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by

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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 the 'Great Moderation' (2000-2007) and the 'Great Recession' (2008-2009) separately. All models consistently beat naïve AR benchmarks. More data does not necessarily improve forecasting accuracy: For the factor model, adding monthly indicators from national economies can lead to more uneven forecasting accuracy, notably when forecasting components of euro area GDP during the Great Recession. This suggests that the merits of national data may reside in better estimation of heterogeneity across GDP components, rather than in improving headline GDP forecasts for individual euro area countries. Comparing factor models to the much simpler PMI model, we find that the dynamic factor model dominates the latter during the Great Moderation. However, during the Great Recession, the PMI model has the advantage that survey-based measures respond faster to changes in the outlook, whereas factor models are more sluggish in adjusting. Consequently, the dynamic factor model has relatively more difficulties beating the PMI model, with relatively large errors in forecasting some countries or components of euro area GDP.

JEL classification: C50, C53, E37, E47
Bank classification: Econometric and statistical methods; International topics

Résumé

Les auteurs cherchent à évaluer comment la plus ou moins grande richesse des données utilisées influe sur la qualité des prévisions touchant la zone euro. Pour ce faire, ils comparent trois approches : 1) la prévision au moyen d'un modèle simple fondé sur les indices des directeurs d'achats (ci-après « modèle PMI » pour *Purchasing Managers' Indices*); 2) le recours à un modèle factoriel dynamique estimé à partir de données en temps quasi réel se rapportant à l'ensemble de la zone euro; 3) le recours au modèle et aux statistiques en question en conjonction avec des données relatives aux économies nationales. Les auteurs établissent des prévisions concernant le PIB global de la zone euro, ses composantes et le PIB de chacun des pays membres de la zone euro pour le trimestre précédent, le trimestre courant et le trimestre à venir. Ils examinent aussi séparément les prévisions obtenues pour la période 2000-2007 (ce qu'on a appelé la « Grande Modération ») et la période 2008-2009 (la « Grande Récession »). Les modèles considérés produisent des prévisions systématiquement meilleures que des modèles autorégressifs simples. L'emploi de données plus riches ne procure pas toujours un gain de précision. L'ajout au modèle factoriel d'indicateurs nationaux mensuels peut altérer la qualité de la prévision, surtout lorsqu'il s'agit de prévoir l'évolution des composantes du PIB de la zone euro durant les années 2008 et 2009. Les données nationales seraient donc plus utiles pour l'estimation de l'hétérogénéité des composantes du PIB global que pour la prévision des PIB nationaux. Si l'on s'en tient aux prévisions élaborées pour la période 2000-2007, le modèle factoriel dynamique l'emporte sur le modèle PMI, beaucoup plus simple. Si l'on se penche sur les années 2008-2009, toutefois, le second modèle offre un avantage sur le premier, puisque les mesures tirées d'enquêtes réagissent plus rapidement aux modifications des perspectives que les modèles factoriels. Le modèle factoriel dynamique ne domine plus alors le modèle PMI, et les prévisions obtenues pour certains pays ou certaines composantes du PIB de la zone euro comportent des erreurs relativement importantes.

Classification JEL : C50, C53, E37, E47
Classification de la Banque : Méthodes économétriques et statistiques; Questions internationales

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.[1] Given its economic structure, forecasting the euro area is particularly challenging, as it requires not only an analysis of different components of euro area GDP, but also examining economic developments at national levels (that is, in individual euro area countries). Both GDP components and national economic developments can contain important information. Since the euro area comprises 16 members (and will likely expand further), rendering analysis of the euro area a potentially labour-intensive task.[2]

From a forecasting perspective, different 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.

In recent years, factor models have become very popular, and 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 identification 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)[3] 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

[1] '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).

[2] 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.

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

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 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 high and low volatility is lacking. Results from Stock and Watson (2004) suggest that forecasting performance can be uneven over time, and 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'. We evaluate forecasting performance of dynamic factor models with different information sets against a more parsimonious indicator model using PMIs.[4] 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[5], 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 very well, and 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

[4]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.

[5]More precisely, we label the forecasting during the period 2000-2007 as forecasting during the 'Great Moderation'; strictly speaking, the Great Moderation has likely started earlier, as volatility of key macroeconomic series has started falling sharply in the late 1980s.

and forecasts. That said, its forecasting accuracy can be uneven, and forecast errors for some countries 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 leading indicator.[6]

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 Related literature and in-sample forecasts

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 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

[6] 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.

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.[7] 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. We compare 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.

An important advantage of the PMIs lies in their timeliness. While the first release of euro area GDP is only available (roughly) two months after the end of the reference quarter, PMIs are released one working day after the reference month. This makes them one of the most timely indicators of real activity. From a forecasting perspective, an additional advantage is that PMIs are basically not revised.[8] 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:

$$\hat{y}_{t+h} = \beta_h(L)PMI_t + \gamma_h(L)y_t + \epsilon_{t+h} \tag{1}$$

[7]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.

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

whereby y_{t+h} denotes our GDP forecast (with h denoting the forecast horizon), PMI_t is the value 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.[9]

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 2.3).

