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In 2011 all ECB publications feature a motif taken from the €100 banknote.

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2 Corresponding author: European Central Bank, Kaiserstrasse 29, D-60311 Frankfurt, Germany; email: marco.lombardi@ecb.europa.eu.
3 Bank of Canada, International Department, 234 Wellington, Ottawa, ON, K1A 0G9, Canada; e-mail: pmaier@bankofcanada.ca.

Address
Kaiserstrasse 29
60311 Frankfurt am Main, Germany

Postal address
Postfach 16 03 19
60066 Frankfurt am Main, Germany

Telephone
+49 69 1344 0

Internet
http://www.ecb.europa.eu

Fax
+49 69 1344 6000

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CONTENTS

Abstract

We evaluate forecasts for the euro area in data-rich and 'data-lean' environments by comparing three different approaches: a simple PMI model based on Purchasing Managers' Indices (PMIs), a dynamic factor model with euro area data, and a dynamic factor model with data from the euro plus data from national economies (pseudo-real time data). We estimate backcasts, nowcasts and forecasts for GDP, components of GDP, and GDP of all individual euro area members, and examine forecasts for periods of low and high economic volatility (more specifically, we consider 2002-2007, which falls into the 'Great Moderation', and the 'Great Recession' 2008-2009). We find that all models consistently beat naive AR benchmarks, and overall, the dynamic factor model tends to outperform the PMI model (at times by a wide margin). However, accuracy of the dynamic factor model can be uneven (forecasts for some countries have large errors), with the PMI model dominating clearly for some countries or over some horizons. This is particularly pronounced over the Great Recession, where the dynamic factor model dominates the PMI model for backcasts, but has considerable difficulties beating the PMI model for nowcasts. This suggests that survey-based measures can have considerable advantages in responding to changes during very volatile periods, whereas factor models tend to be more sluggish to adjust.
Keywords: Forecasting, Dynamic factor model, PMI model
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Non-technical Summary

Monetary policymakers need up to date information on the state of the economy, and the complex nature of monetary policy often involves tracking and forecasting numerous variables. Given its economic structure, forecasting the euro area is particularly challenging, as it requires not only an analysis of economic activity in the euro area as a whole, but also examining economic developments at national levels (that is, in individual euro area countries). Since the euro area comprises 17 members, analysis of the euro area is a potentially very labour-intensive task. To facilitate this activity, this study evaluates different methodologies to forecast economic activity – here: quarterly GDP and its components – in the euro area.

Several avenues exist. One alternative is to choose a relatively parsimonious data set by selecting a a few timely, forward-looking indicators. Among those indicators, survey-based measures, such as the Purchasing Managers' Indices (PMIs), are released well before first estimates of GDP become available, and may exhibit very good predictive properties. Also, surveys can react to changes in the economic outlook very quickly, whereas forecasts made with more traditional time series models often exhibit a high degree of persistence. A second option is to use a large data set, and employ modern econometric tools to process it efficiently. For this avenue, dynamic factor models, in particular, have been proposed as a class of models to facilitate short-term forecasting. By extracting common patterns (factors) from multiple data series, factor models can reduce the dimensionality of the data and thus the complexity of the task.

In recent years, factor models have become very popular, and the usefulness of factor models for forecasting has been documented extensively. However, two issues remain still unresolved. First, a key assumption underlying factor models is that 'data rich' environments yield better forecasts, as more data allows better estimation of the factors; in practice however, more data may not always be advantageous. We ask how much forecasting accuracy would deteriorate, for both the euro area and individual countries, if we discard national monthly indicators. Our euro area dataset confirms that in many cases, GDP forecasts actually improve with the more restricted data sets, notably for components of euro area GDP. This suggests that national monthly indicators help forecasting heterogeneity of GDP components, rather than forecasting country-specific, idiosyncratic developments.

The second issue is a more fundamental one. Despite a large literature comparing different forecasting approaches, an in-depth evaluation of the usefulness of data-rich vs. 'lean data' environments during periods of low and high volatility is lacking. The end of the Great Moderation and the sharp increase in volatility in economic indicators during 2008/2009 provides us with a new opportunity to examine the usefulness of different models during periods of low and high volatility.

In light of this, we evaluate forecasting performance of dynamic factor models with different information sets against a more parsimonious indicator model using PMIs. These comparisons can be viewed as evaluating a very 'lean data'

technique – the PMI model, which just uses lagged GDP and the PMI – to factor models with different information sets. To this end, we focus on backcasts (forecasting last quarter's GDP, before its official release), nowcasts (predicting current quarter GDP in pseudo real-time) and short-term forecasts (predicting next quarter's GDP). We compare out-of-sample projections for euro area GDP, components of euro area GDP and GDP of all national euro area countries during the Great Moderation[1], as well as and during the Great Recession of 2008-2009, when economic developments within the euro area turned out to be particularly volatile and heterogeneous.

We find that both models perform well in that they beat naive benchmarks. However, we also conclude that more data does not always yield better forecasts, and that the very simple, 'lean data' PMI model is not always easily beaten by the much more data-intensive factor model. The first factor in the dynamic factor model is very highly correlated with the euro area PMI, suggesting that both identify very similar economic developments. In light of this, simple PMI models are a 'low-tech' way to generate surprisingly accurate GDP forecasts for many euro area countries during periods of low and high volatility, with the advantage that they do not require processing or maintaining large data sets. Investigating why the dynamic factor model does not outperform the PMI model more clearly, we find that the PMI model seems to perform particularly well when very rapid changes to the economic outlook occur. Our analysis shows that survey-based measures like the PMI change almost 'instantly', while factor models – like many other forecasting tools – are relatively more sluggish in adjusting. This could justify putting a relatively higher weight on information obtained from PMIs during periods of high volatility. However, exploiting rich data sets enables factor models to outperform the simpler PMI models for backcasts and, in many cases, for nowcasts and forecasts. That said, its forecasting accuracy can be uneven, and forecast errors for some countries or components of GDP are substantially higher than the PMI models.

Overall, our results suggest that for most practical purposes, PMI models provide simple, yet accurate tools for forecasting headline GDP in the euro area and its members. However, factor models provide several conceptual advantages. Factor models adjust the weights attached to each economic indicator according to their relevance at different points in time. This additional flexibility of factor models can accommodate for possible structural breaks in the series. In contrast, indicator models, such as the PMI model, will only retain their forecasting ability if the specific indicator chosen remains a valid coincident indicator.

[1] More precisely, we label the forecasting during the period 2002-2007 as forecasting during the 'Great Moderation'; strictly speaking, the Great Moderation has started earlier, as volatility of key macroeconomic series has started falling sharply in the late 1980s.

1 Introduction

Monetary policymakers need up to date information on the state of the economy, and the complex nature of monetary policy often involves tracking and forecasting numerous variables.[2] Given its economic structure, forecasting the euro area is particularly challenging, as it requires not only an analysis of economic activity in the euro area as a whole, but also examining economic developments at national levels (that is, in individual euro area countries). Since the euro area comprises 17 members, analysis of the euro area is a potentially very labour-intensive task.[3] To facilitate this activity, this study evaluates different methodologies to forecast economic activity – here: quarterly GDP and its components – in the euro area.

Several avenues exist. One alternative is to choose a relatively parsimonious data set by selecting a a few timely, forward-looking indicators. This is the strategy pursued, for example, by Camacho and Perez-Quiros (2010) and de Bondt and Hahn (2010). Among those indicators, survey-based measures, such as the Purchasing Managers' Indices (PMIs), are released well before first estimates of GDP become available, and may exhibit very good predictive properties (Godbout and Jacob, 2010). Also, surveys can react to changes in the economic outlook very quickly, whereas forecasts made with more traditional time series models often exhibit a high degree of persistence. A second option is to use a large data set, and employ modern econometric tools to process it efficiently. For this avenue, dynamic factor models, in particular, have been proposed as a class of models to facilitate short-term forecasting. By extracting common patterns (factors) from multiple data series, factor models can reduce the dimensionality of the data and thus the complexity of the task.

The usefulness of factor models for forecasting has been documented extensively (for the euro area, Barhoumi et al., 2008, provide a recent overview). However, two issues remain still unresolved. First, a key assumption underlying factor models is that 'data rich' environments yield better forecasts, as more data allows better estimation of the factors. In practice, more data may not always be advantageous, as Boivin and Ng (2006) have shown that forecasting power can decrease, when idiosyncratic errors are cross-correlated, or when factors that dominate small datasets are less prominent in a larger dataset. In an earlier study, Marcellino et al. (2003)[4] examined whether the euro area is better forecasted by euro-area wide models or by aggregating country-specific forecasts. Turning Marcellino et al. (2003) on its head, we ask how much forecasting accuracy would deteriorate, for both the euro area and individual countries, if we *discard* national monthly indicators. Our euro area dataset confirms that in many cases, GDP forecasts actually improve with the more restricted data

[2] 'Fed economists track hundreds, if not thousands, of variables as they prepare for upcoming meetings of the Open Market Committee. Unless the staff economists are wasting their time, one must assume that these hundreds of variables help them isolate the structural shocks currently impacting the economy' (Stock and Watson, 2002).

[3] An additional complication is that historical data series are often relatively short, and given changes in the composition of the euro area, series may contain structural breaks.

[4] A version with more country-specific results is available as Marcellino et al. (2001).

sets, notably for components of euro area GDP. This suggests that national monthly indicators help forecasting heterogeneity of GDP components, rather than forecasting country-specific, idiosyncratic developments.

The second is a more fundamental one. Despite a large literature comparing different forecasting approaches, an in-depth evaluation of the usefulness of data-rich vs. 'lean data' environments during periods of low and high volatility is lacking. Results from Stock and Watson (2004) suggest that forecasting performance of any given model can be uneven over time (i.e. forecast errors for some periods can be very large). Most notably, models can differ in how well they can forecast when volatility of underlying economic data changes. For instance, D'Agostino et al. (2006) and D'Agostino and Giannone (2006) show that factor models – as well as other forecasting methods – have difficulties beating naive benchmarks after the substantial drop in in volatility associated with the 'Great Moderation'. The end of the Great Moderation and the sharp increase in volatility in economic indicators during 2008/2009 provides us with a new opportunity to examine the usefulness of different models during periods of low and high volatility.

In light of this, we evaluate forecasting performance of dynamic factor models with different information sets against a more parsimonious indicator model using PMIs.[5] These comparisons can be viewed as evaluating a very 'lean data' technique – the PMI model, which just uses lagged GDP and the PMI – to factor models with different information sets. To this end, we focus on backcasts (forecasting last quarter's GDP, before its official release), nowcasts (predicting current quarter GDP in pseudo real-time) and short-term forecasts (predicting next quarter's GDP). We compare out-of-sample projections for euro area GDP, components of euro area GDP and GDP of all national euro area countries during the Great Moderation[6], as well as and during the Great Recession of 2008-2009, when economic developments within the euro area turned out to be particularly volatile and heterogeneous.

To preview the conclusions, we find that both models perform well in that they beat naive benchmarks. However, we also conclude that more data does not always yield better forecasts, and that the very simple, 'lean data' PMI model is not always easily beaten by the much more data-intensive factor model. The first factor in the dynamic factor model is very highly correlated with the euro area PMI, suggesting that both identify very similar economic developments. In light of this, simple PMI models are a 'low-tech' way to generate surprisingly accurate GDP forecasts for many euro area countries during periods of low and high volatility, with the advantage that they do not require processing or maintaining large data sets. Investigating why the dynamic factor model does not outperform the PMI model more clearly, we find that the PMI model seems to perform particularly well when very rapid changes to the economic

[5]We also benchmark both models against a simple AR model, but present the bulk of the results relative to the PMI model, as it is a much tougher benchmark.

[6]More precisely, we label the forecasting during the period 2002-2007 as forecasting during the 'Great Moderation'; strictly speaking, the Great Moderation has started earlier, as volatility of key macroeconomic series has started falling sharply in the late 1980s.

outlook occur. Our analysis shows that survey-based measures like the PMI change almost ‘instantly’, while factor models – like many other forecasting tools – are relatively more sluggish in adjusting. This could justify putting a relatively higher weight on information obtained from PMIs during periods of high volatility. However, exploiting rich data sets enables factor models to outperform the simpler PMI models for backcasts and, in many cases, for nowcasts and forecasts. That said, its forecasting accuracy can be uneven, and forecast errors for some countries or components of GDP are substantially higher than the PMI models.

Overall, our results suggest that for most practical purposes, PMI models provide simple, yet accurate tools for forecasting headline GDP in the euro area and its members. However, factor models provide several conceptual advantages. Factor models adjust the weights attached to each economic indicator according to their relevance at different points in time. This additional flexibility of factor models can accommodate for possible structural breaks in the series. In contrast, indicator models, such as the PMI model, will only retain their forecasting ability if the specific indicator chosen remains a valid coincident indicator.[7]

The structure of the paper is as follows: in the next section, we outline the methodology, and place our study in the literature; in section 3 and 4, we present the results, respectively, for the ‘Great Moderation’ and the ‘Great Recession’ periods. The final section summarizes the main insights and offers some directions for future research.

2 Methodology and related literature

Since the creation of the European Monetary Union (EMU), academics and policymakers have debated the merits of area-wide information versus country-specific information in forecasting economic indicators for Europe. The debate about aggregation versus disaggregation in economic modeling can be traced back to Theil (1954) and Grunfeld and Griliches (1960). On the one hand, the use of disaggregated variables means that it is possible to model their individual dynamic properties more accurately, possibly involving larger and more heterogeneous information sets (see Barker and Pesaran, 1990). Also, when using disaggregated data, forecast errors of components might cancel out (at least in part), leading to more accurate predictions of the aggregate (Clements and Hendry, 2002, discuss forecast combination as bias correction). On the other hand, since it is hard to model economic data without some specification error, aggregating possibly misspecified disaggregate models might not necessarily improve forecast accuracy for the aggregate. Moreover, if shocks are correlated – which is likely the case in the euro area, as economic developments are typically closely related – the forecast errors of some of the forecasts for individual

[7] An important element of the ‘Great Recession’ was a sharp, globally synchronized drop in manufacturing output, which is well captured by the PMI indicator. A domestic housing crisis, for example, might lead to a very different cyclical pattern, and may be less well captured by a PMI model.

countries might go in the same direction, and thus may not cancel out.

