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by Matteo Luciani and Libero Monteforte



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**UNCERTAINTY AND HETEROGENEITY IN FACTOR MODELS FORECASTING**

by Matteo Luciani* and Libero Monteforte**

## Abstract

In this paper, we exploit the heterogeneity in the forecasts obtained by estimating different factor models to measure forecast uncertainty. Our approach is simple and intuitive. It consists first in selecting all the models that outperform some benchmark model, and then in constructing an empirical distribution of the forecasts produced by them. We interpret this distribution as a measure of uncertainty. We illustrate our methodology by means of a forecasting exercise using a large database of Italian data from 1982 to 2009.

**JEL Classification**: C13, C32, C33, C52, C53.
**Keywords**: factor models, model uncertainty, forecast combination, density forecast.

## Contents



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# 1 Introduction[1]

Since the seminal papers of Stock and Watson (2002a) and Forni et al. (2005), factor models have been increasingly used for macroeconomic forecasting by central banks, governments, and market operators. Moreover, the good performance of the factor model[2] has spurred further research, and the literature has suggested many refinement and improvements (Bai and Ng, 2008, 2009).

Nowadays, there are a large number of ways to produce a forecast using a factor model. There are different types of models (dynamic versus static); different estimation methods (principal components, LARS, Boosting); and, finally, each of these models can be specified in many different ways simply by changing the number of factors, or the number of lags.

Although theoretically equally acceptable, these different factor models could end-up by producing very different forecasts, and this heterogeneity represents a serious problem in real-time forecasting. The standard procedure is to select the best model, i.e. the type, the estimation method, and the model specification that minimize some criterion, and then to discard the remainder. We believe, however, that this practice is restrictive and that it does not exploit all available information, such as, the ability to consider alternative scenarios.

In this paper we propose an approach to forecasting with factor models that exploits the heterogeneity of forecasts, and interprets it as a special category of model uncertainty. This approach is useful for policy-making, because by exploiting the forecasts of models with a similar performance to the best model, it provides a warning of possible additional scenarios.

Our method is highly intuitive. It consists first in selecting all the models that out-perform some benchmark model, and then in constructing approximations of the empirical distribution of all the forecasts produced. We interpret this distribution as a measure of uncertainty. By running a forecasting exercise on Italian data, we show that our surprisingly simple method is both meaningful and effective.

Our approach is related two strands of the literature. On the one hand, we make use of a large number of models, in common with the forecast combination literature (Bates and Granger, 1969; Timmermann, 2006) and with the Model Averaging approach (Koop and Potter, 2003). On the other hand, we share the aim of assessing uncertainty with the density forecast literature (Diebold et al., 1998; Tay and Wallis, 2000). However, unlike the first strand, we propose exploiting a large number of models in order to measure forecast uncertainty

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[2]See, among others, Stock and Watson (2002b), Forni et al. (2003), Boivin and Ng (2005), Artis et al. (2005), Schumacher (2007, 2010), D'Agostino and Giannone (2012), and for a review, Eickmeier and Ziegler (2008).

rather than to reduce prediction error. And in contrast with the second strand, we assess the uncertainty between models as opposed to the uncertainty within a model (i.e. the stochastic variability of coefficients and shocks for a given model). This kind of uncertainty is particularly important from a policy perspective as it explains how at the same point in time, and with the same information set, different researchers (or institutions) can produce different forecasts. This approach is new in the literature and it produces forecast distributions that are typically not "well behaved". Our forecast distributions are often bimodal, asymmetric and have tails that are not necessarily increasing with the forecast horizon.

The paper is organized as follows. Section 2 describes the methodology, while Section 3 explains how we constructed a large number of models. Section 4 presents the empirical application, first comparing all the estimated models and then explaining how the different forecasts should be interpreted as a measure of uncertainty. Section 5 concludes.

# 2 Methodology

In this Section we review the methodologies used to estimate our factor models. Results are not derived but instead simply illustrated and therefore we refer the reader to the papers by Stock and Watson (2002a), Efron et al. (2004), Forni et al. (2005), Bai and Ng (2008) and Bai and Ng (2009) for technical details and proofs.

Throughout this Section we refer to the variable for which we want to make a prediction $h$-step ahead as $y^h_{t+h}$, and we refer to the $N$ potential predictors as $x_t$.

## 2.1 Diffusion Indexes

Let $x_t$ be an $N \times 1$ vector of zero mean stationary variables that admits a *static* factor representation such as:

$$x_t = \Lambda F_t + \xi_t = \chi_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T, \tag{1}$$

where $F_t$ is an $r \times 1$ vector containing the static factors, $\Lambda$ is an $N \times r$ matrix of factor loadings, and $\chi_t$ and $\xi_t$ are $N \times 1$ vectors containing respectively the common and the idiosyncratic component. The *Diffusion Index* proposed by Stock and Watson (2002a) forecasts $y^h_{t+h}$ by augmenting an autoregressive model with the first $r$ factors and their first $p_f$ lags:

$$y^h_{t+h} = \alpha(L) y_t + \beta(L) F_t + \varepsilon_t \tag{2}$$

where $\alpha(L)$ and $\beta(L)$ are polynomials of order $p_y$ and $p_f$ respectively. Stock and Watson (2002a) demonstrate that if the idiosyncratic components $\xi_t$ are mildly serial and cross-sectional correlated, the static factors in (1) can be consistently estimated with the principal components method. Having estimated the static factors, Stock and Watson (2002a) suggest estimating equation (2) via OLS. The consistency of this procedure is proved in Bai and Ng (2006).

### 2.2 Dynamic Factor Models

Let $x_t$ be an $N \times 1$ vector of zero mean stationary variables that follows a "Dynamic Factor Model" such as:

$$x_t = C(L)\eta_t + \xi_t = \chi_t + \xi_t, \quad \text{for} \quad t = 1, \ldots, T \tag{3}$$

where $\eta_t$ is a $q \times 1$ vector of *dynamic* factors with $q \ll N$, and $C(L) = \sum_{j=0}^{\infty} C_j L^j$ is an $N \times q$ matrix polynomial in the lag operator with square summable entries. Let us suppose that $y_t$ is one of the entries of a vector $x_t$, say the $i$-th entry for simplicity, then a forecast of $y^h_{t+h} \equiv x^h_{i,t+h}$ can be obtained as the sum of the forecast of the common component and the idiosyncratic component: $x^h_{i,t+h} = \chi^h_{i,t+h} + \xi^h_{i,t+h}$. Forni et al. (2005) (proposition 4) demonstrate that a forecast of the common component that converges to the best linear forecast of $\chi_{i,t+h|t}$ can be obtained by means of a two-step estimator, and they suggest that the idiosyncratic component can be neglected.[3]

**Step 1:** Let $\tilde{\Sigma}^{\chi}(\theta)$ and $\tilde{\Sigma}^{\xi}(\theta)$ be the estimated spectral density matrix of the common and the idiosyncratic component respectively, obtained by the dynamic principal components method: then the covariance matrices of $\chi_t$, $\tilde{\Gamma}^{\chi}_k$, and $\xi_t$, $\tilde{\Gamma}^{\xi}(\theta)$ can be consistently estimated as the inverse Fourier transform of $\tilde{\Sigma}^{\chi}(\theta)$ and $\tilde{\Sigma}^{\xi}(\theta)$ respectively.

**Step 2:** Let $\widehat{Z}$ be the $N \times r$ matrix containing the first normalized $r$ eigenvectors of $\tilde{\Gamma}^{\chi}_0(\tilde{\Gamma}^{\xi}_0)^{-1}$: then the static factors can be estimated as the first $r$ generalized principal components of $x_t$, $\widehat{F}_t = \widehat{Z}' x_t$. The factor loadings $\Lambda$ can then be recovered as the linear projection of the static factors on $x_t$, $\Lambda = \tilde{\Gamma}^{\chi}_0 \hat{Z}(\hat{Z}'\tilde{\Gamma}^{\chi}_0 \hat{Z})^{-1}$. Having estimated both the factors and the loadings the forecast of the common components is obtained as: $\hat{\chi}_{t+h|t} = \tilde{\Gamma}^{\chi}_h \hat{Z}(\hat{Z}'\tilde{\Gamma}^{\chi}_0 \hat{Z})^{-1}\hat{Z}' x_t$.

### 2.3 Least Angle Regressions (LARS)

The purpose of least angle regression is to build recursively an estimate of $y$ by $x\hat{\beta}$ where a regressor is added at each stage. At the first stage the variable most closely correlated with $y$, say $x_j$, is selected, and an OLS regression of $y$ on $x_j$ is run. Define the residual of the first step as $v = y - \gamma\hat{\beta}_j x$, where $\gamma$ is the step length; the algorithm then takes the largest step in the direction of this predictor until it finds another regressor, say $x_l$, that is as closely correlated with $v$. The LARS algorithm then searches for the third variable equiangularly between $x_j$ and $x_l$. At the $k$-th step, $\hat{\beta}$ has $k$ non zero elements and $N - k$ zero elements. In this way

[3] A refinement of the Forni et al. (2005) procedure is proposed in D'Agostino and Giannone (2012) who suggest forecasting the idiosyncratic component as the linear projection of $\xi_{i,t+h|t}$ on $[x_{i,t}\ x_{i,t-1}\ \ldots\ x_{i,t-p}]$.

the variables most closely correlated with $y$ are included one at a time, although LARS also avoids selecting variables that are too "similar". One of the main features of LARS is that the direction of the search, and the updating rule are computed endogenously by the algorithm; the researcher simply needs to set the number of iterations.

### 2.4 Boosting

Boosting (Freund and Schapire, 1997) is a method originating from the machine learning literature that has proved useful in regressions with a large number of predictors (Bühlmann and Yu, 2003; Bühlmann, 2006; Lutz and Bühlmann, 2006). Let $z_t = \{x_{1,t}, \ldots, x_{1,t-p_x}, \ldots, x_{N,t}, \ldots, x_{N,t-p_x}\}'$, be the $\bar{N} \times 1$ matrix containing all the $N$ variables and their $p_x$ lags; the idea of Boosting is to build an estimate of $y_{t+h}$ by recursively estimating regressions of $y_{t+h}$ on $z_{jt}$, where $z_{jt}$ is the most powerful variable in predicting $y_{t+h}$.