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 applications.[10] 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 because of the so-called 'curse of dimensionality', i.e. the fact the number of parameters to estimate grows rapidly. Factor models overcome this

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

[10] 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.

limitation by reducing the dimensionality of the data.[11]. As more information improves identification 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).[12]

Stock and Watson (2002) complement eq. (2) with an equation describing the evolution of the 'target' variable y_t:

$$y_{t+1} = \beta' F_t + \gamma(L) y_t + \epsilon_{t+1}, \tag{3}$$

where $\gamma(L)$ is a polynomial in the lag operator, and forecasts are constructed according to eq. (3). h-step-ahead forecasts can be constructed using the following regression:

$$y_{t+h} = \beta'_h F_t + \gamma_h(L) y_t + \epsilon_{t+h}. \tag{4}$$

The model generated by equations (2) and (3) is commonly referred to as 'static factor model', as no parametric dynamics are imposed on the factors.[13] 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):

$$F_t = \sum_{t=1}^{p} A_p F_{t-p} + u_t, \qquad u_t \sim N(0, Q). \tag{5}$$

This model is akin to dynamic factor structures proposed by Forni et al. (2000), but it is estimated using Likelihood-based, rather than frequency-domain methods. Given that F_t is unobservable, the introduction of equation (5) 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 closed-form likelihood function can be obtained by conditioning on the filtered values and maximizing it to yield parameter estimates. 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

[11] 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)

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

[13] 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.

variables can be constructed as

$$y_{t+h} = \beta' \hat{F}_{t+h} + \gamma(L) y_{t+h-1} + \epsilon_{t+1}.^{14}$$

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.[15]

2.3 Data and forecast horizon

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[16] 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; 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.

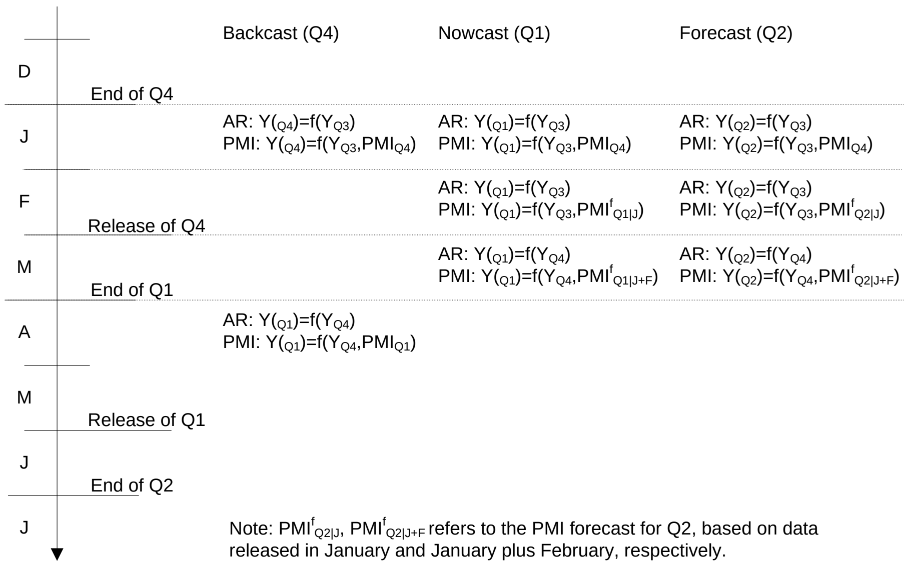
In February, no new data has been released to change the AR back-, now- or forecasts, but the information set changes for the PMI model and the factor model, as nowcasts for Q1 and forecasts for Q2 from these models can now incorporate information released in January. The release of Q4 GDP at the end 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).

[14]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.

[15]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.

[16]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)).

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 rolling 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.[17] 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 8 in the appendix). We divide the data as follows:

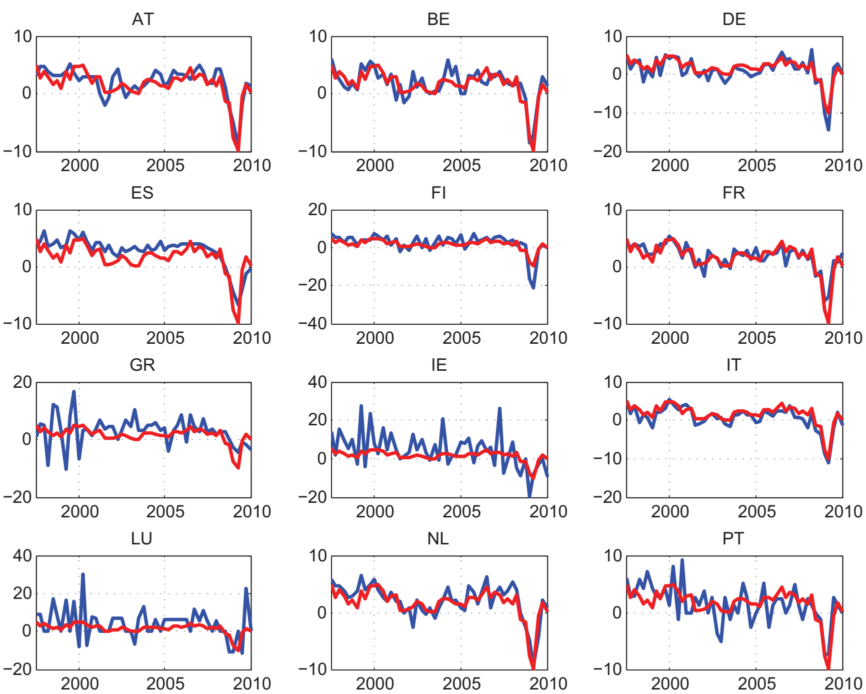
- Full data set: quarterly GDP data for the euro area and all national economies, plus monthly economic indicators for the euro area and all individual countries.
- Restricted data set: quarterly GDP data for the euro area and all national economies, plus monthly economic indicators for the euro area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

[17] 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.

Monthly information from national economies should in principle help improve forecasts for individual countries by expanding the data set, allowing for a better identification of the factors. For example, identification of economic activity or price pressures could be facilitated, if data on industrial production or inflation from *all* euro area countries is included. 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.[18] 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).

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

[18]Table 8 in the appendix contains details on how the series were transformed.

