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MEASURING GDP FORECAST UNCERTAINTY USING QUANTILE REGRESSIONS

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ABSTRACT/RÉSUMÉ

Measuring GDP Forecast Uncertainty Using Quantile Regressions

Uncertainty is inherent to forecasting and assessing the uncertainty surrounding a point forecast is as important as the forecast itself. Following Cornec (2010), a method to assess the uncertainty around the indicator models used at OECD to forecast GDP growth of the six largest member countries is developed, using quantile regressions to construct a probability distribution of future GDP, as opposed to mean point forecasts. This approach allows uncertainty to be assessed conditionally on the current state of the economy and is totally model based and judgement free. The quality of the computed distributions is tested against other approaches to measuring forecast uncertainty and a set of uncertainty indicators is constructed in order to help exploiting the most helpful information.

JEL classification codes: C31; C53

Keywords: Forecasting; quantile regression; uncertainty; density forecasts; GDP

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Mesure de l'incertitude sur les prévisions du PIB à l'aide de régressions quantiles

L'incertitude est inhérente à la prévision, et évaluer l'incertitude autour d'une prévision est aussi important que la prévision elle-même. A la suite de Cornec (2010), une méthode pour évaluer l'incertitude autour des modèles d'indicateurs utilisés à l'OCDE pour prévoir la croissance des six plus grandes économies membres est développée, utilisant des régressions quantiles pour construire une distribution de probabilité du PIB future, plutôt qu'une prévision ponctuelle. Cette approche permet d'évaluer l'incertitude conditionnellement à l'état actuel de l'économie et est fondée sur le modèle, sans jugement. La qualité des distributions calculées est testée contre des approches alternatives de la mesure de l'incertitude, et un ensemble d'indicateurs d'incertitudes est construit pour aider à exploiter les informations les plus pertinentes.

Codes JEL: C31 ; C53

Mots clés : Prévision ; régression quantile ; incertitude ; prévision de densité ; PIB

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MEASURING GDP FORECAST UNCERTAINTY USING QUANTILE REGRESSIONS

by

Thomas Laurent[1] and Tomasz Koźluk[2,3]

Introduction

1. Uncertainty is inherent to forecasting and assessing the uncertainty surrounding a point forecast is as important as the forecast itself. There are at least two dimensions to the uncertainty: the level of the uncertainty, or the likelihood of large errors, and the balance of risks, or assessing whether there are larger risks to the upside or the downside. Several sources of uncertainty can be identified. First, uncertainty results from the forecasting model itself: misspecification, imprecision of the estimated parameters, data errors and revisions. Second, "real-time" forecasting uncertainty depends on economic conditions and their impact on the size of possible forecasting errors at a given point in time.

2. Identifying the individual sources of uncertainty is difficult, and most commonly the total expected forecast uncertainty is reported. Typically this is presented as either standard deviations (usually with an underlying assumption of normality), or fan charts (densities). Calculation methods differ across the major forecasting institutions. Most common uncertainty measures are explicitly based on past forecasting errors and include those linked to mean-absolute errors (MAE), or root mean squared forecasting errors (RMSFE). They can be derived from a static specification, but are more commonly based on recursive model estimates and are usually simple to calculate and interpret. Such measures are used by a large number of forecasters -- for example, OECD in the Interim Outlook, FOMC and FEDs, Bank of England, Bank of Canada, Sveriges Riksbank (RMSFE's) and ECB/ESCB or Bundesbank (MAE's). The main limitations of the simplest approach are the normality assumption, proneness to large outliers (the ECB and OECD exclude some particularly large outliers from the calculations) and lack of relationship to the most recent developments.

3. The goal of this paper is to use quantile regression to propose a new measure of uncertainty that addresses these shortcomings and therefore varies over time without inertia, is conditional on the state of the economy, and gives an idea of the balance of risks.[4]

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4. An alternative approach has been implemented using Monte Carlo simulations to approximate the empirical distribution of the monthly indicators forecasts and compute, through bridge equations, a probability distribution of the quarterly GDP growth forecast (see Rusticelli, 2012).

4. The first section reviews existing practices to assess the uncertainty related to current economic conditions. The second section describes the quantile regression (QR) method and its application to GDP forecasts. The third section presents estimates of the distribution forecast obtained through this method, and accuracy tests. Potential representations of such estimates are then discussed. Finally, Annex I contains an overview of several potential improvements of the model.

