A look into the factor model black box

Publication lags and the role of hard and soft data in forecasting GDP

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November 2006

Abstract

We derive forecast weights and uncertainty measures for assessing the role of individual series in a dynamic factor model (DFM) to forecast euro area GDP from monthly indicators. The use of the Kalman filter allows us to deal with publication lags when calculating the above measures. We find that surveys and financial data contain important information beyond the monthly real activity measures for the GDP forecasts. However, this is discovered only, if their more timely publication is properly taken into account. Differences in publication lags play a very important role and should be considered in forecast evaluation.
Keywords: dynamic factor models, forecasting, filter weights

JEL classification: E37, C53

*The authors would like to thank E. Angelini, G. Camba-Méndez, D. Giannone, and L. Reichlin for useful discussions. The paper was written while Marta Bańbura was affiliated with the European Central Bank. The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank.

1 Introduction

The first estimate of euro area quarterly GDP is released about six weeks after the end of the quarter. To assess macro-economic conditions, market participants meanwhile rely on data of higher frequency, among them financial series, surveys, and monthly data on real economic activity (e.g. industrial production). The former two categories reflect market expectations and are often labelled as 'soft' data, as opposed to the 'hard' indicators on real activity that directly measure certain components of GDP. The soft data are promptly available, while real activity data are published with a significant delay. Overall, the large number of the available indicators and their different release dates, which result in unbalanced data sets, make the efficient use of the information contained in the various indicators a difficult task. Put differently, it is not straightforward to attach appropriate weights to the individual indicators when producing a GDP forecast.[1]

Partly for these reasons, factor models have emerged as an interesting alternative for the short-term forecasting of real activity. In relating the individual indicators to a few latent factors, weights are implicitly attached to the former in a parsimonious way (e.g. Stock and Watson, 2002; Forni et al., 2003; Altissimo et al. 2006; Breitung and Schumacher, 2006). However, the *explicit* calculation of these weights, although straightforward for a static model and complete data, faces difficulties in a fully dynamic context with unbalanced data sets.

The lack of diagnostic statistics on the role of the individual series in the model forecasts is a general criticism of factor models. In this paper, we address this issue in the context of a dynamic factor model to forecast GDP from monthly indicators. First, we derive the weights of the series in the forecast and use them to calculate their contributions to the forecasts. Second, we assess the gains in forecast precision from certain series by inspecting the increase in forecast uncertainty once the series are removed from the data set. The statistics are provided by the Kalman filter apparatus. We use a factor model version based on Doz et al. (2005) and Giannone et al. (2005), which implements the common factors as unobserved components in a state space form. Factor dynamics is therefore modelled explicitly. In addition, the Kalman filter handles mixed data frequencies and unbalanced data sets in an efficient way. It is the combination of these features that allows us to assess the evolution of the forecast weights and forecast precision measures in a dynamic context with unbalanced data sets.

[1] We denote a data set as 'unbalanced' if the final observations of the individual series occur at different dates.

The measures may be of use to practitioners in application. In practice, forecasts from a single model are hardly ever used in isolation, but compared against other models and further anecdotal information. In addition, forecasters want to understand the reasons for differences in forecasts from different models and the sources of forecast revisions after new data releases. Both can be achieved from contribution analysis. Another potential use of our measures is model diagnostics. For instance, they may be useful when it comes to choosing the number of factors or fine-tuning the data set, as suggested by Bai and Ng (2006) and Boivin and Ng (2006).

We use these measures to investigate the role of real activity, survey and financial data in forecasting euro area GDP. Studies in general report that soft data contain little information beyond the real activity data, but they mostly use quarterly data or ignore publication lags (e.g. Rünstler and Sédillot, 2002; Forni et al., 2003; Stock and Watson, 2003; Banerjee et al., 2005). Exceptions to this rule are the studies by Giannone et al. (2005) and Hansson et al. (2005). Giannone et al. (2005) use a model-based uncertainty measure to assess the news content of data vintages that arrive within the month. They find the largest declines in uncertainty after the releases of surveys and financial data. Hansson et al. (2005) report that the inclusion of summary measures of survey data into VAR models improves out-of-sample forecasts, but they use a small data set and only quarterly data.

We are particularly interested in the effects of differences in publications lags on the contributions of the series. Similar to Altissimo et al. (2006), we use a pseudo real-time forecast design to replicate the information sets that are available in each month within the quarter. We then obtain a sequence of GDP forecasts from data vintages as from the individual months of the preceding, current and subsequent quarters.

The application shows that the inspection of forecast weights and model-based uncertainty measures can be very informative and provide insight into the model properties that can hardly be obtained from forecast errors. We find, for instance, that forecast weights are concentrated among a relatively small set of series and that they show substantial variation across different horizons. Most importantly, differences in publication lags have large effects on the contributions of hard and soft data to the forecasts. For a counterfactual balanced data set, we find - in line with other studies - that real activity data are the most important source of information. However, once their less timely publication is taken into account, the real activity data become much less relevant, while surveys take their place. Similarly, financial data gain importance in the latter case.

2 The model

Dynamic factor models (DFMs) are designed to explain the dynamics in a panel of series by a few common sources of variation. Consider a vector of n stationary monthly series $x_t = (x_{1,t}, \dots, x_{n,t})'$, $t = 1, \dots, T$, which have been standardised to mean zero and variance one. The DFM by Doz et al. (2005) is given by the equations

$$
\begin{aligned}
x_t &= \Lambda f_t + \xi_t, && \xi_t \sim \mathbb{N}(0, \Sigma_\xi), && (1)\\
f_t &= \sum_{i=1}^{p} A_i f_{t-i} + \zeta_t, && && (2)\\
\zeta_t &= B\eta_t, && \eta_t \sim \mathbb{N}(0, I_q).
\end{aligned}
$$

From a matrix of factor loadings Λ, equation (1) relates the monthly series x_t to a $r \times 1$ vector of latent factors $f_t = (f_{1,t}, \dots, f_{r,t})'$ plus an idiosyncratic component $\xi_t = (\xi_{1,t}, \dots, \xi_{n,t})'$. The latter is assumed to be multivariate white noise with diagonal covariance matrix Σ_ξ. Equation (2) describes the law of motion for the latent factors f_t, which are driven by q-dimensional standardised white noise η_t, where B is a $r \times q$ matrix, where $q \leq r$. Hence $\zeta_t \sim \mathbb{N}(0, BB')$. We assume that the stochastic process for f_t is stationary.

We extend on Doz et al. (2005) by combining the monthly factor model with a forecast equation for mean-adjusted quarterly GDP in a mixed-frequency approach (e.g. Mariano and Murasawa, 2003). For this purpose, we introduce the forecast of monthly GDP growth $\widehat{y}_t$ as a latent variable, which is related to the common factors by the static equation

$$\widehat{y}_t = \beta' f_t. \tag{3}$$

In the 3^{rd} month of each quarter, we evaluate the forecast for quarterly GDP growth, $\widehat{y}_t^Q$, as the quarterly average of the monthly series,[2]

$$\widehat{y}_t^Q = \frac{1}{3}(\widehat{y}_t + \widehat{y}_{t-1} + \widehat{y}_{t-2}) \tag{4}$$

and define the forecast error $\varepsilon_t^Q = y_t^Q - \widehat{y}_t^Q$. We assume that ε_t^Q is distributed with $\varepsilon_t^Q \sim \mathbb{N}(0, \sigma_\varepsilon^2)$. Innovations ξ_t, ζ_t, and ε_t^Q are assumed to be mutually independent at all leads and lags. This completes the description of the model.

[2] This aggregation rule implies that $\widehat{y}_t$ represents 3-month growth rates, i.e. growth rates vis-a-vis the same month of the previous quarter. It is suggested by the fact that equivalent transformations have been applied to monthly series x_t (see Appendix A). For aggregating monthly growth rates see Mariano and Murasawa (2003).

Equations (1) to (4) can be cast in state space form, which is illustrated below for the case of $p = 1$. To deal with the mixed frequencies, we construct a series y_t^Q at monthly frequency such that it contains mean-adjusted quarterly GDP growth in the 3^{rd} month of the respective quarter, whereas the remaining observations are treated as missing. The final row of observation equation (5), related to y_t^Q, is defined only for the 3^{rd} month of the quarter and otherwise is skipped in application (see section 3).

Aggregation rule (4) is implemented in a recursive way in equation (6), as from $\widehat{y}_t^Q = \Xi_t \widehat{y}_{t-1}^Q + \frac{1}{3}\widehat{y}_t$, where $\Xi_t = 0$ for t corresponding to the 1^{st} month of the quarter and $\Xi_t = 1$ otherwise (Harvey, 1989:309ff). As a result, expression (4) holds in the 3^{rd} month of each quarter. The inclusion of the GDP forecast in the state vector, $\alpha_t' = (f_t', \widehat{y}_t, \widehat{y}_t^Q)$, greatly facilitates the calculation of the various statistics discussed below.

$$\begin{bmatrix} x_t \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_t \\ \widehat{y}_t \\ \widehat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \xi_t \\ \varepsilon_t^Q \end{bmatrix} \tag{5}$$

$$\begin{bmatrix} I_r & 0 & 0 \\ -\beta' & 1 & 0 \\ 0 & -\frac{1}{3} & 1 \end{bmatrix} \begin{bmatrix} f_{t+1} \\ \widehat{y}_{t+1} \\ \widehat{y}_{t+1}^Q \end{bmatrix} = \begin{bmatrix} A_1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Xi_{t+1} \end{bmatrix} \begin{bmatrix} f_t \\ \widehat{y}_t \\ \widehat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \zeta_{t+1} \\ 0 \\ 0 \end{bmatrix} \tag{6}$$

The estimation of the model parameters $\theta = (\Lambda, A_1, \ldots, A_p, \beta, \Sigma_\xi, B, \sigma_\varepsilon^2)$ is discussed in Giannone et al. (2005). Briefly, Λ is estimated from static principal components analysis applied to a balanced sub-sample of data $\{x_s\}_{s=1}^T$. This also gives sample estimates of the common factors. The latter are used to estimate equation (2) and a quarterly version of (3) by standard regression techniques. Matrix B is estimated from principal components analysis applied to the estimated residuals $\widehat{\zeta}_t$.

3 Forecast weights and uncertainty with unbalanced data

In real-time application, data sets typically contain missing observations at the end of the sample due to publications lags. Moreover, the number of missing data differs across series due to the different timing of data releases. To obtain efficient forecasts of GDP growth y_t^Q from such unbalanced data sets, the Kalman filter and smoother recursions can be applied to the state space form (5) and (6).

In the recursive application of the model, we will account for publication lags by replicating the pattern of missing data that is found at the end of the sample. Let $z_t' = (x_t', y_t^Q)$ and consider a data set $\mathcal{Z}_T = \{z_s\}_{s=1}^T$ that has been downloaded on a certain day of the month. Define with $\mathcal{Z}_t = \{z_s\}_{s=1}^t$

the observations from the original data set $\mathcal{Z}_T$ up to period t, but with observation $z_{i,t-h}$, $h \geq 0$, eliminated, if observation $z_{i,T-h}$ is missing in $\mathcal{Z}_T$. That is, $\mathcal{Z}_t$ and $\mathcal{Z}_T$ have the same pattern of missing data with respect to period t and T, respectively.[3]

For our uncertainty measures, we will also inspect GDP forecasts based on certain subsets of indicators, for instance forecasts that ignore survey or financial data. For this, we assume that *all* observations of the respective series are unavailable. Formally, partition the vector of monthly series $x_t = (x_t^{1\prime}, \ldots, x_t^{j\prime}, \ldots, x_t^{m\prime})'$ into m subvectors x_t^j and let x_t^{-j} coincide with x_t but with all observations of x_t^j being treated as missing.

