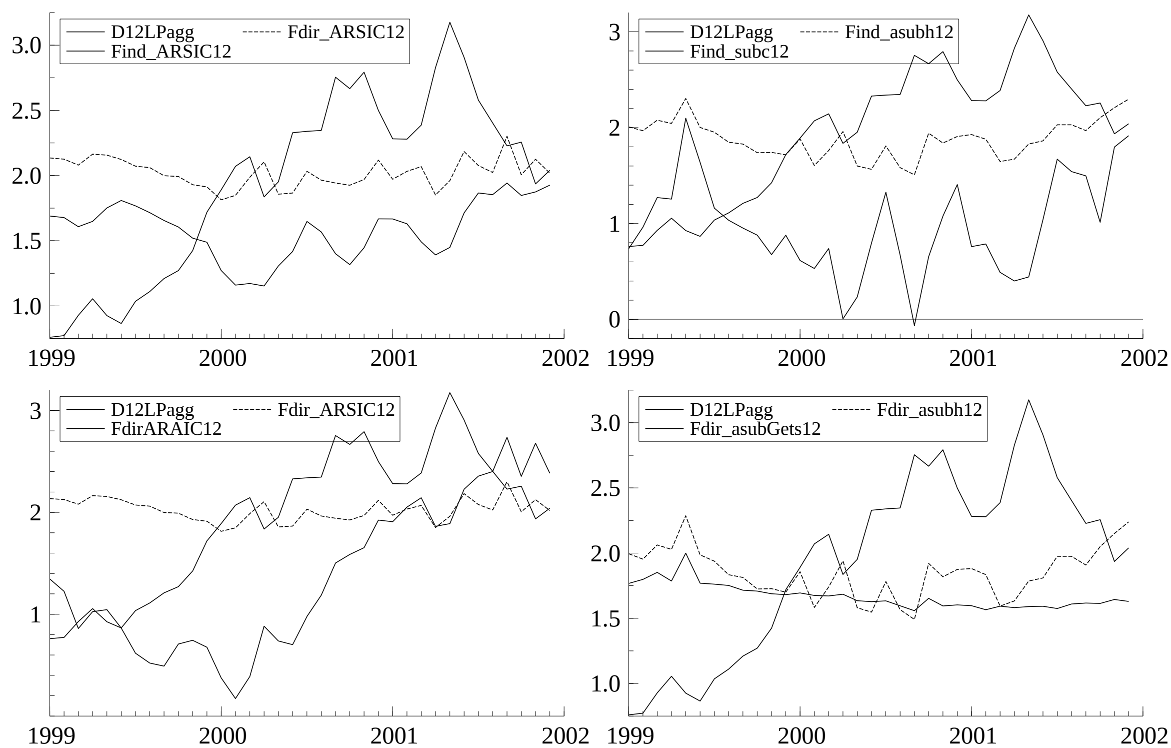

Figure 5: Euro area year-on-year inflation rate and forecasts in %, 12 months ahead, solid line: actual, Fdir: direct forecast of aggregate, Find: indirect forecast of aggregate