Assessing uncertainty conditionally to the economic environment

5. Measures of uncertainty can be derived from surveys of professional forecasters, including disagreement (distribution of point forecasts) and uncertainty (density forecasts, where the probability of the forecast variable to fall into various bins is reported) among professional forecasters (Confitti, 2009; Bundesbank, 2010). These surveys may well reflect real-time market uncertainty about the outlook, but their wider use is inhibited by a number of serious data limitations. Firstly, availability - point forecasts can be gathered relatively easily for the main OECD countries (on inflation, GDP, unemployment), though the degree of comparability (*e.g.* point in time when projection was made, coverage of variables or forecast horizon) varies from survey to survey. The most popular surveys, which guarantee a high degree of comparability are those conducted by the Fed, ECB and HM Treasury. Still, as often mentioned (D'Amico and Orphanides, 2006), dispersion of point forecasts is only a weak proxy of the forecasters uncertainty;[5] hence distributions around a central forecast may appear more attractive. In turn, these are also harder to come by, and potentially of poorer quality. Quality may also be general issue -- the black-box approach assumes that forecasters use all available information, at the same point in time, use high-quality tools and are independent, which may not always be the case.

6. A number of institutions construct indicators of forecast uncertainty that are related to the current state of the economy by skewing and rescaling measures of past-forecast performance using assessment of risk and simulations. The BoE produces asymmetric fan charts for its inflation and GDP forecasts, by skewing and rescaling past forecast errors based on the MPC members' judgment of risks. In a somewhat different manner the Bank of Japan aggregates distribution forecasts of its board members. The IMF global growth forecasts for the World Economic Outlook are not based on an explicit model (being an aggregate of individual country forecasts); hence asymmetric fan charts are based on an automated assessment of risks related to four global risk factors: financial conditions (term spread and stock market returns), oil prices and global interest rates (Elekdag and Kannan, 2009). The volatility and market expectations on developments of these risk factors are used to rescale and skew the past forecast errors to arrive at a probability distribution. Alternatively, the Norges Bank, the Bank of Canada (for longer horizons) and on some occasions the CPB (Lansen and Krankendonk, 2008), use model-based stochastic simulations, where the confidence intervals are derived from shocking the underlying variables and model coefficients. Among reasons for such an approach, can be structural changes in the economy or exceptional events which would have affected past forecast errors.

7. Cornec (2010) proposes quantile regressions as a way of estimating the distribution of forecasts and using the dispersion of the estimated quantiles for calculating an uncertainty index. As discussed in more detail below, quantile regression estimates have the advantage of estimating the distribution directly and conditionally (*i.e.* based on the state of the economy). Hence, by construction, the information on economic uncertainty present in up-to-date short-term indicators affects the expected forecast uncertainty. They impose no normality assumption, allowing, for example, for fat-tailed distributions, which is potentially interesting when attempting to forecast extreme events (*e.g.* a large crisis). The approach is relatively flexible as it allows for the inclusion of additional variables that may be irrelevant for the central

5. For instance, if forecasters individually display large uncertainty about the exact value of their forecasts, but the actual forecasts centred on a similar value, disagreement will be low, but aggregated uncertainty high.

forecast but affect the more extreme quantiles. A variation of this method has been adopted by INSEE to construct a fan chart GDP forecast in the "Note de Conjuncture" (15 December 2011).

8. The approach here follows Cornec (2010) and applies it to the OECD indicator model framework, which is used to forecast aggregate GDP growth over the next two quarters using a range of monthly indicators (as described in Pain and Sédillot 2003). The approach is subsequently extended in several dimensions.

Using quantile regression in the OECD indicator model framework

Overview of the OECD indicator model

9. The indicator models used at OECD[6] are based on the correlation between the quarterly GDP and monthly indicators, which are released earlier and more frequently than the quarterly GDP estimates. These indicators are both hard (industrial production, household consumption, *etc.*) and soft indicators (business and household surveys, *etc.*). For every country, there are three models: using only hard, only soft and a mix of both hard and soft data. There is a two-stage framework. First, for the indicators, the missing months over the forecast horizon are projected using autoregressive models. Then the GDP is forecasted using the quaterlised indicators. The final "consensus" forecast is the unweighted mean of the three models. Even if some uncertainty may come from the forecasting of unknown months of indicators, the focus of this paper is on the uncertainty surrounding the final forecast.