Formally, suppose that the algorithm was run $k$ times; let $\hat{\mu}^k$ be the prediction obtained after $k$ steps, and define the residual $u^k = y_{t+h} - \hat{\mu}^k$, then:

1. for each $i = 1 \ldots \bar{N}$, regress $u^k$ on $z_i$, thus obtaining $\hat{b}_i$, and define $\hat{e}_i = u^k - z_i\hat{b}_i$, and $ssr_i = \hat{e}_i'\hat{e}_i$;
2. select the variable $j$ such that $ssr_j = \min_{i=1,\ldots,\bar{N}}\{ssr_i\}$;
3. update the prediction as $\hat{\mu}^{k+1} = \hat{\mu}^k + \gamma z_j \hat{b}_j$, where $0 < \gamma \leq 1$ is the step length.

At the $(k+1)$-th iteration, the estimator $\hat{\beta}_{k+1}$ is obtained as $\hat{\beta}_{k+1} = \hat{\beta}_k + \gamma \hat{b}_{k+1}^{\dagger}$, where $\hat{b}_k^{\dagger}$ is an $\bar{N} \times 1$ vector in which all entries are zero except element $j$, which is equal to $\hat{b}_j$, and the forecast of $y_{t+h}$ is obtained as $\hat{y}_{t+1}^{k+1} = \hat{\beta}_{k+1} z_t$.[4]

## 3 Constructing a large number of factor models

In this Section we explain how we construct a large number of forecasts. Forecasts are produced by means of eight different methods that can be grouped into two main types: Diffusion Indexes and Dynamic Factor models. Table 1 contains the complete list of the methods used in this paper.

Method DI is the classic diffusion index proposed by Stock and Watson (2002a), while methods DI2, LDI, DIB and DIB2 are all variants of DI. Originally proposed by Bai and Ng (2008), DI2 consists in extracting the factors from a panel that includes both the normal variables and their squared values and then estimating a diffusion index. Similarly, LDI (Bai and Ng, 2008) consists in extracting the factors from a panel with only a few predictors selected using the LARS algorithm and then estimating a diffusion index. Finally, DIB and DIB2 (Bai and Ng, 2009) consists in estimating equation (2) by Boosting rather than by OLS.

[4] This is the *component-wise* algorithm proposed by Bühlmann and Yu (2003). Bai and Ng (2009) suggest another algorithm labelled *block-wise* Boosting, which works exactly like the *component-wise* one but treats lags of the same variable in $Z_t$ jointly rather than as a distinct variable.

**Table 1:** *Estimated models*

Benchmark Model

| N° | Model | Forecast equation |
|---|---|---|
| 0 | AR | $y^h_{t+h} = a(L)y_t + v_t$ |

Diffusion Indexes

| N° | Method | Forecast equation | Factors extracted from: | Estimation method |
|---|---|---|---|---|
| 1 | DI | $y^h_{t+h} = \alpha(L)y_t + \beta(L)F_t + \varepsilon_t$ | $x_t$ | OLS |
| 2 | DI2 | - - | $[x_t\ x_t^2]$ | OLS |
| 3 | LDI | - - | $\tilde{x}_t$ | OLS |
| 4 | DIB | - - | $x_t$ | Boosting |
| 5 | DI2B | - - | $[x_t\ x_t^2]$ | Boosting |

Dynamic Factor Models:

| N° | Method | Forecast equation | Estimation of idiosyncratic component |
|---|---|---|---|
| 6 | FHLR$_a$ | $x^h_{t+h} = \chi^h_{t+h}$ | none |
| 7 | FHLR$_b$ | $x^h_{t+h} = \chi^h_{t+h} + \xi^h_{t+h}$ | AR OLS |

Method DF$_a$ simply implements the proposal of Forni et al. (2003, 2005), while DF$_b$ implements the refinement suggested by D'Agostino and Giannone (2012).

As explained in the introduction, with each of these methods we can produce different forecasts simply by choosing different model specifications, i.e. by varying the number of static/dynamic factors, or the number of lags. Above all, *a priori* all these methods and specifications are (theoretically) equally acceptable. In this paper we produce 267 different factor forecasts plus 4 different benchmark AR forecasts. Table 2 contains the complete list of specifications used in this paper.

The factors are extracted from a panel of 118 quarterly series, 100 describing the Italian economy and 18 representing the rest of the world. The variables cover different categories: GDP and Components, Value Added by Sector, Unit labor cost, Employee Compensation, Employment, Interests Rates, Monetary Aggregates, Prices, Industrial Production, Exchange Rates, Business, and Confidence and Survey indicators. Moreover, to account for world business cycle fluctuations we also include GDP, CPI, and the Unemployment Rate for France, Germany, UK, US and Japan, and the Interest Rate of UK, US and Japan. All variables are first transformed to reach stationarity and then demeaned and standardized. As in Stock and Watson (2002b) we take the second difference of the logarithm of both prices and monetary indicators, and the first difference of interest rates. After transformation all variables are stationary according to the Augmented Dickey Fuller test. For any further information on the database the complete list of variables and transformations is reported in the Appendix.

We use the method of direct forecast (Stock and Watson, 2002b): let $Y_t$ be the raw variable assumed to be integrated of order one; then $y^h_{t+h}$ is defined as $y^h_{t+h} = \log(Y_{t+h}) - \log(Y_t)$, that is the growth rate between period $t$ and period $t + h$. On the other hand, the autoregressive

**Table 2:** *List of model specifications*

| | |
|---|---|
| AR: | we performed forecasts for $p = 1, \ldots, 4$, where $p$ is the order of the autoregression (4 specifications); |
| DI: | we allow $p_y = 1, \ldots, 4$, $p_f = 1, \ldots, 4$, $r = 1, \ldots, 5$, where $p_y$ and $p_f$ are the number of lags of the endogenous variable and the static factors respectively, and $r$ is the number of static factors (80 specifications); |
| DI2: | same as DI (80 specifications); |
| LDI: | same as DI but the matrix $\tilde{x}_t$ from which the factors are extracted contains half of the variables in $x_t$, meaning the first 59 variables selected by the LARS algorithm (80 specifications); |
| DIB: | we include all possible regressors in the forecast equation ($p_y = 4$, $p_f = 4$, and $r = 5$, 24 regressors); we set the step length $\gamma$ equal to 0.5; we estimate the model by both the *component-wise* and the *block-wise* algorithm; and we save the forecast obtained after 5, 10 and 20 iterations (6 specifications); |
| DIB2: | same as DIB (6 specifications); |
| DF$_a$: | we select 3 dynamic factors as indicated by the Hallin and Liška (2007) criteria and by the Onatski (2009) test, and we allow for a number of static factors ranging from 3 to 5, which is consistent with the indication obtained from information criteria (Bai and Ng, 2002; Alessi et al., 2010) (3 specifications);* |
| DF$_b$: | for the common component, the same as DF$_a$, while for the idiosyncratic component we produced forecasts by setting $p_\xi = 1, \ldots, 4$ (12 specifications). |

* To save space the results of these tests are not reported here.

variable on the right-hand side $y_t$ is defined as $y_t = \log(Y_t) - \log(Y_{t-1})$.[5]

# 4 Empirical analysis

## 4.1 Comparing factor based forecasts

In this Section we evaluate the performance of different factor models. Forecasts are produced by a recursive scheme and are computed with a forecast horizon from one to eight-steps ahead. The first estimation is carried out on a sample from 1982:3 to 2002:2 ($T = 80$), while the last estimation is on a sample from 1982:3 to 2009:2. Overall we produced 29 forecasts for the one-step ahead, 28 for the two-steps ahead, and 22 for the eight-steps ahead.

From Table 3 to Table 7 we present relative mean squared errors for a large number of macroeconomic variables. The benchmark is an AR forecast. An entry lower than 1 means that the $m$-th model beats the benchmark AR forecast, while an entry greater than 1 means that model $m$ performs worse than an AR. For each method (benchmark model, diffusion indexes and dynamic factor models) we select the best specification, i.e. the one, within the range of different parameter configurations presented in Section 3, that produces the smallest

[5] Given that the outcome of models 6-7 is different from the one obtained with models 1-5, some manipulations are needed for correct comparison. Let $X_{it}$ be the non standardized growth rate of the $i$-th variable, then $x_{it} = (X_{it} - \mu_{X_i})/\sigma_{X_i}$, and therefore $x^h_{i,t+h} = (X^h_{i,t+h} - \mu_{X_i})/\sigma_{X_i}$. Hence, when forecasting with DF$_a$ and DF$_b$ we have that $Y^h_{t+h}$ can be obtained as $Y^h_{t+h} = \sum_{j=1}^{h}(x^j_{i,t+j}\sigma_{X_i} + \mu_{X_i})$.

mean squared error.

In this Section, we provide a simple bird's eye view of the results by variable. The aim is to identify the variable for which the factor models can improve on a simple AR model, not to compare the forecasting ability of the different factor models considered.[6]

**GDP:** Factor models outperform the AR model when forecasting GDP in both the short run and the long run (Table 3). It is worth noting that the gain from factor-based forecasts is increasing at longer time horizons.

**Labour market:** Factor models do quite well in predicting the number of persons employed, but they are outperformed by the AR model in predicting the unemployment rate (Table 4). Regarding employment but the advantage of a large information set is negligible for forecasting other sectors.

**Gross Value Added:** Factor models perform particularly well in predicting VA in the services sector (Table 5). They also perform well in predicting education, health, and other private and public services.

**Consumption:** Factor models consistently improve on the AR model in predicting aggregate consumption (Table 6). In particular, they perform well in predicting consumption of non-durable goods and services.

**Investments:** Factor models do better than the AR benchmark at the one-step ahead horizon, while their performance is similar at longer forecast horizons (Table 7).

To conclude this Section, in Table 8 we report the number of specifications within each type of factor models that does worse than the benchmark AR in predicting GDP. Results show that most specifications (i.e. regardless of the number of factors, the number of lags, etc.) perform better than the AR, as found in Bulligan et al. (2012). Moreover, none of the estimated factor models perform worse than the AR after the $4^{th}$ forecast horizon. These results justify our approach: as most of the 267 estimated models have at least some predictive power, why select only one of them?

[6] There exists a wide applied literature that has compared the forecasting performances of DI versus FHLR type forecasts without, however, reaching a conclusion. den Reijer (2005), Cheung and Demers (2007) and Schumacher (2007) compare DI versus FHLR when forecasting GDP for the Netherlands, Canada and Germany. den Reijer (2005) and Schumacher (2007) find that FHLR outperforms DI, while Cheung and Demers (2007) find no noticeable difference between the two methods. Boivin and Ng (2005), analysing US monthly data on a large number of series, conclude that DI performs better because it does not impose a factor structure and therefore the forecast can more easily adapt to the data. D'Agostino and Giannone (2012), analysing a similar dataset, criticize this conclusion and find that FHLR performs similarly to DI. For a complete review of factor model forecasting performance see Eickmeier and Ziegler (2008).