The discussion about aggregation versus disaggregation is highly relevant when forecasting euro area data, and various studies have investigated the relative merits of both methodologies. Marcellino et al. (2003) compare forecasts generated with aggregate and individual-country (that is, national) data, using univariate time series models as well as a factor model. Overall, they conclude that over the period considered (1982-1997) the best forecast for the euro area is given by aggregating time series forecasts made for each individual euro area country. Other studies have used large data sets and built factor models to incorporate national economic data into forecasts of economic activity or inflation in the euro area (Angelini et al., 2001; Cristadoro et al., 2001) directly.[8] The benefits of using large data sets is also illustrated in Banbura and Rünstler (2010), who find that surveys and financial data contain important information beyond the monthly real activity measures for the GDP forecasts.

We build on these studies, and forecast euro area GDP and GDP of national economies within parsimonious and rich data environments. Rather than comparing bottom/up vs. forecasting the euro area directly, we use both national and euro area-wide data as inputs, and compare their usefulness when analyzing two classes of models: a simple indicator model using Purchasing Managers' Indices, and a dynamic factor model.

2.1 A PMI indicator model

Purchasing Managers' Indices (PMIs) are survey-based indicators for economic activity. Available on a monthly basis since 1998 for the euro area and for most euro area economies, PMIs report the percentage of purchasing managers that indicate that business conditions are improving, relative to the previous month (for many countries, sectoral breakdowns are available, too). PMIs are diffusion indices, and values over 50 indicate that the economy is expanding, while values below 50 suggest a slowing economy. As such, they only convey the direction of economic activity, and do not provide reliable signals about the pace of expansion or contraction. Given that PMIs are (coincident) indicators of economic activity, it's no surprise that they can be effectively used for tracking GDP developments.

Yet, an important advantage of the PMIs over other measures of economic activity (e.g. industrial production) lies in their timeliness. PMI data are typically the first economic indicator to be released, published on day after the end of the reference month. As such, they are one of the most timely indicators of real activity, and available substantially earlier than any 'hard data' (like

[8]While we focus on the merits of national versus euro area data, a conceptually related issue involves whether forecasts for GDP are better constructed directly, or as the sum of GDP components. For the euro area, this issue is e.g. examined by Angelini et al. (2008), who forecast growth in euro area GDP and GDP components with a dynamic factor model. This study finds that poor estimates of GDP components can worsen estimates of overall GDP, unless national accounts identities are incorporated into the model. Similarly, Hubrich (2003) finds that aggregating forecasts for HICP components does not necessarily improve overall accuracy of euro area inflation forecasts.

industrial production) or first estimates of euro area GDP (which are typically released about two months after the end of the reference quarter). For this reason, we base our 'lean' forecasting model on the PMI.

From a forecasting perspective, an additional advantage is that PMIs are basically not revised.[9] Based on these two advantages, we decided to adopt a very parsimonious specification and only include the PMI.[10] In previous studies, Harris (1991) and Koening (2002) investigate the forecasting properties of PMIs for the United States, Godbout and Jacob (2010) for the euro area, and Rossiter (2010) uses PMIs to provide a nowcast of the global economy. All studies conclude that indicator models using PMIs can deliver very accurate forecasts.

Following Godbout and Jacob (2010), the general structure of our PMI model is a simple, univariate indicator model based on a bridge equation:

$$\hat{y}^{Q}_{t|t+h} = \beta_h(L)PMI^{Q}_{t} + \gamma_h(L)y^{Q}_{t} \tag{1}$$

whereby $\hat{y}^{Q}_{t|t+h}$ denotes our GDP forecast (with h denoting the forecast horizon), PMI^{Q}_{t} is a quarterly estimate of the PMI at time t, and $\beta_h(L)$ a polynomial lag structure. We estimate by OLS, and determine the optimal number of lags by the Schwartz criterion. Given that PMIs are released at monthly frequency, while GDP is released at quarterly frequency, we use a bridge equation (Parigi and Golinelli, 2007) to relate quarterly output growth to the monthly observation.[11] More specifically, in order to construct PMI^{Q}_{t}, we use the average of the monthly values that are already available during the relevant quarter.

In the estimation of all models, we took into account the timeliness of the data releases. This is done by using a pseudo-real time dataset, i.e. suppressing observations which would not have been available at the time the forecast is made (a detailed description of the forecast horizon and the available data is given in section 3.1).

2.2 Factor models

The PMI model is a 'lean data' model, using a very small data set. As such, the model is very simple and easy to maintain, but hinges entirely upon the ability of the PMI index to track and anticipate movements in GDP. In contrast, factor models are based on the idea that there is no need to select relevant indicators a priori, since a large dataset can be represented using a small number of components, which are sufficient to characterize the main features of the data. This mimics the problems policy-makers face when making decisions (looking at a wide set of indicators of different nature and extracting the key piece of information they contain about the status of the economy). Since Sargent and Sims (1977), factor models have been increasingly used for macroeconomic

[9] The only revisions to the PMI are annual updates to seasonal adjustment factors, which are generally small (Koening, 2002).

[10] By opting for a parsimonious model, we limit the set of parameters to estimate, which can help reduce uncertainty.

[11] Bridge equations have been found to be good forecasting tools, see Diron (2008).

applications.[12] Formally, a factor model expresses a N-dimensional multiple time series X_t as

$$X_t = \Lambda F_t + e_t, \tag{2}$$

where F_t is a K-dimensional multiple time series of factors (with $K \ll N$), Λ is a matrix of loadings, relating the factors to the observed time series, and e_t are idiosyncratic disturbances. Equation (2) is not a standard regression model, as the factors are unobservable variables and F_t has to be estimated. This can be accomplished consistently by using the first K principal components of the data, i.e. the first K eigenvectors of the variance-covariance matrix of X_t.

Factor models can be viewed as a parsimonious alternative to large VAR models. Modeling interrelations among a large set of variables in a VAR system is not feasible in a frequentist framework because of the so-called 'curse of dimensionality', i.e. the fact the number of parameters to estimate grows rapidly.[13] Factor models overcome this limitation by reducing the dimensionality of the data.[14]. As more information improves estimation of the factors, factor models benefit from large data sets. An additional benefit is that by extracting information from many series, factor models have been found to compensate for deficiencies in single economic indicators (e.g. measurement errors or possible structural breaks).[15]

The model generated by equation (2) is commonly referred to as 'static factor model', as no parametric dynamics are imposed on the factors.[16] The idea of looking at the dynamic structure of the factors dates back to Geweke (1977), who extends the framework to allow a relatively limited number of structural shocks to cause comovements among macroeconomic variables at all leads and lags, and has been studied extensively by Forni et al. (2000). Giannone et al. (2008) tackle the issue of short-term forecasting by postulating a parametric model to the evolution of the factors, i.e. an AR(p):

[12] The use of factor models originated in the finance literature, where researchers are faced with (for instance) large cross-sections of stock returns. The capital asset pricing model (Sharpe, 1964) and arbitrage pricing theory (Ross, 1976). A drawback of factor models is that one cannot give an economic interpretation to the 'factors'. While this is a valid criticism, it is less relevant in a forecasting environment, where the main focus is on prediction accuracy. Lastly, Boivin and Giannoni (2006) show how to incorporate factors into a DSGE environment.

[13] We remark, however, that using a Bayesian approach would overcome the dimensionality problem, as the lack of curvature of the likelihood function is compensated by the use of informative prior distributions. A recent approach that has been found to be effective especially for forecasting purposes is the so-called Bayesian shrinkage (De Mol et al. (2008), Banbura et al. (2010a), Carriero et al. (2011)).

[14] The use of factors in a pure VAR framework has been advocated by Bernanke et al. (2005) for the evaluation of monetary policy effects, and Bai and Ng (2007) established limiting and convergence results for VAR models, augmented with factors (FAVARs)

[15] If data quality differs across euro area members, this benefit could be substantial.

[16] Static factor models have e.g. been used by Schumacher and Breitung (2006) to forecast for German GDP and by Perevalov and Maier (2010) to forecast U.S. GDP. In addition to the dynamic factor model presented in this study, we also estimated a static factor model. However, in our analysis we found that the dynamic model outperforms the static model, so the remainder of this study focuses on forecasts obtained using a dynamic factor model.

$$F_t = \sum_{t=1}^{p} A_p F_{t-p} + u_t, \quad u_t \sim N(0, Q). \tag{3}$$

This model is akin to dynamic factor structures proposed by Forni et al. (2000), but it is estimated using principal components rather that Likelihood-based methods. Given that F_t is unobservable, the introduction of equation (3) transforms the factor model into a (linear and Gaussian) state-space model, which can be dealt with by the Kalman filter, as shown in Doz et al. (2006). A by-product of the procedure is a series of filtered values $\hat{F}_t$, computed using the Kalman filter, which can also comprise forecast values. Hence, h-quarter ahead projections for the target variables can be constructed as

$$\hat{y}^{Q}_{t|t+h} = \beta' \hat{F}_{t+h} + \gamma(L) y_{t+h-1}.$$ [17]

Giannone et al. (2008) as well as the meta-analysis conducted by Eickmeier and Ziegler (2006) suggest that dynamic factor models work better than naive AR-benchmarks or static factor models, especially when US data is concerned.[18]

3 Forecasting economic developments in the euro area

3.1 Forecast horizon and data

We focus on forecasting GDP and GDP components of the euro area, as well as all headline GDP for individual member countries. We use pseudo real-time data[19] both at the euro area and the country level. Figure 1 shows the timing of the forecasting exercise and the available data at each point in time (as an illustration, we give the intuition for a simple AR forecast and the PMI model;

[17] When the target variable is quarterly and the factors are monthly, as in our case, monthly projections are converted to quarterly frequency according to Mariano and Murasawa (2003). Note that the forecasting structure differs slightly from the PMI model, in that the h step ahead forecast in the dynamic factor model is a function of the $h-1$ step ahead forecast, not a direct forecast. We estimated both possibilities, and the specifications reported here yielded superior results for the respective model.
As for the lag lenght, we kept a fixed specification over the whole forecasting horizon, although in principle this could also have been optimized at each step.

[18] Dynamic factor models have been developed for numerous countries, including Marcellino et al. (2001) and Angelini et al. (2008) for the euro area, Den Reijer (2005)'s for Dutch GDP and Banerjee et al. (2006) for the new EU member countries. Also, several studies have focused on using dynamic factor models to forecast inflation, including Cristadoro et al. (2001) for the euro area, Artis et al. (2004) for the United Kingdom, Matheson (2006) for New Zealand and Gosselin and Tkacz (2001) for Canadian inflation.

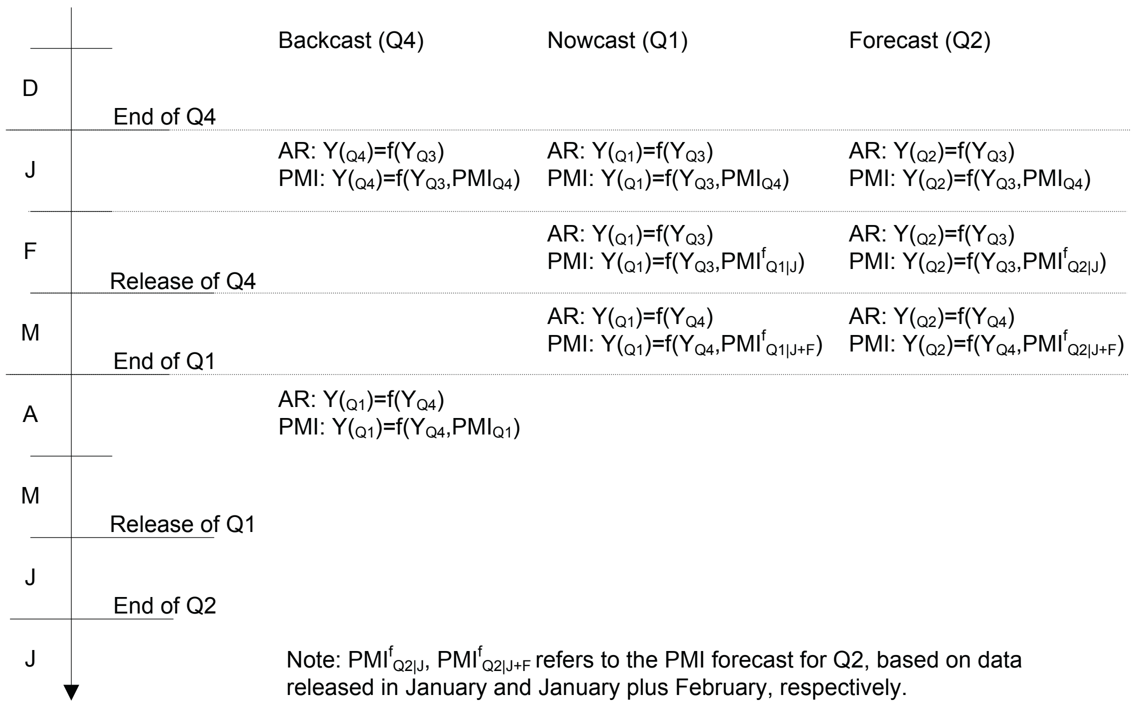
[19] We follow Rünstler and Sédillot (2003) and Giannone et al. (2008) in taking account publication lags in the individual monthly series, and consider a sequence of forecasts to replicate the flow of monthly information that arrives within a quarter. This excludes the effects of data revisions, which have been found to be relatively small for euro area data (see Giannone et al, 2010; Diron, 2008)). In addition, we remark that we consider the first official releases in order to compute publication lags, hence diregarding flash estimates.

the dynamic factor model is estimated analogously to the PMI model). Suppose that we are in mid-January. Given that GDP for Q4 is only released towards the end of February, we are interested in three estimates:

- First, a projection of GDP from Q4 (backcast), using GDP data from Q3 and the average of the PMI (or the dynamic factors) recorded in Q4;
- Second, a projection of GDP in the current quarter (Q1, 'nowcast'); based on the same information
- Third, a forecast for Q2, based on the same information set as the nowcast.