Overview of the quantile regression method

10. This section presents a very simple example to illustrate the interest of quantile regression. Consider the relation between quarterly GDP growth and the growth of the (quarterlised) industrial production index for Germany. Plotting the two variables on a two way graph (see Figure 1) immediately reveals a correlation between the two variables, which can be exploited to forecast GDP based on IPI, which is available earlier. The standard way to do it is to use linear regression, *i.e.* fitting a line that is closest "on average" to the observations cloud. This line minimises the sum of the squared distances between observations and the line, or, put differently, its parameters satisfy:

$$(\hat{\alpha}, \hat{\beta}) = arg\ min_{(\alpha,\beta)\in R^2} \sum (GDP - \alpha - \beta * IPI)^2$$

This is the Ordinary Least Squares methodology. While this line (the "mean" line in Figure 1) is the best description of the average relationship between the two variables, it can be seen that there are some outliers, *i.e.* quarters where GDP is unusually high or low, given the level of the IPI. To capture the behaviour of those outliers, the basic idea is to replace our "mean" line with one which divides the observations cloud between a share θ below the line and a share 1- θ above, while minimising the absolute distance between the observation cloud and the line. These lines are called quantile curves. Figure 1 shows the lines corresponding to the first and the third quartiles - θ is equal to 0.25 and 0.75 respectively. That is for the first quartile, one fourth of observations are below the line and for the third quartile, and three fourths are below it. In this example, they offer a better fit for the observations situated below and above the "mean" line, respectively. When GDP growth is below the mean, industrial production appears to be less correlated with GDP growth than when it is above.

6. These models are used for the interim press conference every six months (March and September) and more frequently for internal purposes. The OECD's *Economic Outlook* projections are not based on these models.

11. Koenker and Basset (1978) proposed a method (referred after as quantile regression) that provides a best fit estimate of the quantiles, the metric being based on the absolute regression errors. In our two variables example, the parameters of the θ-quantile line verify:

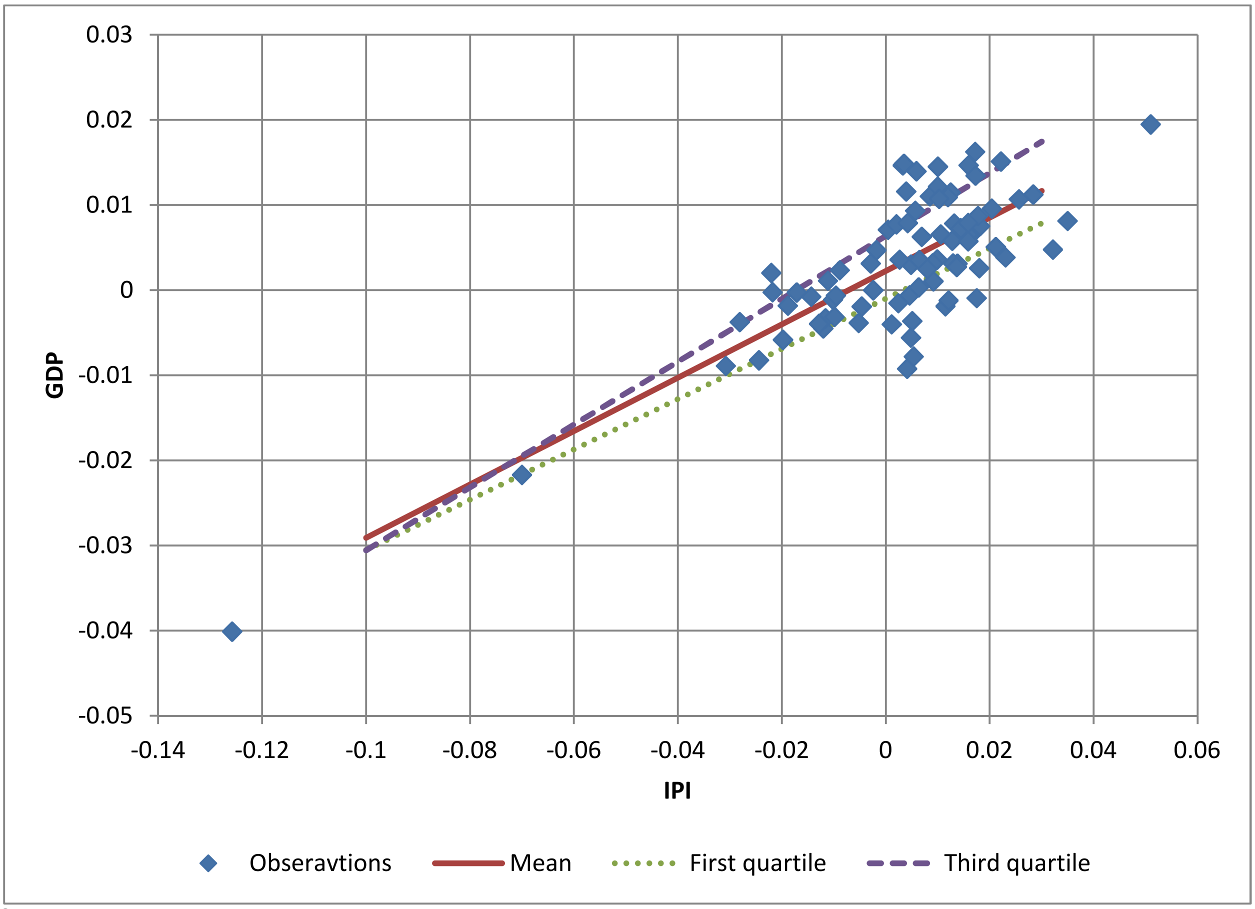
$$(\tilde{\alpha}_\theta, \tilde{\beta}_\theta) \in Arg\ min_{(\alpha,\beta)\in R^2} \sum \rho_\theta(GDP - \alpha - \beta * IPI)$$