## 4.2 Two examples of model uncertainty

As we have just shown, there are many ways to produce a macroeconomic forecast using a factor model. There are different types of models and different estimation methods; each of the models can be specified in many different ways. However, although $(i)$ theoretically all these models are equally acceptable, and $(ii)$ most of them outperform a standard AR model (Table 8), they can end-up by producing very different forecasts. The question then becomes: can we somehow exploit these different forecasts?

The literature has already addressed this issue, and it is now well known that the prediction error can be reduced by combining different forecasts (Timmermann, 2006). However, our claim is that the different forecasts can be used to measure forecast uncertainty in the context of factor modelling.

In what follows, we explain the workings of our method. It has the desirable feature of being extremely intuitive as it consists first in selecting all the models that outperform some benchmark model, and then in approximating the empirical distribution of the forecasts produced by them. We interpret this distribution as a measure of uncertainty. As our approach is aimed mainly at policy-makers, we present it here by means of a practical example.

Suppose that in the middle of the global crisis, say the beginning of 2009, the policy-maker asked us to provide forecasts for the next two years. To mimic this situation we produce forecasts of GDP with our 267 factor models. The question is then: what is the relevant information that we want to report to the policy-maker?

The first option is to use the standard approach: we identify the *best* model for each forecast horizon and then we report the implied path of forecasts. Table 9 presents forecasts of GDP for 2009 and 2010, that is the forecast from one to eight-steps ahead obtained using data from the beginning of the sample up to 2008Q4. Each entry reports the predicted average percentage quarter-on-quarter growth rate between $t$ and $t+h$: $100 \times \frac{1}{h}(\widehat{GDP}_{t+h} - GDP_t)$. If we reported only the path of forecast suggested by the *best* models (bold entries), we would have shown the policy-maker a critical situation (i.e. negative growth rates for the following two years). However, we would have not been able to say much more beyond this statement. We could have said what the *best* forecast is, but we could not have considered alternative scenarios delivered by equally acceptable models. Our method aims to do so.

In Figure 1 we show the forecasts of the 20 best models in terms of mean squared error, i.e. the 20 factor models (irrespective of type/estimation method/specification) that produce the smallest MSE. Clearly, although we are considering models with similar predicting ability, the forecast that they produce is very different, thus showing a high degree of uncertainty. However, despite this additional piece of information, the main conclusion of our report would not have changed as 18 of the 20 models predicted negative growth.

The question is then: why restrict the analysis to twenty models? What happens if we consider a larger number of models? In Figure 2 we answers this question.

Figure 2 shows the distribution of the 50 best forecasts together with the kernel approximation of the empirical function.[7] The forecasts produced by the 50 best models are not normally distributed, instead they exhibit fat tails, asymmetry and multimodality. Moreover, this measure of uncertainty is not necessarily, by construction, increasing with the forecast horizon. These characteristics differentiate these functions from the standard predictive densities. In our example, the baseline projection would have not changed by looking at the 50 best forecasts, as most of the models predicted a recession for the next two years. However, we would have been able to warn the policy-maker about the high degree of uncertainty affecting our forecast.[8]

To conclude our example, Figure 3 shows the box plot of all the forecasts produced by those models with an MSE smaller than the benchmark AR (179 models for 2009Q1, 183 for 2009Q2, 256 for 2009Q3, 265 for 2009Q4, and all the 267 models for the whole of 2010).[9] If we had also considered Figure 3, we would have refined our report to the policy-maker by concluding that we predict negative average growth for the first three quarters of 2009, but positive growth for 2010 as suggested by the median forecast.[10]

With this example we showed how it is possible to exploit the information delivered by a large number of factor models, and how this information can be used to measure forecast uncertainty. However, in order to validate our method we need to show that, if we repeat the same exercise on a period of low volatility, the forecasts produced by different factor models exhibit a smaller degree of heterogeneity.

In Figures 4 to 6 we show forecasts produced at the end of 2006, well before the global recession. Figure 4 shows that the range of the forecasts for 2007 and 2008 is much smaller than for 2009-10, especially at the first (0.37 against 0.69) and the second (0.16 against 0.42) forecasting horizon. Similarly, Figure 5 shows that although the forecasts are not normally distributed, their range is consistently smaller than the one obtained in the previous example (one-step ahead 0.62 against 0.96, two-step ahead 0.34 against 0.53). Moreover, Figure 6 shows that the interquartile range is quite small at all forecast horizons. Finally, Table 10, which reports the standard deviation and the range of the forecasts, shows that forecast uncertainty increased considerably during the global recession.

[7] The distribution approximation is produced using a smoothing density with normal kernel function.

[8] It is also worth noting that, in contrast with the results in Table 9, among the 50 best available models some predicted a recovery for 2010, as actually happened.

[9] It is worth emphasizing that although the decision to consider only the models that do better than the benchmark model is arbitrary, it is reasonable and in line with the literature. Indeed, the benchmark model is always a simple model and in the forecasting literature it is always considered a lower bound: a model that on average does worse than the benchmark model is therefore considered a "bad" model.

[10] It is also worth noting that in some circumstances economic uncertainty can be greater in the short run then in the long run. This may be the case with an economy hit by large temporary demand shocks. In our view, our measure of uncertainty, which is not always increasing with the horizon, is more general than standard measures.

## 5 Conclusions

In this paper, we propose exploiting the heterogeneity of the forecasts obtained by estimating different factor models to measure (a special category of) forecast uncertainty. We present our approach by means of a forecasting exercise on a large database of Italian data from 1982 to 2008. We estimate as many as 267 factor models using all the main techniques available in the literature and we show that most of these estimated factor models beat a standard time series benchmark.

Our approach is simple and intuitive. It consists in selecting all the models that outperform some benchmark model, and then in approximating the empirical distribution of the forecasts produced by these models. The moments higher than the first characterize this measure of uncertainty.

We present two historical examples, before and during the crisis. We show that the forecast distributions obtained by many models are asymmetric, multimodal, and with fat tails. As expected, our measure of uncertainty increased considerably during the recent global recession. A structural and general analysis of these empirical forecast distributions is left for future work.

# Appendix - Data Description and Data Treatment

| N | C. | DSmnemonic | Name | Source | Unit | SA | F. | T. |
|---|---|---|---|---|---|---|---|---|
| 1 | | ITGDP...D | GDP | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 2 | | ITFNLUSED | Final Uses | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 3 | Gross | ITGVACLCD | GVA - com., lodging, catering& rep | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 4 | Domestic | ITGVACOND | GVA - construction | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 5 | Product | ITGVAEDUD | GVA - ed.,health,oth.priv.& pub.svs. | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 6 | | ITGVAFMID | GVA - fuel & mining industries | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 7 | | ITGVAIXCD | GVA - industry excl. construction | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 8 | | ITGVASVSD | GVA - services | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 9 | | ITINVCHYD | CHANGE IN STOCKS | ISTAT | $p_{t-1}$ | 1 | Q | 0 |
| 10 | | ITCNPCDGD | PC - durable goods | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 11 | | ITCNPCFTD | PC - food alcohol & tobacco | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 12 | | ITCNPCFGD | PC - foreigners in italy | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 13 | | ITCNPCRAD | PC - italian residents abroad | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 14 | Consumption | ITCNPCNDD | PC - non-durable goods | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 15 | | ITCNPCNFD | PC - non-food | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 16 | | ITCNPCSDD | PC - semi-durable goods | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 17 | | ITCNPCSVD | PC - services | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 18 | | ITCNPER.D | FDC - households | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 19 | | ITCNGOV.D | FDC - public | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 20 | | ITRVSTAXA | STATE BUDGET: TAX REVENUE | BdI | 2000Bil€ | 2 | M | 3 |
| 21 | Government | ITEXSCURA | STATE BUDGET: CURRENT EXPENDITURE | BdI | 2000Bil€ | 2 | M | 3 |
| 22 | | ITEXSCAPA | STATE BUDGET: CAPITAL EXPENDITURE | BdI | 2000Bil€ | 2 | M | 1 |
| 23 | | ITGOVBAAA | STATE BUDGET: BALANCE | BdI | 2000Bil€ | 0 | M | 2 |
| 24 | | ITGFCF..D | gross fixed capital formation | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 25 | Investment | ITFCPCOND | GFCF - construction | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 26 | | ITFCPMCHD | GFCF - machinery & equipment | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 27 | | ITFCPTRND | GFCF - means of transport | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 28 | | ITEXPGD.D | exports of goods | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 29 | Net | ITEXPSV.D | exports of services | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 30 | Export | ITIMPGD.D | imports of goods | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 31 | | ITIMPSV.D | imports of services | ISTAT | 2000Mil€ | 1 | Q | 3 |
| 32 | | ITULCAFFE | ULC - agriculture forestry & fishing | ISTAT | 2000=100 | 1 | Q | 3 |
| 33 | | ITULCCNSE | ULC - construction | ISTAT | 2000=100 | 1 | Q | 3 |
| 34 | Unit | ITULCOTHE | ULC - education, welfare, oth.public & private svs | ISTAT | 2000=100 | 1 | Q | 3 |
| 35 | Labor | ITULCCATE | ULC - hotels, trade, repair, public establishments | ISTAT | 2000=100 | 1 | Q | 3 |
| 36 | Cost | ITLCOST.E | ULC - industry excluding construction | ISTAT | 2000=100 | 1 | Q | 3 |
| 37 | | ITULCCAPE | ULC - credit & insurance | ISTAT | 2000=100 | 1 | Q | 3 |
| 38 | | ITCNCTOTB | employee compensation | ISTAT | Mil€ | 1 | Q | 3 |
| 39 | | ITCNCAFFB | EC - agriculture, forestry & fishing | ISTAT | Mil€ | 1 | Q | 3 |
| 40 | | ITCNCCONB | EC - construction | ISTAT | Mil€ | 1 | Q | 3 |
| 41 | | ITCNCEDCB | EC - education, health, oth. priv. & pub. svs. | ISTAT | Mil€ | 1 | Q | 3 |
| 42 | Employee | ITCNCFMIB | EC - fuel & mining industries | ISTAT | Mil€ | 1 | Q | 3 |
| 43 | Compensation | ITCNCHLTB | EC - health care | ISTAT | Mil€ | 1 | Q | 3 |
| 44 | | ITCNCHTCB | EC - hotels & pub. trnsp. & comm. repairs | ISTAT | Mil€ | 1 | Q | 3 |
| 45 | | ITCNCIXCB | EC - industry excluding construction | ISTAT | Mil€ | 1 | Q | 3 |
| 46 | | ITCNCSVRB | EC - services | ISTAT | Mil€ | 1 | Q | 3 |
| 47 | | ITUN%TOTQ | unemployment rate | ISTAT | % | 1 | Q | 2 |
| 48 | | ITCNETOTO | Employment | ISTAT | Thous. | 1 | Q | 3 |
| 49 | | ITCNEAFFO | E - agriculture forestry & fishing | ISTAT | Thous. | 1 | Q | 3 |
| 50 | | ITCNECONO | E - construction | ISTAT | Thous. | 1 | Q | 3 |
| 51 | | ITCNEEDUO | E - education health & other private & public svs. | ISTAT | Thous. | 1 | Q | 3 |
| 52 | Employment | ITCNEFMIO | E - fuel & mining industries | ISTAT | Thous. | 1 | Q | 3 |
| 53 | | ITCNEHLTO | E - health care | ISTAT | Thous. | 1 | Q | 3 |
| 54 | | ITCNEHTCO | E - hotels & public trnsp. & communication repairs | ISTAT | Thous. | 1 | Q | 3 |
| 55 | | ITCNEINDO | E - industry | ISTAT | Thous. | 1 | Q | 3 |
| 56 | | ITCNEIDCO | E - industry excluding construction | ISTAT | Thous. | 1 | Q | 3 |
| 57 | | ITCNESVSO | E - services | ISTAT | Thous. | 1 | Q | 3 |