Further, let $z_t^{-j} = (x_t^{-j\prime}, y_t^Q)'$ and define data $\mathcal{Z}_t^{-j} = \left\{ z_s^{-j} \right\}_{s=1}^{t} \subset \mathcal{Z}_t$. Let $\mathcal{Z}_t^{-0} = \mathcal{Z}_t$.

For state space form

$$\begin{aligned} z_t &= W(\theta)\alpha_t + u_t, \qquad u_t \sim N(0, \Sigma_u(\theta)) \\ \alpha_{t+1} &= T_t(\theta)\alpha_t + v_t, \qquad v_t \sim N(0, \Sigma_v(\theta)), \end{aligned} \tag{7}$$

with fixed θ and any data set $\mathcal{Z}_t^{-j}$, $j = 0, \ldots, m$, the Kalman filter and smoother provide minimum mean square linear (MMSE) estimates $a_{t+h|t}^{-j}$ of the state vector and their precision, $P_{t+h|t}^{-j}$,

$$a_{t+h|t}^{-j} = \mathbb{E}\left[\alpha_{t+h} | \mathcal{Z}_t^{-j}\right] \tag{8}$$

$$P_{t+h|t}^{-j} = \mathbb{E}\left[a_{t+h|t}^{-j} - \alpha_{t+h}\right]\left[a_{t+h|t}^{-j} - \alpha_{t+h}\right]', \tag{9}$$

for $h > -t$. To handle missing observations, the rows in equation (7) corresponding to the missing observations in z_t are simply skipped when applying the recursions (Durbin and Koopman, 2003:92f).

We will consider three measures to investigate the role of individual series or groups of series in the GDP forecast $\widehat{y}_{t+h|t}^Q$ based on data $\mathcal{Z}_t$. Because $\widehat{y}_t^Q$ is an element of the state vector, α_t, these measures can be directly obtained from the Kalman smoother output in the 3^{rd} month of each quarter.

1. *Forecast weights and contribution analysis.* The weights of the individual observations in the estimates of the state vector can be obtained from an algorithm by Harvey and Koopman (2003). Again, weights can be calculated for an arbitrary information set with those weights

[3] Quarterly GDP growth requires a slightly different treatment, as it is published only once a quarter. For ease of notation we abstract from that in this section. Our empirical analysis will account for it.

related to missing data being set to zero. This allows expressing forecasts $a^{-j}_{t+h|t}$ as the weighted sum of available observations in $\mathcal{Z}^{-j}_t$,

$$a^{-j}_{t+h|t} = \sum_{k=0}^{t-1} \Omega^{-j}_k(t,h) z^{-j}_{t-k} \ , \tag{10}$$

with weights $\Omega^{-j}_k(t,h)$. Crucially, though the weights depend both on period t and the data set used, they are time-invariant for our definition of $\mathcal{Z}^{-j}_t$. More precisely, assuming a large enough t such that the Kalman filter has approached its steady state it holds approximately $\Omega^{-j}_k(t,h) = \Omega^{-j}_k(t+r,h)$ for $r > 0$. Hence, let $\Omega^{-j}_k(h) = \Omega^{-j}_k(t,h)$ for large enough t.[4]

For equations (5) and (6), the desired steady state weights $\omega_k(h)$ for the GDP forecast based on data $\mathcal{Z}_t$ are obtained from the final rows of matrices $\Omega_k(h)$, $k = 1, \ldots, t-1$, related to element $\widehat{y}^Q_{t+h}$ in the state vector. From the expression

$$\widehat{y}^Q_{t+h|t} = \sum_{k=0}^{t-1} \omega_k(h) z_{t-k} \ , \tag{11}$$

we can calculate the cumulative forecast weights $\sum_{k=0}^{t-1} \omega_{k,i}(h)$ for series i, where $\omega_{k,i}(h)$ is the ith element of $\omega_k(h)$, $i = 1, \ldots, n$. The contribution of series i to the forecast is calculated as $\sum_{k=0}^{t-1} \omega_{k,i}(h) z_{i,t-k}$.

2. *Filter uncertainty.* Giannone et al. (2005) have proposed to use filter uncertainty as a model-based uncertainty measure. From equation (5), the variance of the forecast error for y^Q_{t+h} can be decomposed into

$$\text{var}(\widehat{y}^{Q,-j}_{t+h|t} - y^Q_{t+h}) = \pi^{-j}_{t+h|t} + \sigma^2_\varepsilon \ , \tag{12}$$

where $\pi^{-j}_{t+h|t} = \text{var}(\widehat{y}^{Q,-j}_{t+h|t} - \widehat{y}^{Q,-j}_{t+h})$ represents the effect stemming from the uncertainty in forecasts $f^{-j}_{t+h|t}$ of the latent factors (see equations (3) and (4)). We denote $\pi^{-j}_{t+h|t}$ as filter uncertainty, as opposed to residual uncertainty σ^2_ε. For state space form (5) and (6), $\pi^{-j}_{t+h|t}$ is obtained from the corresponding element in $P^{-j}_{t+h|t}$.

We measure the marginal gain in forecast precision stemming from series x^j_t from the increase in $\pi^{-j}_{t+h|t}$ against $\pi_{t+h|t}$. That is, we consider the increase in filter uncertainty $\pi^{-j}_{t+h|t}$ from forecasts based on data $\mathcal{Z}^{-j}_t$, which exclude x^j_t, against $\pi_{t+h|t}$ based on the full data set $\mathcal{Z}_t$.

[4] Inspection of the Kalman filter recursion shows that both $\Omega^{-j}_k(t,h)$ and below matrices $P^{-j}_{t+h|t}$ do not depend on the observations. However, apart from parameters θ, they are affected by the pattern of missing observations, which influences the Kalman gain (Durbin and Koopman, 2001:92f).

With parameters θ being estimated from data $\mathcal{Z}_t$ in both cases, it can be shown that

$$\pi_{t+h|t}^{-j} = \pi_{t+h|t} + \mathrm{var}\left[\widehat{y}_{t+h|t}^{Q,-j} - \widehat{y}_{t+h|t}^{Q}\right] \ . \tag{13}$$

Hence, $\pi_{t+h|t}^{-j} \geq \pi_{t+h|t}$ and filter uncertainty necessarily increases when information is withdrawn. Again, measures $\pi_{t+h|t}^{-j}$ are time-invariant in the sense defined above.

3. *Recursive forecasts.* The model-based filter uncertainty measure ignores parameter uncertainty as it is conditional on a fixed value of parameters θ. To examine the robustness of our conclusions against the latter, we also run recursive forecasts from both data sets $\mathcal{Z}_t^{-j}$ and $\mathcal{Z}_t$. More precisely, for a certain sample $t = t_0, \ldots, T$, we obtain the forecasts $\widehat{y}_{t+h|t}^{Q}$ and $\widehat{y}_{t+h|t}^{Q,-j}$ from data $\mathcal{Z}_t$ and $\mathcal{Z}_t^{-j}$, respectively and compare the root mean squared errors from the two forecasts.

It should perhaps be stressed that, when evaluating either forecast uncertainty measure for data $\mathcal{Z}_t^{-j}$, we always use parameters θ as estimated from the full data $\mathcal{Z}_t$. In keeping θ fixed, we assess the gains in forecast precision from series x_t^j for the model as it stands. For diagnostic purposes, this has the advantage that the comparison is not blurred by potential changes to the factor structure. Re-estimating parameters θ for subsets of series may eliminate important dimensions of the data space and thereby change the factor loadings of the remaining series with unsystematic effects on uncertainty measures. Clearly, our diagnostic differs from model selection, for which θ would be re-estimated for any data set.

As to the timing of estimation, for the recursive forecasts we re-estimate θ in each period from data $\mathcal{Z}_t$. The forecast weights and filter uncertainty measures shown in section 4 are based on full sample estimates of θ.

4 Hard and soft data in forecasting euro area GDP

We apply the above forecast weights and uncertainty measures to investigate the role of real activity, survey and financial data in forecasting quarterly euro area GDP growth from the DFM presented in section 2. We will conduct forecasts based on different amounts of monthly information within the quarter and we will run counterfactual exercises to assess the effect of publication lags.

Our euro area data set ($\mathcal{Z}_T$) has been downloaded on 30, June 2006 and ranges back to the 1^{st} quarter of 1993. The data contain 76 monthly series, which are listed in the annex (Table A.1), together with publication lags and the data transformations applied to render them stationary. The real activity data ($\mathcal{R}_T$) contain 32 series, among them components of industrial production, retail sales, employment data, and BoP extra area trade values. As to survey data ($\mathcal{S}_T$), we use 22 series from the European Commission business, consumer, retail and construction surveys. The financial data ($\mathcal{F}_T$) comprise 22 series, including exchange and interest rates, equity price indices, and various raw material prices.

4.1 Publication lags and forecast design

Real activity data are subject to longer publication lags as compared to the soft data. The surveys and monthly averages of financial data are published right at the end of the respective month. In our data set from 30, June 2006, survey and financial data are therefore already available for June 2006. By contrast, the most important real activity series, industrial production and retail sales, are published about 6 to 8 weeks after the end of the month. They are therefore available only up to April 2006, being subject to a publication lag of two months. The employment and trade data are subject to even longer delays.

To construct the monthly data sets for our recursive forecasts, we proceed as described in section 3. Starting from our original data, $\mathcal{Z}_T$, we re-construct the data sets $\mathcal{Z}_t$, which have been available in earlier periods $t < T$, by shifting the pattern of publication lags embodied in $\mathcal{Z}_T$ recursively back in time. That is, observation $z_{i,t-h}$, $h \geq 0$ is eliminated in $\mathcal{Z}_t$, if and only if observation $z_{i,T-h}$ is missing in $\mathcal{Z}_T$.[5]

Our *main* data set uses the original pattern of publication lags as from 30, June 2006. To see the effect of publication lags on our forecast and uncertainty measures, we will also consider two alternative artificial data sets with reduced publications lags in $\mathcal{R}_T$. In the *extended* data set we reduce the publication lag in all real activity series by one month. This corresponds roughly to the situation that would prevail at around 20, July. In our *balanced* data set, we assume a publication lag of zero for all series. Such balanced data are often used in forecast evaluation studies.[6]

[5] Our approach differs from a perfect real-time design only insofar as data revisions are ignored. Such real-time data are not yet available for the euro area.

[6] Industrial production and retail sales data for May have been released on 18, July. However, the release dates of employment and trade data vary over time. Since we want to assess the role of publication lags, we prefer to use an artificial data set rather than the actual data from 18, July. This has also the advantage that the effects of possible revisions of backdata are excluded.

We now turn to our forecast design. We inspect seven forecasts of GDP growth in a given quarter obtained in consecutive months. We start with forecasting in the 1^{st} month of the preceding quarter and stop in the 1^{st} month of the subsequent quarter, 3 weeks before the first estimate of GDP is released by Eurostat. For example, for the 2^{nd} quarter of the year, we start forecasting in January and stop in July. We index the forecasts according to the period at which the forecast is produced. We will denote the forecasts done between January and March as the *preceding quarter forecast (Q(-1) M1 - Q(-1) M3)*, the forecasts done between April and June as *current quarter* forecasts or *nowcasts* (*Q(0) M1 - Q(0) M3*), and the final one in July as *backcast (Q(+1) M1)*.

As to the model specification, we follow Altissimo et al. (2006) and use values of $r = 5$ and $q = 2$ for the number of latent factors and common innovations, respectively, and $p = 2$ lags in equation (2). Using a slightly extended data set, Altissimo et al. (2006) report a good forecast performance of the dynamic factor model compared to other forecasting tools used at the European Central Bank.