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

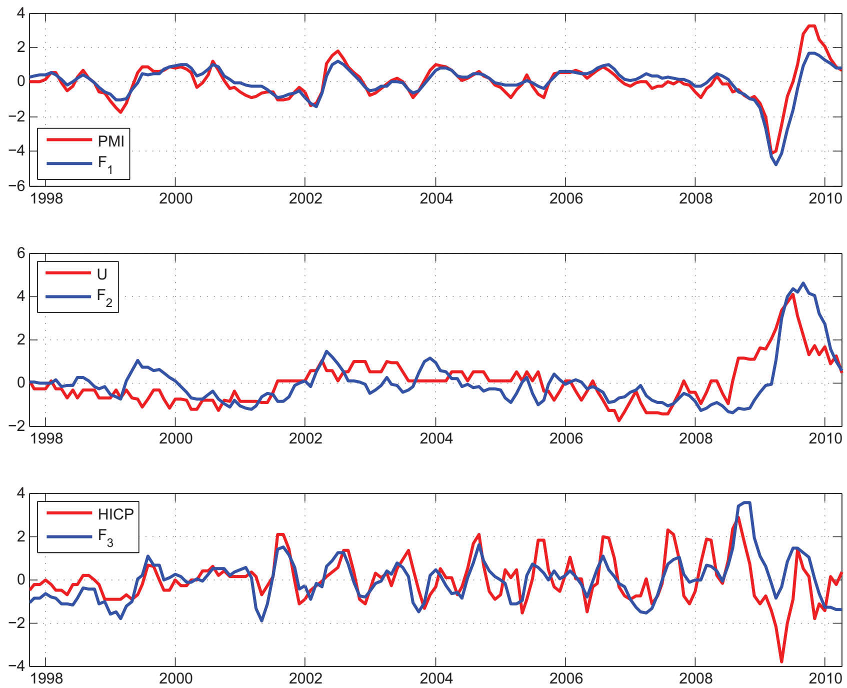
	Mean	Std. dev.	Minimum
EA	**1.6179**	**2.6297**	**-9.9729**
AT	2.0395	2.6101	-9.2668
BE	1.7764	2.6997	-8.5718
DE	1.0541	3.4856	-14.2938
ES	2.8068	2.5687	-6.6956
FI	2.4493	5.0285	-21.2978
FR	1.8443	2.1950	-5.9754
GR	3.0407	4.9884	-10.2701
IE	4.5089	9.1636	-19.4729
IT	0.7156	2.9513	-11.0883
LU	4.1511	8.0241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

2.4 In-sample model performance

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 plot the first three factors together with the euro area PMI, unemployment and inflation (we use the ECB's Harmonized Index of Consumer Prices). 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 still interesting to see that the first factor co-moves very closely with (changes in) the PMI index. This justifies using the PMI model as a benchmark, as the PMI seems to be a simple alternative way to summarize the bulk of the information in the data. 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 points to a faster recovery with higher 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).

In Figure 4, we report the (monthly) in-sample fit of both models for forecasting euro area GDP growth. Due to the use of timely and/or forward-looking indicators, both the PMI and the factor model display good performance in tracking and anticipating the outset of the crisis. Considering the early recession period in particular, it seems that both models correctly forecasted the large drop in GDP in late 2008, but the factor model seems to be better able to predict the depth of the recession, as well as the duration.

Figure 3: First, second and third principal components of the data, together with the euro area PMI, unemployment (U) and inflation (HICP)

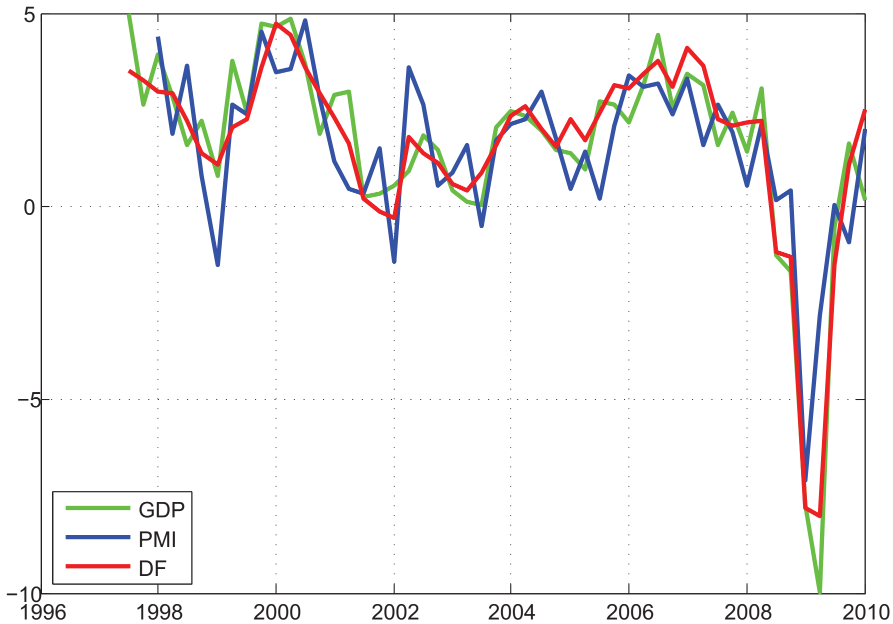


3 Forecasting economic developments in the euro area

3.1 Comparing the models against an AR benchmark

A first sense of the forecasting performance of the two models can be gained by comparing them to a simple AR benchmark over an out-of sample window of five years (2004-2009, see tables 9 and 10 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 B, 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

Figure 4: In-sample fit of the PMI model (blue line) and dynamic factor model (red line) for the euro area GDP (green line).