NOTE: Variables 47 is backdated by using OECD Economic Outlook Data (DSMNEMONIC: ITOCFUNRQ). Variables 20-23 are deflated by using variable 77.

| N | C. | DSmnemonic | Name | Source | Unit | SA | F. | T. |
|---|---|---|---|---|---|---|---|---|
| 58 | | ITPRATE. | Discount Rate - Short Term euro repo rate | ECB | % | 0 | M | 2 |
| 59 | | ECITLST | ITALY EURO-LIRE T/N (FT/ICAP/TR) | TR | % | 0 | M | 2 |
| 60 | | ECITL1M | ITALY EURO-LIRE 1M (FT/ICAP/TR) | TR | % | 0 | M | 2 |
| 61 | | ECITL3M | ITALY EURO-LIRE 3M (FT/ICAP/TR) | TR | % | 0 | M | 2 |
| 62 | Interest | ECITL6M | ITALY EURO-LIRE 6M (FT/ICAP/TR) | TR | % | 0 | M | 2 |
| 63 | Rates | ECITL1Y | ITALY EURO-LIRE 1 YR (FT/ICAP/TR) | TR | % | 0 | M | 2 |
| 64 | | ITBI0257 | EXPECTED GROSS MEAN YIELD (CCT) | BdI | % | 0 | M | 2 |
| 65 | | ITQ61... | GOVT BOND YIELD - LONGTERM | IFS | % | 0 | M | 2 |
| 66 | | ITQ60B.. | MONEY MARKET RATE ( FEDERAL FUNDS ) | IFS | % | 0 | M | 2 |
| 67 | | ITQ60C.. | TREASURY BILL RATE | IFS | % | 0 | M | 2 |
| 68 | | | ITQ61B.. - ITQ60B.. | ML | % | 0 | M | 2 |
| 69 | Monetary | ITM1....A | M1 - IT contribution to the euro area | BdI | Mil€ | 2 | M | 4 |
| 70 | Aggregates | ITM3....A | M3 - IT contribution to the euro area | BdI | Mil€ | 2 | M | 4 |
| 71 | | ITOCP009F | Consumer Price Index | MEI | 2005=100 | 2 | M | 4 |
| 72 | | ITOCP041F | CPI - energy | MEI | 2005=100 | 2 | M | 4 |
| 73 | | ITOCP042F | CPI - excluding food & energy | MEI | 2005=100 | 2 | M | 4 |
| 74 | Prices | ITOCP019F | CPI - food | MEI | 2005=100 | 2 | M | 4 |
| 75 | | ITOCP057F | CPI - housing | MEI | 2005=100 | 2 | M | 4 |
| 76 | | ITOCP064F | CPI - services less housing | MEI | 2005=100 | 2 | M | 4 |
| 77 | | ITGDPIPDE | Implicit Price Deflator - GDP | ISTAT | 2000=100 | 1 | Q | 4 |
| 78 | | ITIPDGOVE | Implicit Price Deflator - Gov. | ISTAT | 2000=100 | 1 | Q | 4 |
| 79 | | ITOPRI35G | production of total industry (excluding construction) | MEI | 2005=100 | 1 | M | 3 |
| 80 | Industrial | ITOPRI49G | production of total manufactured consumer goods | MEI | 2005=100 | 1 | M | 3 |
| 81 | Production | ITOPRI61G | production of total manufactured intermediate goods | MEI | 2005=100 | 1 | M | 3 |
| 82 | | ITOPRI70G | production of total manufactured investment goods | MEI | 2005=100 | 1 | M | 3 |
| 83 | Exchange | ITOCC011 | real effective exchange rate - cpi based | MEI | 2005=100 | 2 | M | 3 |
| 84 | Rates | ITOCC016 | us cents to euro (ep) | MEI | $/€ | 0 | M | 3 |
| 85 | | ITOSLI05E | total car registrations | MEI | 2005=100 | 1 | M | 1 |
| 86 | | ITESP35GF | PPI: MANUFACTURE OF GAS | EUR | 2005=100 | 2 | M | 4 |
| 87 | Business | UKOILBREN | AVERAGE BRENT OIL PRICE | DEUK. | $ | 0 | M | 4 |
| 88 | | ITOSP001F | share prices - ise mib storico | MEI | 2005=100 | 0 | M | 3 |
| 89 | | ITOL1117Q | CLI - reference series | MEI | * | 1 | M | 1 |
| 90 | Confidence | ITOL0637Q | CLI - orderbooks or demand (fut. tend.) | MEI | % | 1 | M | 1 |
| 91 | Leading | ITOL0376Q | CLI - production - future tendency | MEI | % | 1 | M | 1 |
| 92 | Indicators | ITOL0577Q | CLI - volume net new orders (mfg.) | MEI | * | 1 | M | 1 |
| 93 | | ITBIPCI.F | BdI Price Competitiveness Indicator - italy | BdI | 1999=100 | 2 | M | 1 |
| 94 | | ITOBS083Q | BTS manufacturing - exports order books | MEI | % | 1 | M | 1 |
| 95 | | ITOBS082Q | BTS manufacturing - future selling prices | MEI | % | 1 | M | 1 |
| 96 | | ITOBS077Q | BTS manufacturing - finished goods stocks | MEI | % | 1 | M | 1 |
| 97 | Survey | ITOBS084Q | BTS manufacturing - future production | MEI | % | 1 | M | 1 |
| 98 | | ITOBS078Q | BTS manufacturing - order books | MEI | % | 1 | M | 1 |
| 99 | | ITCSECFTQ | ISAE CS economic climate index - future | ISAE | 1980=100 | 1 | M | 1 |
| 100 | | ITCSECPRQ | ISAE CS economic climate index - present | ISAE | 1980=100 | 1 | M | 1 |
| 101 | | BDGDP...D | Ger - GDP | SBW | 2000Bil€C | 1 | Q | 3 |
| 102 | | FRGDP..FD | Fra - GDP | INSEE | 2000Mil€ | 1 | Q | 3 |
| 103 | | USGDP...D | Us - GDP | BEA | 2005Bil$ | 1 | Q | 3 |
| 104 | | JPGDP...D | Jpn - GDP | COJ | 2005Bil€ | 1 | Q | 3 |
| 105 | | UKGDPMKTD | Uk - GDP | ONS | 2005Mil£C | 1 | Q | 3 |
| 106 | | BDCP7500F | Ger - CPI | SBW | 1975=100 | 1 | M | 4 |
| 107 | | FRCONPRCF | Fra - CPI | INSEE | 1998=100 | 1 | M | 4 |
| 108 | Foreign | USCONPRCF | Us - CPI | BLS | ** | 1 | M | 4 |
| 109 | Countries | JPCPIEIAF | Jpn - CPI | MIAC | 2005=100 | 1 | M | 4 |
| 110 | | UKD7BTQ.F | Uk - CPI | ONS | 2005=100 | 1 | Q | 4 |
| 111 | | BDUN%TOTR | Ger - Unemployment Rate | DB | % | 2 | M | 2 |
| 112 | | FRUN%TOTQ | Fra - Unemployment Rate | INSEE | % | 1 | Q | 2 |
| 113 | | USUN%TOTQ | Us - Unemployment Rate | BLS | % | 1 | M | 2 |
| 114 | | JPUN%TOTQ | Jpn - Unemployment Rate | MIAC | % | 1 | M | 2 |
| 115 | | UKUN%TOTQ | Uk - Unemployment Rate | ONS | % | 1 | M | 2 |
| 116 | | USFEDFUN | FED Funds Rate | FED | % | 0 | M | 2 |
| 117 | | UKPRATE. | BoE Base Rate | BoE | % | 0 | M | 2 |
| 118 | | JPBANKR. | PRIME RATE - LONG TERM | BoJ | % | 0 | M | 2 |

NOTE: Variable 101 is backdated by using OECD Economic Outlook Data (DSMNEMONIC: WGOCFGDPD), while variable 110 is backdated by OECD Main Economic Indicators Data (DSMNEMONIC: UKOCP009F):
* Actual number - RATIO TO TREND;
** 1982.1984=100.