In February, no new data has been released to change the AR back-, now- or forecasts, but the information set changes for the PMI model and the factor model, as nowcasts for Q1 and forecasts for Q2 from these models can now incorporate information released in January. The release of Q4 GDP at the end of February means that we no longer need to backcast GDP in March. Also, the nowcast and the forecast will now be based on Q4 GDP (plus the latest monthly indicators).

Figure 1: The forecasting exercise comprises backcasts, nowcasts and forecasts of next quarter's GDP, and is updated with new (pseudo real-time) data every month



We evaluate forecasting accuracy at the end of each month for the nowcast and next quarter's forecast, as well as for the backcast during the first two months of the quarter. Our evaluation is based on a recursive estimation of the models on an expanding window, covering 60 months (our first estimation is based on the sample from January 1997 to March 2005). We use two data sets, both of which contain quarterly GDP data, including all GDP components (exports, imports, capital formation, government expenditure and consumption) for the euro area and all member countries.[20] In addition, we consider 22 monthly series, which include a set of price and industrial production indices, monetary and credit aggregates, stock markets and confidence indicators, plus the effective exchange rate of the euro (a complete list of series is given in table 10 in the appendix). We divide the data as follows:

- Full data set: quarterly GDP data for the euro area and all national economies, plus monthly economic indicators for the euro area and all individual countries.

- Restricted data set: quarterly GDP data for the euro area and all national economies, plus monthly economic indicators for the euro area (but not for individual countries).

Monthly information from national economies should in principle help improve forecasts for individual countries by expanding the data set, allowing for a better estimation of the factors. For example, estimation of economic activity or price pressures could be facilitated, if data on industrial production or inflation from *all* euro area countries is included. Moreover, some national data is released earlier than their European counterpart (for instance, German trade or industrial production data is published before the European indicators are available). However, the use of too many heterogeneous series may also blur the signal, especially taking into account the fact that a limited number of factors has to be employed in practice.

Prior to the estimation of the models, all series have been transformed to account for deterministic or stochastic trends;[21] in addition to this, all series were de-meaned and standardized. In Figure 2, we plot the annualized quarter-on-quarter growth rates of GDP (summary statistics are reported in Table 1). Note that growth within the euro area has been heterogeneous, and some countries display a much higher degree of volatility than others (notably Ireland, Luxembourg, Portugal and Greece).

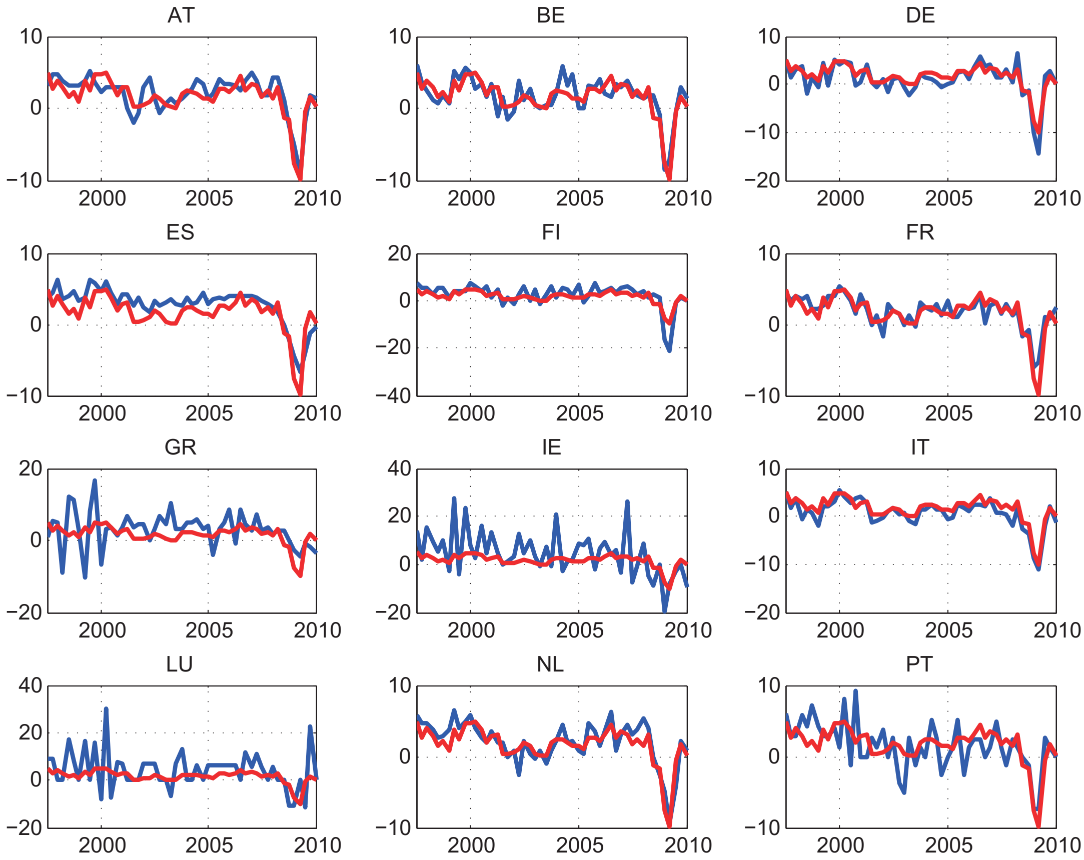
3.2 Preliminary investigation

To get a first idea how the two forecasting models capture the dynamics of the data, we have estimated them over the full sample, and constructed their in-sample fit. In Figure 3, we report the (monthly) in-sample fit of both models for forecasting euro area GDP growth. Both models seem to track GDP fairly well. As the general structure of the model forecasts is relatively similar – future developments are expressed as a function of lagged values, plus additional

[20] We restrict ourselves to the EU12, as data coverage for the EU16 is more limited. We cover Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, the Netherlands and Portugal.

[21] Table 10 in the appendix contains details on how the series were transformed.

Figure 2: Annualized quarter-on-quarter growth rates of GDP for euro area countries (blue) and the euro area aggregate GDP growth rate (red)



Note: We use the following country codes: Austria: AT; Belgium: BE; Germany: DE; Spain: ES; Finland: FI; France: FR; Greece: GR; Ireland: IE; Italy: IT; Luxembourg: LU; the Netherlands: NL; Portugal: PT

information in the form of the PMI or of one or more factors – it is interesting to compare the inputs into the forecasts. To this end, Figure 4 plots the first three factors together with the euro area PMI, unemployment and inflation (we use the ECB's Harmonized Index of Consumer Prices). In particular we would like to highlight a striking resemblance between our first factor and the PMI index. Although principal components are identified only up to a constant of scale and a rotation matrix, and thus cannot be directly related to economic indicators, it is noteworthy that the key information extracted from a very large data set is so similar to the PMI index. This suggests the following:

- The PMI is an timely way to obtain information early in the month not too dissimilar from what the factor model extracts from dozens of series;

- Conversely, this justifies using the PMI model as a benchmark, as the PMI is a simple, but potentially very useful alternative way to summarize the bulk of the information in the data.

Table 1: Mean, standard deviation and minimum of annualized GDP growth rates for the euro area and member states.

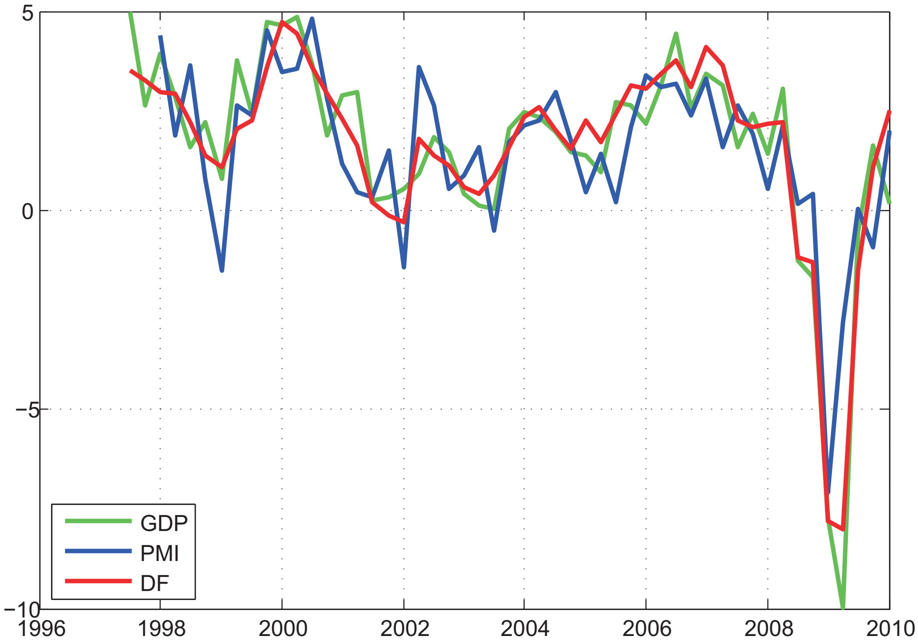
	Mean	Std. dev.	Minimum
EA	**1.6179**	**2.6297**	**-9.9729**
AT	2.0395	2.6101	-9.2668
BE	1.7764	2.6997	-8.5718
DE	1.0541	3.4856	-14.2938
ES	2.8068	2.5687	-6.6956
FI	2.4493	5.0285	-21.2978
FR	1.8443	2.1950	-5.9754
GR	3.0407	4.9884	-10.2701
IE	4.5089	9.1636	-19.4729
IT	0.7156	2.9513	-11.0883
LU	4.1511	8.0241	-11.4293
NL	2.0190	2.9977	-9.4122
PT	1.4985	3.3488	-7.4536

Note, however, two things: first, the PMI is, on average, more volatile than the first factor; second, focusing on the 2008/09 recession, the PMI point to a faster recovery, but also a sharper deceleration of economic activity in late 2009. As for the other factors, the second factor seems related to real activity via unemployment, and the third corresponds to a nominal-measure such as the Harmonized Index of Consumer Prices (HICP) – at least before the outset of the recession. This finding is in line with other studies using factor models, e.g. in Stock and Watson (2002).

3.3 Forecasting performance over the full sample

A first sense of the forecasting performance of the two models can be gained by comparing them to a simple AR benchmark (see tables 11 and 12 in the appendix). We find that both models substantially outperform the AR benchmark when projecting euro area GDP, GDP of most member countries, and for most components of euro area GDP. Not surprisingly, the performance of both models typically improves, as more data arrives, so forecasting accuracy in the second month of the quarter is typically higher than in the first month of the quarter (particular when forecasting the next quarter). As regards the PMI model in table 11, we report two variants, one in which we use the euro area PMI to construct forecasts for individual euro area countries, and one in which we use each country's national PMI to forecast its own GDP (reported in column 'R' and 'F', respectively). By and large both perform similarly well. Lastly, when considering forecasts for components of euro area GDP, both models are excellent at backcasting. We also see that over the entire sample, the factor model typically outperforms the AR for relative volatile components (investment, trade), but performs rather poorly when forecasting consumption and government expenditures. In contrast, the forecasting performance of the PMI model is more stable, consistently beating the AR over almost all horizons and components

Figure 3: In-sample fit of the PMI model (blue line) and dynamic factor model (red line) for the euro area GDP (green line).



(government expenditure at some horizons being the only exception).

Tables 2 and 3 show the performance of the dynamic factor model and the PMI model over the full sample. We report the relative RMSE of the factor model over the PMI model – numbers larger than 1 indicate that the PMI model outperforms the dynamic factor model – for the full data set under the headers 'F' and for the restricted data set under the headers 'R'.[22] Observations where one model statistically outperforms the other at the 5 per cent level according to the Diebold and Mariano (1995). Table 2 reveals that over the entire sample, the dynamic factor model tends to outperform the PMI model when back-, now- and forecasting euro area GDP, as well as GDP for most national economies (in fact, Spain is the only country in which the PMI model seems to outperform the dynamic factor model fairly consistently). As regards the components (table 3), the picture is more mixed, with some important euro area GDP components such as consumption and investment being better forecasted by the PMI model.

In what follows, we turn to the core of our investigation and examine out-of-sample forecasting accuracy over two subsamples, namely a period falling into the 'Great Moderation' (2002-2007) and the 'Great Recession' (2008/2009).

[22] The Bai and Ng (2002) information criterion suggest the use of 5 factors in the factor model for both the full and the restricted data set. The selection of the number of factors is a tricky problem and still has to be resolved, especially in what concerns the choice of an optimal number of factors for the purpose of forecasting. Alternative lag length selection criteria point to the same number of factors, including Amengual and Watson (2007) – a simple generalization of Bai and Ng (2002) to dynamic factors – and Alessi et al. (2010), which was recommended in Barhoumi et al. (2010) to yield better forecasts than Bai and Ng (2002). Given the potential sensitivity of the results to the number of lags, we also conducted robustness check by varying the numbers of factors (see table 8).