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

In what follows, we turn to out-of-sample forecasting accuracy over two subsamples, namely the 'Great Moderation' period between 2000 and 2007, and the 'Great Recession' (2008/2009).

3.2 Forecasting during the 'Great Moderation'

Our first set of results considers the 'Great Moderation' period between 2000 and 2007. Table 2 shows estimation results for euro area GDP and GDP of each euro area member country. We report the relative RMSE of the factor model over the PMI model – numbers larger than one 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'.[19] Observations where

[19]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 (note, however, that we only use the criterion as a rough guide, as it was developed for static factor models, and we conducted robustness check by retained alternative numbers of factors).

one model statistically outperforms the other at the 5 per cent level according to the Diebold and Mariano (1995) test are marked with an asterisk.

Several features stand out. First, during the Great Moderation, the dynamic factor model is clearly the better model for back-, now- and forecasting euro area GDP, as it beats the PMI model over all horizons. Second, the dynamic factor model is better at backcasting, with – at time – large improvements over the PMI model (relative RMSE's for backcasts for Greece, for instance, show improvements in accuracy of 20-40 per cent). Third, however, despite its parsimonious approach, the PMI model remains a tough benchmark for the dynamic factor model, and in fact outperforms the factor model in 74 out of 208 cases. 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 2). 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 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, and that (ii) the PMI model's accuracy improves, as more data becomes available, while the dynamic factor model has its greatest advantages early in the quarter.

Figure 6 plots the relative RMSE's of the dynamic factor model, relative to the PMI model. Dropping those observations that are not statistically different from each other according to the Diebold and Mariano (1995) test, each dot represents the relative RMSE of a 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 'hits' and 'misses' of the dynamic factor model are relatively evenly distributed; even for the nowcast case – where the dynamic factor model, on average, outperforms the PMI model – accuracy of some country forecasts is relatively low (in some cases more than 25 per cent below forecast accuracy of the PMI model). Also, somewhat surprisingly, as more data becomes available, forecasts of the dynamic factor model tend to become more uneven, as in particular the clear 'misses' in February and March for both nowcasts and forecasts shows.

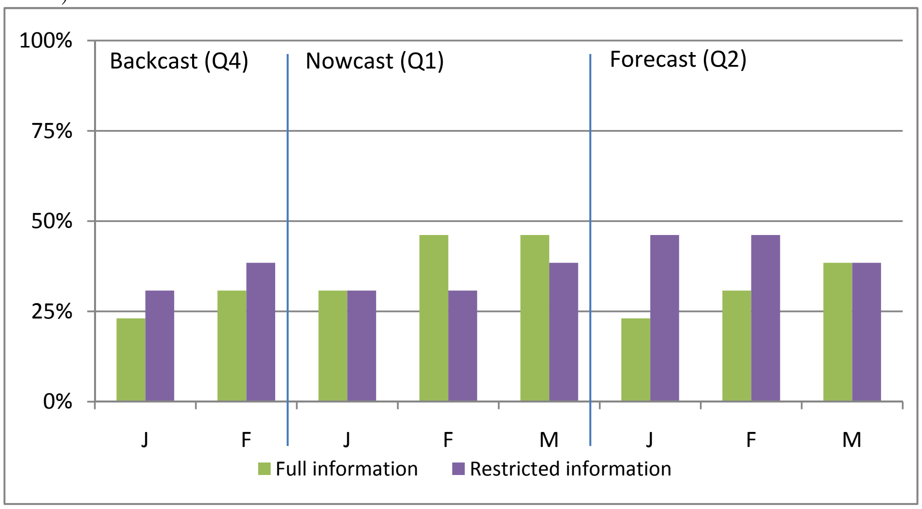
Looking at table 2's results by country, the picture is somewhat mixed. As noted earlier, the dynamic factor model beats the PMI model consistently for the euro area, but at the country level, the PMI model tends to outperform the factor model for 4 out of the 12 countries (Austria, Italy, Luxembourg, Spain). An important consideration in evaluating forecast accuracy for individual countries is the size of the country – having high accuracy for a large euro area country is arguably more important than having an excellent forecast for Luxembourg. It is not evident that the relative forecasting performance of the two models is related to the size of the country, as the PMI forecast for Germany is, by and large, relatively comparable to the dynamic factor model model, but accuracy for France, Italy or Spain is higher. No single model yielded consistently

Table 2: 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	0.87*	0.91	0.93	0.93	0.79*	0.77*	0.83*	0.78*	0.92	0.87	0.87	0.90	0.77*	0.82*	0.84	0.85
AT	1.30	1.31*	1.14	1.18	1.02	1.09	0.89*	0.90	1.39	1.44*	0.98*	1.02	0.98*	1.03	1.04	1.08
BE	0.64*	0.53*	0.68*	0.57*	0.75	0.66*	0.79*	0.77*	0.71*	0.64*	0.77*	0.74*	1.03	1.03	0.74	0.61*
DE	0.90*	0.98	0.98	1.06	0.90	0.92	0.95	0.91	1.07	1.04	0.92	0.89	0.87*	0.87*	0.84*	0.86*
ES	0.94	1.26*	1.01	1.51*	1.01*	1.36*	1.16	1.51*	1.21	1.58*	0.89	1.00	0.92	1.13	1.04*	1.26*
FI	0.97	0.87	1.02	0.93	0.95	0.82	1.06	0.81*	1.25	0.99	1.04	1.04	0.72*	0.82*	0.76*	0.85
FR	1.01	1.09	1.09	1.11	0.88	0.90	1.11	1.07	1.11	1.20	0.82*	0.97	0.69*	0.87	0.78	0.92
GR	0.70	0.61*	0.79	0.74*	1.03	0.83	1.05*	0.79*	0.95	0.71*	0.94	0.87*	1.00	0.93	0.97	0.90
IE	0.93	0.87	1.00	0.95	0.85	0.90	0.81*	0.90	0.96	0.99	0.80*	0.85*	0.81	0.83*	0.98	0.99
IT	1.01	1.03	0.97	1.03	0.97	1.06	1.07	1.15	1.07	1.09	0.99	1.09	0.97*	1.10*	1.01	1.14
LU	0.77	0.74*	0.77	0.86	1.06	1.23*	1.02	1.13	0.84	0.90	1.01	1.05	1.17*	1.15*	1.19	1.22
NL	0.78*	0.82*	0.85*	0.79*	0.89*	0.80*	0.80*	0.73*	0.91*	0.84*	0.89*	0.83*	0.86*	0.81*	0.89*	0.82*
PT	0.64*	0.67*	0.67*	0.72*	0.76*	0.79*	0.68*	0.75*	0.70*	0.75*	1.03	1.08	1.31	1.23	1.51*	1.39*