## List of Abbreviations

| Source | | Transformations | | Seasonally Adjustement | |
|---|---|---|---|---|---|
| IFS | Internationl Financial Statistics, IMF | 1 | none | 0 | Not Seasonally Adjusted |
| EUR | Eurostat | 2 | $\Delta$ | 1 | Seasonally Adjusted |
| MEI | OECD Main Economic Indicators | 3 | $\Delta log$ | 2 | SA with dummy variables regression |
| ONS | OFFICE FOR NATIONAL STATISTICS | 4 | $\Delta\Delta log$ | | |
| BdI | Bank of Italy | | | | |
| FED | Federal Reserve Bank | | | | |
| BLS | Bureau of Labor Statistics | | | | |
| SBW | STATISTISCHES BUNDESAMT, WIESBADEN | | | | |
| MIAC | Ministry of Intarnal Affairs & Communications | | | | |
| BEA | Bureau of Economic Analysis | | | | |
| DB | DEUTSCHE BUNDESBANK | | | | |
| BoE | Bank of England | | | | |
| BoJ | Bank of Japan | | | | |
| COJ | Cabinet Office, Japan | | | | |
| DEUK | Department of Energy, U.K | | | | |
| TR | Thomson Reuters | | | | |

# Tables

**Table 3:** *Relative Mean Squared Error*
*GDP*

| $h$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| DI | 0.68 | 0.74 | 0.65 | 0.63 | 0.64 | 0.61 | 0.58 | 0.56 |
| DI2 | 0.77 | 0.80 | 0.68 | 0.64 | 0.63 | 0.57 | 0.50 | 0.46 |
| LDI | 0.69 | 0.71 | 0.61 | 0.53 | 0.61 | 0.63 | 0.55 | 0.51 |
| DIB | 0.73 | 0.80 | 0.70 | 0.68 | 0.66 | 0.66 | 0.63 | 0.64 |
| DI2B | 0.89 | 0.93 | 0.76 | 0.69 | 0.65 | 0.63 | 0.60 | 0.60 |
| DF$_a$ | 0.81 | 0.76 | 0.80 | 0.80 | 0.81 | 0.82 | 0.79 | 0.80 |
| DF$_b$ | 0.80 | 0.76 | 0.80 | 0.80 | 0.81 | 0.82 | 0.79 | 0.80 |

Each cell reports relative mean squared errors, which are computed relative to an AR model.

**Table 4:** *Relative Mean Squared Error*
*Labor Market*

| | $h$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| ur | DI | 0.99 | 1.11 | 1.04 | 1.18 | 1.33 | 1.36 | 1.35 | 1.40 |
| | DI2 | 1.20 | 1.57 | 1.22 | 1.34 | 1.46 | 1.45 | 1.40 | 1.35 |
| | LDI | 0.97 | 1.15 | 1.06 | 1.33 | 1.71 | 1.71 | 1.59 | 1.29 |
| | DIB | 1.32 | 1.43 | 1.21 | 1.40 | 1.48 | 1.37 | 1.33 | 1.33 |
| | DIB2 | 1.24 | 2.06 | 1.42 | 1.46 | 1.71 | 1.65 | 1.43 | 1.44 |
| | $DF_a$ | 1.44 | 1.74 | 1.67 | 1.60 | 1.62 | 1.50 | 1.40 | 1.34 |
| | $DF_b$ | 1.38 | 1.74 | 1.66 | 1.59 | 1.62 | 1.49 | 1.39 | 1.34 |
| L | DI | 0.85 | 0.74 | 0.68 | 0.68 | 0.81 | 0.95 | 0.96 | 0.95 |
| | DI2 | 0.86 | 0.84 | 0.60 | 0.67 | 0.82 | 0.87 | 0.83 | 0.71 |
| | LDI | 0.79 | 0.76 | 0.66 | 0.60 | 0.91 | 1.03 | 1.01 | 0.93 |
| | DIB | 0.91 | 0.79 | 0.71 | 0.77 | 0.88 | 0.95 | 0.93 | 0.83 |
| | DIB2 | 0.90 | 0.75 | 0.66 | 0.73 | 0.81 | 0.89 | 0.86 | 0.81 |
| | $DF_a$ | 0.85 | 0.71 | 0.65 | 0.69 | 0.75 | 0.82 | 0.78 | 0.70 |
| | $DF_b$ | 0.83 | 0.69 | 0.63 | 0.69 | 0.74 | 0.80 | 0.75 | 0.67 |
| L.aff | DI | 1.01 | 1.01 | 1.00 | 0.91 | 0.90 | 0.91 | 0.85 | 0.76 |
| | DI2 | 1.01 | 1.02 | 0.98 | 0.81 | 0.66 | 0.71 | 0.53 | 0.40 |
| | LDI | 1.03 | 1.02 | 1.04 | 0.89 | 1.00 | 1.00 | 0.89 | 0.77 |
| | DIB | 1.06 | 1.12 | 1.07 | 0.99 | 1.12 | 1.06 | 0.94 | 0.87 |
| | DIB2 | 1.04 | 1.09 | 1.05 | 1.04 | 0.96 | 0.88 | 0.62 | 0.45 |
| | $DF_a$ | 1.12 | 1.29 | 1.14 | 1.04 | 1.16 | 1.10 | 0.98 | 0.98 |
| | $DF_b$ | 1.07 | 1.20 | 1.06 | 1.02 | 1.11 | 1.02 | 0.94 | 0.93 |
| L.cons | DI | 0.91 | 0.82 | 0.83 | 0.89 | 0.95 | 1.03 | 1.06 | 1.10 |
| | DI2 | 0.76 | 0.76 | 0.77 | 0.90 | 1.01 | 1.11 | 1.12 | 0.98 |
| | LDI | 0.91 | 0.82 | 0.85 | 0.96 | 1.05 | 1.22 | 1.33 | 1.23 |
| | DIB | 0.92 | 1.00 | 0.97 | 1.01 | 1.07 | 1.15 | 1.04 | 1.13 |
| | DIB2 | 0.78 | 0.76 | 0.92 | 1.08 | 1.12 | 1.14 | 1.11 | 1.02 |
| | $DF_a$ | 0.91 | 0.90 | 0.98 | 1.08 | 1.04 | 1.04 | 1.06 | 1.08 |
| | $DF_b$ | 0.90 | 0.89 | 0.97 | 1.08 | 1.03 | 1.04 | 1.05 | 1.08 |
| L.ind | DI | 0.54 | 0.47 | 0.63 | 0.82 | 0.97 | 1.07 | 1.03 | 1.06 |
| | DI2 | 0.58 | 0.51 | 0.54 | 0.89 | 1.08 | 1.17 | 1.03 | 0.98 |
| | LDI | 0.56 | 0.52 | 0.64 | 0.75 | 1.06 | 1.21 | 1.20 | 1.10 |
| | DIB | 0.68 | 0.59 | 0.66 | 0.84 | 1.01 | 1.08 | 1.03 | 0.97 |
| | DIB2 | 0.56 | 0.47 | 0.57 | 0.84 | 0.99 | 1.06 | 0.97 | 0.91 |
| | $DF_a$ | 0.68 | 0.63 | 0.75 | 0.87 | 1.03 | 1.17 | 1.09 | 1.06 |
| | $DF_b$ | 0.67 | 0.63 | 0.75 | 0.87 | 1.03 | 1.16 | 1.07 | 1.05 |
| L.serv | DI | 0.88 | 0.84 | 0.74 | 0.61 | 0.57 | 0.68 | 0.65 | 0.68 |
| | DI2 | 0.95 | 0.97 | 0.68 | 0.62 | 0.59 | 0.64 | 0.59 | 0.60 |
| | LDI | 0.87 | 0.90 | 0.73 | 0.63 | 0.70 | 0.68 | 0.56 | 0.63 |
| | DIB | 1.09 | 1.06 | 0.71 | 0.59 | 0.61 | 0.65 | 0.53 | 0.52 |
| | DIB2 | 1.10 | 1.05 | 0.72 | 0.61 | 0.56 | 0.63 | 0.65 | 0.61 |
| | $DF_a$ | 0.88 | 0.79 | 0.62 | 0.59 | 0.51 | 0.58 | 0.53 | 0.52 |
| | $DF_b$ | 0.86 | 0.78 | 0.61 | 0.59 | 0.51 | 0.57 | 0.53 | 0.51 |

Each cell reports relative mean squared errors, which are computed relative to an AR model. ur = Unemployment Rate; L = Employment; L.aff = Employment in agriculture and forestry; L.cons = Employment in Constructions; L.ind = Employment in Industry; L.serv = Employment in services.

**Table 5:** *Relative Mean Squared Error*
*Gross Value Added*

| | $h$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| GVA.clcr | DI | 0.81 | 0.82 | 0.77 | 0.74 | 0.67 | 0.61 | 0.55 | 0.54 |
| | DI2 | 0.81 | 0.80 | 0.77 | 0.71 | 0.63 | 0.52 | 0.43 | 0.40 |
| | LDI | 0.89 | 0.82 | 0.77 | 0.62 | 0.54 | 0.57 | 0.55 | 0.46 |
| | DIB | 0.97 | 0.98 | 0.86 | 0.83 | 0.73 | 0.73 | 0.63 | 0.64 |
| | DIB2 | 0.95 | 0.90 | 0.85 | 0.82 | 0.73 | 0.68 | 0.57 | 0.58 |
| | $DF_a$ | 1.00 | 0.97 | 0.93 | 0.88 | 0.82 | 0.79 | 0.73 | 0.75 |
| | $DF_b$ | 0.99 | 0.96 | 0.93 | 0.88 | 0.82 | 0.79 | 0.73 | 0.75 |
| GVA.cons | DI | 0.96 | 0.98 | 0.85 | 0.93 | 1.12 | 1.34 | 1.49 | 1.58 |
| | DI2 | 1.03 | 1.25 | 1.02 | 1.10 | 1.31 | 1.50 | 1.63 | 1.46 |
| | LDI | 0.96 | 1.04 | 0.82 | 1.15 | 1.59 | 1.81 | 1.90 | 1.34 |
| | DIB | 0.97 | 0.90 | 0.90 | 1.06 | 1.13 | 1.30 | 1.36 | 1.37 |
| | DIB2 | 1.16 | 1.45 | 0.99 | 1.16 | 1.27 | 1.44 | 1.38 | 1.46 |
| | $DF_a$ | 0.92 | 0.88 | 0.89 | 1.04 | 1.13 | 1.24 | 1.28 | 1.29 |
| | $DF_b$ | 0.92 | 0.88 | 0.87 | 1.02 | 1.12 | 1.23 | 1.27 | 1.28 |
| GVA.indLc | DI | 0.77 | 0.79 | 0.80 | 0.72 | 0.68 | 0.66 | 0.65 | 0.63 |
| | DI2 | 0.80 | 0.92 | 0.81 | 0.74 | 0.70 | 0.66 | 0.63 | 0.58 |
| | LDI | 0.71 | 0.75 | 0.68 | 0.57 | 0.57 | 0.61 | 0.59 | 0.56 |
| | DIB | 0.86 | 0.85 | 0.84 | 0.77 | 0.75 | 0.72 | 0.69 | 0.71 |
| | DIB2 | 0.82 | 0.93 | 0.86 | 0.76 | 0.70 | 0.66 | 0.64 | 0.63 |
| | $DF_a$ | 0.92 | 0.85 | 0.88 | 0.85 | 0.83 | 0.84 | 0.81 | 0.82 |
| | $DF_b$ | 0.87 | 0.84 | 0.88 | 0.85 | 0.83 | 0.84 | 0.81 | 0.81 |
| GVA.serv | DI | 0.60 | 0.64 | 0.52 | 0.55 | 0.52 | 0.47 | 0.41 | 0.40 |
| | DI2 | 0.50 | 0.64 | 0.58 | 0.62 | 0.56 | 0.49 | 0.42 | 0.41 |
| | LDI | 0.59 | 0.56 | 0.50 | 0.49 | 0.56 | 0.53 | 0.39 | 0.43 |
| | DIB | 0.58 | 0.66 | 0.55 | 0.63 | 0.59 | 0.58 | 0.56 | 0.59 |
| | DIB2 | 0.51 | 0.60 | 0.67 | 0.66 | 0.62 | 0.59 | 0.56 | 0.54 |
| | $DF_a$ | 0.55 | 0.61 | 0.65 | 0.77 | 0.77 | 0.78 | 0.73 | 0.76 |
| | $DF_b$ | 0.55 | 0.60 | 0.64 | 0.76 | 0.76 | 0.77 | 0.73 | 0.76 |