4.2 Forecast weights

We start with the results on forecast weights and contributions. Chart 1 shows the evolution of the cumulative forecast weights, $\sum_{k=0}^{t-1} \omega_{k,i}(h)$ for each series over the sequence of the seven forecasts.[7] For the various data sets, separate plots are shown of the weights of real activity, survey and financial data. Charts A.1 to A.3 in the annex display the 30 series with the highest absolute weights for the forecasts done in the 1^{st} month of each quarter.

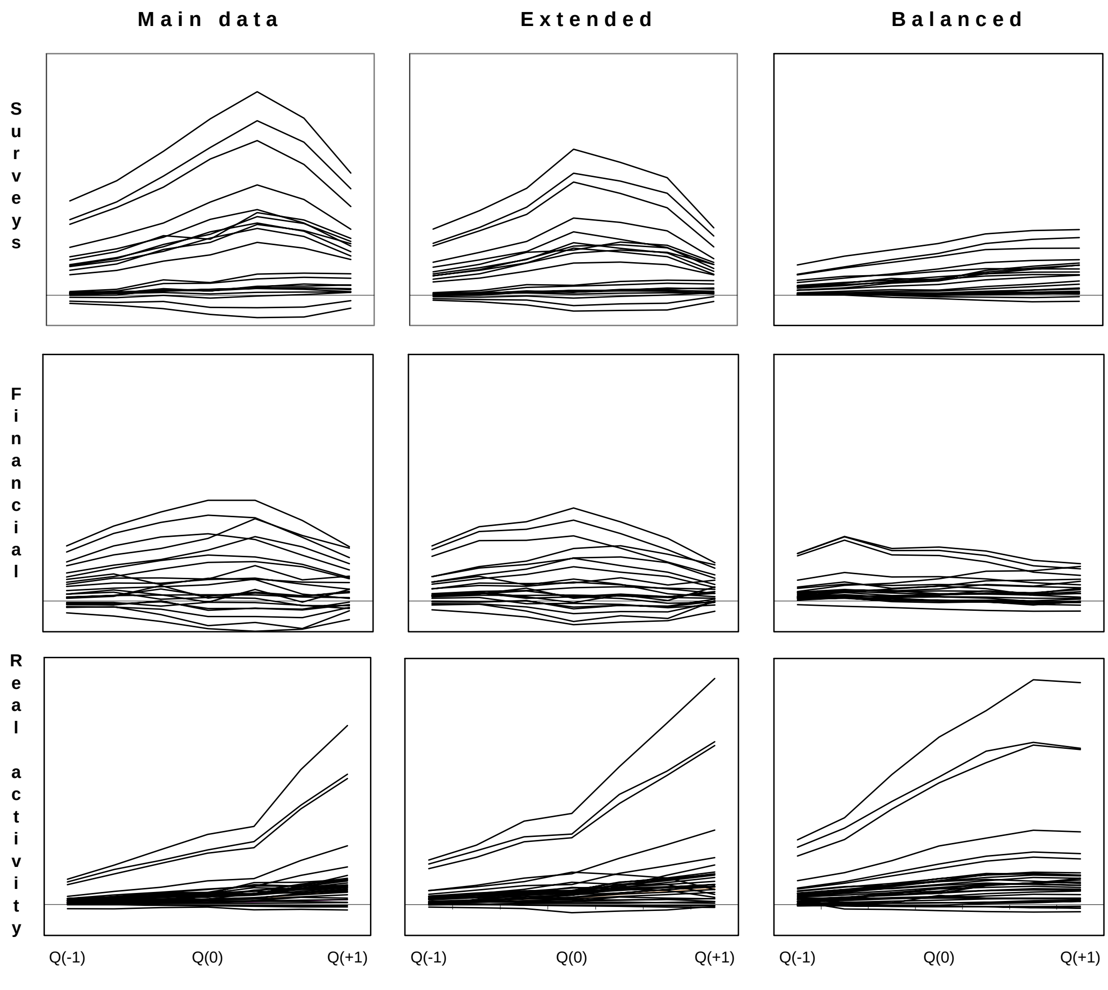
A few patterns stand out: first, the forecast weights are concentrated among a rather limited number of series. For the main data set, the 20 indicators with the highest weights account for about 75% of the overall sum of weights. These series mostly represent the forward-looking items of business surveys, such as overall confidence, orders, export orders and production expectations; among financial data, various measures of the euro area effective exchange rate (EER) and short-term interest rates; and, among the real activity data, the broad measures of industrial production (see Chart A.1). Many of these indicators show high mutual correlations within the groups and are in some cases almost identical by definition. This applies, for instance, to the three series related to the EER or to the main industrial production series. It seems a plausible outcome of factor models that highly correlated series are altogether attached either high or low weights, because they would

[7] The cumulative weights give the cumulative impact of current and past values of the indicator to the forecast.

attain similar factor loadings.

Second, the weights of the hard and soft data evolve in very different ways over the forecast horizon. Note that the stationarity of the model implies that the weights would tend to decline as the forecast horizon increases and eventually converge to zero for large horizons. The weights of real activity data do follow this pattern, but the weights of most of the survey and financial data peak at forecasts Q(0) and decline for very short horizons. As a result, the weights of real activity data relative to the soft data are very low at longer horizons, but they gain considerable importance for shorter horizons. For the backcast Q(+1) M1, the three main industrial production series rank first.

Chart 1: Cumulative forecast weights across data sets



Third, eliminating the publication lags in the real activity data has strong effects on the forecast weights. For the balanced data set, in particular, the weights of survey data drop sharply against the main data set, while the weights of financial data are less affected. This drop is aligned with increases in the weights of real activity data. The main industrial production series now attain the highest weights over the entire horizon (Chart A.3).

These patterns are mirrored in the contributions of the data groups to the recursive forecasts. Table 1 reports the mean absolute value of contributions (MACs) from the three data groups to the forecasts, evaluated over the period from 1998 Q1 to 2005 Q4. For the main data set, surveys yield uniformly the highest MAC at all horizons with a relative MAC of more than 50%. Financial data come next, but their relative MACs decline for shorter horizons. The MACs from real activity are small and increase only for the very short horizons, Q(0) M3 and Q(+1) M1, when observations on industrial production for the relevant quarter become available.

Table 1: Mean absolute contributions (MAC) of data groups

(1998 Q1 - 2005Q4)

Data	Main				Extended				Balanced			
	Fcst	Contributions (%)			Fcst	Contributions (%)			Fcst	Contributions (%)		
	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$
Q(-1) M1	0.158	60 %	57 %	14 %	0.156	51 %	53 %	23 %	0.135	34 %	46 %	46 %
Q(-1) M2	0.183	58 %	57 %	15 %	0.176	52 %	54 %	21 %	0.163	32 %	46 %	44 %
Q(-1) M3	0.196	61 %	56 %	16 %	0.190	50 %	54 %	25 %	0.192	28 %	42 %	49 %
Q(0) M1	0.227	62 %	50 %	16 %	0.222	56 %	47 %	20 %	0.188	34 %	40 %	48 %
Q(0) M2	0.245	63 %	42 %	17 %	0.222	51 %	40 %	28 %	0.199	35 %	35 %	47 %
Q(0) M3	0.230	61 %	37 %	25 %	0.215	50 %	35 %	34 %	0.206	35 %	29 %	52 %
Q(+1) M1	0.210	53 %	35 %	32 %	0.202	38 %	31 %	48 %	0.200	37 %	29 %	50 %

Column Fcst shows the mean absolute values of the forecasts for mean-adjusted GDP. The remaining columns show the percentage values of the respective contributions of the 3 data groups, real activity (R), survey (S), and financial data (F) to Fcst. The sum of the percentage values of the MACs across data groups exceeds one, because in some periods contributions are of conflicting signs.

For our artificial data sets, real activity data become substantially more important. For the balanced data set, in particular, the MACs from real activity surpass those from the survey and financial data at all horizons. The increases occur mostly at the expense of survey data, with their MACs being about halved, while the declines are more moderate for financial data. The recursive forecasts from the main and balanced data sets, together with the contributions, are plotted in Charts A.4 and A.5.

4.3 Uncertainty measures

The marginal gains in forecast precision that stem from the individual data groups can be assessed from the filter uncertainty measure, $\sqrt{\pi^{-j}_{t+h|t}}$, which is shown in Table 2. Note, first, that filter uncertainty declines markedly for the shorter horizons, as the information set expands. As discussed in section 3, the marginal gains are measured from the increase in filter uncertainty, once the respective group is eliminated from the data set.

Table 2: Filter uncertainty

(Full-sample parameter estimates)

	Main				Extended				Balanced			
	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$
Q(-1) M1	.178	.185	.182	178	.178	.184	.179	.178	.176	.180	.176	178
Q(-1) M2	.160	.172	.166	.160	.159	.170	.162	.160	.158	.165	.158	.160
Q(-1) M3	.137	.152	.145	.138	.137	.150	.140	.138	.135	.143	.135	.138
Q(0) M1	.100	.112	.119	.100	.099	.110	.111	.100	.091	.097	.091	.100
Q(0) M2	.070	.078	.100	.071	.064	.071	.076	.071	.056	.060	.056	.071
Q(0) M3	.037	.042	.068	043	.030	.034	.045	.043	.021	.023	.023	.043
Q(+1) M1	.029	.033	.043	042	.020	.023	.022	.042	.020	.023	.022	.042

The findings from the filter uncertainty measure are largely in line with those from the forecast weights. For our main data set, they indicate a dominance of survey against real activity data, apart from the very short horizons, and moderate marginal gains from financial data for the preceding quarter forecasts Q(-1). Real activity series $\mathcal{R}$ hardly add to forecast precision. Their removal (compare data $\mathcal{SF}$ against $\mathcal{Z}$) has negligible effects on filter uncertainty, although with the exception of the nowcast Q(0) M3 and the backcast Q(+1) M1. The removal of survey data (see data $\mathcal{RF}$), in turn, induces increases in uncertainty over the entire horizon, although the latter are small for forecasts Q(-1). The removal of financial data (see data $\mathcal{RS}$) results in moderate increases in the uncertainty of forecasts Q(-1).[8]

In case of the balanced data set, the role of surveys and real activity data is turned on its head. The latter now dominate surveys at all horizons. Forecast uncertainty generally declines as the information from real activity data expands. However, the removal of survey data now has hardly any effect on filter uncertainty, while the removal of real activity does increase uncertainty. Financial data continue to contribute to forecast precision, but to a lesser extent compared to the main data.

[8]Results for the single groups $\mathcal{R}, \mathcal{S}$,and $\mathcal{F}$ are in line with the reported patterns. They are available upon request.

The results for the recursive forecasts, shown in Table 3, should be read with some caution given the short evaluation sample. Note that, with minor exceptions, eliminating data does not improve on the forecasts from the full data $\mathcal{Z}$. The comparison of the filter uncertainty and RMSE measures shows that filter uncertainty constitutes a minor element in the overall forecast uncertainty. This underlines the need to use filter uncertainty measures as a diagnostic tool rather than as a model selection statistics. The table also reports the RMSE from a quarterly autoregressive model for GDP, which is clearly outperformed by the factor model.

Table 3: RMSE from recursive forecasts

(1998 Q1 - 2005Q4)

	AR	Main				Extended				Balanced			
		$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$
Q(-1) M1	.38	.33	37	.32	.33	.33	.36	.31	.33	.33	.35	.32	.33
Q(-1) M2	.35	.32	.36	.31	.32	.31	.36	.30	.32	.31	.33	.31	.32
Q(-1) M3	.35	.28	.33	.29	.28	.28	.31	.27	.28	.28	.30	.29	.28
Q(0) M1	.35	.28	.30	.30	.28	.27	.29	.27	.28	.26	.27	.26	.28
Q(0) M2	.31	.28	31	.29	.28	.26	.29	.26	.28	.25	.26	.24	.28
Q(0) M3	.31	.25	.28	.27	.27	.24	.26	.24	.27	.24	.25	.24	.27
Q(+1) M1	.31	.24	.25	.24	.27	.23	.24	.23	.27	.23	.24	.23	.27

The table shows the root mean squared error of the recursive forecasts from the various subgroups. AR denotes the recursive forecasts from a quarterly first-order autoregression for GDP. The step decreases in the RMSE from the AR forecasts occur in the 2^{nd} month of the quarter, reflecting the publication of GDP data.