where ρ_θ is the pinball loss function (see Biau and Patra, 2009):

$$\rho_\theta(y) = \begin{cases} (1-\theta)|y|, & y < 0 \\ \theta|y|, & y \geq 0 \end{cases}$$

12. Therefore, the median or central quantile (θ =0.5) is effectively the least mean absolute error estimator. This methodology can be easily extended to more variables, and any quantile θ. Different relationships for observations that are unusually high or low with respect to the set of explanatory variables can be estimated. Finally, the estimation of the 99 percentile lines in addition to the standard "mean" line makes possible the production of not only a mean forecast, but a distribution of forecasts around this mean. Actually, considering that each of the 99 percentile lines is a different forecast drawn from the distribution forecast, any summary statistics of this distribution can be computed empirically based on this set of 99 different forecasts.

Figure 1. Relation between GDP and IPI for Germany



Sample: 1991-2011

Source: OECD calculations.

Estimating quantiles for the indicators model "consensus" forecast

13. This section presents how the QR methodology is used to assess the uncertainty of the indicator model forecast. Taking as a starting point the OECD's indicator model setup (Pain and Sedillot, 2003) for selected countries, the following methodology has been adopted:

- At every estimation point, for the three models (soft, hard and mixed) and the different sets of monthly information (from 0 to 3 months of within quarter information), the 99 percentiles are estimated using the same set of information (variables and lags) that is used when estimating the standard indicator model point forecast, and the Koenker and Basset (1978) methodology.[7]

- Due to the schedule of information releases, the availability of within-quarter information differs upon indicator and point in time (hard information tends to be available later than soft), the main "consensus" prediction used here is constructed as an average of three models for each country: two-month soft models (2s) and one month hard and mixed models (1h), mimicking the information set most likely available upon the releases of OECD's Interim Outlook. This is labelled as the Interim Consensus (IC or2s1h). On several occasions, other forecasts are also constructed and labelled isjh depending on the number of months of soft and hard indicators know within the quarter (respectively i and j).

- The consensus quantile prediction is obtained by ordering[8] the 297 values of the percentiles obtained from the three models (with individual within-quarter data availability) and keeping every third quantile value (the 2th, 5th, 8th…), thus merging quantile intervals 3 by 3. This enables a good approximation of the whole distribution to be calculated, with 99 percentiles. Even if most of the results presented below use only the 9 deciles, the computation of the whole set of percentiles permits a better approximation of the deciles.

Results and comparison with previous measure of uncertainty

14. This methodology allows the full distribution of the forecast to be constructed for any given quarter. This rich information set can be summarised in many ways, as discussed below, but for purpose of illustration, Figure 2 presents the density plot of the computed forecast distribution for Germany in 2009Q1, with the 2s1h model. This quarter has been chosen because it displayed the largest disagreement between the three models (soft-, hard- and mix indicators models). The distributions for each model (dotted lines) are both non-parametric and asymmetric, and the combined density derived from the three models can be approximate as the average of the three densities. The fact that the combined density is not the actual average is an artefact of the kernel smoothing.

15. As such, the "variability" comes from two main sources:

- The disagreement between the models, which point to three different mean forecasts, part of which may be due to the different release schedules of the data in the individual models. In particular, the availability of more up-to-date soft indicator data which may point to a change in developments with respect to the (then obsolete) hard data will underlie the disagreement. Under the traditional approach of averaging the three (OLS) model forecasts, the mean of these forecasts would be reported, while QR provides a distribution based on the three models.