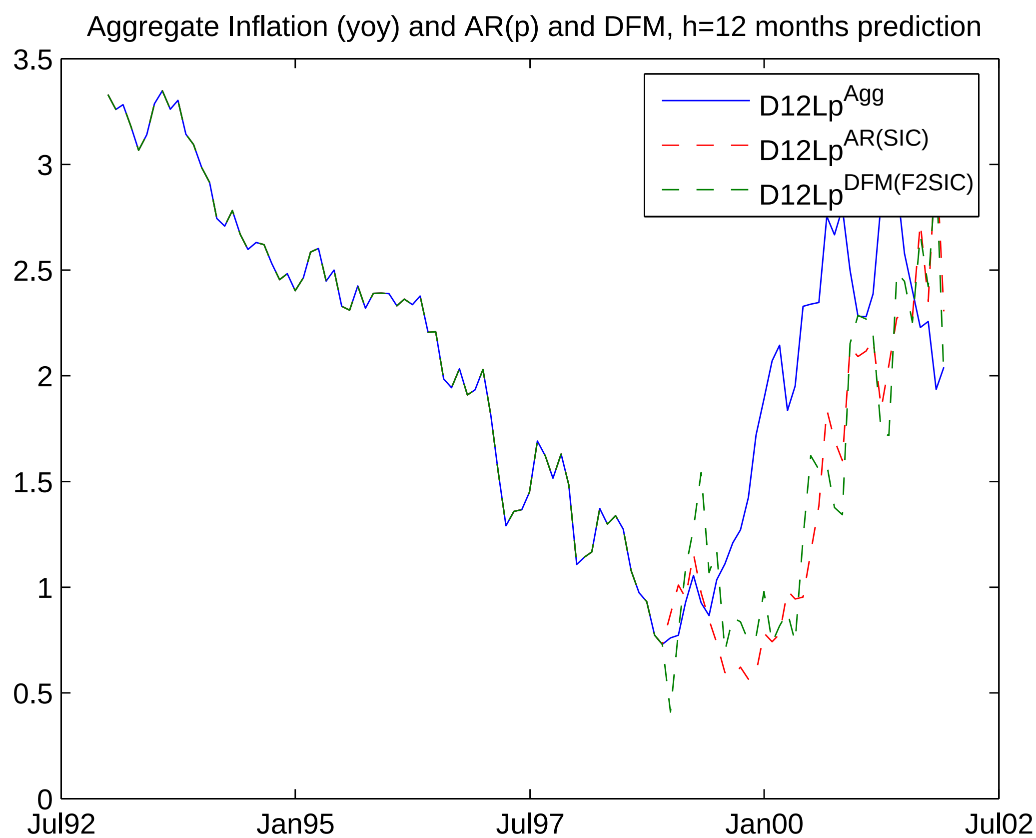

Figure 6: Euro area year-on-year inflation rate and forecasts in %, 12 months ahead, solid line: actual, slashed lines: Factor model and AR model forecast of the aggregate, sample 1990(1) - 2001(12)

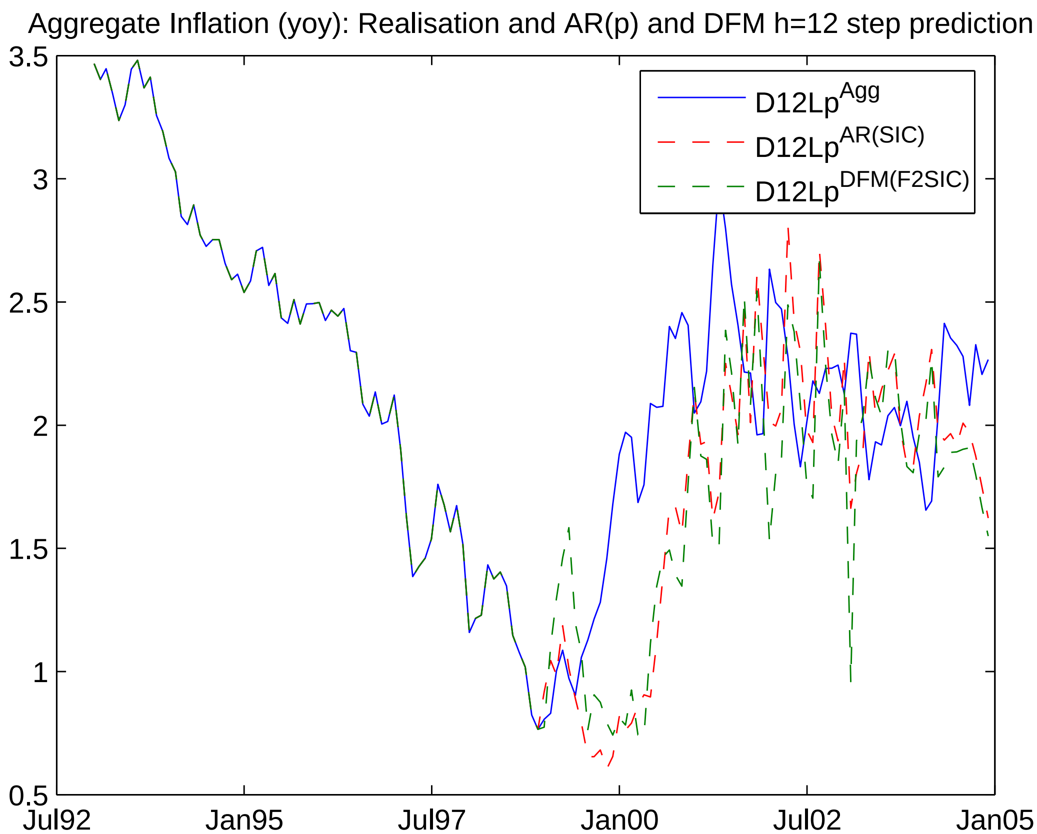

Figure 7: Euro area year-on-year inflation rate and forecasts in %, 12 months ahead, solid line: actual, slashed lines: Factor model and AR model forecast of the aggregate, sample 1990(1) - 2004(12)