Overall, the results broadly support the findings from the filter uncertainty measure. One difference in the RMSE compared to the filter uncertainty measure is a somewhat less important role for survey data against the real activity data. In the main data set, data $\mathcal{RF}$ and $\mathcal{SF}$ now fare about equally well, while $\mathcal{RF}$ tends to outperform $\mathcal{SF}$ in the extended and balanced data sets.

However, while the above results on forecast weights and filter uncertainty are reasonably stable across sub-samples and robust to changes in the model specification, this holds less so for the RMSE measure. For the latter, alternative specifications actually restore the dominance of survey against the real activity data in the main data set. Tables A.2 in the annex present results for three alternative specifications, with the numbers of common factors and common shocks (r, q) set to values of $(3, 2)$, $(8, 2)$, and $(8, 4)$, respectively. Generally, the alternative specifications fare slightly worse, but the RMSE increases more strongly for data $\mathcal{RF}$. As a result, again, the removal of real activity data has little effect on the RMSE measure, whereas the removal of survey data results in larger losses.

5 Conclusions

This paper has proposed various statistics to investigate the role of individual series and groups of series, respectively, in forecasts from a dynamic factor model. The statistics can be obtained once the latent factors are modelled as unobserved components in a state space framework. In this case, the Kalman filter apparatus yields forecast weights and allows for an analysis of the marginal gains in forecast precision stemming from certain groups of series. Crucially, the Kalman filter also provides efficient forecasts in case of unbalanced data sets, as they arise in short-term forecasting due to the different timing of data releases. As another advantage, parameters need not be re-estimated when applying the model to reduced data sets. Hence, sharper results can be obtained as compared to conventional evaluation exercises, which use sample measures of forecast precision.

We have used the measures to investigate the role of real activity data, surveys, and financial data for the nowcasting and short-term forecasting of euro area GDP from monthly data. We find that both forecast weights and forecast precision measures attribute an important role to survey data, whereas real activity data attain rather low weights, apart perhaps from the backcasts. Moreover, financial data provide complementary information to both real activity and survey data for nowcasts and one quarter-ahead forecasts of GDP.

However, these patterns are discovered only, once publication lags are properly accounted for. Indeed, for a counter-factual balanced data set, as often used in forecast evaluation exercises, real activity data appear as the most important source of information. With real activity data and surveys containing similar information, the forecast weights from the latter would decline strongly, while their contribution to forecast precision almost vanishes. Similarly, the weights of financial data would decline, although to a lesser extent.

We, hence, find that differences in the timeliness of data releases can have strong effects on the weights of individual series in the forecast and on their contribution to forecast precision. This suggests that high attention should be paid in forecast evaluation exercises to the precise information set that is available in real time. In this sense, our findings are also relevant for the adaptation of variable selection methods in factor models, as, e.g., those suggested by Bai and Ng (2006) to a dynamic context. Indeed, it might be the failure to account for differences in publication lags, which results in the predominant role attributed to real activity data in many applications of so-called bridge equations to forecast GDP from monthly data (e.g. Rünstler and Sédillot, 2002; Baffigi et al., 2004). Similarly, while studies have concluded that financial data contribute little to short-term forecasts of real activity (e.g. Stock and Watson, 2003; Forni et al., 2003), again their results are based on balanced data sets.

One question that we could not address with our data set is the role of subsequent revisions to the initial releases of real activity data. The larger noise component in the initial data releases may shift the evidence even further towards soft data. However, the findings of Diron (2006) suggest that this effect is very limited.

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Table A.1: Data

No.	Name	Series	Group	Publ lag (mon)	Transf code
1	Trade Intra12 X	Total trade - Intra Euro 12 trade, Export Value	R	2	2
2	Trade Extra12 X	Total trade - Extra Euro 12 trade, Export Value	R	2	2
3	Trade Intra12 M	Total trade - Intra Euro 12 trade, Import Value	R	2	2
4	Trade Extra12 M	Total trade - Extra Euro 12 trade, Import Value	R	2	2
5	Retail vol	Retail trade, except of motor vehicles and motorcycles	R	2	2
6	IP total	IP-Total industry	R	3	2
7	IP x cns	IP-Total Industry (excl construction)	R	2	2
8	IP manuf	IP-Manufacturing	R	2	2
9	IP cns	IP-Construction	R	3	2
10	IP x ce	IP-Total Industry excl construction and MIG Energy	R	2	2
11	IP energy	IP-Energy	R	2	2
12	IP capital	IP-MIG Capital Goods Industry	R	2	2
13	IP D con	IP-MIG Durable Consumer Goods Industry	R	2	2
14	IP MIG energy	IP-MIG Energy	R	6	2
15	IP IM goods	IP-MIG Intermediate Goods Industry	R	2	2
16	IP ND con	IP-MIG Non-durable Consumer Goods Industry	R	2	2
17	IP metals	IP-Manufacture of basic metals	R	2	2
18	IP chemicals	IP-Manufacture of chemicals and chemical products	R	2	2
19	IP electric	IP-Manufacture of electrical machinery and apparatus	R	2	2
20	IP machinery	IP-Manufacture of machinery and equipment	R	2	2
21	IP paper	IP-Manufacture of pulp, paper and paper products	R	2	2
22	IP plastic	IP-Manufacture of rubber and plastic products	R	2	2
23	New cars	New passenger car registrations	R	1	2
24	URX	Unemployment rate, total	R	2	3
25	Empl cnstr	Index of Employment, Construction	R	3	2
26	Empl manuf	Index of Employment, Manufacturing	R	3	2
27	Empl total	Index of Employment, Total Industry	R	3	2
28	Empl x cnstr	Index of Employment, Total Industry (excluding construction)	R	3	2
29	US URX	US, Unemployment rate	R	1	1
30	US IP	US, IP total excl construction	R	1	2
31	US empl	US, Employment, civilian	R	1	2
32	US retail vol	US, Retail trade	R	1	2
33	Surv Bus conf	Industry Survey: Industrial Confidence Indicator	S	0	1
34	Surv Bus prod rec	Industry Survey: Production trend observed in recent months	S	0	1
35	Surv Bus Orders	Industry Survey: Assessment of order-book levels	S	0	1
36	Surv Bus X orders	Industry Survey: Assessment of export order-book levels	S	0	1
37	Surv Bus ret stocks	Industry Survey: Assessment of stocks of finished products	S	0	1
38	Surv Bus prod exp	Industry Survey: Production expectations for the months ahead	S	0	1
39	Surv Bus emp exp	Industry Survey: Employment expectations for the months ahead	S	0	1
40	Surv Con conf	Consumer Survey: Consumer Confidence Indicator	S	0	1
41	Surv Con last 12m	Consumer Survey: General economic situation over last 12 months	S	0	1
42	Surv Con next 12m	Consumer Survey: General economic situation over next 12 months	S	0	1
43	Surv Con URX exp	Consumer Survey: Unemployment expectations over next 12 months	S	0	1
44	Surv Cns conf	Construction Survey: Construction Confidence Indicator	S	0	1
45	Surv Cns prod rec	Construction Survey: Trend of activity compared with preceding months	S	0	1
46	Surv Cns orders	Construction Survey: Assessment of order books	S	0	1
47	Surv Cns emp exp	Construction Survey: Employment expectations for the months ahead	S	0	1
48	Surv Ret conf	Retail Trade Survey: Retail Confidence Indicator	S	0	1
49	Surv Ret current	Retail Trade Survey: Present business situation	S	0	1
50	Surv Ret stocks	Retail Trade Survey: Assessment of stocks	S	0	1
51	Surv Ret prod exp	Retail Trade Survey: Expected business situation	S	0	1
52	Surv Ret emp exp	Retail Trade Survey: Employment expectations	S	0	1
53	US prod exp	US, Production expectations in manufacturing	S	0	1
54	US con exp	US, Consumer expectations index	S	0	1
55	NEER	ECB Nominal effective exch. rate	F	0	2
56	REER CPI	ECB Real effective exch. rate CPI deflated	F	0	2
57	REER PPI	ECB Real effective exch. rate producer prices deflated	F	0	2
58	USD	Exch. rate: USD/EUR	F	0	2
59	GBP	Exch. rate: GBP/EUR	F	0	2
60	YEN	Exch. rate: YEN/EUR	F	0	2
61	Raw mat prices	World market prices of raw materials in Euro, total, HWWA	F	0	2
62	Raw mat prices x oil	World market prices of raw materials in Euro, total, excl energy, HWWA	F	0	2
63	Oil price	World market prices, crude oil, USD, HWWA	F	1	2
64	Gold price	Gold price, USD, fine ounce	F	0	2
65	Oil 1m fwd	Brent Crude, 1 month fwd, USD/BBL converted in euro	F	0	2
66	Euro500	Eurostoxx 500	F	0	2
67	Euro325	Eurostoxx 325	F	0	2
68	US SP500	US S&P 500 composite index	F	0	2
69	US DowJ	US, Dow Jones, industrial average	F	0	2
70	US 3m	US, Treasury Bill rate, 3-month	F	0	1
71	US 10-year	US Treasury notes & bonds yield, 10 years	F	0	1
72	10-year	10-year government bond yield	F	0	1
73	3-mon	3-month interest rate, Euribor	F	0	1
74	1-year	1-year government bond yield	F	0	1
75	2-year	2-year government bond yield	F	0	1
76	5-year	5-year government bond yield	F	0	1

Transformation code: 1 = 3-month difference, 2 = 3-month growth rate, 3 = annual difference of 3-mon difference

Table A.2.1: Mean absolute contributions

Alternative specifications for the main data set

(1998 Q1 - 2005Q4)

Data	(r=3, q=2)				(r=8, q=2)				(r=8, q=4)			
	Fcst	Contributions (%)			Fcst	Contributions (%)			Fcst	Contributions (%)		
	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$	$\mathcal{Z}$	$\mathcal{S}$	$\mathcal{F}$	$\mathcal{R}$
Q(-1) M1	0.143	65 %	56 %	5 %	0.144	65 %	47 %	17 %	0.168	70 %	48 %	12 %
Q(-1) M2	0.170	65 %	55 %	7 %	0.167	67 %	51 %	17 %	0.186	64 %	57 %	13 %
Q(-1) M3	0.183	68 %	57 %	9 %	0.182	68 %	50 %	17 %	0.208	57 %	60 %	14 %
Q(0) M1	0.214	62 %	46 %	11 %	0.225	67 %	45 %	16 %	0.231	59 %	58 %	15 %
Q(0) M2	0.218	63 %	40 %	13 %	0.248	74 %	51 %	18 %	0.225	67 %	59 %	19 %
Q(0) M3	0.207	62 %	36 %	20 %	0.241	65 %	49 %	26 %	0.209	63 %	53 %	30 %
Q(+1) M1	0.200	53 %	33 %	30 %	0.223	47 %	43 %	37 %	0.179	44 %	44 %	51 %

Table A.2.2: Filter uncertainty

Alternative specifications for the main data set

(Full-sample parameter estimates)