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 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: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter ('January', 'February' and 'March'), respectively. A value below 50 per cent indicates that, on average, the dynamic factor model outperforms the country forecasts of the PMI.

superior forecasting performance for all countries during the Great Moderation. As regards the added value of national monthly indicators, our findings over the Great Moderation period suggest that 'more is (usually) better'. With full information, the dynamic factor model beats the PMI model more often in backcasting and forecasting better, although accuracy of nowcasts deteriorate somewhat. Also, average forecast errors are actually in many lower with the restricted data set.[20]

A broadly similar picture emerges when considering forecasts for components of euro area GDP. Table 3 and Figure 7 summarize our results. As can be seen, backcasts and forecasts for GDP components are typically better performed by the dynamic factor model. However, consumption – a relatively less volatile component of euro area GDP – is almost always better predicted using the PMI model, suggesting that the main advantage of the factor model lies in improved accuracy for relatively more volatile components of GDP.

Taken together, we can summarize our results as follows. The dynamic factor model is the better tool for backcasting, and yields good nowcasts and forecasts for many countries, but performance can be uneven. In many cases, the PMI model, despite its simplicity, is a tough benchmark, and each model per-

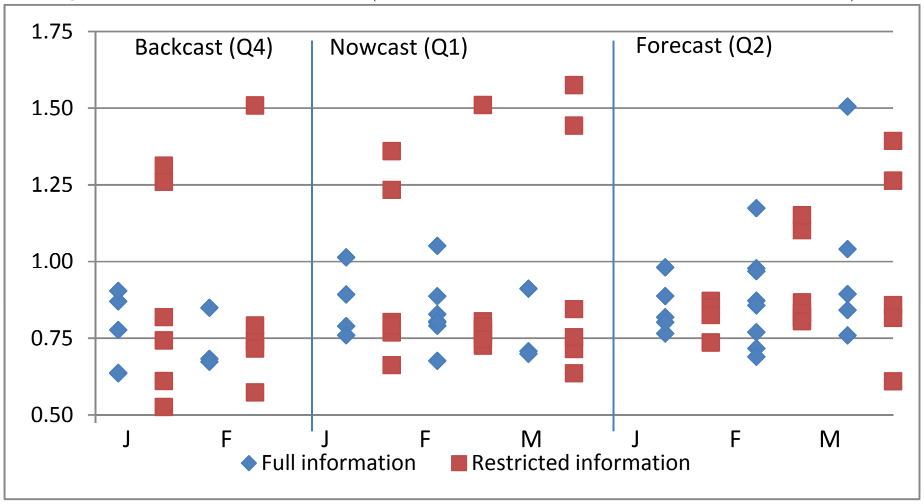
[20]This supports the findings of Giannone and Reichlin (2006), which suggest that output fluctuations in the euro area are mainly explained by common shocks; in contrast, it seems that components of euro area GDP are less well proxied by common shocks.

Table 3: 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
C	1.15*	1.15	1.18*	1.20*	1.40	1.34	1.29*	1.32	1.14*	1.15	0.90	0.92	0.84	0.89	0.99	1.04
G	0.91*	0.89	1.00*	0.96	0.91*	0.95	1.04*	1.03	1.05	1.03	0.82	0.77	0.84	0.79	0.81*	0.81
I	0.92	0.94	1.02	0.96	0.90*	0.87*	0.91	0.90*	1.00	0.96	0.90	0.96	0.90	0.96	0.84*	0.85*
X	0.73	0.81	0.76	0.80	0.75	0.82	0.78	0.96	0.81	0.91	1.11*	1.15*	0.96*	1.03*	0.77*	0.87*
M	0.65	0.74	0.68*	0.76	0.98*	1.01*	0.77*	0.87	0.67	0.85	0.95*	0.96	0.86*	0.89*	0.95	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. C, G, I, X, M refer to consumption, government, investment, exports and trade, respectively.

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: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter, respectively. Each dot represents a country forecast where the dynamic factor model and the PMI model differ significantly (at the 5 per cent level).

forms well for some economies and/or some horizons, and less well at others.[21] Lastly, while the dynamic factor model yields superior forecasts for relatively more volatile components, consumption is typically better predicted by the PMI model.