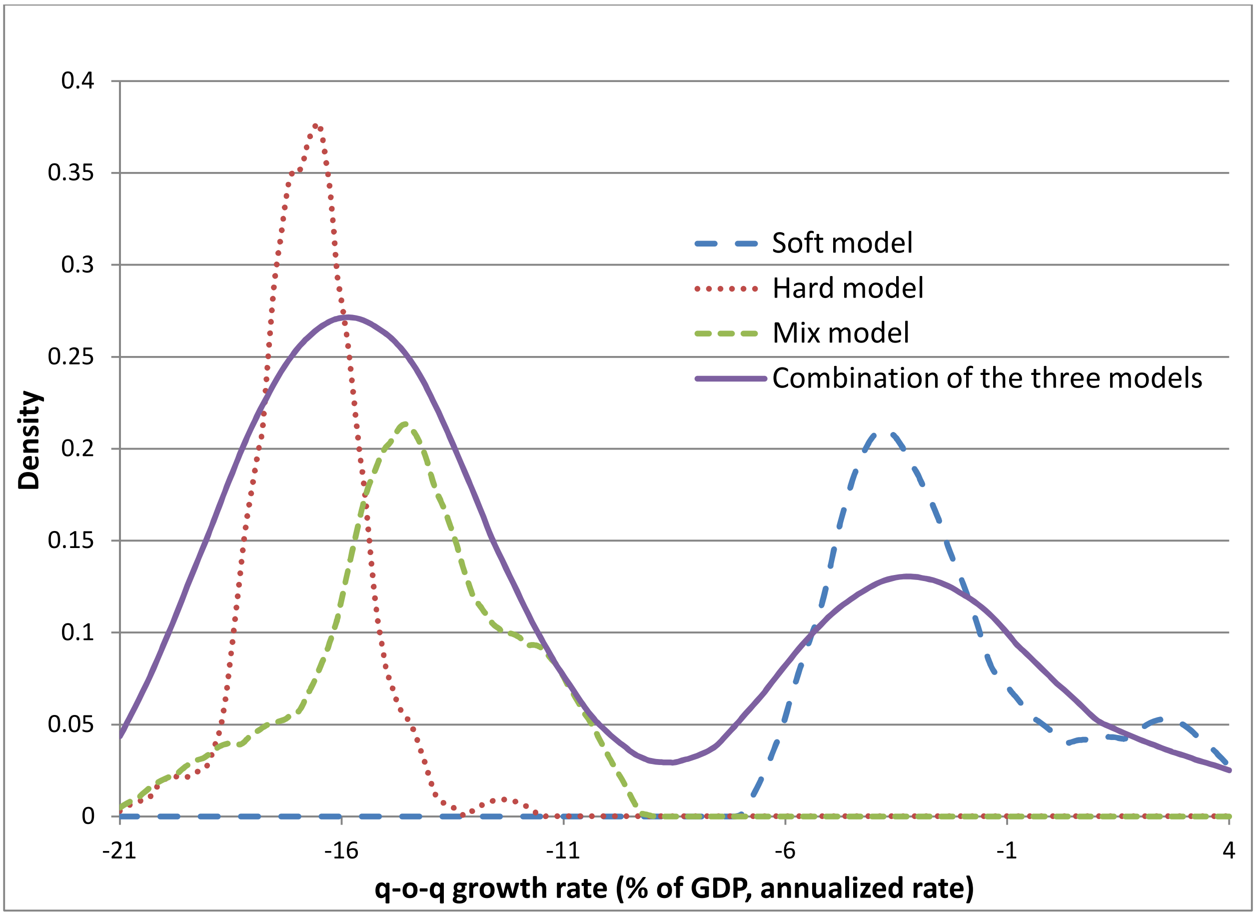
7. Using the EViews *qreg* procedure.

8. This reordering of the quantiles allows also to handle the issue of quantile crossing, or non monotony of the quantiles curves (see Chernozukov *et al*., 2010).

- The uncertainty inside each model, evaluated by quantile regression. Here the difference from the traditional OLS forecasts is that the distributions are not normal by construction, allowing for skews or multiple modes.

16. Simple variance decomposition allows these two sources to be separated (Figure 3). While on average a small share of total uncertainty (as measured by the variance), the disagreement between the three models drives the changes in the total uncertainty. In particular, the rise in uncertainty measured in 2009 is mainly due to a higher-than-usual disagreement between the three models at that time.[9] There is also some variability inside each model, which highlights the conditionality of the QR method.