	(r=3, q=2)				(r=8, q=2)				(r=8, q=4)			
	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$
Q(-1) M1	.187	.192	.189	.187	.177	.179	.179	.178	.211	.220	.213	.211
Q(-1) M2	.167	.176	.171	.167	.171	.173	.174	.171	.191	.203	.194	.191
Q(-1) M3	.141	.155	.147	.141	.159	.162	.164	.159	.166	.178	.172	.166
Q(0) M1	.095	.115	.109	.095	.122	.130	.136	.122	.126	.135	.143	.127
Q(0) M2	.059	.079	.077	.059	.085	.097	.108	.085	.095	.101	.124	.096
Q(0) M3	.030	.048	.049	.033	.042	.056	.069	.048	.057	.064	.087	.067
Q(+1) M1	.027	.036	.037	.032	.034	.043	.047	.045	.044	.050	.059	.063

Table A.2.3: RMSE from recursive forecasts

Alternative specifications for the main data set

(1998 Q1 - 2005Q4)

	AR	(r=3, q=2)				(r=8, q=2)				(r=8, q=4)			
		$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$	$\mathcal{Z}$	$\mathcal{RS}$	$\mathcal{RF}$	$\mathcal{SF}$
Q(-1) M1	.38	.33	.36	.35	.34	.34	.38	.34	.34	.36	.38	.35	.36
Q(-1) M2	.35	.33	.36	.34	.34	.33	.35	.34	.33	.34	.37	.34	.34
Q(-1) M3	.35	.30	.32	.32	.30	.30	.32	.33	.30	.29	.35	.32	.29
Q(0) M1	.35	.29	.30	.34	.30	.29	.30	.36	.30	.27	.33	.34	.28
Q(0) M2	.31	.29	.29	.31	.30	.30	.30	.35	.31	.27	.33	.34	.28
Q(0) M3	.31	.26	.27	.28	.28	.27	.30	.30	.30	.28	.31	.29	.30
Q(+1) M1	.31	.25	.24	.25	.27	.24	.25	.25	.29	.25	.27	.25	.28

Chart A.1: Absolute cumulative weights

Main data

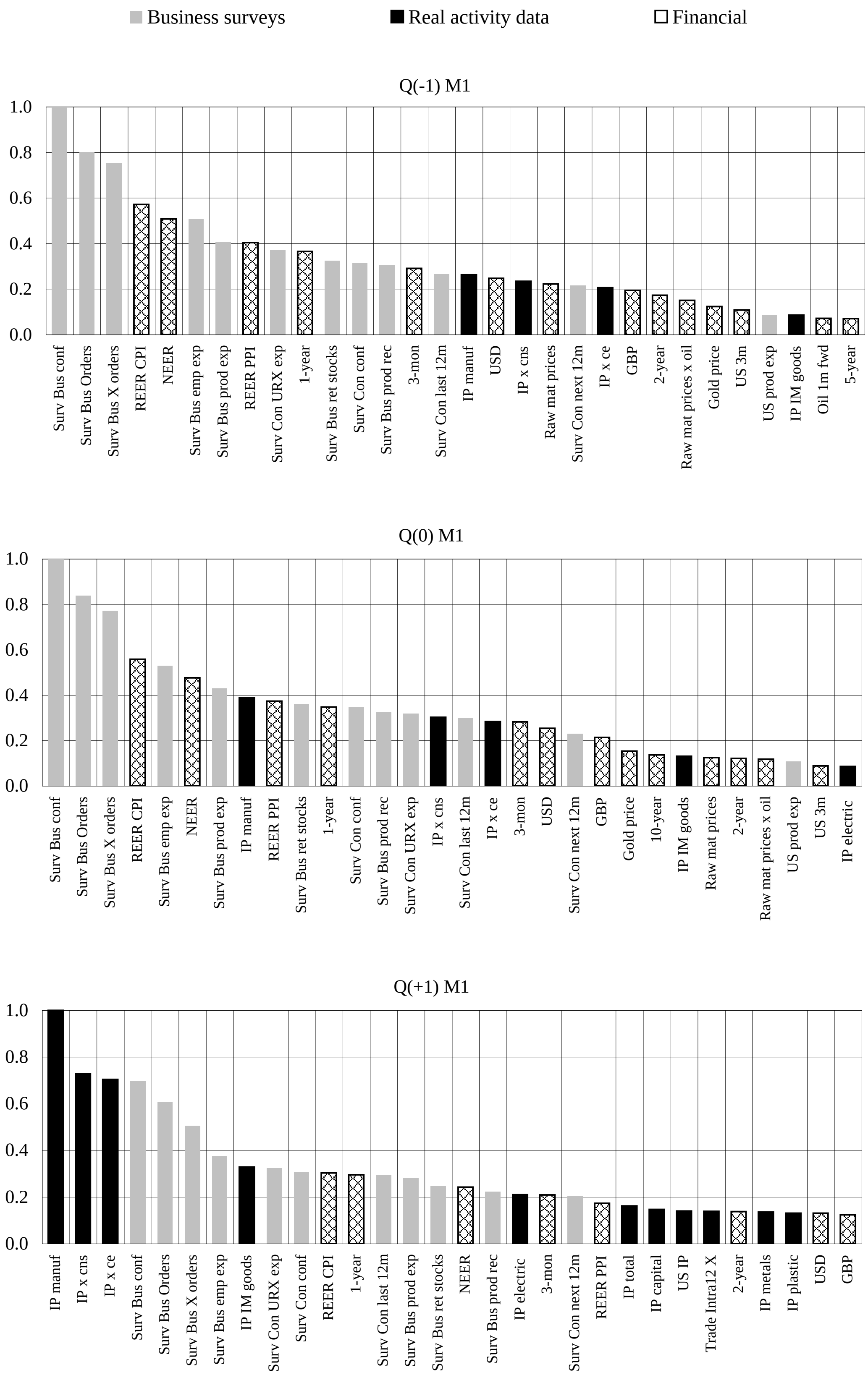
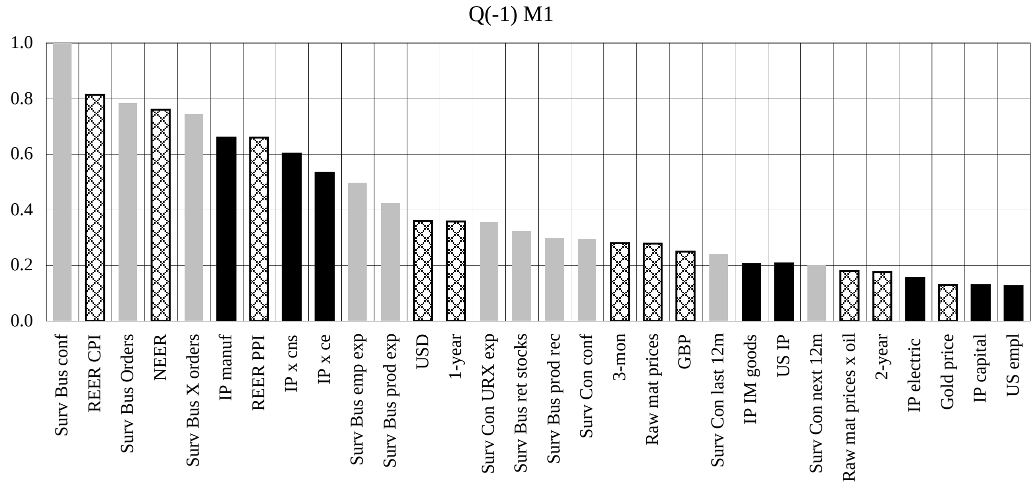
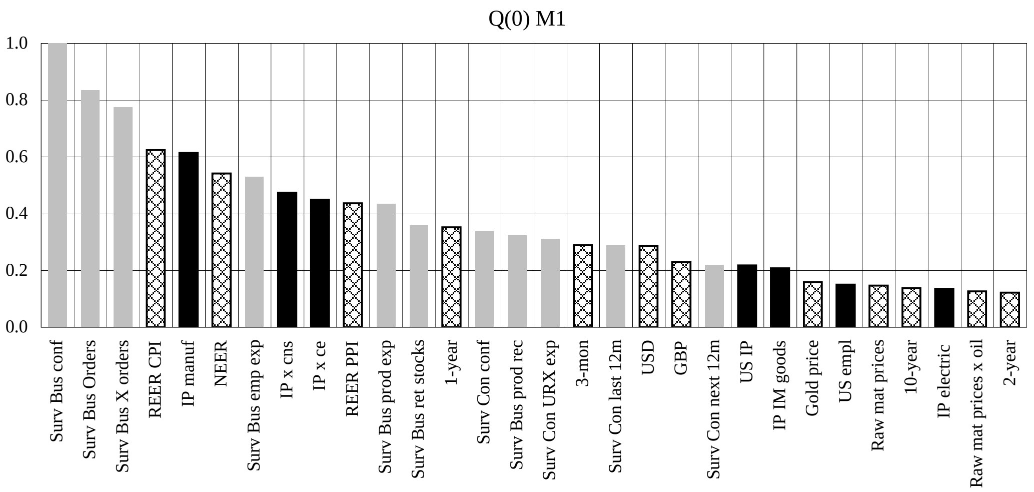


Chart A.2: Absolute cumulative weights

Extended data

Business surveys   Real activity data   Financial





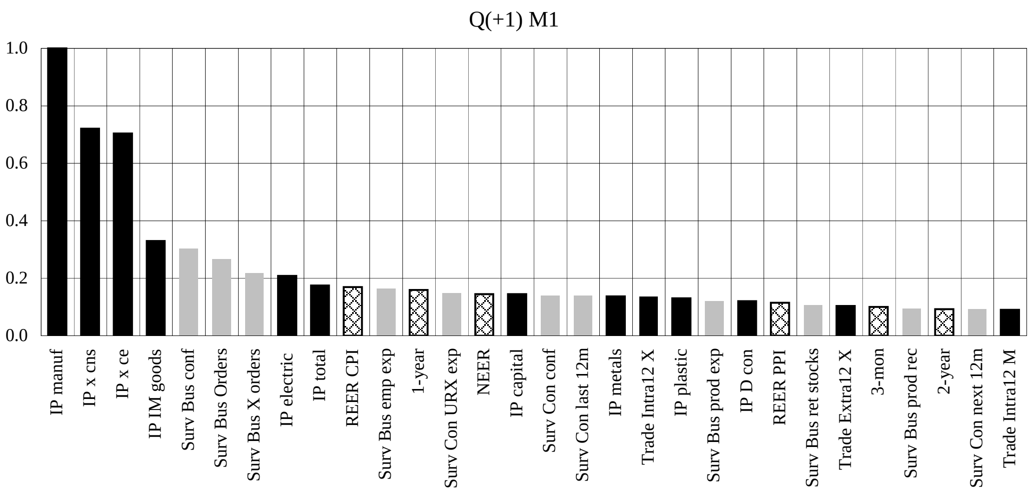
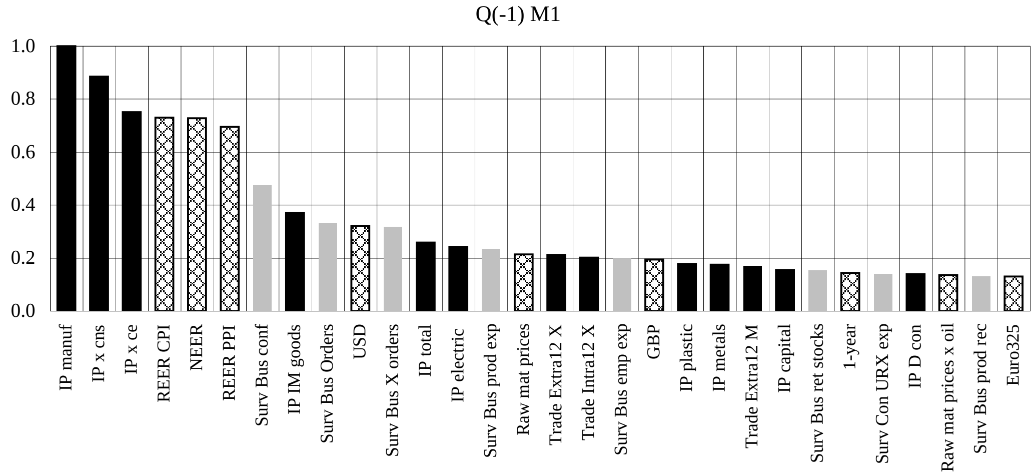
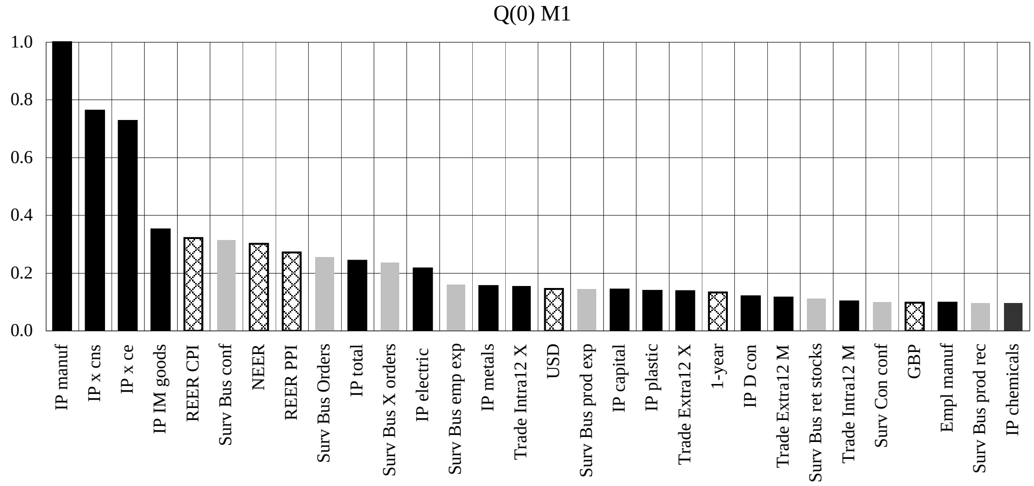