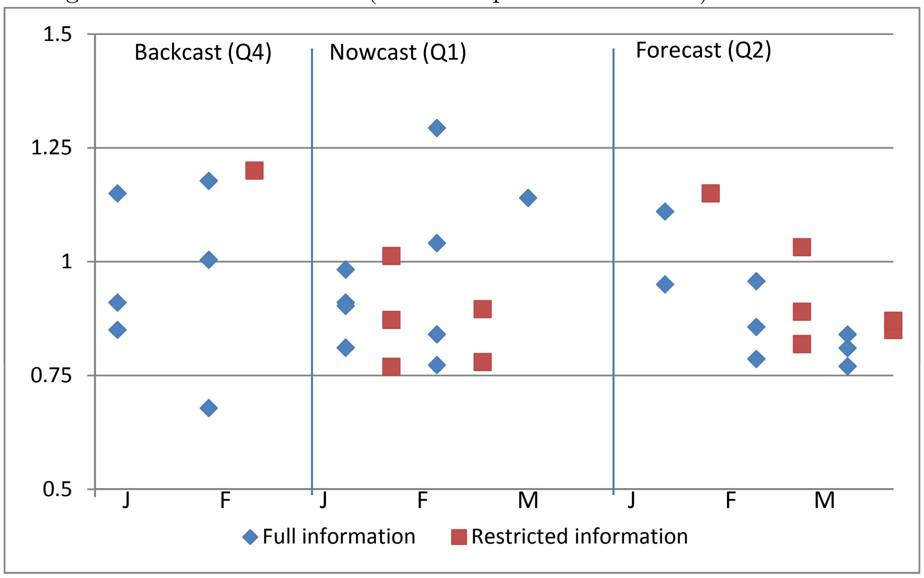
3.3 Forecasting during the 'Great Recession'

Next, we analyze the 2008/2009 period, which was characterized by a global recession.[22] 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 were particularly affected in this early phase of the downturn. By late 2009, the focus had shifted more to differences in fiscal positions, turning the global recession into a European debt crisis (and prompting a sharp decline of the euro exchange rate). As

[21] 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.

[22] 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.)

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



Note: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter, respectively.

countries like Greece adopted fiscal austerity measures, their economic activity fell sharply, while export-oriented economies started benefiting from the depreciation of the euro. 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 4. Figures 8 and 9 show, as before, how often the dynamic factor model outperforms the PMI model and – for those forecasts that are statistically different – the relative RMSE's. The first thing to note is that the factor model dominates the backcast of the PMI model for almost all countries (Figure 8), while accuracy of the nowcast and the forecast is uneven (Figure 9). Also, the magnitudes of the improvements of the backcast over the PMI model are impressive, as the backcast errors of the PMI model are, in some cases, more than twice as large as the backcast errors of the factor model. However, when nowcasting or forecasting, the PMI model performs very well, while the factor model has clearly some big 'misses', and is dominated by the PMI model in 91 out of 156 cases. Some large countries (Italy, Spain) continue to be typically better projected with the PMI model.

As before, we find that at the country level, more data does not always help the factor model to provide more accurate forecasts during the 'Great recession'. Excluding backcasts, the dynamic factor model is beaten by the PMI model in

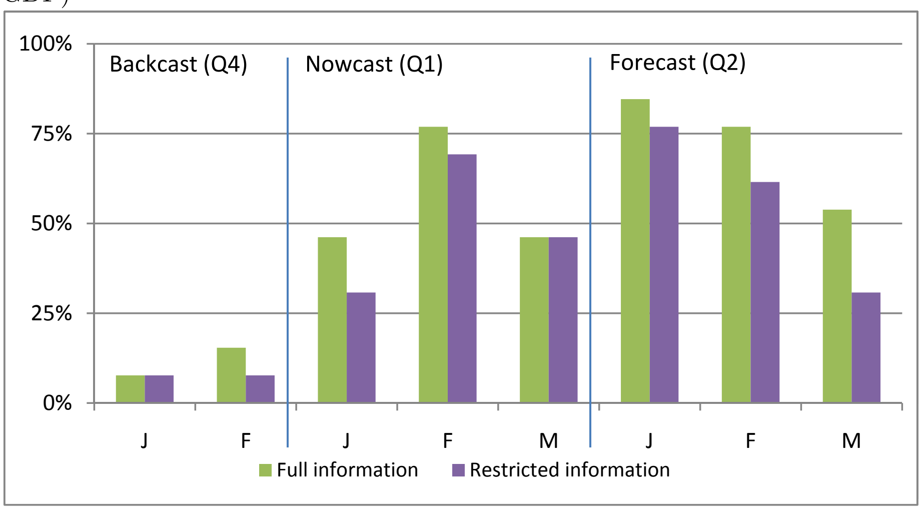
Table 4: Relative RMSE of the dynamic factor model over the PMI model by country during the 'Great Recession'

	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	0.75*	0.85	0.80*	0.71*	0.89	0.93	1.06	1.11	0.80	0.90	1.11	1.02	1.06	1.01	0.96	0.90*
AT	0.77*	0.74	0.92	0.81	0.81*	0.79*	1.05	1.04	0.81	0.84	1.12*	1.06*	1.07	1.07	1.12	1.17*
BE	0.75*	0.66*	0.85	0.66*	0.94*	0.92	1.13	1.05*	1.14	1.05	0.97	0.93*	0.90*	0.96	0.94	0.99
DE	0.58*	0.60*	0.61*	0.55*	0.90*	0.97	0.97	1.02	0.72*	0.76*	1.15	1.05	1.01	0.95	0.89	0.87*
ES	0.74*	0.80*	1.06	1.03	0.87*	0.93	1.14*	1.16	1.08	1.21	1.24*	1.18*	1.42*	1.34*	1.49*	1.39*
FI	0.62*	0.69*	0.78*	0.84*	1.24*	1.23	1.09	1.03	0.82*	0.81*	1.15	1.07	1.09	1.02	0.99	0.95
FR	0.76*	0.89	0.97*	0.87	1.07	0.99	1.52	1.45*	1.12*	1.17	1.05	0.99	1.01	1.00	1.04	1.00
GR	0.51*	0.38*	0.47*	0.51*	1.37*	1.01	1.15*	0.99	0.88	0.79*	1.84*	1.31*	1.54*	1.20	1.15*	0.93
IE	0.73*	0.83	0.86*	0.81*	1.55*	1.75*	1.32*	1.54*	1.10*	1.24	1.33	1.38	1.18	1.27	1.67	1.80*
IT	1.00	1.03	1.02	0.86	1.02	1.01	1.24	1.19*	1.12	1.14*	1.07	1.01	1.09	1.04	1.05*	1.00
LU	0.58*	0.50*	0.75*	0.65*	0.84	0.85	0.79	0.93	0.87*	0.96	1.14	1.03	0.95	0.89*	0.73	0.66*
NL	0.58*	0.68*	0.64*	0.63*	0.77*	0.78*	0.83*	0.88*	0.94	1.04	0.98	0.94	0.90	0.91*	0.83	0.86*
PT	0.60*	0.63*	0.84	0.82	1.14*	0.99	1.07	0.93	1.15	0.97	1.26*	1.08	1.09	1.01	1.07	1.00