Table 2: Relative RMSE of the dynamic factor model over the PMI model by country (full sample)

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
EA	0.78*	0.72*	0.69*	0.53*	0.90*	0.87*	0.98	1.02	0.83	0.87	1.02	0.99	0.99	0.97	0.96	0.93
AT	0.93	0.92	0.90	0.88	0.97	0.96	0.98	1.00	0.83	0.86	1.07	1.09	1.05	1.06	1.08	1.14*
BE	0.74*	0.72*	0.72*	0.69*	0.87*	0.86*	1.00	0.95	1.01	0.95	0.88*	0.90*	0.90*	0.96	0.79*	0.85*
DE	0.62*	0.65*	0.63*	0.60*	0.96	0.95	0.92	0.99	0.75*	0.77*	1.08*	1.03	1.01	0.97	0.96	0.94
ES	0.94	0.97	0.99	0.94	1.17*	1.25*	0.99	1.09	1.02	1.20	0.91*	0.97	1.00	1.07*	1.43*	1.40*
FI	0.71*	0.74*	0.68*	0.70*	1.11*	1.05	0.98	0.96	0.79*	0.76*	1.04	1.05	1.08	1.06	1.01	0.99
FR	0.77*	0.76*	0.78*	0.69*	0.88	0.86	1.09	1.12	1.13	1.15	0.90	0.90	0.86	0.87	0.98	1.00
GR	0.59*	0.57*	0.61*	0.58*	1.06	0.96	0.94	0.90	0.74*	0.76*	1.37*	1.21*	1.29*	1.15	1.04	0.97
IE	0.88*	0.86*	0.85*	0.81*	1.07	1.13*	1.07	1.11*	1.09	1.12	0.96	0.99	0.91	0.98	1.15	1.23
IT	0.97	0.87	0.86	0.74*	1.00	0.97	1.10	1.13*	1.11	1.11	0.99	0.96	1.01	0.97	1.05	1.03
LU	0.65*	0.62*	0.63*	0.63*	0.96	1.01	1.01	1.07	0.87*	0.89	0.97	0.97	0.92	0.98	0.87	0.84
NL	0.70*	0.67*	0.68*	0.60*	0.91*	0.85*	0.81*	0.80*	0.88*	0.89	0.89	0.86*	0.83*	0.83*	0.87*	0.86*
PT	0.66*	0.74*	0.65*	0.72*	1.07	0.99	0.98	0.92*	1.07	0.99	1.14	1.08	1.11	1.08	1.02	0.99

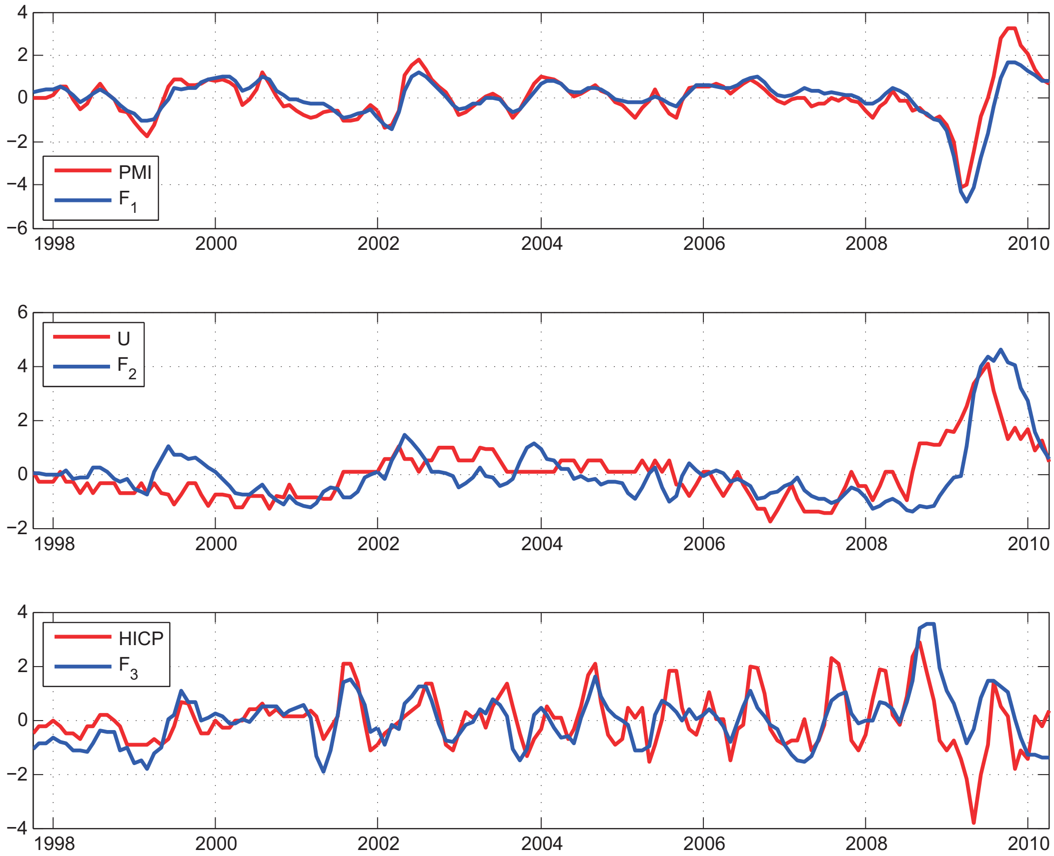
Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. Country codes are given in table 2.

Table 3: Relative RMSE of the dynamic factor model over the PMI model by component (full sample)

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
Y	0.78*	0.72*	0.69*	0.53*	0.90*	0.87*	0.98	1.02	0.83	0.87	1.02	0.99	0.99	0.97	0.96	0.93
C	0.87*	0.88	0.84*	0.81*	1.29*	1.25*	1.18*	1.20*	1.12*	1.18*	1.03	1.02	1.05	1.03	1.37*	1.33*
G	0.96	0.99	0.89*	0.93	1.01	1.08	1.10*	1.15*	1.15*	1.21*	0.87*	0.90	0.90*	0.94	0.88*	0.97
I	0.74*	0.79*	0.67*	0.64*	1.11*	1.08	0.95	1.04	0.91	1.05	1.07	1.03	1.09	1.04	1.17*	1.16*
X	0.69*	0.67*	0.66*	0.57*	1.01	0.95	1.03	1.02	0.94	0.92	0.95	0.94	0.98	0.96	0.94	0.92
M	0.58*	0.64*	0.56*	0.57*	0.96	0.91*	0.88	0.94	0.83	0.92	0.95	0.94	0.94	0.94	0.97	0.99

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. C, G, I, X, M refer to consumption, government, investment, exports and trade, respectively.

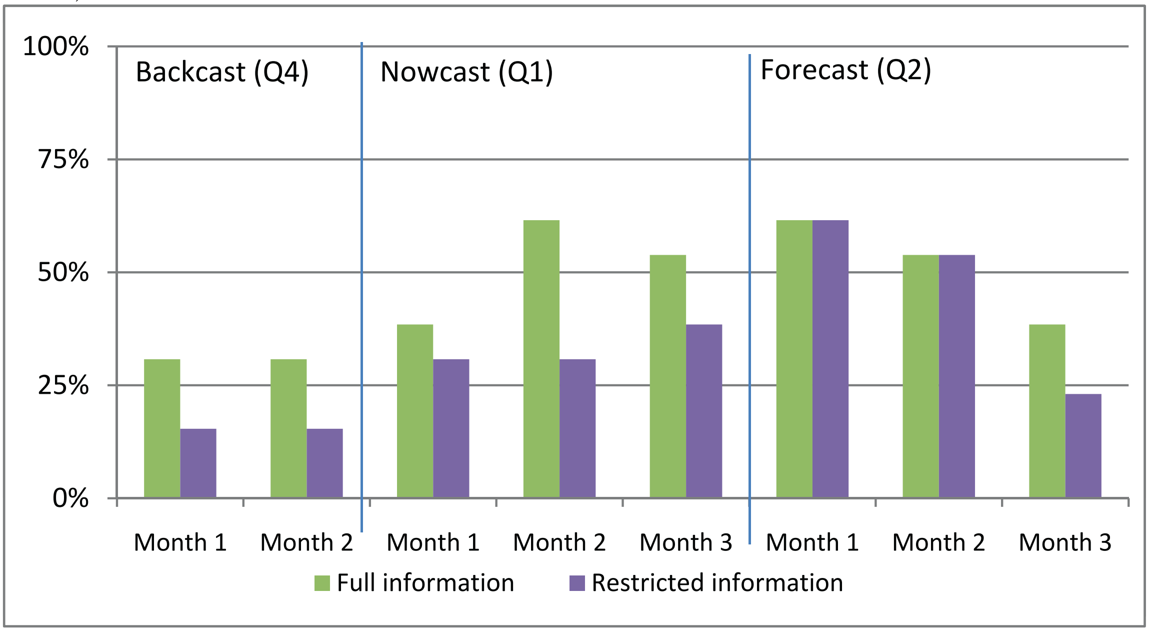
Figure 4: First, second and third principal components of the data, together with the euro area PMI, unemployment (U) and inflation (HICP)



3.4 Forecasting during the 'Great Moderation'

Our first set of results considers a period during the 'Great Moderation' (we focus on 2002-2007). Table 4 shows estimation results for euro area GDP and GDP of each euro area member country. Several features stand out. First, when forecasting GDP for the euro area as a whole, the dynamic factor model is typically the better model, as it beats the PMI model in 12 of the 16 projection exercises reported. Second, the dynamic factor model is particularly good at backcasting, with – at times – very substantial improvements over the PMI model (relative RMSE's for backcasts for Greece, Portugal or the Netherlands, for instance, show improvements in accuracy of 20-40 per cent). Most likely this reflects the fact that the factor model also incorporates 'hard' data, while the PMI model only uses 'soft' (survey) data. Third, more information is not always better: Figure 5 graphs how many times the PMI model outperforms the dynamic factor model during the 'Great Moderation' period in forecasting euro area or individual countries' GDP (in per cent of all country forecasts reported in Table 4). Values below 50 per cent indicate that, on average, the dynamic factor model yields more accurate country forecasts than the PMI model, while values above 50 would suggest that on average, the PMI model is more likely to yield

Figure 5: Per cent of country forecasts where the PMI model beats the dynamic factor model during the 'Great Moderation' (euro area and individual countries' GDP)



Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. A value below 50 per cent indicates that, on average, the dynamic factor model outperforms the country forecasts of the PMI.

accurate GDP forecasts than the dynamic factor model. While Figure 5 does not contain information about the magnitude of the forecast errors, it illustrates that (i) the dynamic factor model generally outperforms the PMI model, (ii) that the more restricted data set without information from individual euro area countries performs, on average, better.[23]

There is, however, a drawback of the dynamic factor model. Consider Figure 6, in which we focus on those observations that are statistically different from each other according to the Diebold and Mariano (1995) test. We plot the relative RMSE's of the dynamic factor model, relative to the PMI model, with each dot representing the relative RMSE of one forecast for GDP of either the euro area or an individual country (a value lower than 1 indicates that the factor model outperforms the PMI model). Interestingly, this graph shows that the dynamic factor model has a lot of 'hits', but also some fairly large 'misses', where the PMI model outperforms the dynamic factor model. This suggests that while the dynamic factor model is useful in many cases, the PMI model may still be more appropriate for forecasting GDP for specific countries within the euro area (for Spain, for instance, the PMI model always dominates the dynamic factor model).

Looking more closely at the results by country, table 4 reveals a mixed

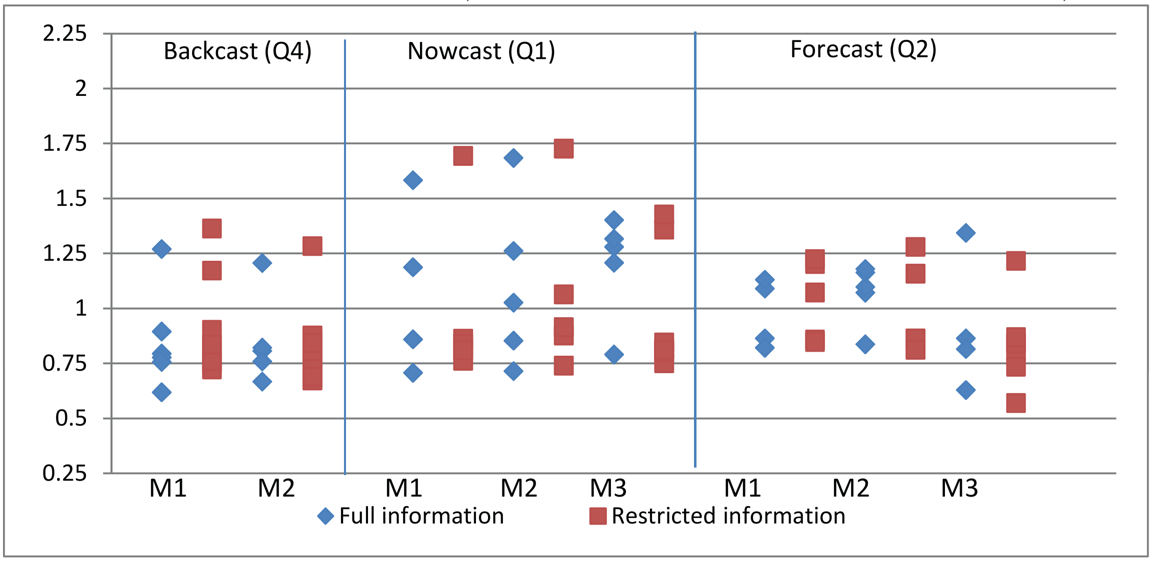
[23]The fact that 'more' information is not always better has also been found when forecasting French GDP (see Barhoumi et al., 2009).

Table 4: Relative RMSE of the dynamic factor model over the PMI model by country during the 'Great Moderation'

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
EA	0.91	0.82*	0.92	0.74*	0.99	0.86*	1.05	0.88*	1.11	0.97	1.10	1.08	0.98	0.98	0.88	0.81*
AT	1.27*	1.36*	1.21*	1.28*	0.92	0.95	0.96	0.96	1.28*	1.36*	0.79	0.82*	0.82	0.86*	0.85	0.84*
BE	0.79*	0.75*	0.81*	0.77*	0.92	0.97	0.95	0.93	1.00	0.89	0.92	0.86*	1.07*	1.05	0.63*	0.57*
DE	0.92	0.87	0.93	0.84*	1.03	0.96	1.04	0.99	1.21*	1.13	1.09*	1.05	1.04	1.01	0.97	0.95
ES	1.16	1.17*	1.15	1.20	1.58*	1.69*	1.68*	1.73*	1.40*	1.43*	1.09	1.17	1.07	1.14	1.03	1.13
FI	0.90*	0.90*	0.90	0.88*	1.12	0.94	1.15	0.95	0.96	0.82*	0.96	1.00	0.95	1.00	1.04	1.15
FR	0.86	0.86	0.86	0.81*	0.97	0.84*	1.13	0.96	1.18	1.08	1.14	1.20*	0.95	0.97	0.80	0.93
GR	0.78*	0.72*	0.82*	0.72*	0.99	0.98	0.97	0.91*	0.82	0.75*	1.03	0.99	1.05	1.01	0.94	0.95
IE	1.05	0.98	1.00	0.94	0.99	1.02	1.03*	1.06*	1.01	0.98	0.89	0.88	0.88	0.88	0.86*	0.87*
IT	1.06	0.91	1.03	0.90	1.19*	1.08	1.26*	1.08	1.32*	1.07	1.13*	1.07*	1.10*	1.00	1.05	0.98
LU	0.92	0.71	0.89	0.67*	1.07	1.02	1.08	1.03	0.93	0.80*	1.08	1.22*	1.16*	1.28*	1.34*	1.22*
NL	0.76*	0.76*	0.76*	0.69*	0.86*	0.76*	0.85*	0.74*	0.90	0.84*	0.86*	0.85*	0.84*	0.81*	0.82*	0.73*
PT	0.62*	0.84*	0.67*	0.84*	0.71*	0.81*	0.72*	0.92	0.79*	0.81*	1.09	1.09	1.18*	1.16*	1.04	0.92

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. Country codes are given in table 2.