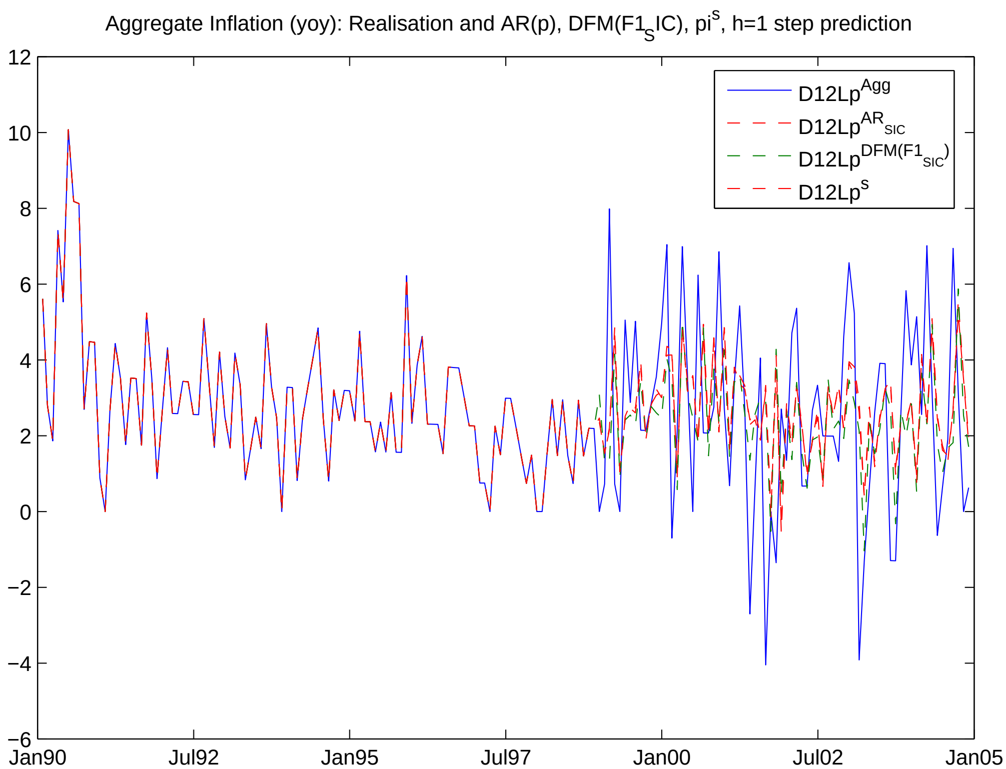

Figure 8: US year-on-year inflation rate and forecasts in %, 1 month ahead, solid line: actual, slashed lines: forecasts of the aggregate from factor and AR model and aggregate model including services prices, sample 1980(1)-2004(12)