Chart A.3: Absolute cumulative weights

Balanced data

Business surveys Real activity data Financial





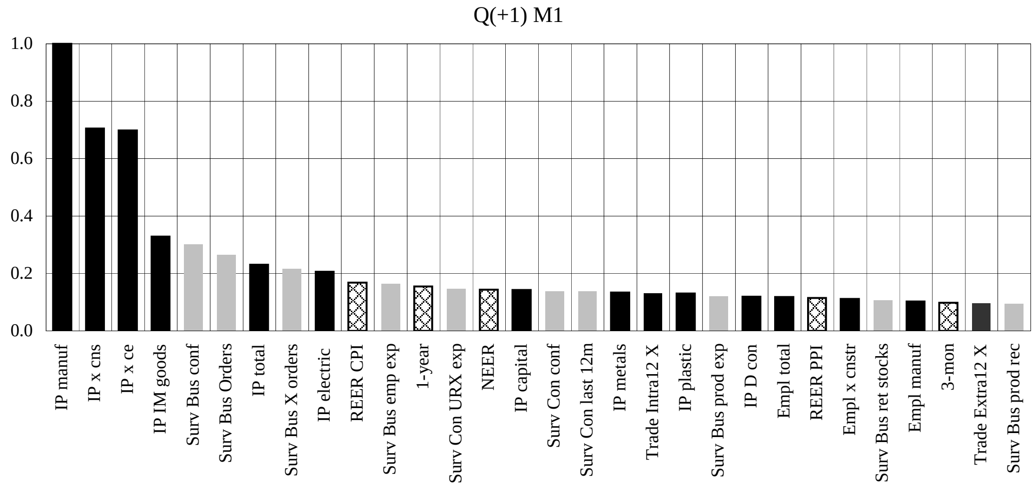


Chart A.4: Contributions to the historical forecast

Main data

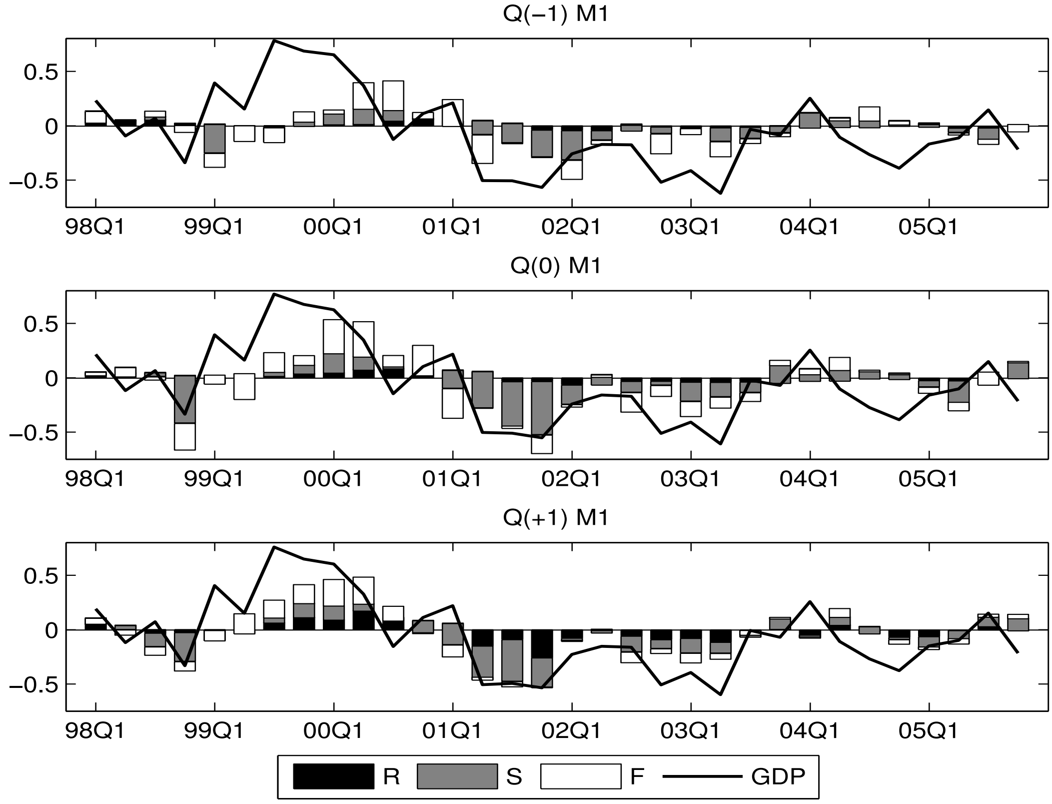


Chart A.5: Contributions to the historical forecast

Balanced data

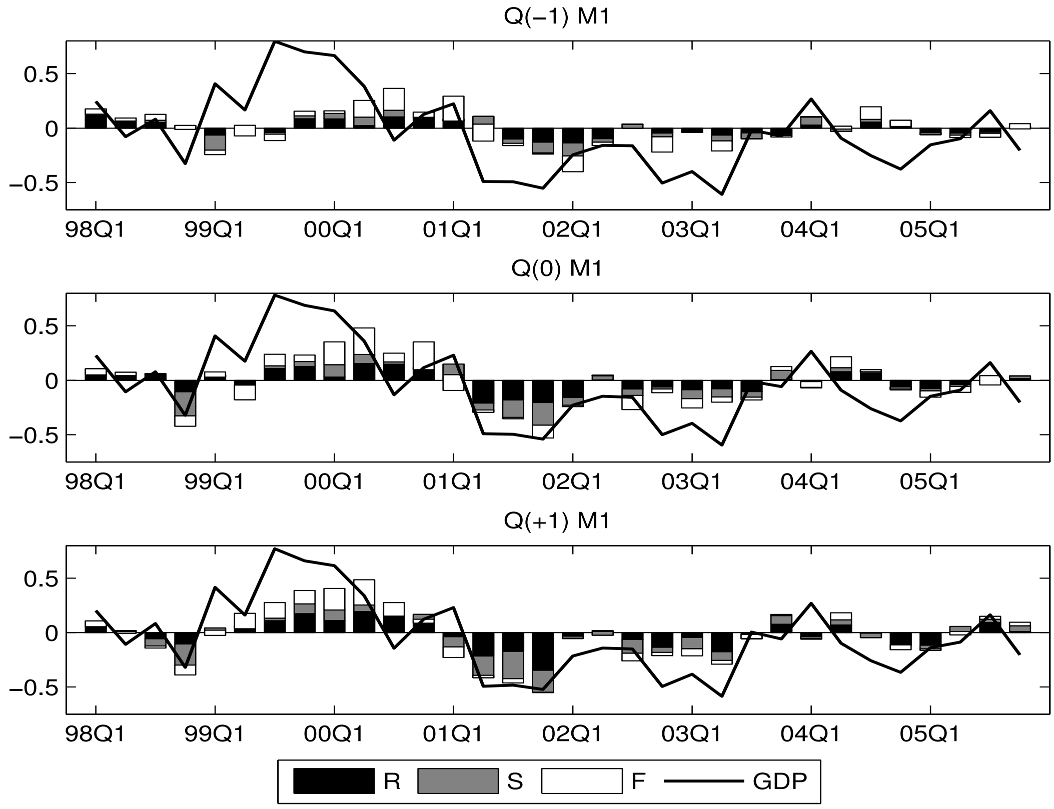


Table A.3: Cumulative forecast weights (main data)