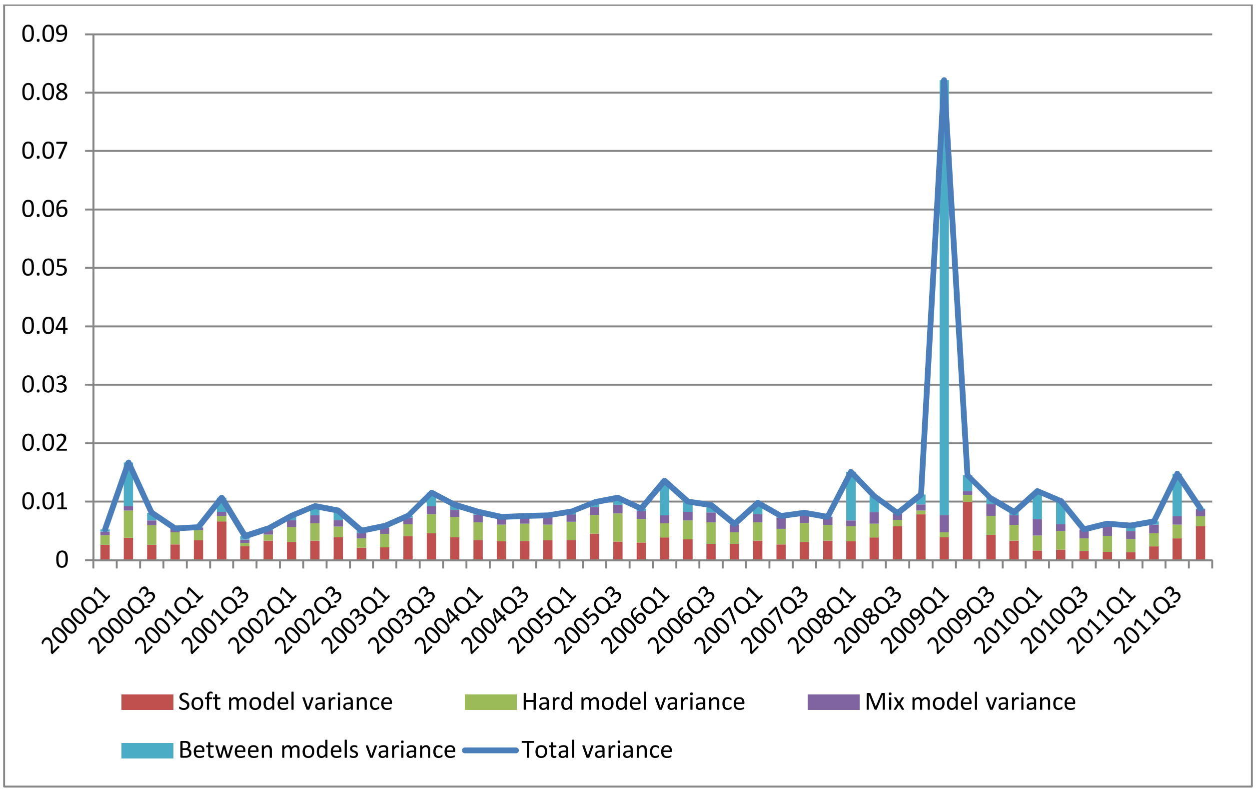
Figure 2. Density forecast for Germany in 2009Q1



Source: S21H model for Germany, 2009Q1. Densities are evaluated by Epanechnikov Kernel smoothing on the sets of quantiles. Note that the three individual model densities as been rescaled by 1/3 to be comparable with the combined density.

9. Though not the case in this particular setting, disagreement levels can be related to the different release schedules between the (soft and hard) indicators. For instance, when the economy is at a turning point, hard data, which come with a longer lag, may reflect the situation before the turning point, while the soft, which are more up-to-date may already reflect the turnaround. Therefore, disagreement is likely to be higher at the turning point of the economy.

Figure 3. Decomposition of the distribution Variance for the German model



Source: S21H model, sample 2000-2011.

Accuracy tests: Talagrand diagram

17. One way to test the accuracy of forecasted quantiles is to compare the empirical distribution of growth with the forecasted one. As a different distribution is forecasted for each quarter, the two distributions cannot be plotted on the same graphs. Therefore, Talagrand diagrams are used to test the accuracy of the forecast. For each quarter, the 9 deciles (or any other regularly-spaced quantiles) form 10 intervals, or bins, into which GDP should fall with a 10% probability each. Formally, the random variable B_i such that at each date i , $B_i = b$ if the GDP falls into bin b, should be independently and uniformly distributed on the integer segment $[\![1; 10]\!]$. The Talagrand diagram is the histogram of the number of times GDP falls into each bin. Ideally GDP should be likely to fall equally in each forecasted quantile, resulting in a flat distribution. Talagrand diagrams for the six countries and three forecast models (1s0h, 2s1h and 3s2h) are presented in Figure 4.