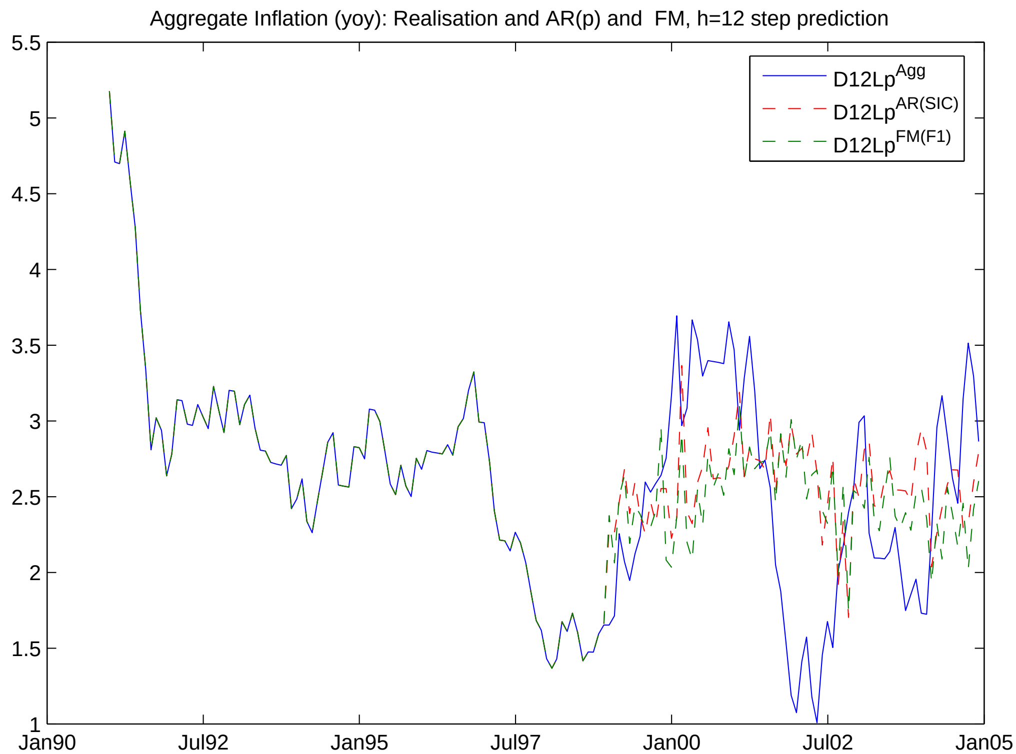

Figure 9: US year-on-year inflation rate and forecasts in %, 12 months ahead, solid line: actual, slashed lines: forecasts of the aggregate from factor and AR model and aggregate model including energy prices, sample: 1990(1)-2004(12)

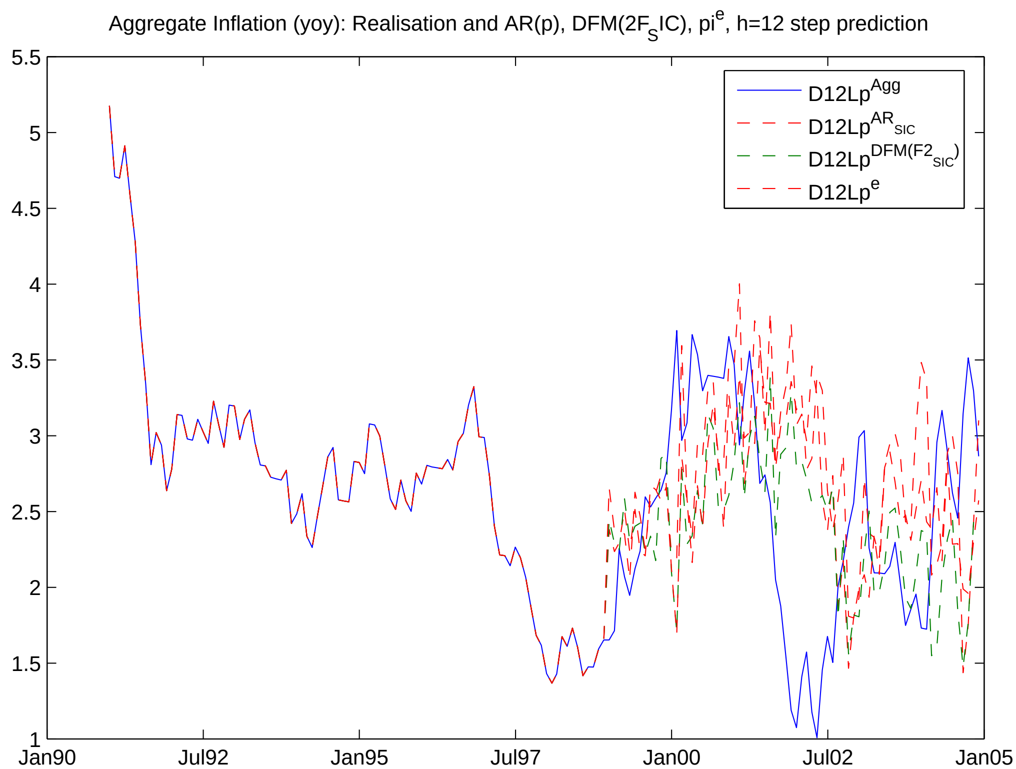

Figure 10: US year-on-year inflation rate and forecasts in %, 12 months ahead, solid line: actual, slashed lines: forecasts of the aggregate from factor and AR model and aggregate model including energy prices, sample 1980(1)-2004(12)