Figure 6: Relative RMSE's of the dynamic factor, divided by the PMI model, during the 'Great Moderation' (euro area and individual countries' GDP)



Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. Each dot represents a country forecast where the dynamic factor model and the PMI model differ significantly (at the 5 per cent level).

picture. The PMI model tends to outperform the factor model for Italy, Spain and Luxembourg. For Germany and France, the dynamic factor model performs very well for backcasting, while nowcasts of the PMI model tend to be more accurate.

A broadly similar picture emerges when considering forecasts for components of euro area GDP. Table 5 and Figure 7 summarize our results. As can be seen, the dynamic factor model typically outperforms the PMI model, notably for the volatile trade components. An interesting finding when examining forecasts for GDP components is that the full data set tends to provide better forecasts for euro area components than the restricted data set. This suggests that the merits of the richer data set lies in forecasting components of GDP, rather than individual countries.[24]

Taken together, we can summarize our results as follows. The dynamic factor model dominates the PMI model in many cases, but some large errors makes its overall performance somewhat uneven. In many cases, the PMI model, despite its simplicity, is a tough benchmark, and each model performs well for some economies and/or some horizons, and less well at others.[25] Lastly, the restricted data set tends to yield better forecasts for euro area countries, while having more data tends to help project components of GDP at different horizons.

[24]This supports the findings of Giannone and Reichlin (2006), which suggest that output fluctuations in the euro area are mainly explained by common shocks; in contrast, it seems that components of euro area GDP are less well proxied by common shocks.

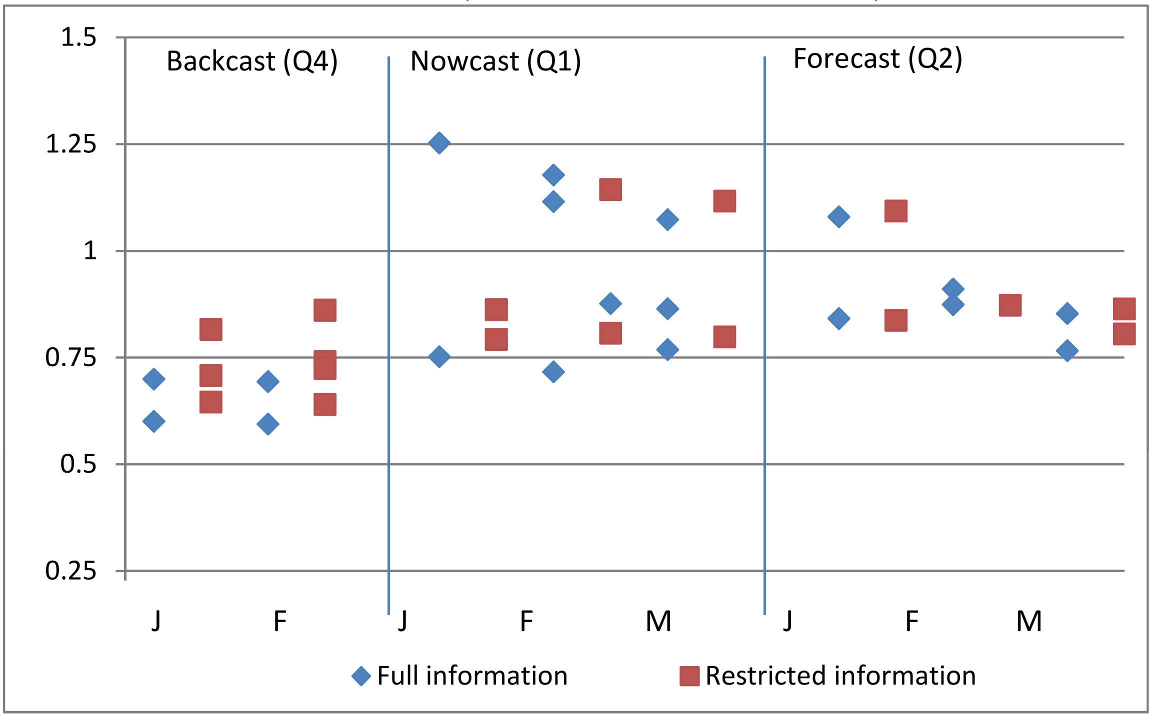
[25]Examining forecasts from dynamic factor models for output across the G7, Stock and Watson (2004) also conclude that forecasting accuracy can be uneven, with the model forecasting very well for some countries, but being beaten by naive benchmarks for other countries.

Table 5: Relative RMSE of the dynamic factor model over the PMI model by component during the 'Great Moderation'

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
Y	0.91	0.82*	0.92	0.74*	0.99	0.86*	1.05	0.88*	1.11	0.97	1.10	1.08	0.98	0.98	0.88	0.81*
C	0.95	0.91	0.93	0.89	1.25*	1.13	1.18*	1.06	1.18	1.08	0.90	0.94	0.91*	0.94	1.07	1.04
G	0.94	1.00	0.89	0.93	1.00	1.00	1.12*	1.14*	1.07*	1.12*	0.84*	0.84*	0.87*	0.87*	0.85*	0.86*
I	0.94	0.94	0.94	0.86*	1.02	1.04	1.01	1.06	1.04	1.13	1.02	0.92	1.13	1.05	1.11	1.04
X	0.70*	0.65*	0.69*	0.64*	0.94	0.93	0.94	0.91	0.86*	0.80*	1.08*	1.09*	0.95	0.97	0.77*	0.90
M	0.60*	0.71*	0.59*	0.72*	0.75*	0.79*	0.72*	0.81*	0.77*	0.83	1.03	1.04	0.89	0.92	0.83	0.86

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. C, G, I, X, M refer to consumption, government, investment, exports and trade, respectively.

Figure 7: Relative RMSE's of the dynamic factor, divided by the PMI model, during the 'Great Moderation' (GDP components euro area)



Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made.

3.5 Forecasting during the 'Great Recession'

Next, we analyze the 2008/2009 period, which was characterized by a global recession.[26] This period is interesting for two reasons. First, by exploiting a rich data set with additional forward-looking indicators besides the PMIs, factors models are, at least in theory, well-positioned to forecast periods of high volatility. Second, given the differences in economic structures, euro area countries experienced different cyclical patterns over this period. In late 2008, for instance, a key feature of the global recession was a sharp drop in trade. Export-oriented economies like Germany, the Netherlands or Ireland may have been particularly affected in this early phase of the downturn by the drop in global demand. By late 2009, the focus had shifted more to differences in fiscal positions, turning the global recession into a European debt crisis. As countries like Greece adopted fiscal austerity measures, their economic activity fell sharply, while export-oriented economies started benefiting from the recovery in global demand. Given these divergent developments, the 2008/2009 period will also shed light on whether focusing on euro area indicators alone is indeed sufficient to provide a thorough assessment of not only the euro area aggregate, but also individual countries.

We report the complete results in Table 6. Figures 8 and 9 show, as before, how often the dynamic factor model outperforms the PMI model and – for

[26]The 2008/09 period is also referred to as the 'Great Recession' (e.g. P. Krugman, 2009, The Great Recession versus the Great Depression, New York Times, March 20.)

those forecasts that are statistically different – the relative RMSE's. The first thing to note is that the factor model clearly dominates the backcast of the PMI model for the euro area and all countries, often by a wide margin (improvements can be up to 60 per cent, relative to the PMI model). However, as Figure 9 shows, accuracy of the nowcast and, in particular, the forecast can be very uneven (the errors increase substantially, if the factor model does not have timely data, such as for the forecasts). Even for countries where, on average, the dynamic factor model is more accurate, over some horizons forecast errors of the factor model can be large (e.g. forecast errors for Greece are, in some cases, more than 50 per cent higher than using the PMI model). Also, while the full information set lead to a deterioration of accuracy for country projections over the Great Moderation, it now improves accuracy for the nowcast. This suggests that during volatile periods, a broader set of information has additional merits.

Looking more closely at projections by country, the dynamic factor model now yields in most cases – on average – better forecasts. The PMI model now beats the dynamic factor model in only 33 out of 104 forecasts (during the Great Moderation, the PMI model beat the factor model in 48 cases out of 104 cases). Also, average relative RMSE is now similar for both the restricted and the full data set (previously, the restricted data set yielded a somewhat lower average RMSE). Interestingly, the dynamic factor model's biggest weakness during the crisis period is projecting components of euro area GDP. While backcasting performance still dominates the PMI model in most cases, nowcasting and forecasting accuracy for almost all components deteriorates substantially, relative to the PMI model (Figure 10). This holds for both the full and the restricted information set, suggesting that during the Great Recession, country-specific information did not help forecast components of euro area GDP.

3.6 On the merits of 'lean' and 'rich' forecasting environments

One of the key findings so far is that the dynamic factor model yields in most cases projections superior to the PMI model, but with some large 'misses' (a more detailed investigation of the errors is given in appendix B). This could suggest that either our selection of factors was overly restrictive, or that some countries are simply harder to forecast. We investigate both possibilities.

First, we examine whether by changing the number of factors we retain, we can improve forecasting accuracy. On the one hand, given the heterogeneity of the euro area, more factors might be needed to fully exploit the richness of the data;[27] on the other hand, by including more factors, forecasting performance might deteriorate, as more coefficients need to be estimated. In Table 8 we report the performance of the dynamic factor model for the euro area, compared to the PMI model, for different number of factors. The performance in backcasting seems to increase as more factors are included, but this is not

[27] In this spirit, Barhoumi et al. (2009) conclude that the Bai and Ng criterion tends to suggest too few factors, and that more factors can improve forecasting accuracy.

Table 6: Relative RMSE of the dynamic factor model over the PMI model by country during the 'Great Recession'

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
EA	0.67*	0.67*	0.57*	0.39*	0.88*	0.87*	0.98	1.04	0.82	0.85	1.03	0.99	0.99	0.96	0.96	0.93
AT	0.78	0.76	0.77	0.67	0.97	0.96	0.98	1.01	0.81	0.79	1.14*	1.15*	1.10*	1.11*	1.15*	1.21*
BE	0.63*	0.61*	0.57*	0.44*	0.86*	0.85*	1.04	0.95	1.05	0.97	0.90*	0.93*	0.87*	0.93	0.89	0.96
DE	0.52*	0.53*	0.51*	0.46*	0.93	0.95	0.92	0.99	0.69*	0.68*	1.11*	1.04	1.02	0.96	0.92	0.94
ES	0.91	0.91	0.99	0.86	1.12	1.21	0.96	1.06	1.08	1.19	0.87*	0.95	0.97	1.07*	1.47*	1.42*
FI	0.47*	0.61*	0.42*	0.52*	1.11*	1.07	0.97	0.95	0.78*	0.76*	1.07	1.06	1.09	1.07	0.99	0.97
FR	0.55*	0.60*	0.57*	0.42*	0.89	0.88	1.15	1.22	1.20	1.21	0.88	0.86*	0.84	0.85	1.00	1.01
GR	0.42*	0.38*	0.40*	0.36*	1.17*	0.91	0.95	0.84	0.81*	0.72*	1.78*	1.50*	1.51*	1.26	1.11	0.92
IE	0.62*	0.66*	0.60*	0.53*	1.20*	1.34*	1.03	1.19	1.12	1.26	1.03	1.11	0.95	1.07	1.65*	1.79*
IT	0.95	0.87	0.82	0.60*	0.97	0.94*	1.13	1.15*	1.15	1.13	0.99	0.95	0.99	0.96	1.04	1.03
LU	0.48*	0.57*	0.53*	0.61*	0.87	1.00	0.90	1.09	0.88*	0.94	0.91*	0.90*	0.72*	0.86*	0.72	0.67*
NL	0.59*	0.64*	0.56*	0.51*	0.90*	0.90	0.82*	0.86*	0.93	0.96	0.91	0.87	0.82*	0.83*	0.87	0.90
PT	0.51*	0.59*	0.44*	0.49*	1.21*	1.04	0.96	0.90	1.08	0.98	1.17	1.03	1.03	0.98	1.10	1.05

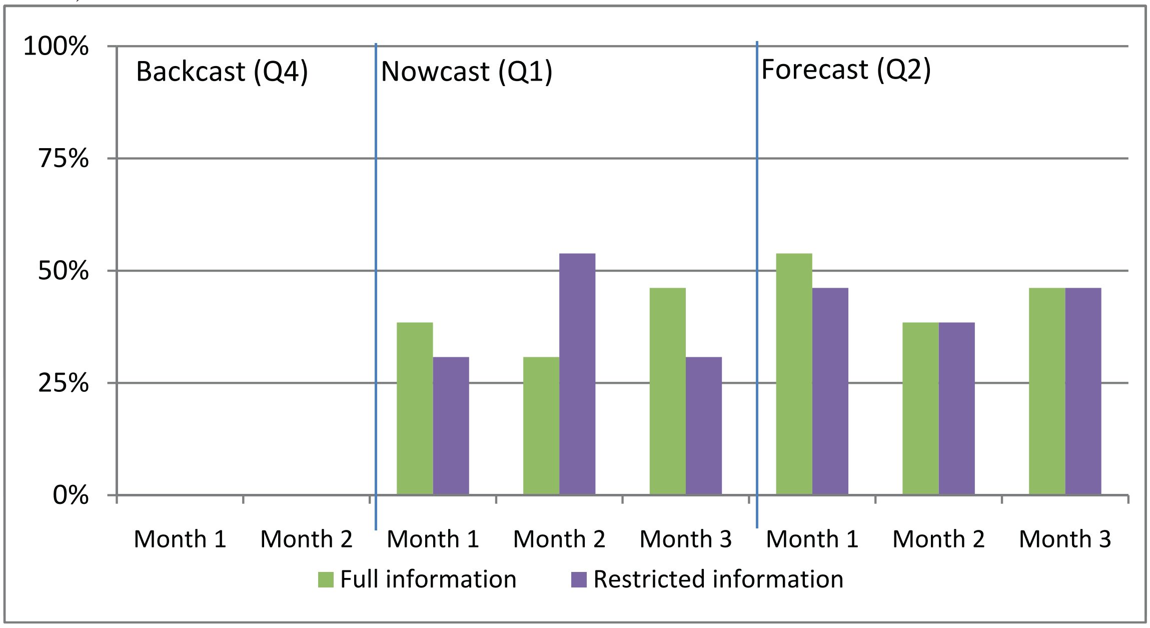
Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. Country codes are given in table 2.