Each cell reports relative mean squared errors, which are computed relative to an AR model. GVA.clcr = Gross Value Added in com., lodging, catering& rep; GVA.cons = Gross Value Added in Construction; GVA.indLc = Gross Value Added in Industry less Construction; GVA.serv = Gross Value Added in Services.

**Table 6:** *Relative Mean Squared Error*
*Consumption*

| | $h$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| C. | DI | 0.72 | 0.91 | 0.52 | 0.36 | 0.23 | 0.22 | 0.23 | 0.28 |
| | DI2 | 0.87 | 0.97 | 0.51 | 0.50 | 0.37 | 0.36 | 0.30 | 0.28 |
| | LDI | 0.74 | 0.74 | 0.68 | 0.45 | 0.36 | 0.30 | 0.22 | 0.30 |
| | DIB | 0.69 | 0.70 | 0.50 | 0.45 | 0.42 | 0.43 | 0.44 | 0.48 |
| | DIB2 | 0.69 | 0.70 | 0.48 | 0.52 | 0.56 | 0.60 | 0.62 | 0.67 |
| | DF$_a$ | 0.77 | 0.80 | 0.72 | 0.69 | 0.66 | 0.67 | 0.67 | 0.72 |
| | DF$_b$ | 0.76 | 0.79 | 0.71 | 0.68 | 0.65 | 0.66 | 0.66 | 0.71 |
| C.D | DI | 1.03 | 1.23 | 1.01 | 0.70 | 0.64 | 0.65 | 0.63 | 0.75 |
| | DI2 | 1.12 | 1.24 | 1.04 | 0.63 | 0.57 | 0.54 | 0.53 | 0.69 |
| | LDI | 1.19 | 1.14 | 0.95 | 0.50 | 0.60 | 0.67 | 0.57 | 0.71 |
| | DIB | 1.05 | 1.15 | 0.76 | 0.64 | 0.64 | 0.68 | 0.72 | 0.83 |
| | DIB2 | 1.23 | 1.35 | 0.75 | 0.62 | 0.66 | 0.75 | 0.83 | 1.02 |
| | DF$_a$ | 1.09 | 1.11 | 0.83 | 0.74 | 0.74 | 0.77 | 0.78 | 0.84 |
| | DF$_b$ | 1.08 | 1.10 | 0.83 | 0.73 | 0.74 | 0.77 | 0.77 | 0.84 |
| C.nonD | DI | 0.73 | 0.66 | 0.75 | 0.73 | 0.66 | 0.65 | 0.67 | 0.72 |
| | DI2 | 0.76 | 0.69 | 0.76 | 0.69 | 0.69 | 0.71 | 0.72 | 0.71 |
| | LDI | 0.77 | 0.67 | 0.78 | 0.85 | 0.76 | 0.79 | 0.73 | 0.81 |
| | DIB | 0.80 | 0.71 | 0.79 | 0.78 | 0.78 | 0.77 | 0.83 | 0.83 |
| | DIB2 | 0.84 | 0.69 | 0.70 | 0.74 | 0.79 | 0.79 | 0.89 | 0.87 |
| | DF$_a$ | 0.79 | 0.65 | 0.75 | 0.86 | 0.85 | 0.85 | 0.84 | 0.81 |
| | DF$_b$ | 0.80 | 0.64 | 0.75 | 0.85 | 0.85 | 0.85 | 0.83 | 0.81 |
| C.semiD | DI | 0.53 | 0.54 | 0.39 | 0.43 | 0.40 | 0.39 | 0.36 | 0.35 |
| | DI2 | 0.48 | 0.59 | 0.38 | 0.43 | 0.43 | 0.44 | 0.41 | 0.40 |
| | LDI | 0.61 | 0.78 | 0.44 | 0.36 | 0.34 | 0.44 | 0.38 | 0.35 |
| | DIB | 0.82 | 0.83 | 0.50 | 0.58 | 0.54 | 0.59 | 0.49 | 0.56 |
| | DIB2 | 0.80 | 0.86 | 0.54 | 0.56 | 0.56 | 0.57 | 0.51 | 0.59 |
| | DF$_a$ | 0.93 | 0.91 | 0.74 | 0.73 | 0.70 | 0.68 | 0.63 | 0.69 |
| | DF$_b$ | 0.87 | 0.88 | 0.74 | 0.73 | 0.70 | 0.68 | 0.63 | 0.68 |
| C.serv | DI | 0.79 | 0.78 | 0.60 | 0.45 | 0.39 | 0.30 | 0.27 | 0.27 |
| | DI2 | 0.77 | 0.59 | 0.54 | 0.48 | 0.46 | 0.33 | 0.31 | 0.29 |
| | LDI | 0.83 | 0.81 | 0.61 | 0.48 | 0.39 | 0.46 | 0.34 | 0.34 |
| | DIB | 0.81 | 0.74 | 0.61 | 0.50 | 0.45 | 0.41 | 0.45 | 0.49 |
| | DIB2 | 0.83 | 0.74 | 0.58 | 0.50 | 0.49 | 0.41 | 0.42 | 0.44 |
| | DF$_a$ | 0.90 | 0.82 | 0.78 | 0.74 | 0.74 | 0.70 | 0.64 | 0.65 |
| | DF$_b$ | 0.88 | 0.79 | 0.76 | 0.71 | 0.71 | 0.67 | 0.63 | 0.63 |

Each cell reports relative mean squared errors, which are computed relative to an AR model. C. = Consumption; C.D = Consumption of Durable Goods; C.nonD = Consumption of Non Durable Goods; C.semiD = Consumption of Semi-Durable Goods; C.serv = Consumption of services.

**Table 7:** *Relative Mean Squared Error*
*Investments*

| | $h$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| GFCF | DI | 0.74 | 0.75 | 0.51 | 0.57 | 0.67 | 0.73 | 0.74 | 0.80 |
| | DI2 | 0.92 | 1.06 | 0.74 | 0.66 | 0.76 | 0.76 | 0.74 | 0.78 |
| | LDI | 0.81 | 0.74 | 0.50 | 0.51 | 0.70 | 0.78 | 0.76 | 0.60 |
| | DIB | 0.79 | 0.73 | 0.63 | 0.67 | 0.73 | 0.74 | 0.76 | 0.82 |
| | DIB2 | 0.88 | 0.90 | 0.77 | 0.73 | 0.78 | 0.80 | 0.79 | 0.84 |
| | $DF_a$ | 0.80 | 0.71 | 0.69 | 0.74 | 0.83 | 0.87 | 0.88 | 0.93 |
| | $DF_b$ | 0.80 | 0.71 | 0.69 | 0.74 | 0.82 | 0.87 | 0.88 | 0.93 |
| GFCFcons | DI | 0.90 | 0.81 | 0.72 | 0.81 | 1.02 | 1.20 | 1.28 | 1.21 |
| | DI2 | 0.98 | 0.98 | 0.83 | 0.91 | 1.08 | 1.25 | 1.38 | 1.39 |
| | LDI | 0.88 | 0.88 | 0.72 | 1.00 | 1.31 | 1.42 | 1.51 | 1.06 |
| | DIB | 0.92 | 0.82 | 0.79 | 0.94 | 1.05 | 1.09 | 1.29 | 1.32 |
| | DIB2 | 0.94 | 0.89 | 0.85 | 0.92 | 1.15 | 1.26 | 1.48 | 1.53 |
| | $DF_a$ | 0.91 | 0.84 | 0.81 | 0.92 | 1.02 | 1.10 | 1.13 | 1.18 |
| | $DF_b$ | 0.90 | 0.83 | 0.80 | 0.91 | 1.01 | 1.10 | 1.13 | 1.17 |
| GFCFmach | DI | 0.73 | 0.78 | 0.55 | 0.55 | 0.57 | 0.61 | 0.62 | 0.67 |
| | DI2 | 0.76 | 0.94 | 0.71 | 0.60 | 0.62 | 0.60 | 0.59 | 0.60 |
| | LDI | 0.75 | 0.75 | 0.46 | 0.38 | 0.49 | 0.57 | 0.57 | 0.50 |
| | DIB | 0.77 | 0.76 | 0.61 | 0.62 | 0.64 | 0.62 | 0.67 | 0.73 |
| | DIB2 | 0.89 | 0.89 | 0.68 | 0.61 | 0.63 | 0.64 | 0.66 | 0.72 |
| | $DF_a$ | 0.73 | 0.70 | 0.67 | 0.68 | 0.71 | 0.73 | 0.76 | 0.83 |
| | $DF_b$ | 0.74 | 0.70 | 0.66 | 0.68 | 0.71 | 0.73 | 0.76 | 0.83 |
| GFCFtrans | DI | 0.66 | 0.60 | 0.34 | 0.49 | 0.49 | 0.46 | 0.47 | 0.54 |
| | DI2 | 0.77 | 1.00 | 0.55 | 0.65 | 0.63 | 0.57 | 0.53 | 0.56 |
| | LDI | 0.67 | 0.67 | 0.47 | 0.53 | 0.54 | 0.57 | 0.59 | 0.53 |
| | DIB | 0.73 | 0.68 | 0.50 | 0.66 | 0.64 | 0.60 | 0.59 | 0.57 |
| | DIB2 | 0.79 | 0.81 | 0.64 | 0.72 | 0.70 | 0.72 | 0.68 | 0.75 |
| | $DF_a$ | 0.77 | 0.76 | 0.68 | 0.81 | 0.87 | 0.91 | 0.87 | 0.89 |
| | $DF_b$ | 0.76 | 0.76 | 0.68 | 0.81 | 0.87 | 0.91 | 0.86 | 0.89 |

Each cell reports relative mean squared errors, which are computed relative to an AR model. GFCF = Gross Fixed Capital Formation; GFCFcons = Gross Fixed Capital Formation in Construction; GFCFmach = Gross Fixed Capital Formation in Machinery and Equipment; GFCFtrans = Gross Fixed Capital Formation in Transport.