Table 1: **RMSFE of euro area year-on-year inflation in percentage points, Recursive estimation samples 1992(1) to 1998(1),...,2000(12)**

horizon	1		6		12	
method	direct $\Delta_{12}\widehat{p}^{agg}$	indirect $\Delta_{12}\widehat{p}^{agg}_{sub}$	direct $\Delta_{12}\widehat{p}^{agg}$	indirect $\Delta_{12}\widehat{p}^{agg}_{sub}$	direct $\Delta_{12}\widehat{p}^{agg}$	indirect $\Delta_{12}\widehat{p}^{agg}_{sub}$
AR^{SIC}	0.137	0.139	0.431	0.478	0.740	0.880
AR^{AIC}	0.139	0.141	0.404	0.478	0.921	0.904
VAR$^{sub}_{(2)}$		0.151		0.670		1.402
VAR$^{agg,sub}_{(0)}$	0.138	0.138	0.448	0.448	0.766	0.771
VAR$^{agg,sub}_{(1)}$	0.143	0.144	0.451	0.449	0.800	0.803
VAR$^{agg,sub}_{Gets}$	0.134	0.134	0.465	0.459	0.832	0.821
VAR$^{agg,i,s,pf}_{(1)}$	0.141		0.444		0.771	
VAR$^{agg,e,uf,pf}_{(1)}$	0.138		0.435		0.756	
VAR$^{agg,e,uf}_{(1)}$	0.138		0.439		0.762	

Note: super and subscripts indicate model selection procedure, SIC: Schwarz criterion, AIC: Akaike criterion, VAR^{sub}: VAR only including subcomponents, lag order, $p = 2$, VAR^{agg,sub}: VAR with aggregate and subcomponents $p = 0$ (SIC), $p = 1$ (AIC), VAR$^{agg,sub}_{Gets}$: VAR with aggregate and subcomponents selected by PcGets, liberal strategy Hendry & Krolzig (2001)

Table 2: **Correlation matrix of first differences of euro area log aggregate and subcomponent prices: upper triangle sample until 1998(1), lower triangle sample until 2001(12)**

	Δp^{agg}	Δp^{uf}	Δp^{pf}	Δp^{i}	Δp^{s}	Δp^{e}
Δp^{agg}	1	0.27931	0.43579	0.63135	0.70929	0.60797
Δp^{uf}	0.3229	1	-0.22429	-0.1362	-0.13113	0.036102
Δp^{pf}	0.34893	0.028023	1	0.41859	0.52704	0.0048911
Δp^{i}	0.53733	0.044988	0.28777	1	0.61273	0.085604
Δp^{s}	0.49376	-0.06515	0.51041	0.45057	1	0.10458
Δp^{e}	0.7071	0.0076403	-0.078966	0.039373	-0.06116	1

Table 3: **Euro area, RMSFE ratios of direct forecast of annualised inflation; Factor and single predictor models based on disaggregate prices; Sample up to 2001(12)**

horizon	1	6	12
RMSFE AR^{SIC}	0.183	0.404	0.779
RMSFE ratios over AR^{SIC}			
$FM(f1)$	1.028	1.113	1.093
$FM(f2)$	0.986	1.062	1.039
$FM(f3)$	1.056	1.038	1.045
$FM(f4)$	1.061	1.083	1.094
$DFM(f1)^{SIC}$	1.044	1.196	1.117
$DFM(f2)^{SIC}$	0.993	1.163	0.998
$DFM(f3)^{SIC}$	1.067	1.119	0.927
$DFM(f4)^{SIC}$	1.132	1.256	1.156
p^{uf}	0.995	0.960	0.955
p^{pf}	0.988	1.056	1.060
p^{i}	1.052	1.052	1.053
p^{s}	1.042	1.062	1.052
p^{e}	1.016	1.023	1.014
p^{comb}	1.010	1.016	1.018

Note: RMSFE (not annualised) for AR$^{(SIC)}$ model in percentage points, Recursive estimation samples 1992(1) to 1998(1),...,2000(12), Super and subscripts indicate model selection procedure, SIC: Schwarz criterion, pre-test: 5% sign. level, based on Newey-West adjusted heteroscedastic-serial consistent least-squares regression, FM(f): factor models with 1,2,3,4 factors, DFM(f)^{SIC}: dynamic factor models with 1,2,3,4 factors with factor lag lengths chosen by SIC, p^{uf}, p^{pf}, p^{i}, p^{s}, p^{e}: models with respective subcomponent as predictor, p^{comb}: simple average of the forecasts with the five disaggregate component models