Table 7: Relative RMSE of the dynamic factor model over the PMI model by component during the 'Great Recession'

	Backcast				Nowcast—						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
Y	0.67*	0.67*	0.57*	0.39*	0.88*	0.87*	0.98	1.04	0.82	0.85	1.03	0.99	0.99	0.96	0.96	0.93
C	0.83	0.84	0.70*	0.60*	1.47*	1.38*	1.38*	1.40*	1.24	1.30	1.05	1.03	1.11	1.08	1.56*	1.51*
G	0.90	0.89*	0.97	0.84	1.15*	1.26*	1.05	1.13	1.40*	1.42*	1.44*	1.42*	1.26	1.30*	1.29	1.45*
I	0.55*	0.69*	0.48*	0.39*	1.11*	1.10	0.94	1.06	0.84*	1.04	1.10	1.05	1.08	1.04	1.19*	1.18*
X	0.68*	0.70*	0.68	0.48*	1.03	0.95	1.13	1.07	1.05	0.97	0.96	0.93	0.96	0.94	0.93	0.90
M	0.50*	0.58	0.52*	0.42*	0.97	0.94	0.99	0.99	0.91	0.96	0.95	0.92	0.95	0.94	1.00	1.02

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. C, G, I, X, M refer to consumption, government, investment, exports and trade, respectively.

Figure 8: Per cent of country forecasts where the PMI model beats the dynamic factor model during the 'Great Recession' (euro area and individual countries' GDP)



Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. A value below 50 per cent indicates that, on average, the dynamic factor model outperforms the country forecasts of the PMI.

valid for nowcasting and forecasting: there, it seems that more parsimonious models have higher chances of beating the PMI benchmark. Overall, we are thus comfortable with our selection of factors.

In addition, we have investigated whether the optimal number of factors depend on the period over which we forecast (Great Moderation vs. Great Recession). Interestingly, when regressing GDP on the estimated factors, we find that during the great moderation the first four factors explain most of the variance, whereas during the recession period, the first factors have much less explanatory power, while factors of higher order become increasingly important. As some of the 'unusual' volatility in the data during the Great Recession period is not captured in the first four factors, the selection of factors is not time-invariant. Overall, these tests illustrate the sensitivity of the results to the number of factors, and suggest that the Bai and Ng (2002) information criterion may not always recommend an optimal number of factors from a forecasting perspective.[28]

Second, to see whether some countries are simply harder to forecast – possibly because of a higher degree of economic volatility – we estimate dynamic factor models for each individual country, but using only data from that country (that is, we discard all euro area information from the country-specific data sets). This provides an assessment how well factor models perform when esti-

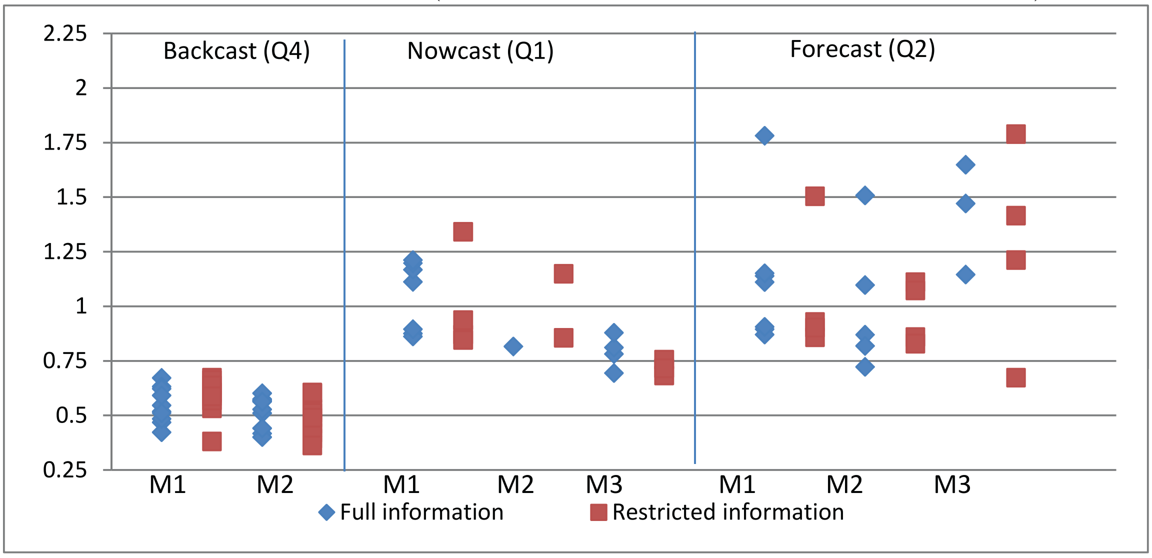
[28]An additional difficulty here is that optimizing the number of factors conditional on a specific subsample may risk overfitting or 'data mining'.

Table 8: Relative RMSE of the dynamic factor model over the PMI model for the euro area during the 'Great Recession' for different numbers of factors

	Backcast		Nowcast			Forecast		
Number of factors retained	Month 1	Month 2	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
1	1.03	0.95	0.79*	0.99	0.92	0.97	0.94	1.02
2	1.02	0.93	0.75*	0.99	0.95	1.03	0.94	1.08
3	0.87	0.64*	0.89	1.03	0.89	1.05	1.00	0.98
4	0.91	0.66*	0.93	1.09	0.88	1.07	1.02	0.92
5	0.85*	0.71*	0.93	1.11	0.90	1.02	1.01	0.90*
6	0.80*	0.53*	0.86*	1.04	0.89	1.01	0.97	0.92
7	0.77*	0.53*	0.87	1.07	0.91	1.05	1.00	0.92
8	0.73*	0.46*	0.88	1.08	0.93	1.05	1.01	0.93
9	0.64*	0.44*	0.89	1.08	0.92	1.07	0.99	0.94
10	0.63*	0.43*	0.86	1.05	0.91	1.02	0.96	0.92

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test.

Figure 9: Relative RMSE's of the dynamic factor, divided by the PMI model, during the 'Great Recession' (euro area and individual countries' GDP)

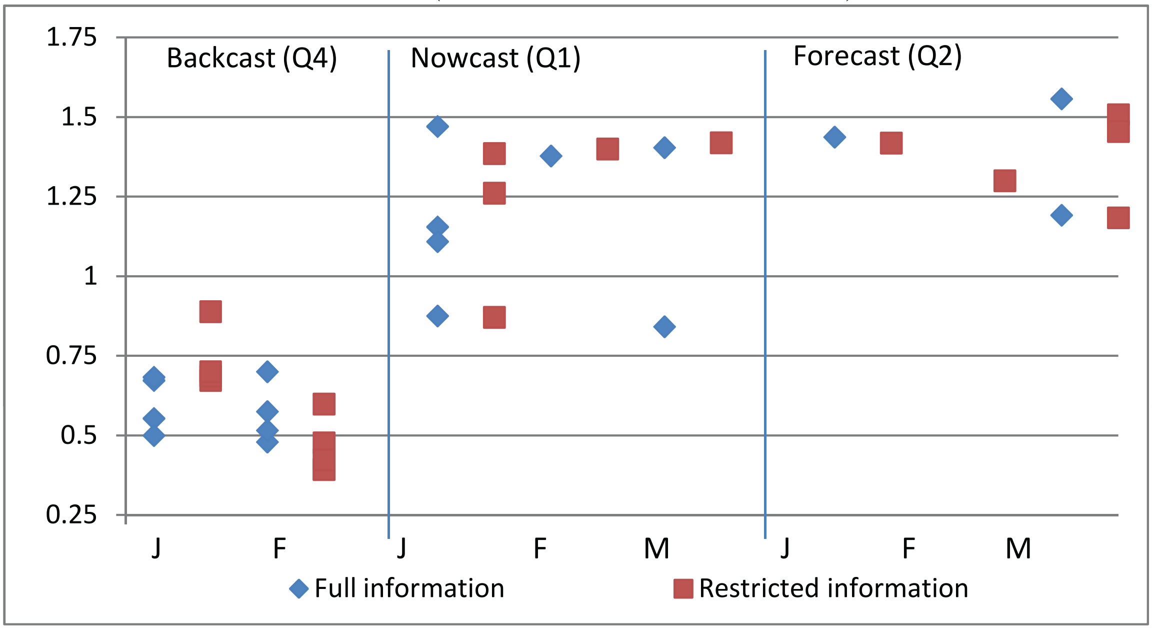


Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. Each dot represents a country forecast where the dynamic factor model and the PMI model differ significantly (at the 5 per cent level).

mated for each national economy individually, using only data from that country (this also reduces the possibility that national information might 'get lost' in an area-wide data set). Table 9 shows RMSEs of the dynamic factor model, estimated using only country-specific data, divided by the RMSE of the models using our restricted euro area data set. Overall, it seems that disregarding aggregate data in favor of country-specific information leads to a deterioration of the forecasts, as most of the significant outcomes point to an advantage of the model using euro-area data. On the basis of this, we conclude that providing the factor model with euro area information to forecast individual countries is helpful. Hence, the uneven forecasting performance of the dynamic factor model – relative to the PMI model – is likely not driven by lack of suitable information.

Why then is it the case that despite employing a much broader information set, the dynamic factor model has relatively more difficulties beating the PMI model during the Great Recession than during the Great Moderation? Given that the forecasting structure of the two models is relatively comparable, one remaining possible explanation is that the PMI model is better during periods of high volatility because a survey-based measure like a PMI reacts faster to changes in the outlook than our factors. This could be because we impose that the factors follow an AR process (without break in the time series properties over the entire sample), whereas a survey could be less persistent and thus reacting faster to new information. Additional analysis confirms that this seems indeed to be the case: as seen earlier in figure 4, the PMI and the first factor are closely correlated, but diverge somewhat during the Great Recession period. We also extracted the first factor from two data sets, one containing PMIs, one that

Figure 10: Relative RMSE's of the dynamic factor, divided by the PMI model, during the 'Great Recession' (GDP components euro area)



Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made.

excluded the PMIs. As figure 11 shows, the first factor extracted from the data set including the PMI indicates a deeper trough in economic activity, and shows a sharper rebound. These features ultimately bring the first factor closer to mimicking the PMI, and thus help improve forecasting performance. Lastly, the AR root of the PMI is 0.88, and thus lower than the AR root of 0.93 of the first factor in the dynamic factor model. Based on this, we conclude that the survey-based PMI adjusted comparatively faster. This suggests that such indicators can be particularly valuable during periods of high volatility.

Taken together, the dynamic factor model remains a superior backcasting tool, as the relatively richer data set translates into better capturing relevant economic developments for backcasting not just GDP for the euro area or its member states, but also components of euro area GDP. However, during the Great Recession, the value of the dynamic factor model as nowcasting or forecasting tool is less obvious. Also, somewhat surprisingly, the PMI model outperforms the dynamic factor model for the component forecasts. Survey-based measures like the PMI can react instantly to changes in the economic outlook, enabling it to perform relatively well, despite the relative simplicity and parsimony of the model.

4 Conclusion

This study has compared forecasting in data-rich and 'data-lean' environments. We employ a simple PMI indicator model and a dynamic factor model – with two different data sets, one comprising only euro area data and one with euro

Table 9: Relative RMSEs of two dynamic factor models: one dynamic factor model estimated with the restricted data set, divided by a factor model estimated using only national indicators.

	Backcast		Nowcast			Forecast		
	Month 1	Month 2	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
AT	0.87*	0.82*	0.75*	0.80*	0.79*	0.92	0.85*	0.80*
BE	0.92	0.75*	0.79*	0.80*	0.81*	0.88	0.79*	0.76*
DE	1.03	1.02	1.02	1.05	1.01	0.97	0.95*	0.97
ES	1.04	1.08*	0.94	1.02	1.03	1.02	0.97	1.02
FI	0.92*	0.88*	0.95	0.93*	0.87*	0.99	0.93*	0.92
FR	0.97	0.87*	0.82*	0.85*	0.88*	0.94	0.94	0.84*
GR	0.84*	0.78*	1.34*	1.03	0.81*	1.51*	1.75*	1.76*
IE	1.04	1.14*	1.00	0.98	0.99	1.19*	1.04	1.06
IT	0.92	0.79*	0.70*	0.78*	0.88*	0.96	0.90*	0.87
LU	1.17	1.12	0.92	1.02	1.23	1.02	1.03	0.88
NL	0.95	0.98	0.82*	0.86*	0.84*	0.92	0.89*	0.87*
PT	0.89	1.11	1.23*	1.17*	0.91	0.88	0.82	1.04

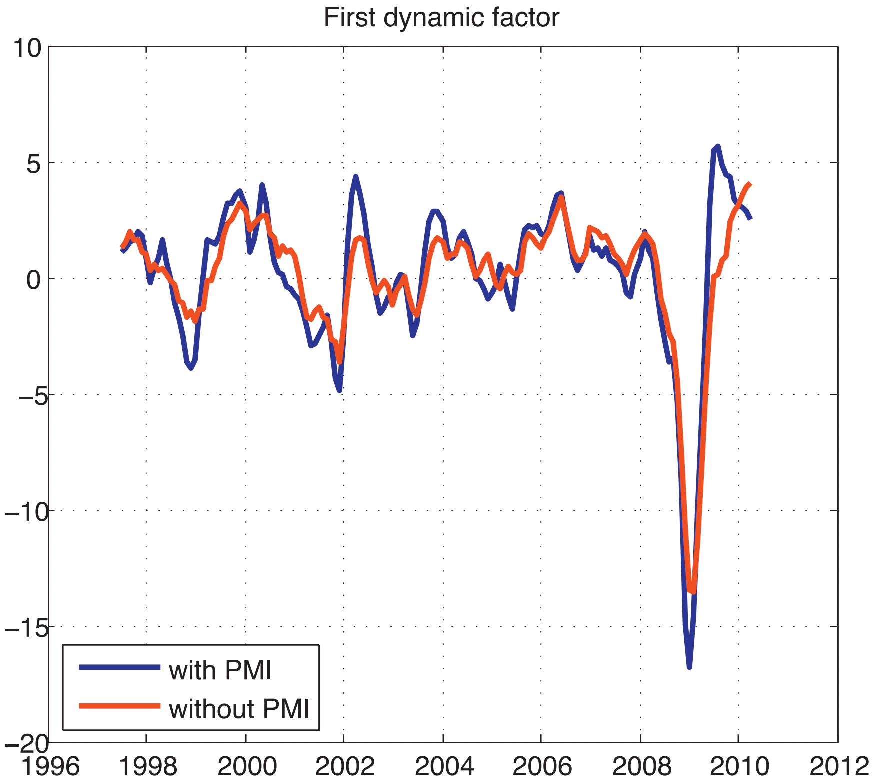
Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made. An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test.

area indicators and data from national sources – to forecast economic developments in the euro area. As is known in the literature, both techniques can yield forecasts that easily beat naive benchmarks; but most studies primarily consider forecasting accuracy during the low-volatility environment of the Great Moderation. We compare forecasting accuracy with different information sets both during the Great Moderation and during the Great Recession (that is, during periods of low and high volatility).