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.

almost 64 per cent of all GDP forecasts with the full information set, compared to 53 per cent of all cases with the restricted information set.[23] Also, average relative RMSE is lower when using the restricted data set, albeit not by much. However, it seem to be the cases that forecasting accuracy is somewhat less uneven with the full data set (for instance, relative RMSE's tend to be less dispersed for nowcasts and forecasts, as illustrated in Figure 9). 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), especially forecasts with the full information set.

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: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter, respectively. A value below 50 per cent indicates that, on average, the dynamic factor model outperforms the country forecasts of the PMI.

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

The fact that the dynamic factor model yields relatively poor forecasts for some euro area countries 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

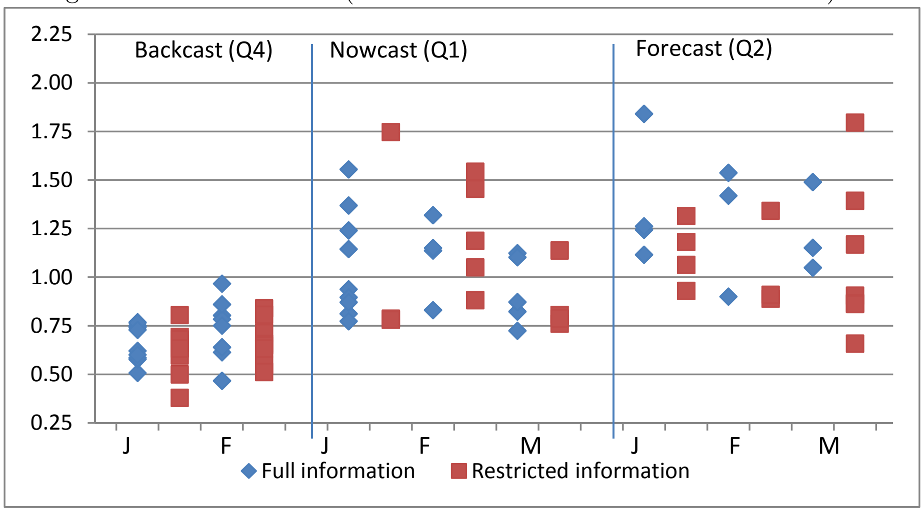
[23]The fact that 'more' information is not always better has also been found when forecasting French GDP (see Barhoumi et al., 2009).

Table 5: 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
C	0.88	1.01	0.95	0.91	1.54	1.47	1.61	1.57	1.18	1.20	1.23	1.15	1.28*	1.20	1.51	1.46
G	0.85	0.93	1.08	1.12	1.24	1.38	1.16	1.23	1.36	1.42	1.47	1.39	1.36	1.32	1.38	1.48
I	0.59*	0.80*	0.69*	0.72*	1.11	1.13*	1.06	1.14*	0.85*	1.07	1.24*	1.15	1.20*	1.13*	1.18*	1.13
X	0.79	0.80	1.01	0.83	1.05*	1.01*	1.23	1.11*	1.10*	1.04*	1.03*	0.95*	1.00*	0.93*	0.96*	0.87*
M	0.60	0.72	0.75	0.70	1.07*	1.00*	1.10*	1.03*	0.96	0.97	1.05	1.01	1.05*	1.05	1.01*	1.01*

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



Note: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter, respectively. Each dot represents a country forecast where the dynamic factor model and the PMI model differ significantly (at the 5 per cent level).

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;[24] on the other hand, by including more factors, forecasting performance might deteriorate, as more coefficients need to be estimated. In Table 6 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 valid for nowcasting and forecasting: there, it seems that more parsimonious models have higher chances of beating the PMI benchmark. 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 show suggest that the Bai and Ng (2002) information criterion may not always recommend an optimal number of factors from a forecasting perspective.