**Table 8:** *Number of Specifications with* $RMSE > 1$
*GDP*

| $h$ | DI | DI2 | LDI | DIB | DI2B | $DF_a$ | $DF_b$ |
|---|---|---|---|---|---|---|---|
| 1 | 4 | 67 | 14 | 0 | 3 | 0 | 0 |
| 2 | 6 | 67 | 8 | 0 | 3 | 0 | 0 |
| 3 | 2 | 2 | 7 | 0 | 0 | 0 | 0 |
| 4 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Each cell reports the number of specifications that does worse than the benchmark AR model. The total number of estimated specifications within each class of model are: DI = 80, DI2 = 80, LDI = 80, DIB = 6, DI2B= 6, $DF_a = 3$, $DF_b = 12$.

**Table 9:** *GDP Growth Forecasts*

| Quarter | AR | DI | DI2 | LDI | DIB | DI2B | DF$_a$ | DF$_b$ |
|---|---|---|---|---|---|---|---|---|
| 2009Q1 | -0.0125 | **-0.6368** | -0.0674 | -0.8648 | -0.3724 | -0.2250 | -0.3668 | -0.3745 |
| 2009Q2 | 0.0709 | -0.4166 | -0.0341 | **-0.5515** | -0.1118 | 0.1021 | -0.1756 | -0.1829 |
| 2009Q3 | 0.1775 | -0.3156 | -0.2440 | **-0.3821** | -0.1513 | -0.0378 | -0.0056 | -0.0067 |
| 2009Q4 | 0.2297 | -0.2393 | -0.2183 | **-0.3848** | -0.2316 | -0.0352 | 0.0303 | 0.0274 |
| 2010Q1 | 0.3051 | -0.2127 | -0.1504 | **-0.2482** | -0.1431 | -0.0068 | 0.0683 | 0.0692 |
| 2010Q2 | 0.3369 | -0.1982 | **-0.1275** | -0.3574 | -0.0671 | -0.0031 | 0.1284 | 0.1288 |
| 2010Q3 | 0.3385 | -0.1726 | **-0.1417** | -0.2482 | -0.0434 | -0.0196 | 0.1398 | 0.1387 |
| 2010Q4 | 0.3351 | -0.1352 | **-0.1092** | -0.1842 | -0.0031 | 0.0303 | 0.1748 | 0.1739 |

For each of the eight methods, we select the specification that produces the minimum MSE. Bold entries are the *best* forecast for each forecasting horizons.

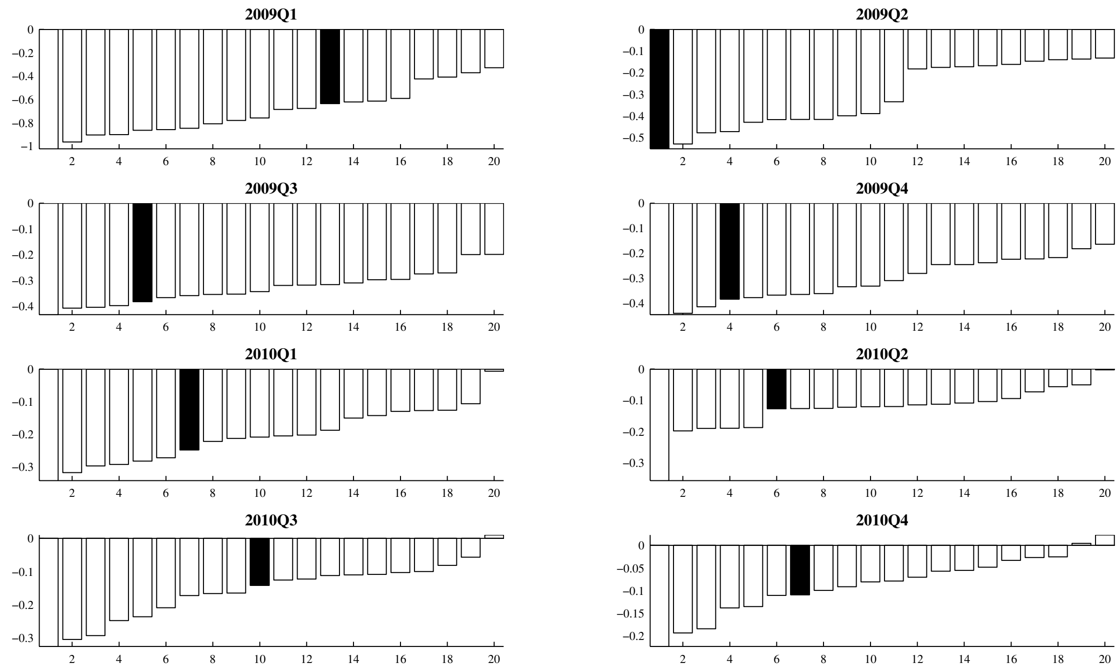
**Table 10:** *Variability of the Forecasts*

| | $t_0$ | h | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|---|
| Standard Deviation | 2006Q4 | 20*best* | 0.14 | 0.04 | 0.10 | 0.07 | 0.09 | 0.08 | 0.06 | 0.12 |
| | | 50*best* | 0.17 | 0.06 | 0.11 | 0.07 | 0.09 | 0.09 | 0.07 | 0.11 |
| | | *all* | 0.18 | 0.09 | 0.11 | 0.12 | 0.12 | 0.11 | 0.10 | 0.10 |
| | 2008Q4 | 20*best* | 0.20 | 0.15 | 0.06 | 0.09 | 0.08 | 0.07 | 0.09 | 0.06 |
| | | 50*best* | 0.20 | 0.15 | 0.08 | 0.10 | 0.09 | 0.12 | 0.10 | 0.08 |
| | | *all* | 0.28 | 0.18 | 0.16 | 0.18 | 0.17 | 0.18 | 0.17 | 0.15 |
| Range | 2006Q4 | 20*best* | 0.37 | 0.16 | 0.32 | 0.27 | 0.30 | 0.31 | 0.20 | 0.36 |
| | | 50*best* | 0.62 | 0.34 | 0.43 | 0.27 | 0.41 | 0.34 | 0.27 | 0.38 |
| | | *all* | 0.23 | 0.13 | 0.14 | 0.17 | 0.13 | 0.14 | 0.14 | 0.09 |
| | 2008Q4 | 20*best* | 0.69 | 0.42 | 0.23 | 0.28 | 0.34 | 0.35 | 0.34 | 0.25 |
| | | 50*best* | 0.96 | 0.53 | 0.31 | 0.41 | 0.36 | 0.46 | 0.41 | 0.38 |
| | | *all* | 0.42 | 0.30 | 0.27 | 0.28 | 0.29 | 0.27 | 0.25 | 0.24 |

The rows 20*best* show standard deviation and range of the 20 models with minimum Mean Squared Error. The rows 50*best* show standard deviation and range of the 50 models with minimum MSE. Rows *all* show standard deviation and range of all the models that have an MSE smaller than the benchmark AR. Define $\widehat{Y}^{m}_{t+h}$ the h step ahead forecast obtained with the $m$-th model, than for 20*best* and 50*best* "range" means $\widehat{Y}^{max}_{t+h} - \widehat{Y}^{min}_{t+h}$, while for *all* is the interquartile range.

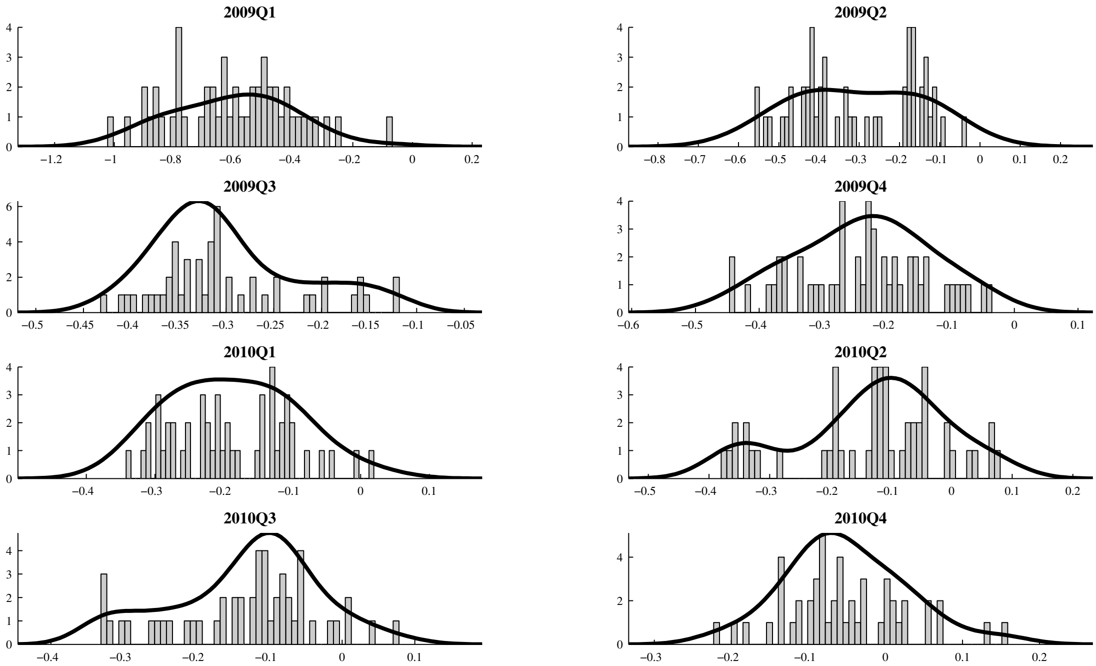
# Graphs

**Figure 1:** *20 Best Forecast*




Forecast are plotted from the lowest to the highest. They are not ranked in terms of MSE. The Black Bar is the Best Forecast