Table 4: **Euro area, RMSFE ratios of direct forecast of annualised inflation; Factor and single predictor models based on euro area disaggregate prices; Sample up to 2004(12)**

horizon	1	6	12
RMSFE AR^{SIC}	0.149	0.328	0.562
RMSFE ratios over AR^{SIC}			
$FM(f1)$	1.055	1.077	1.067
$FM(f2)$	1.010	1.073	1.054
$FM(f3)$	1.129	1.107	1.111
$FM(f4)$	1.066	1.106	1.133
$DFM(f1)^{SIC}$	1.055	1.167	1.120
$DFM(f2)^{SIC}$	1.141	1.230	1.157
$DFM(f3)^{SIC}$	1.306	1.338	1.297
$DFM(f4)^{SIC}$	1.115	1.237	1.336
p^{uf}	1.006	0.964	0.997
p^{pf}	1.019	1.038	1.047
p^{i}	1.030	1.040	1.045
p^{s}	1.057	1.057	1.046
p^{e}	1.031	1.058	1.031
p^{comb}	1.013	1.016	1.021

Note: RMSFE (not annualised) for AR$^{(SIC)}$ model in percentage points , Recursive estimation samples 1992(1) to 1998(1),...,2003(12), Super and subscripts indicate model selection procedure, SIC: Schwarz criterion, pre-test: 5% sign. level, based on Newey-West adjusted heteroscedastic-serial consistent least-squares regression, FM(f): factor models with 1,2,3,4 factors, DFM(f)^{SIC}: dynamic factor models with 1,2,3,4 factors with factor lag lengths chosen by SIC, p^{uf}, p^{pf}, p^{i}, p^{s}, p^{e}: models with respective subcomponent as predictor, p^{comb}: simple average of the forecasts with the five disaggregate component models

Table 5: **US, RMSFE ratios of direct forecast of annualised inflation; Factor and single predictor models based on disaggregate prices; Sample 1990(1) to 2004(12)**

horizon	1	6	12
RMSFE AR^{SIC}	0.229	0.541	0.781
RMSFE ratios over AR^{SIC}			
$FM(f1)$	1.014	1.024	1.011
$FM(f2)$	1.000	1.054	1.049
$FM(f3)$	0.987	1.021	1.095
$DFM(f1)^{SIC}$	1.031	1.038	1.014
$DFM(f2)^{SIC}$	1.020	1.114	1.159
$DFM(f3)^{SIC}$	1.025	1.008	1.076
p^f	0.997	0.999	1.022
p^i	0.983	1.021	1.035
p^s	1.014	1.006	1.047
p^e	0.972	0.982	1.019
p^{comb}	0.969	0.989	1.015

Note: RMSFE (not annualised) for AR$^{(SIC)}$ model in percentage points, Recursive estimation samples 1990(1) to 1997(1),...,2003(12), Super and subscripts indicate model selection procedure, SIC: Schwarz criterion, pre-test: 5% sign. level, based on Newey-West adjusted heteroscedastic-serial consistent least-squares regression, FM(f): factor models with 1,2,3,4 factors, DFM(f)^{SIC}: dynamic factor models with 1,2,3,4 factors with factor lag lengths chosen by SIC, p^{comb} is a simple average of the forecasts with the four disaggregate component models

Table 6: **US, RMSFE ratios of direct forecast of annualised inflation; Factor and single predictor models based on disaggregate prices; Sample 1980(1) to 2004(12)**

horizon	1	6	12
RMSFE AR^{SIC}	0.230	0.623	0.978
RMSFE ratios over AR^{SIC}			
$FM(f1)$	1.010	0.923	0.888
$FM(f2)$	1.057	0.921	0.885
$FM(f3)$	1.042	0.940	0.926
$DFM(f1)^{SIC}$	0.928	0.879	0.802
$DFM(f2)^{SIC}$	1.038	0.880	0.765
$DFM(f3)^{SIC}$	0.965	0.926	0.891
p^f	1.002	0.982	0.944
p^i	1.006	0.978	0.985
p^s	0.989	0.937	0.921
p^e	1.011	0.930	0.886
p^{comb}	1.000	0.938	0.897

Note: RMSFE (not annualised) for AR$^{(SIC)}$ model in percentage points , Recursive estimation samples 1980(1) to 1997(1),...,2003(12), Super and subscripts indicate model selection procedure, SIC: Schwarz criterion, pre-test: 5% sign. level, based on Newey-West adjusted heteroscedastic-serial consistent least-squares regression, FM(f): factor models with 1,2,3,4 factors, DFM(f)^{SIC}: dynamic factor models with 1,2,3,4 factors with factor lag lengths chosen by SIC, p^{comb} is a simple average of the forecasts with the four disaggregate component models