No.	Name	Q(-1) M1	Q(-1) M2	Q(-1) M3	Q(0) M1	Q(0) M2	Q(0) M3	Q(+1) M1
1	Trade Intra12 X	0.1455	0.2324	0.2735	0.3587	0.4384	0.6378	0.8096
2	Trade Extra12 X	0.0647	0.1244	0.1565	0.2681	0.3512	0.5207	0.6355
3	Trade Intra12 M	0.0925	0.1513	0.1816	0.2415	0.2977	0.4324	0.5401
4	Trade Extra12 M	0.0544	0.1166	0.1617	0.2612	0.3519	0.4805	0.5582
5	Retail vol	0.0325	0.0527	0.0650	0.0763	0.0903	0.1323	0.1607
6	IP total	0.1431	0.2657	0.3775	0.4846	0.6031	0.5927	0.9423
7	IP x cns	0.7353	1.1347	1.4319	1.7672	2.0379	3.2173	4.2195
8	IP manuf	0.8207	1.2723	1.7796	2.2727	2.5280	4.3636	5.7960
9	IP cns	0.0042	0.0132	0.0303	0.0334	0.0437	0.0532	0.0716
10	IP x ce	0.6450	0.9900	1.3275	1.6601	1.8415	3.0949	4.0812
11	IP energy	0.0081	-0.0019	-0.0257	-0.0404	-0.0554	-0.0741	-0.0791
12	IP capital	0.1525	0.2418	0.2991	0.3601	0.4265	0.6586	0.8517
13	IP D con	0.1021	0.1686	0.2284	0.2770	0.3234	0.5366	0.6982
14	IP MIG energy	-0.0010	-0.0058	-0.0163	-0.0201	-0.0313	-0.0373	-0.0335
15	IP IM goods	0.2685	0.4213	0.5619	0.7655	0.8383	1.4278	1.9043
16	IP ND con	0.0513	0.0892	0.1258	0.1688	0.1984	0.3252	0.4186
17	IP metals	0.1246	0.1913	0.2362	0.3217	0.3495	0.5871	0.7898
18	IP chemicals	0.0653	0.0993	0.1240	0.1841	0.2038	0.3584	0.4761
19	IP electric	0.1947	0.3125	0.4017	0.5048	0.5851	0.9421	1.2189
20	IP machinery	0.0647	0.1090	0.1369	0.1765	0.2186	0.3190	0.4013
21	IP paper	0.0415	0.0654	0.0867	0.1091	0.1277	0.2332	0.2127
22	IP plastic	0.1234	0.1740	0.2344	0.3123	0.3589	0.5810	0.7618
23	New cars	0.0158	0.0307	0.0697	0.0576	0.1144	0.1406	0.1571
24	URX	0.0451	0.0813	0.1267	0.1480	0.1759	0.2521	0.3157
25	Empl cnstr	0.0014	0.0232	0.0497	0.0627	0.1039	0.0964	0.0701
26	Empl manuf	0.0536	0.1485	0.2502	0.3143	0.4278	0.3914	0.5109
27	Empl total	0.0644	0.2198	0.3817	0.3987	0.6451	0.5958	0.6171
28	Empl x cnstr	0.0628	0.1877	0.3249	0.3580	0.5428	0.5019	0.5764
29	US URX	0.1268	0.1510	0.1810	0.1683	0.3616	0.3806	0.4314
30	US IP	0.1997	0.2486	0.3621	0.3439	0.7121	0.7248	0.8104
31	US empl	0.1882	0.2166	0.2824	0.2304	0.4697	0.5353	0.6045
32	US retail vol	-0.1355	-0.1374	-0.1002	-0.0831	-0.1705	-0.1546	-0.1797
33	Surv Bus conf	3.1260	3.7955	4.7635	5.8394	6.7376	5.8624	4.0482
34	Surv Bus prod rec	0.9503	1.1446	1.4550	1.8963	2.2104	1.9454	1.3013
35	Surv Bus Orders	2.5062	3.0932	3.9443	4.8907	5.7774	5.0706	3.5301
36	Surv Bus X orders	2.3510	2.9065	3.5820	4.5112	5.1236	4.3343	2.9341
37	Surv Bus ret stocks	1.0169	1.2514	1.6055	2.1044	2.3932	2.1251	1.4457
38	Surv Bus prod exp	1.2746	1.5386	1.9247	2.5178	2.8375	2.3938	1.6304
39	Surv Bus emp exp	1.5876	1.9560	2.3970	3.0868	3.6528	3.1716	2.1852
40	Surv Con conf	0.9829	1.2181	1.6806	2.0238	2.6003	2.3774	1.7868
41	Surv Con last 12m	0.8304	1.0374	1.5178	1.7505	2.3418	2.1441	1.7117
42	Surv Con next 12m	0.6786	0.8269	1.1316	1.3380	1.7489	1.5607	1.1887
43	Surv Con URX exp	1.1685	1.4484	1.9772	1.8608	2.7360	2.4949	1.8823
44	Surv Cns conf	0.1216	0.1992	0.5125	0.4236	0.7048	0.7340	0.7169
45	Surv Cns prod rec	-0.0062	0.0056	0.1830	0.1493	0.2775	0.3767	0.3289
46	Surv Cns orders	0.0379	0.0686	0.2174	0.1478	0.2987	0.3057	0.3417
47	Surv Cns emp exp	0.0807	0.1395	0.3868	0.3963	0.5449	0.5967	0.5676
48	Surv Ret conf	0.0537	0.0665	0.1568	0.1485	0.2305	0.2486	0.2223
49	Surv Ret current	0.0865	0.1065	0.1697	0.1988	0.2511	0.2499	0.1878
50	Surv Ret stocks	0.0958	0.1162	0.1319	0.1943	0.2252	0.1956	0.1167
51	Surv Ret prod exp	-0.0663	-0.0814	-0.0032	-0.0880	-0.0244	0.0258	0.1004
52	Surv Ret emp exp	0.0458	0.0596	0.0954	0.0474	0.0994	0.1113	0.1083
53	US prod exp	-0.2686	-0.3351	-0.4429	-0.6315	-0.7396	-0.7155	-0.4261
54	US con exp	-0.1953	-0.2324	-0.2050	-0.4043	-0.4126	-0.3908	-0.1754
55	NEER	1.5890	2.1947	2.5500	2.7872	2.7041	2.0706	1.4081
56	REER CPI	1.7864	2.4326	2.8863	3.2647	3.2651	2.6119	1.7604
57	REER PPI	1.2656	1.7855	2.0768	2.1811	1.9947	1.4853	1.0101
58	USD	0.7758	1.0708	1.3151	1.4884	1.4272	1.1899	0.7593
59	GBP	0.6092	0.7934	1.0321	1.2514	1.2799	1.1078	0.7215
60	YEN	0.1259	0.1758	0.1919	0.1993	0.1987	0.1311	0.1035
61	Raw mat prices	0.6979	0.8777	0.5276	0.7354	0.6908	0.2251	0.0813
62	Raw mat prices x oil	0.4716	0.5781	0.5725	0.6939	0.7451	0.5489	0.3840
63	Oil price	-0.0459	-0.0460	-0.1658	-0.0427	-0.0522	-0.1438	-0.2424
64	Gold price	-0.3871	-0.4915	-0.6667	-0.8978	-0.9831	-0.9156	-0.6046
65	Oil 1m fwd	0.2258	0.2863	0.0537	0.1135	0.0885	-0.1551	-0.1509
66	Euro500	0.1179	0.1772	0.3870	0.1582	0.2871	0.1660	0.2671
67	Euro325	0.0879	0.1486	0.4956	0.0957	0.2570	0.1448	0.3106
68	US SP500	-0.1223	-0.1285	0.0022	-0.3015	-0.2307	-0.2667	-0.0371
69	US DowJ	-0.0873	-0.0974	-0.0302	-0.2438	-0.2390	-0.2962	-0.1183
70	US 3m	0.3376	0.4141	0.4639	0.5216	0.7093	0.6111	0.5948
71	US 10-year	-0.1835	-0.1994	-0.2689	-0.5018	-0.5030	-0.5416	-0.2127
72	10-year	-0.2102	-0.1880	-0.4419	-0.8021	-0.6957	-0.8937	-0.3160
73	3-mon	0.9098	1.1583	1.3472	1.6533	2.0856	1.7543	1.2137
74	1-year	1.1425	1.4914	1.7050	2.0319	2.6667	2.1250	1.7153
75	2-year	0.5420	0.7418	0.7493	0.7095	1.1487	0.6857	0.8036
76	5-year	0.2225	0.3595	0.2026	-0.0364	0.3712	-0.0363	0.3760

Table A.4: Cumulative forecast weights (extended data)

No.	Name	Q(-1) M1	Q(-1) M2	Q(-1) M3	Q(0) M1	Q(0) M2	Q(0) M3	Q(+1) M1
1	Trade Intra12 X	0.2406	0.3385	0.4002	0.4531	0.7322	0.8349	0.9951
2	Trade Extra12 X	0.0269	0.1108	0.1947	0.3269	0.5662	0.6552	0.7574
3	Trade Intra12 M	0.1514	0.2185	0.2614	0.3025	0.4866	0.5595	0.6601
4	Trade Extra12 M	0.0097	0.0950	0.1858	0.3059	0.5064	0.5784	0.6525
5	Retail vol	0.0646	0.0850	0.0963	0.0962	0.1451	0.1701	0.1965
6	IP total	0.1938	0.3238	0.4286	0.5442	0.5828	0.9555	1.2886
7	IP x cns	1.3244	1.7496	2.2006	2.2912	3.5805	4.3397	5.2931
8	IP manuf	1.4504	1.9336	2.7165	2.9675	4.4862	5.8968	7.3476
9	IP cns	0.0030	0.0132	0.0359	0.0371	0.0437	0.0721	0.0948
10	IP x ce	1.1722	1.5352	2.0459	2.1728	3.2888	4.1980	5.1694
11	IP energy	0.0431	0.0272	-0.0190	-0.0415	-0.0522	-0.0775	-0.0915
12	IP capital	0.2841	0.3782	0.4527	0.4608	0.7186	0.8723	1.0609
13	IP D con	0.1693	0.2454	0.3466	0.3576	0.5604	0.7175	0.8799
14	IP MIG energy	0.0025	-0.0027	-0.0124	-0.0198	-0.0261	-0.0317	-0.0290
15	IP IM goods	0.4571	0.6282	0.8627	1.0048	1.5110	1.9512	2.4220
16	IP ND con	0.0719	0.1172	0.1827	0.2152	0.3335	0.4283	0.5221
17	IP metals	0.2174	0.2932	0.3707	0.4276	0.6578	0.8149	1.0065
18	IP chemicals	0.0988	0.1372	0.1879	0.2428	0.3803	0.4886	0.5990
19	IP electric	0.3412	0.4721	0.6136	0.6529	1.0194	1.2634	1.5323
20	IP machinery	0.1059	0.1549	0.1933	0.2184	0.3427	0.4065	0.4889
21	IP paper	0.0591	0.0894	0.0812	0.1048	0.2458	0.2121	0.1925
22	IP plastic	0.1987	0.2478	0.3493	0.4032	0.6209	0.7814	0.9609
23	New cars	0.0604	0.0849	0.1294	0.1522	0.1531	0.1675	0.1028
24	URX	0.0676	0.1106	0.1871	0.1827	0.2638	0.3302	0.4034
25	Empl cnstr	-0.0130	0.0118	0.0392	0.0578	0.0822	0.0622	0.0455
26	Empl manuf	0.0278	0.1310	0.2354	0.3279	0.3778	0.4907	0.5783
27	Empl total	-0.0008	0.1700	0.3351	0.3931	0.5380	0.5798	0.5802
28	Empl x cnstr	0.0245	0.1600	0.3002	0.3618	0.4645	0.5456	0.5904
29	US URX	0.2473	0.3162	0.3791	0.5570	0.5075	0.4609	0.2390
30	US IP	0.4562	0.5809	0.7432	1.0551	0.9769	0.8704	0.4930
31	US empl	0.2768	0.3537	0.4960	0.7273	0.6591	0.6541	0.3346
32	US retail vol	-0.0786	-0.1013	-0.1268	-0.2622	-0.2114	-0.1778	-0.0522
33	Surv Bus conf	2.1964	2.8061	3.5408	4.8342	4.4035	3.8918	2.2330
34	Surv Bus prod rec	0.6541	0.8297	1.0717	1.5609	1.4313	1.2801	0.6969
35	Surv Bus Orders	1.7241	2.2508	2.9170	4.0383	3.7845	3.3819	1.9614
36	Surv Bus X orders	1.6347	2.1342	2.6787	3.7484	3.3754	2.8973	1.6013
37	Surv Bus ret stocks	0.7090	0.9181	1.1847	1.7371	1.5526	1.4014	0.7891
38	Surv Bus prod exp	0.9303	1.1725	1.4497	2.0995	1.8567	1.5819	0.8891
39	Surv Bus emp exp	1.0927	1.4252	1.7844	2.5587	2.4137	2.1310	1.2123
40	Surv Con conf	0.6469	0.8512	1.1993	1.6297	1.6673	1.5702	1.0222
41	Surv Con last 12m	0.5316	0.7121	1.0657	1.3911	1.4981	1.4228	1.0204
42	Surv Con next 12m	0.4426	0.5708	0.7958	1.0656	1.1010	1.0139	0.6761
43	Surv Con URX exp	0.7807	1.0276	1.4255	1.4999	1.7646	1.6568	1.0908
44	Surv Cns conf	0.0903	0.1554	0.3534	0.3266	0.4562	0.4991	0.4859
45	Surv Cns prod rec	-0.0082	-0.0003	0.1129	0.1041	0.1657	0.2457	0.2093
46	Surv Cns orders	0.0279	0.0540	0.1444	0.1063	0.1890	0.2076	0.2454
47	Surv Cns emp exp	0.0543	0.1017	0.2591	0.3086	0.3448	0.4001	0.3753
48	Surv Ret conf	0.0334	0.0435	0.1038	0.1109	0.1430	0.1622	0.1359
49	Surv Ret current	0.0557	0.0734	0.1222	0.1606	0.1666	0.1692	0.1067
50	Surv Ret stocks	0.0621	0.0794	0.0984	0.1604	0.1485	0.1289	0.0490
51	Surv Ret prod exp	-0.0443	-0.0594	-0.0214	-0.0897	-0.0352	0.0071	0.0840
52	Surv Ret emp exp	0.0442	0.0571	0.0751	0.0391	0.0714	0.0807	0.0767
53	US prod exp	-0.1591	-0.2157	-0.3238	-0.5208	-0.4982	-0.4852	-0.2064
54	US con exp	-0.1080	-0.1402	-0.1541	-0.3426	-0.2847	-0.2658	-0.0473
55	NEER	1.6695	2.2548	2.3271	2.6211	2.1909	1.6656	1.0649
56	REER CPI	1.7861	2.4061	2.5694	3.0154	2.5638	2.0276	1.2426
57	REER PPI	1.4500	1.9557	1.9653	2.1133	1.7165	1.2655	0.8449
58	USD	0.7886	1.0716	1.1839	1.3869	1.1489	0.9372	0.5375
59	GBP	0.5480	0.7214	0.8641	1.1098	0.9374	0.7966	0.4331
60	YEN	0.1367	0.1850	0.1788	0.1901	0.1614	0.1111	0.0899
61	Raw mat prices	0.6131	0.7977	0.5206	0.7092	0.5386	0.2290	0.1423
62	Raw mat prices x oil	0.3984	0.5025	0.4768	0.6128	0.5250	0.3923	0.2498
63	Oil price	0.0904	0.1116	-0.0904	-0.0818	-0.1091	-0.2228	-0.1306
64	Gold price	-0.2869	-0.3825	-0.5209	-0.7673	-0.6904	-0.6390	-0.3352
65	Oil 1m fwd	0.2003	0.2640	0.0918	0.1327	0.0857	-0.0720	-0.0434
66	Euro500	0.1756	0.2321	0.3270	0.1447	0.2253	0.1392	0.2447
67	Euro325	0.1709	0.2293	0.4145	0.0909	0.2073	0.1296	0.3018
68	US SP500	-0.0287	-0.0327	0.0165	-0.2538	-0.1398	-0.1644	0.0612
69	US DowJ	-0.0092	-0.0156	-0.0020	-0.1972	-0.1448	-0.1886	-0.0141
70	US 3m	0.2347	0.3076	0.3398	0.4276	0.4621	0.4180	0.3765
71	US 10-year	-0.0842	-0.0946	-0.1929	-0.4136	-0.3445	-0.3586	-0.0324
72	10-year	-0.1306	-0.1025	-0.3292	-0.6673	-0.4822	-0.5659	0.0076
73	3-mon	0.6158	0.8481	1.0298	1.3987	1.4287	1.2384	0.7358
74	1-year	0.7863	1.1138	1.2894	1.7029	1.7930	1.5139	1.1722
75	2-year	0.3872	0.5785	0.5654	0.5876	0.7528	0.5201	0.6778
76	5-year	0.1564	0.2891	0.1350	-0.0500	0.1964	0.0134	0.4532