18. The histograms appear quite far from the expected uniform distribution (*i.e.* flat histograms). The main deviation is a clear tendency for higher frequencies at the lower end (*i.e.* left on the graph) bins of the distribution, indicating that QR forecasts have tended to be on the optimistic side on this sample period, regarding both the growth rate and the extent of uncertainty. There are, in many cases, between 4 and 8 more observations in the bottom decile than expected, including the worst quarters of the most recent crisis, but also some other downturns. To a lesser extent, some tendency for higher frequencies in the top is also observed (especially for the United States and the United Kingdom). The German model seems to have the most uniform fit.

Figure 4.The distribution of historical GDP realisations with respect to forecasted quantiles

Talagrand diagrams

Note: Histograms of historical GDP realisations versus QR predicted bins (current quarter) from the Interim Consensus model (S2H1) and S1H0, S3H2. Recursive estimation sample ranges: 1980-2011Q2.

Source: OECD calculations.

Accuracy tests: G-test

19. A more formal assessment of the quality of the fit of the forecast distribution can be done by testing whether each Talagrand diagram significantly deviates from the theoretical distribution. The Talagrand diagram is based on 10 cells, each representing one inter-decile interval, hence the better the fit of the proposed measure of uncertainty, the closer actual GDP should follow the forecasted distribution and the random variable B_i should follow a uniform discrete law on $[\![1;10]\!]$. This null hypothesis can be tested using a G-test. The test statistic is $G = \sum_{i=1}^{10} O_i \, ln\left({O_i}/{E_i}\right)$ where O_i is the observed frequency in bin i and E_i the theoretical frequency. This statistic follows a Chi² with 9 degrees of freedom (10 bins minus one restriction on the size of the sample). A p-value of less than 0.05 means the null hypothesis of a uniform distribution can be rejected at the 95% confidence level (Table 1). On a sample ranging from 1998 to 2011q3, this is only the case for 2 models: the Japanese 3s2h and the Italian 2s1h. This indicates these models tend to have a poorer fit, in the sense that the distribution of actual GDP realisations deviates

significantly from that of the forecasted distribution. For all the other models, taking into account the low number of observations there is no significant deviation from the expected distribution.

Table 1. G-test of the uniformity of the Talagrand diagrams

Country	United-States			Japan			Germany		
Model	**1s0h**	**2s1h**	**3s2h**	**1s0h**	**2s1h**	**3s2h**	**1s0h**	**2s1h**	**3s2h**
G-test statistic	16.91	6.23	11.16	12.26	15.44	17.80	7.74	7.28	12.45
p-value	0.05	0.72	0.27	0.20	0.08	0.04	0.56	0.61	0.19

Country	France			United-kingdom			Italy		
Model	**1s0h**	**2s1h**	**3s2h**	**1s0h**	**2s1h**	**3s2h**	**1s0h**	**2s1h**	**3s2h**
G-test statistic	10.94	13.78	13.28	13.20	15.88	15.37	12.59	23.23	11.56
p-value	0.28	0.13	0.15	0.15	0.07	0.08	0.18	0.01	0.24

Sample: 1998-2011q3. Models failing the G-test highlighted.

Source: OECD calculations.

20. Models can also be compared on the basis of this statistic which represents the distance between the theoretical and estimated distributions. No systematic link between the quantity of monthly information available and the quality of the fit of the uncertainty estimation can be established. Even if the models with the least information (1s0h) are clearly the most uncertain (with largest mean forecast error on the past), this uncertainty is not, on average, less accurately assessed than the uncertainty related to models including more months of information.