Considering backcasts, nowcasts and forecasts for the euro area, we find that both the PMI indicator model and the dynamic factor model yield large gains over AR models. Overall, it is not evident whether the 'lean' or the 'rich' data environment is preferable. This conclusion is reached through several steps. First, as the dynamic factor model processes the information in our data set, it extracts a first factor that closely resembles the PMI, or put differently: the PMI turns out to be a good way to represent the data flow. Second, on average, the factor model is able to process all available data more efficiently, as – on average – it dominates the PMI model. The improvements in accuracy are particularly large for backcasts, i.e. the more information the dynamic factor model possesses. Still, the parsimonious PMI model provides a 'low tech', fairly accurate way of projecting GDP for both the euro area and national economies, in particular during the Great Recession, where the dynamic factor model often fails to beat the PMI model for nowcasts and forecasts. D'Agostino at al. (2006) and D'Agostino and Giannone (2006) found that the factor models perform better as volatility is increasing; we find the opposite. In our view, a likely explanation lies in the fact that the factor model averages over a wide set of indicators, some of which may be less leading the business cycle than the PMI,[29]

[29]It is indeed the case, in Figure 4, that the first factor appears to slightly lag behind the

Figure 11: The first factor, extracted from a data set with the PMIs (blue line) and a data set that does not include the PMIs (red line)



at least during the Great Recession.[30] As a consequence, the dynamic factor model – like many other forecasting techniques – reacts more sluggishly to new data, while the survey-based PMI adjusts faster. A third striking feature is that for the factor model, 'more is not always better'. In line with Boivin and Ng (2006)'s suggestion that forecasting performance might increase with smaller data sets, we find that the model with the restricted data set tends to yield better forecasts, notably at the country level. Generally speaking, an important insight of our study is that the PMI model tends to be somewhat more consistent, whereas the dynamic factor model has some clear 'hits', but also some big 'misses'. These results supports findings of Stock and Watson (2004), who concluded that dynamic factor models can, in many cases, yield superior forecasts, but accuracy can be unstable over time and across countries.

From a practical perspective, the choice between different forecasting tools does not only depend on their accuracy. A PMI model is simpler to estimate and maintain than a dynamic factor model. However, the dynamic factor model has several conceptual advantages over the PMI model. First, the PMI model can only be updated once a month, and in between PMI releases, there is not straightforward way to say whether incoming data is weaker, stronger, or in

PMI index during the recession period.

[30]In addition, it has to be remarked that D'Agostino at al. (2006) compare their results against plain univariate models.

line with expectations. In contrast, the dynamic factor model can be run every time a new data point is released, showing how *any* economic indicator (not just PMIs) affects the current outlook. Consequently, it is possible to evaluate how a given forecast changes in response to, say a new release of data on unemployment or industrial production, providing a much richer picture of the evolution of a forecast during a given quarter. Second, the dynamic factor model safeguards against possible breaks in any single economic indicator by re-weighting the information, if circumstances change. The particular crisis we examined, with the manufacturing sector at the heart of the crisis, was relatively well suited to project with a PMI model. However, it is not evident that a PMI model will *always* deliver good forecasts, as a housing crisis, for instance, may be much less well reflected in the PMIs. Lastly, however, our results also show that in order to fully exploit the forecasting power of the dynamic factor model, its specification may have to be adjusted over time, as – for instance – the optimal selection of factors during the Great Recession differs from the Great Moderation period. The Bai and Ng (2002) information criterion does not guarantee an optimal factor selection, and lacking 'objective' criteria for optimally choosing the number of factors (or which ones), this task is not trivial, in particular when performed in real time.

In a sense, the PMI model can be viewed as a factor model in which the factor is replaced by the PMI index; and we have indeed shown that the first of the estimated factors is very close to the PMI index. A natural extension to our work could be to better target the factors by extracting them from blocks of homogeneous indicators, rather than from the entire set of economic variables. The theoretical framework has been developed by Hallin and Liska (2007), and the setup has been exploited by Banbura et al. (2010b). For example, a factor extracted only from leading indicators could prove useful in better anticipating the recession. Also, factors extracted from country-based blocks could also improve the performance of the model when the large dataset is concerned. We see this as promising avenues for future research.

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A Data description

All series except the PMI indexes are taken from the OECD MEI database, and range from January 1997 up to March 2010. Quarterly series cover GDP and its subcomponent (consumption, government expenditure, investment, imports, exports and changes in inventories). Monthly series for the euro area aggregate are listed in Table A, together with the relative publication lags (in months) and the type of transformation applied to achieve stationarity. Country-specific data covers roughly the same series, although some of them (e.g. monetary aggregates) were excluded, as they are not available at the country level.

B Errors of the factor model projections, compared to projections with the PMI model

As noted, one of the key findings is that on average, the factor model tends to outperform the PMI model, in particular later in the quarter, when a rich set of information has become available (all else equal, accuracy of the factor model increases, the more information – including 'hard' economic indicators – has been released for the current quarter). A downside, however, is that performance tends to be more uneven across countries than the PMI model, notably for the forecast. Since we discuss relative RMSE's in the main text, this could be due to poor performance of the dynamic factor model, or very high accuracy of the PMI model. The following analysis helps illustrate these findings, showing that it is in fact accuracy of the dynamic factor model that is less consistent when forecasting.

Figures 12, 13 and 14 provide scatter plots of the back-, now- and forecast errors of the two models. Errors of projections of euro area growth are shown as dark circles, while country projections are light red. We also a simple regression line – if both models performed similarly well, the slope of the regression line would be identical to the 45 degree line. We observe the following.

- The backcast errors for the euro area are close to zero for both models (the blue dots). For the national economies, the dynamic factor models yields clearly smaller errors, consistent with the notion that the PMI model is less accurate for backcasting.

- For the nowcast, the errors for the euro area projections of both models are closely clustered around zero. The dispersion of the projections errors of the dynamic factor model is a little tighter than the errors of the PMI model, suggesting higher nowcasting accuracy of the factor model.

- For the forecast, however, the reverse is true. The forecast errors of the dynamic factor model are more dispersed, and the slope of the regression line is no longer close to the 45 degree line, suggesting that the dynamic factor model – on average – overpredicts growth more than the PMI model. Note in particular some very large outliers of the factor model errors; this supports our claim that performance of the factor model can be uneven.

Table 10: Description of the variables for the euro area

Series	Publication lag	Transformation	SA
	Output		
IP, total	3	Δ log	Y
IP, manufacturing	3	Δ log	Y
IP, construction	3	Δ log	Y
Car registrations	2	Δ log	Y
Retail trade volume	2	Δ log	Y
Harmonized unemployment rate	2	Δ	Y
	Prices		
Total HICP	2	Δ log	Y
Consumer prices, food	2	Δ log	Y
Consumer prices, energy	2	Δ log	Y
Producer prices	2	Δ log	Y
	Money and interest rates		
M1	2	Δ log	Y
M3	2	Δ log	Y
EONIA	0	Δ	N
3-m interbank rate	0	Δ	N
10-y government bond yield	0	Δ	N
	Trade		
Real effective exchange rate	0	Δ log	N
Exports	3	Δ log	Y
Imports	3	Δ log	Y
Current account balance	4	Δ	N
BOP direct investments	4	Δ	N
	Confidence and leading indicators		
Business confidence	1	–	Y
Consumer confidence	1	–	Y
OECD CLI	2	–	N
PMI headline	0	–	Y
PMI employment	0	–	Y
PMI inventories	0	–	Y
PMI new orders	0	–	Y
PMI exports	0	–	Y
PMI output	0	–	Y
PMI purchases	0	–	Y
PMI delivery times	0	–	Y