Table A.5: Cumulative forecast weights (balanced data)

No.	Name	Q(-1) M1	Q(-1) M2	Q(-1) M3	Q(0) M1	Q(0) M2	Q(0) M3	Q(+1) M1
1	Trade Intra12 X	0.4267	0.5700	0.6878	0.8434	1.0131	0.9967	0.9496
2	Trade Extra12 X	0.4476	0.5896	0.6240	0.7460	0.8180	0.7605	0.6915
3	Trade Intra12 M	0.2655	0.3626	0.4453	0.5542	0.6664	0.6644	0.6307
4	Trade Extra12 M	0.3595	0.4875	0.5195	0.6248	0.6987	0.6637	0.6272
5	Retail vol	0.0478	0.0727	0.1119	0.1447	0.1844	0.2033	0.1913
6	IP total	0.5449	0.7467	1.0337	1.3222	1.5745	1.7122	1.6614
7	IP x cns	1.8666	2.4868	3.3564	4.1519	4.9896	5.2791	5.0841
8	IP manuf	2.1100	2.8237	4.2314	5.4437	6.3071	7.3082	7.2130
9	IP cns	0.0067	0.0166	0.0449	0.0545	0.0819	0.1316	0.1448
10	IP x ce	1.5833	2.1204	3.1059	3.9610	4.6149	5.1846	5.0393
11	IP energy	-0.0273	-0.0448	-0.0518	-0.0590	-0.0602	-0.0910	-0.1088
12	IP capital	0.3266	0.4532	0.6231	0.7803	0.9703	1.0567	1.0314
13	IP D con	0.2924	0.3998	0.5446	0.6535	0.7802	0.8797	0.8562
14	IP MIG energy	-0.0256	-0.0398	-0.0549	-0.0601	-0.0701	-0.1020	-0.1157
15	IP IM goods	0.7796	1.0417	1.4308	1.9102	2.1644	2.4197	2.3676
16	IP ND con	0.1770	0.2435	0.3179	0.4051	0.4654	0.5207	0.5054
17	IP metals	0.3706	0.4919	0.6455	0.8465	0.9582	1.0090	0.9632
18	IP chemicals	0.2438	0.3128	0.3903	0.5169	0.5576	0.5971	0.5572
19	IP electric	0.5099	0.6951	0.9363	1.1766	1.4149	1.5447	1.4860
20	IP machinery	0.1688	0.2372	0.3019	0.3754	0.4570	0.4826	0.4759
21	IP paper	0.1783	0.0740	0.0588	0.2995	0.2132	0.1903	0.1843
22	IP plastic	0.3749	0.4422	0.5887	0.7571	0.8796	0.9610	0.9403
23	New cars	0.0319	0.0448	0.0575	0.0597	0.0754	0.0964	0.1011
24	URX	0.1243	0.1697	0.2271	0.2630	0.3550	0.4143	0.4416
25	Empl cnstr	-0.0460	-0.0234	-0.0209	-0.0152	0.0315	0.0599	0.1122
26	Empl manuf	0.0965	0.2202	0.3583	0.5294	0.6537	0.7004	0.7359
27	Empl total	0.0176	0.2048	0.3378	0.3676	0.6181	0.7042	0.8522
28	Empl x cnstr	0.0697	0.2227	0.3824	0.4355	0.6332	0.7059	0.8014
29	US URX	0.1124	-0.1410	-0.1596	-0.1917	-0.2244	-0.2402	-0.2342
30	US IP	0.2136	0.2136	0.2136	0.2136	0.2136	0.2136	0.2136
31	US empl	0.1094	0.1356	0.1913	0.2314	0.2808	0.3375	0.3301
32	US retail vol	0.0114	0.0120	-0.0180	-0.0489	-0.0606	-0.0638	-0.0506
33	Surv Bus conf	1.0020	1.2983	1.5051	1.7165	2.0334	2.1417	2.1792
34	Surv Bus prod rec	0.2762	0.3526	0.4339	0.5261	0.6378	0.6854	0.6798
35	Surv Bus Orders	0.6996	0.9402	1.1783	1.3863	1.7189	1.8521	1.9105
36	Surv Bus X orders	0.6723	0.9022	1.0911	1.2861	1.5168	1.5523	1.5579
37	Surv Bus ret stocks	0.3258	0.4248	0.5010	0.6092	0.7130	0.7676	0.7715
38	Surv Bus prod exp	0.4952	0.6258	0.6692	0.7897	0.8815	0.8761	0.8700
39	Surv Bus emp exp	0.4198	0.5683	0.7068	0.8673	1.0830	1.1511	1.1785
40	Surv Con conf	0.2349	0.3153	0.4577	0.5443	0.7674	0.9026	0.9979
41	Surv Con last 12m	0.1759	0.2497	0.4009	0.4730	0.7134	0.8588	0.9970
42	Surv Con next 12m	0.1703	0.2181	0.3085	0.3590	0.5117	0.5941	0.6606
43	Surv Con URX exp	0.2950	0.4009	0.5575	0.5097	0.8246	0.9601	1.0640
44	Surv Cns conf	0.0834	0.1318	0.1826	0.1745	0.2866	0.3692	0.4754
45	Surv Cns prod rec	0.0179	0.0271	0.0577	0.0535	0.1036	0.1700	0.2068
46	Surv Cns orders	0.0361	0.0590	0.0812	0.0748	0.1344	0.1747	0.2401
47	Surv Cns emp exp	0.0534	0.0857	0.1298	0.1373	0.2125	0.2884	0.3679
48	Surv Ret conf	0.0156	0.0190	0.0412	0.0405	0.0734	0.1064	0.1337
49	Surv Ret current	0.0114	0.0168	0.0398	0.0466	0.0711	0.0931	0.1042
50	Surv Ret stocks	0.0118	0.0136	0.0270	0.0382	0.0501	0.0536	0.0476
51	Surv Ret prod exp	0.0115	0.0100	0.0119	-0.0043	0.0166	0.0458	0.0840
52	Surv Ret emp exp	0.0395	0.0512	0.0480	0.0366	0.0507	0.0621	0.0752
53	US prod exp	0.0097	0.0049	-0.0700	-0.1103	-0.1685	-0.2160	-0.1999
54	US con exp	0.0318	0.0383	-0.0038	-0.0478	-0.0648	-0.0776	-0.0447
55	NEER	1.5370	2.0825	1.6372	1.6428	1.4796	1.1465	1.0401
56	REER CPI	1.5421	2.0903	1.7043	1.7476	1.6209	1.3218	1.2146
57	REER PPI	1.4659	1.9719	1.4944	1.4758	1.2732	0.9362	0.8276
58	USD	0.6767	0.9262	0.7776	0.7906	0.7176	0.5938	0.5261
59	GBP	0.4118	0.5464	0.5001	0.5333	0.5134	0.4658	0.4273
60	YEN	0.1346	0.1817	0.1375	0.1397	0.1231	0.0898	0.0866
61	Raw mat prices	0.4513	0.6185	0.4132	0.4834	0.3994	0.1876	0.1215
62	Raw mat prices x oil	0.2863	0.3700	0.2963	0.3241	0.3133	0.2526	0.2418
63	Oil price	0.0615	0.0896	0.0025	0.0243	-0.0130	-0.1097	-0.1386
64	Gold price	-0.1212	-0.1706	-0.2159	-0.2675	-0.3075	-0.3322	-0.3282
65	Oil 1m fwd	0.1469	0.2068	0.1106	0.1365	0.0969	-0.0184	-0.0536
66	Euro500	0.2406	0.3114	0.2592	0.2104	0.2218	0.1885	0.2410
67	Euro325	0.2761	0.3592	0.3359	0.2306	0.2491	0.2213	0.2978
68	US SP500	0.0976	0.1255	0.0910	0.0193	0.0256	0.0069	0.0610
69	US DowJ	0.0921	0.1143	0.0725	0.0181	0.0003	-0.0383	-0.0128
70	US 3m	0.1133	0.1595	0.1631	0.1906	0.2540	0.2705	0.3634
71	US 10-year	0.0889	0.1271	0.0286	-0.0085	-0.0344	-0.0889	-0.0332
72	10-year	0.0272	0.1022	-0.0263	-0.0516	-0.0319	-0.1293	-0.0084
73	3-mon	0.1731	0.2929	0.3861	0.4822	0.6559	0.6786	0.7052
74	1-year	0.3025	0.5083	0.5732	0.7223	0.9636	0.9804	1.1193
75	2-year	0.2080	0.3592	0.3274	0.3900	0.5354	0.4864	0.6386
76	5-year	0.1416	0.2753	0.1741	0.1997	0.3256	0.2445	0.4164