Second, to see whether some countries are simply harder to forecast – pos-

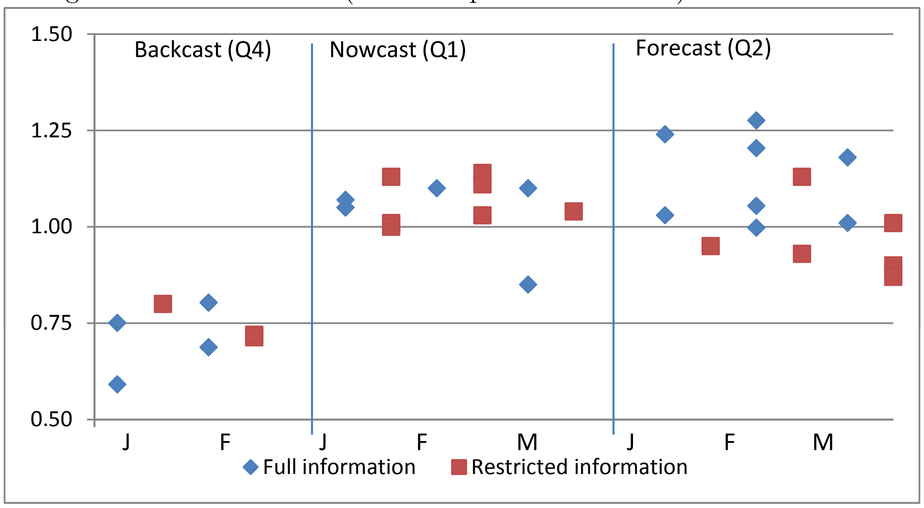
[24] In this spirit, Barhoumi et al. (2009) conclude that the Bai and Ng criterion tends to suggest too few factors, and that more factors can improve forecasting accuracy.

Table 6: Relative RMSE of the dynamic factor model over the PMI model for the euro area during the 'Great Recession' for different numbers of factors

	Backcast		Nowcast			Forecast		
Number of of factors	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; 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.

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



Note: J, F, M refers to back-, now- or forecasts made in the first, second and third month of the quarter, respectively.

sibly 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 estimated for each national economy individually, using only data from that country. Table 7 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 can react faster to changes in the outlook than our factors. This could be because we basically impose that the factors are an AR process, whereas a survey could be less persistent. Additional analysis confirms that this seems indeed to be the case: as see in figure 3, the PMI and the first factor are closely correlated, but diverge

Table 7: 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.

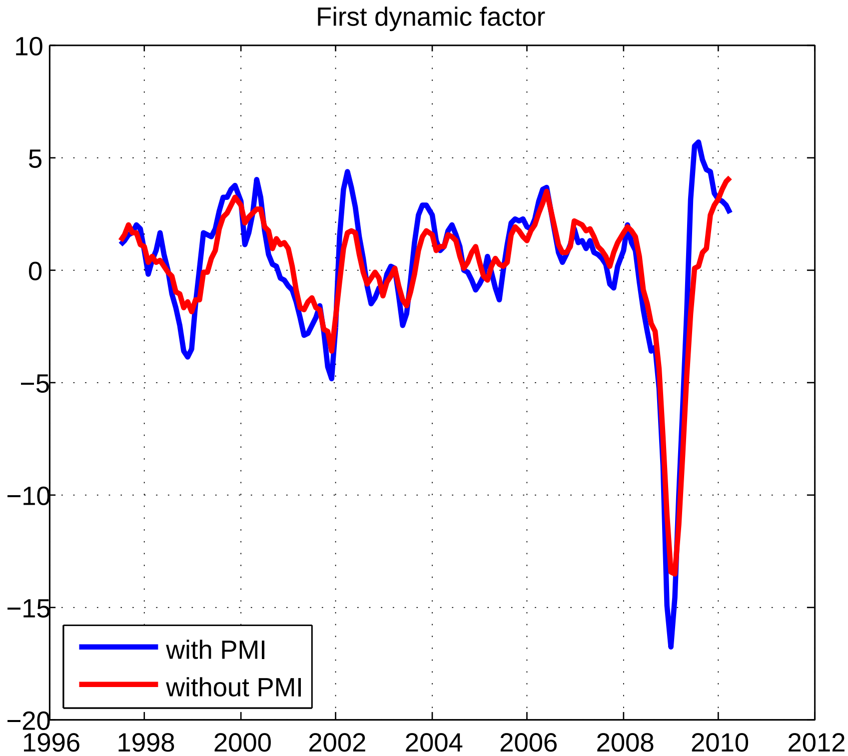
	Backcast		Nowcast			Forecast		
	Month 1	Month 2	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3
AT	0.87*	0.82*	0.75*	0.80*	0.79*	0.92	0.85*	0.80*
BE	0.92	0.75*	0.79*	0.80*	0.81*	0.88	0.79*	0.76*
DE	1.03	1.02	1.02	1.05	1.01	0.97	0.95*	0.97
ES	1.04	1.08*	0.94	1.02	1.03	1.02	0.97	1.02
FI	0.92*	0.88*	0.95	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.

somewhat during the Great Recession period. We also extracted the first factor from two data sets, one containing PMIs, one that 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 survey-based measures like the PMI can adjust comparatively faster, and thus be particularly valuable indicators 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, as the much simpler PMI model yields consistently good forecasts, while accuracy of the dynamic factor model is uneven. Also, somewhat surprisingly, the PMI model outperforms the dynamic factor model for the component forecasts, with the largest improvements in the relatively less volatile components of GDP (consumption, government). Survey-based measures like the PMI can react instantly to changes in the economic outlook, making the PMI model a tough benchmark for the dynamic factor model during the Great Recession. While improvements in the dynamic factor model forecast can be large, in particular for individual euro area countries, it is clearly not the case that the dynamic factor model outperforms the much simple PMI model on all accounts.

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)



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 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 excellent forecasts; 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 are excellent forecasting tools, yielding large gains over naive AR benchmarks. Large information sets can improve forecasting accuracy, but the gains are relatively small and can come at the cost of more uneven forecasts. 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. 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,[25] at least during the Great Recession. 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 during the Great Recession (although accuracy is somewhat less dispersed when using the full data set).

Generally speaking, an important insight of our study is that the PMI model tends to be 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 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

[25] It is indeed the case, in Figure 3, that the first factor appears to slightly lag behind the PMI index during the recession period.

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 and Modugno (2010). 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 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. More specifically, 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 9 and 10 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).

Table 8: Description of the variables for the euro area

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

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 9: 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 10: 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.