Figure 12: Backcast errors of the dynamic factor model and the PMI model

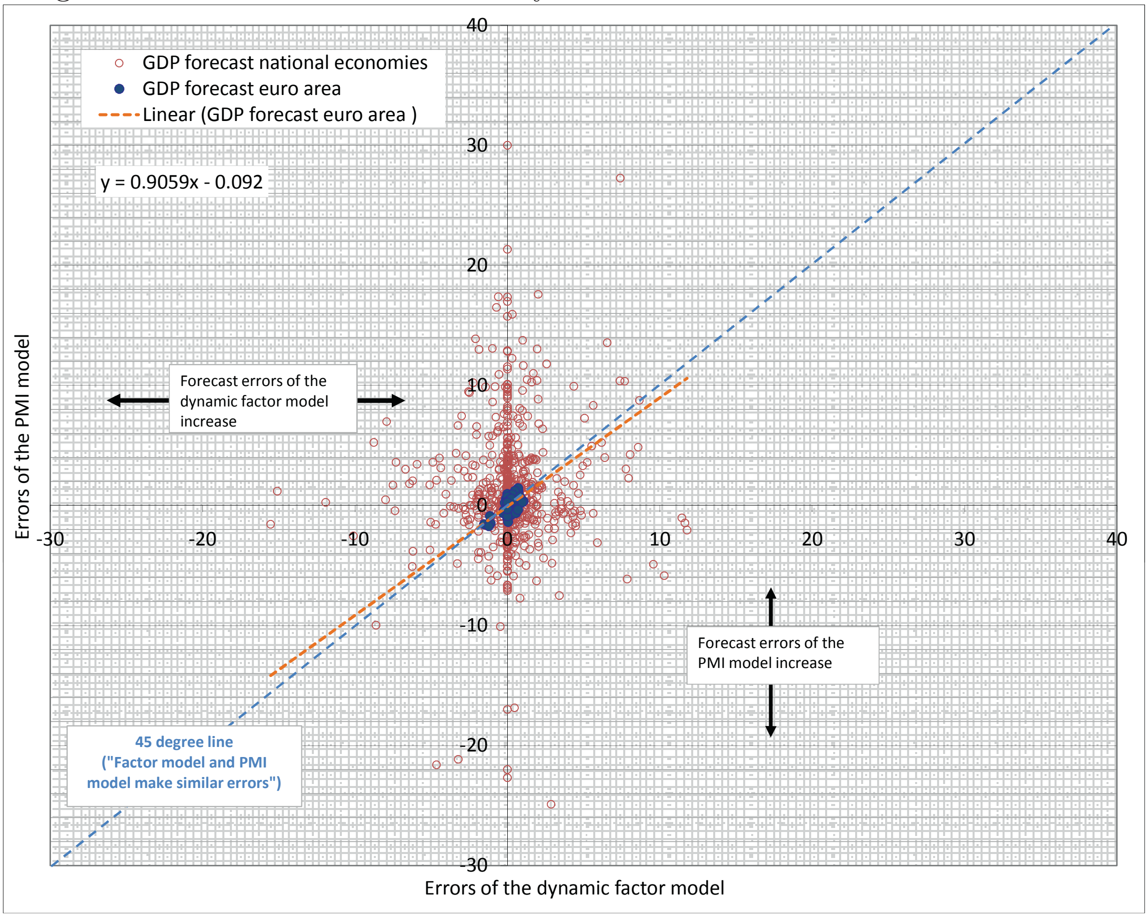


Figure 13: Nowcast errors of the dynamic factor model and the PMI model

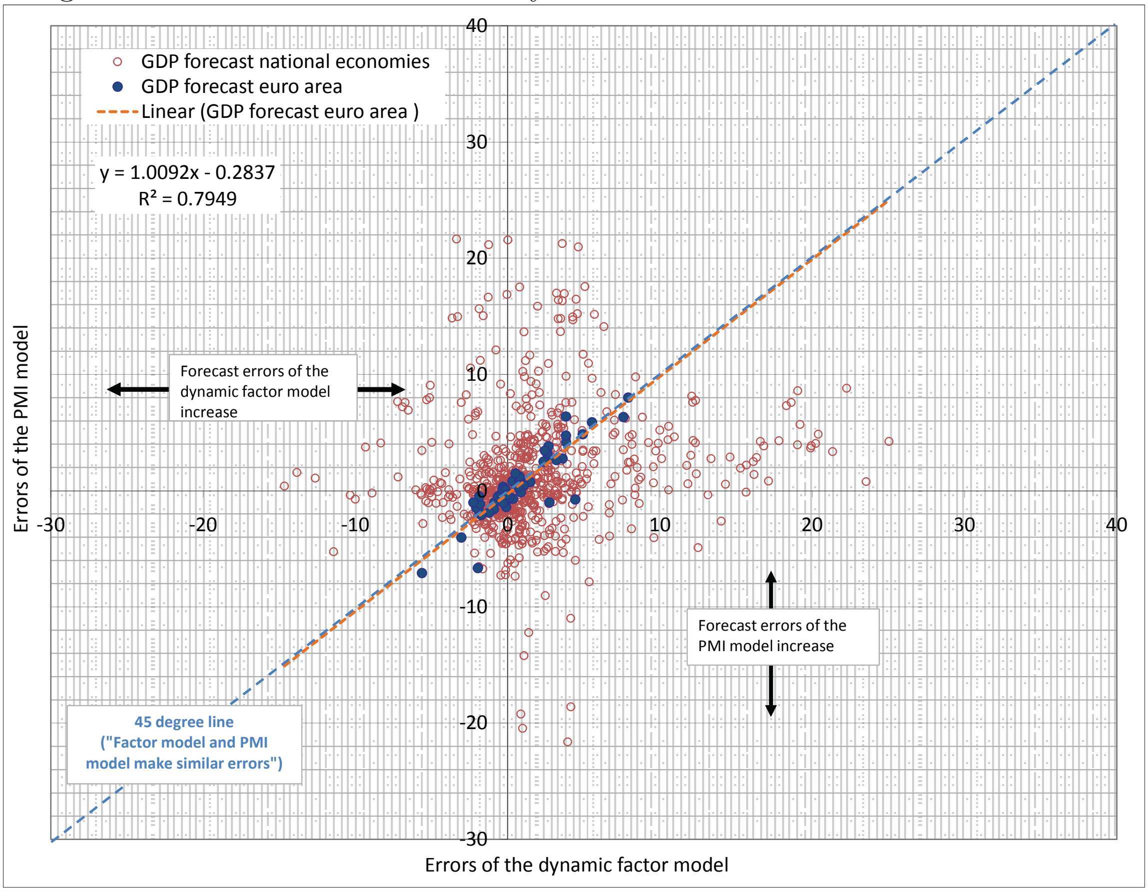
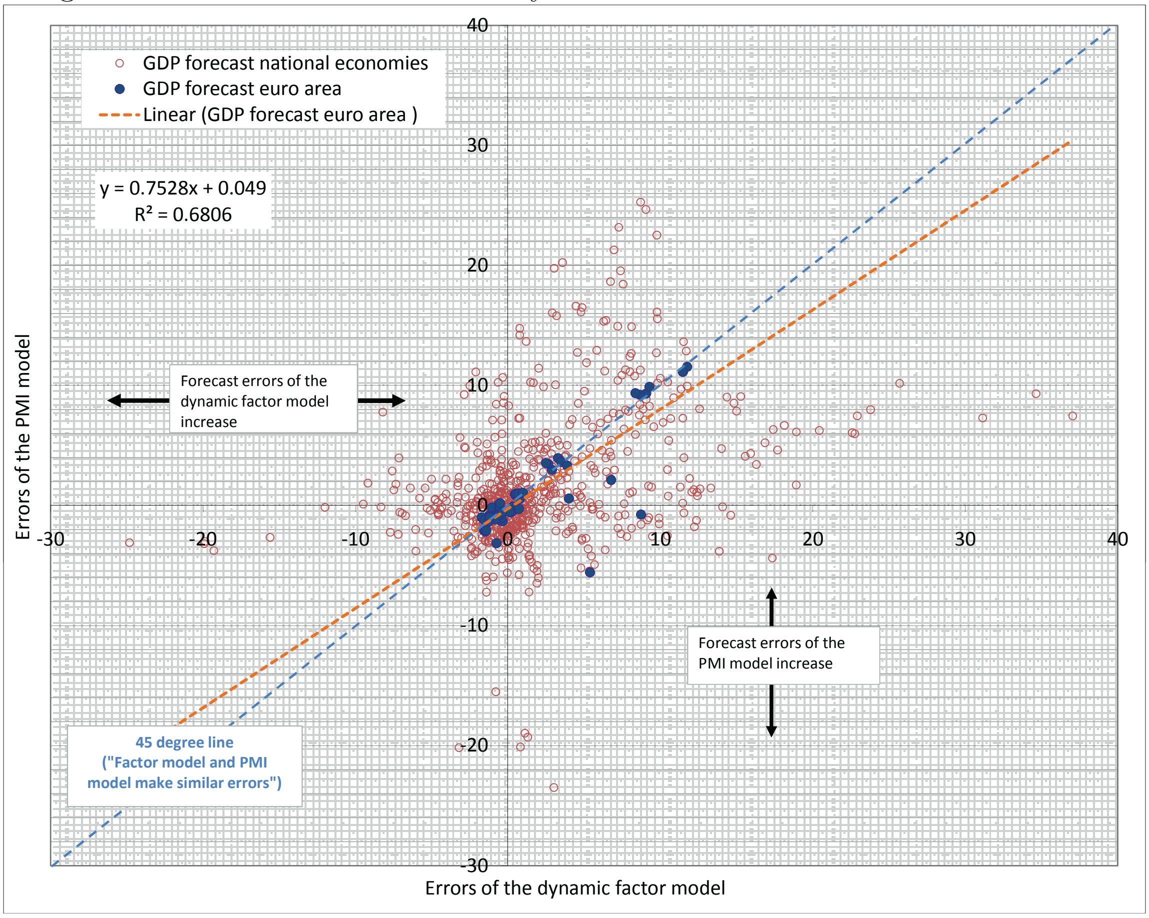


Figure 14: Forecast errors of the dynamic factor model and the PMI model



C Forecasting performance compared to simple AR benchmarks

In the main text, we report relative RMSE's, comparing the factor models to the PMI model. Following the literature, we also estimated simple AR benchmark models for the euro area and all national economies. We estimate:

$$y^h_{t+h} = \mu + \alpha(L)y_t + \epsilon^h_{t+h},$$

with $\alpha(L)$ denoting a scalar lag polynomial and μ being a constant. We also take into account publication lags for the AR, implying that, say, a forecast for Q1 would not contain data from Q4 until the March forecasts (since GDP data is only released with a 2-month lag). Based on the Schwartz criterion, we select up to 3 lags for the AR. Beating this country-AR benchmark model signals that a factor model contain additional information beyond the time series properties.

Tables 11 and 12 show the results for the dynamic factor model and the PMI model, when estimated over the entire sample period. An asterix denotes a significant improvement in forecasting accuracy of the two models, relative to the AR benchmark. As can be seen, both models regularly outperform the AR benchmark for the backcast and nowcast of euro area GDP and GDP in individual member countries. When forecasting GDP for Q2, the AR has an advantage early in Q1 (in January), but as more data becomes available, both models typically outperform the AR for most countries. As regards the component projections, the PMI model fairly consistently outperforms the AR model at all horizons; in contrast, the dynamic factor model typically fails to beat the AR for consumption and government expenditure, but outperforms it very clearly for the more volatile components of GDP (investment and trade).

Overall, the comparison with the AR benchmark demonstrates the good forecasting performance of both models. This confirms findings of earlier studies, as summarized by Barhoumi et al. (2008).

Table 11: Relative RMSEs of the forecasting models over simple country-AR benchmark models (estimated over the entire sample period)

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
	Dynamic Factor Model															
EA	0.44*	0.49*	0.48*	0.44*	0.77*	0.80*	0.71*	0.74*	0.52*	0.58*	1.07	0.98	0.99	0.94	0.84	0.79*
AT	0.70*	0.67*	0.83	0.75*	0.80	0.78*	0.89*	0.88*	0.72*	0.74*	1.13*	1.08*	1.09*	1.09*	1.03*	1.07*
BE	0.46*	0.39*	0.49*	0.39*	0.78*	0.75*	0.77*	0.71*	0.66*	0.60*	1.01	0.96	0.92	0.97	0.90	0.92
DE	0.47*	0.50*	0.49*	0.47*	0.86	0.93	0.77	0.81*	0.61*	0.63*	1.11	1.02	1.02	0.97	0.85	0.83
ES	0.57*	0.63*	0.74*	0.74*	0.58*	0.62*	0.84*	0.87*	0.63*	0.72*	1.17*	1.12*	1.20*	1.14*	1.20*	1.12
FI	0.41*	0.43*	0.47*	0.49*	0.97	0.95	0.87	0.81*	0.71*	0.69*	1.10	1.02	0.98	0.93	0.87	0.84
FR	0.53*	0.57*	0.59*	0.57*	0.88	0.82*	0.79*	0.77*	0.63*	0.65*	1.02	0.97	0.94	0.95	0.88	0.86
GR	0.55*	0.47*	0.57*	0.59*	1.28*	1.00	1.26*	1.08	1.00	0.88	1.51*	1.10	1.48*	1.18	1.25	1.03
IE	0.65*	0.70*	0.74*	0.71*	1.22*	1.35*	1.14	1.30*	0.92	1.00	1.18	1.22	1.15	1.22	1.25	1.32
IT	0.55*	0.56*	0.58*	0.51*	0.80	0.80	0.74*	0.73*	0.61*	0.63*	1.11	1.05	1.03	1.00	0.88	0.84
LU	0.50*	0.44*	0.61*	0.55*	0.85	0.86	0.76	0.86	0.75*	0.81*	1.10	0.99	0.94	0.88	0.80	0.74*
NL	0.59*	0.63*	0.65*	0.61*	0.64*	0.63*	0.72*	0.74*	0.68*	0.71*	0.93	0.89*	0.82*	0.82*	0.72*	0.75*
PT	0.56*	0.61*	0.70*	0.72*	0.97	0.87	1.03	0.93	1.07	0.94	1.25*	1.11	1.06	1.00	1.01	0.96
	PMI model															
EA	0.57*	0.57*	0.57*	0.57*	0.87	0.87	0.68*	0.68*	0.64*	0.64*	0.96*	0.96*	0.94*	0.94*	0.88	0.88
AT	0.87	0.82*	0.89	0.85*	0.99	0.96	0.95	0.86*	0.62*	0.85	1.08	1.03	1.05	1.02	1.00	0.93*
BE	0.64	0.64	0.62*	0.62*	0.85	0.85	0.72*	0.72*	0.63*	0.63*	1.06	1.06	1.00	1.00	0.98	0.98
DE	0.72*	0.72*	0.70*	0.69*	0.97	0.96	0.72*	0.80*	0.70*	0.79*	1.03	0.98	1.03*	1.02	0.99	0.96
ES	0.72*	0.74*	0.70*	0.69*	0.53*	0.66*	0.72*	0.74*	0.52*	0.59*	0.89*	0.95	0.78*	0.85*	0.66*	0.81*
FI	0.58*	0.58*	0.56*	0.56*	0.80	0.80	0.80	0.80	0.84*	0.84*	0.96*	0.96*	0.92	0.92	0.88*	0.88*
FR	0.89	0.60*	0.89	0.59*	0.90	0.84	0.80*	0.56*	0.79*	0.55*	0.95	0.98	1.00	0.97	0.92	0.86*
GR	0.77*	0.99	0.76*	0.98	0.96	1.07	0.93	1.18*	0.92	1.15*	1.07	0.95	1.04	1.04	0.94	1.11
IE	1.03	0.82	0.96	0.80	1.08	0.99	1.05	1.03	1.02	0.87	0.95	1.05	1.00	1.11	1.01	0.92
IT	0.62*	0.55*	0.63*	0.57*	0.76*	0.79	0.72*	0.62*	0.67*	0.55*	1.03	1.03	0.94	0.95	0.81*	0.83*
LU	0.80*	0.80*	0.79*	0.79*	0.96	0.96	0.91	0.91	0.85*	0.85*	0.97	0.97	0.95	0.95	0.99	0.99
NL	0.90*	0.88*	0.89*	0.87*	0.87	0.80*	0.88	0.88	0.77*	0.74*	0.96	0.96	0.89*	0.92*	0.84*	0.87*
PT	0.89	0.89	0.87	0.87	0.95	0.95	1.05	1.05	1.02	1.02	1.03	1.03	0.96	0.96	0.92	0.92

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively (for the PMI model, we report results using individual countries' PMI in the F column, while the R column reports results in which we use the euro area PMI to construct forecasts for individual euro area countries). An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. Country codes are given in table 2.

Table 12: Relative RMSEs of the forecasting models over simple country-AR benchmark models for components of euro area GDP (estimated over the entire sample period)

	Backcast				Nowcast						Forecast					
	Month 1		Month 2		Month 1		Month 2		Month 3		Month 1		Month 2		Month 3	
	F	R	F	R	F	R	F	R	F	R	F	R	F	R	F	R
	Dynamic Factor Model															
C	0.82*	0.87*	0.88*	0.89*	1.30*	1.26*	1.25*	1.25*	1.10*	1.10*	1.39	1.31	1.38*	1.32*	1.29*	1.26*
G	0.85*	0.87*	0.97*	0.95*	1.05*	1.13*	1.05*	1.07*	1.10*	1.11*	1.14	1.09	1.16*	1.12*	1.17*	1.21*
I	0.62*	0.70*	0.70*	0.69*	0.94	0.96	0.91*	0.97	0.76*	0.89*	1.11	1.04	1.06	1.00	1.02	0.98
X	0.42*	0.44*	0.49	0.44	0.70	0.68	0.71	0.66	0.60	0.58	1.01	0.94	0.88*	0.84	0.74*	0.68*
M	0.43*	0.51	0.51*	0.51	0.63*	0.61*	0.67*	0.65*	0.62	0.65	0.97*	0.93*	0.86*	0.85*	0.71*	0.71*
	PMI model															
C	0.84*		0.84*		0.86*		0.84*		0.92*		1.22*		1.18*		0.93*	
G	0.98*		0.98*		0.98*		0.94*		0.95*		1.13		1.13*		1.15*	
I	0.83*		0.84*		0.87*		0.88*		0.84*		0.92*		0.90*		0.89*	
X	0.55*		0.54*		0.69		0.61		0.57		0.98*		0.89*		0.79*	
M	0.71*		0.70*		0.61*		0.65*		0.69		0.93*		0.82*		0.71	

Note: Month 1, Month 2, Month 3 refers to the month in which the forecast is made; F, R refers to full and restricted data set, respectively (for the PMI model, we only report estimations using country-specific PMIs, as contained in the full data set). An asterisk denotes that one model significantly outperforms the other at the 5 percent level, according to the Diebold and Mariano (1996) test. C, G, I, X, M refer to consumption, government, investment, exports and trade, respectively.