**Figure 2:** *Distribution of the 50 Best Forecasts*




These plots show Histograms of the forecasts produced with the 50 *best* models together with the kernel approximation (black line) of the distribution

**Figure 3:** *Box Plot*

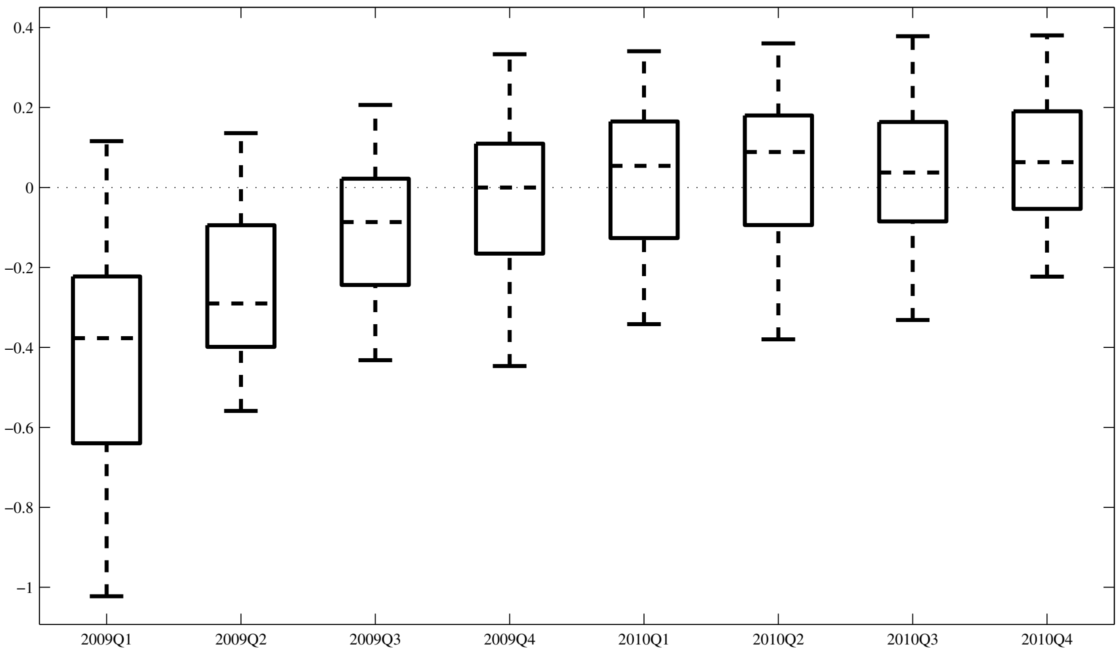
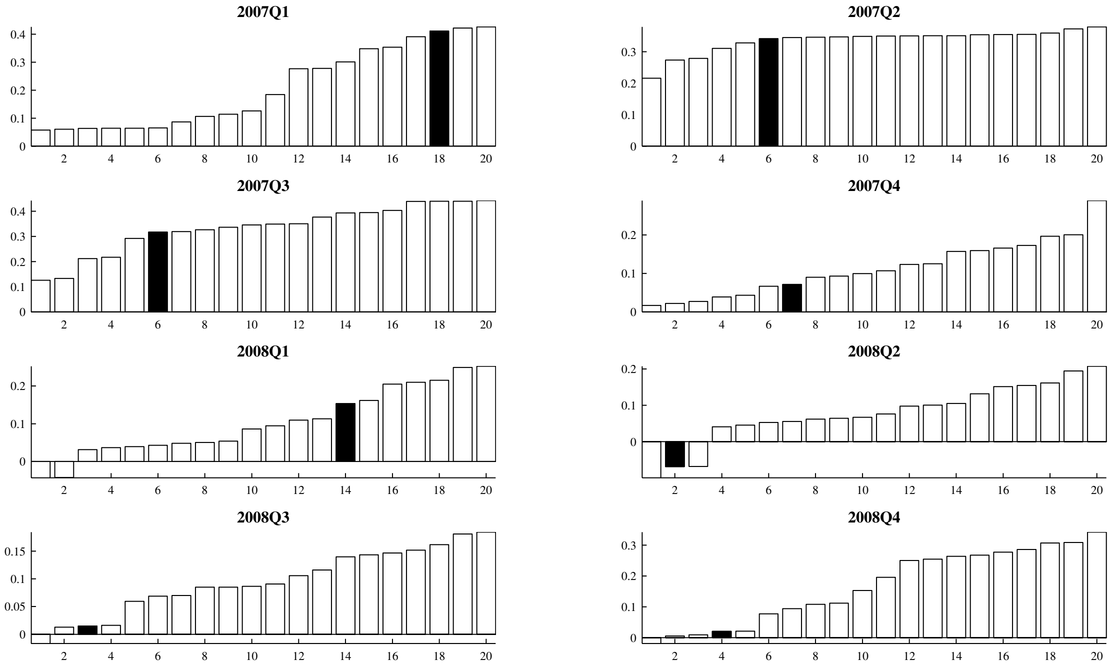
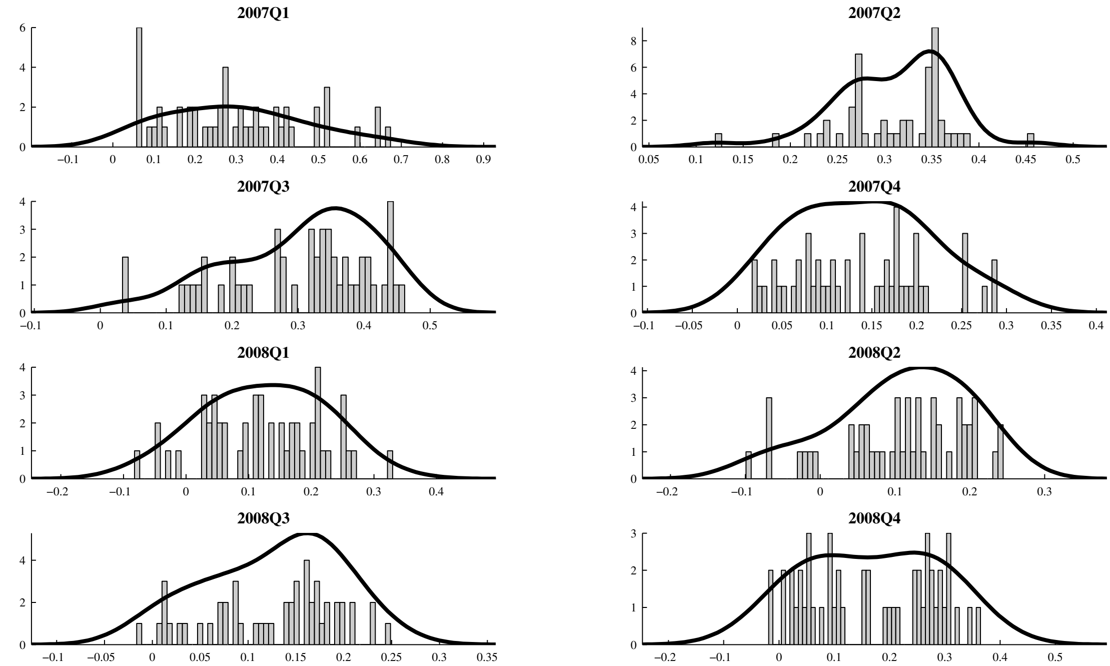


**Figure 4:** *20 Best Forecast*



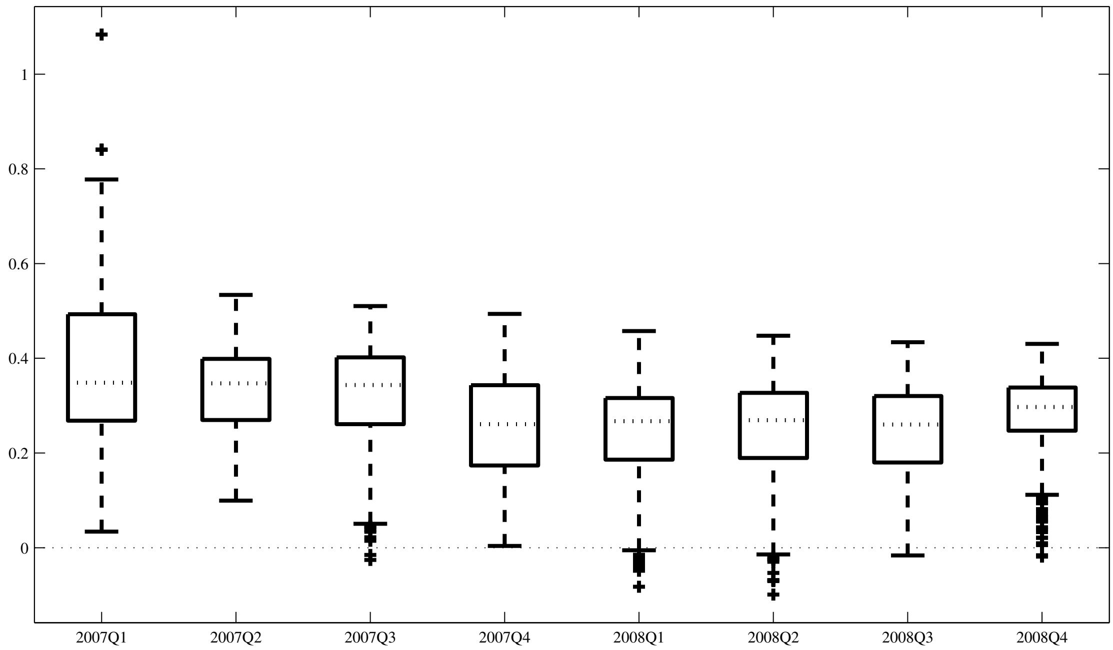

Forecast are plotted from the lowest to the highest. They are not ranked in terms of MSE. The Black Bar is the Best Forecast

**Figure 5:** *Distribution of the 50 Best Forecasts*




These plots show Histograms of the forecasts produced with the 50 *best* models together with the kernel approximation (black line) of the distribution

**Figure 6:** *Box Plot*



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