A look at the estimated coefficients of the quantile regressions

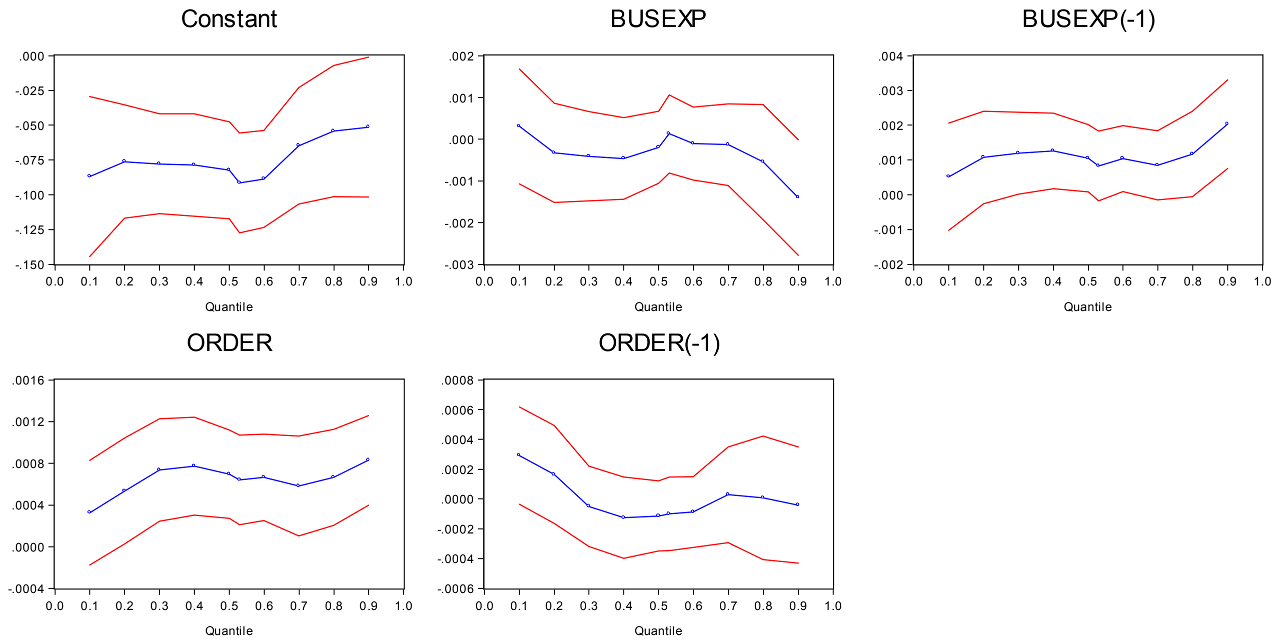
21. In order to better understand what is behind the QR method, the coefficients of three quantile regressions for the German soft, hard and mixed model are presented, as estimated for the sample 1991-2011q2. On each graph (Figures 5 to 7), the central line represents the coefficients estimated for the 9 deciles, from 0.1 to 0.9. The top and bottom lines give the 95% confidence band. The variable coding is as follow:

- BUSEXP stands for Business expectations from the IFO survey
- ORDER stands for industrial orders,
- IPI stands for the index of industrial production (excluding construction),
- IPIC stands for production in the construction sector,
- MCI stands for retail sales.

22. It seems that there is no clear upward or downward pattern for most variables, and moreover that, looking at the confidence bands, the coefficients are not significantly different from each other. This means that there is no variable that has a significantly stronger elasticity with GDP at the bottom or the top of the distribution, which would mean it has a greater influence on one side of the distribution. This implies that in a single model (Soft, Hard, and Mixed) forecasts appear to be rather unconditional. However, the combination of models used for creating the forecasts (through ordering of centiles) still means QR allows relatively large flexibility in the determination of individual quantiles as they can come from different models and hence have different hard/soft determinants.

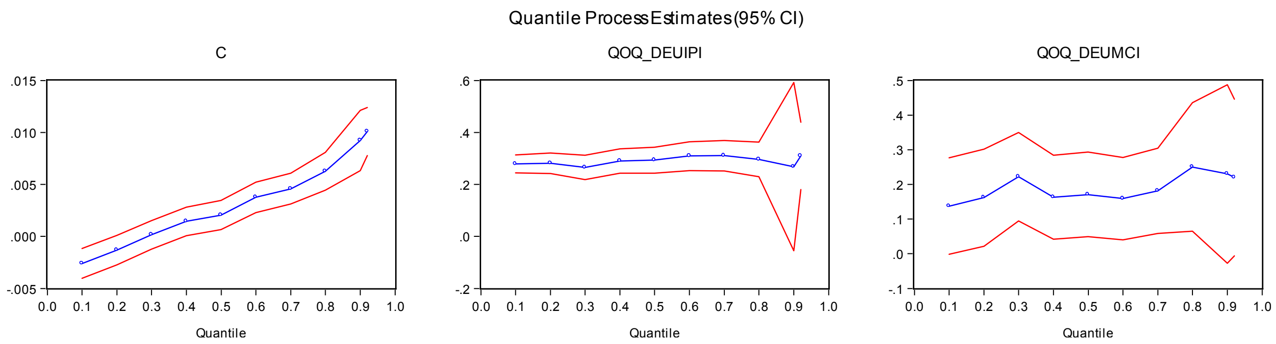
23. Similar patterns are observed for the other countries (not presented here).

Figure 5. Coefficient estimates for the German soft model



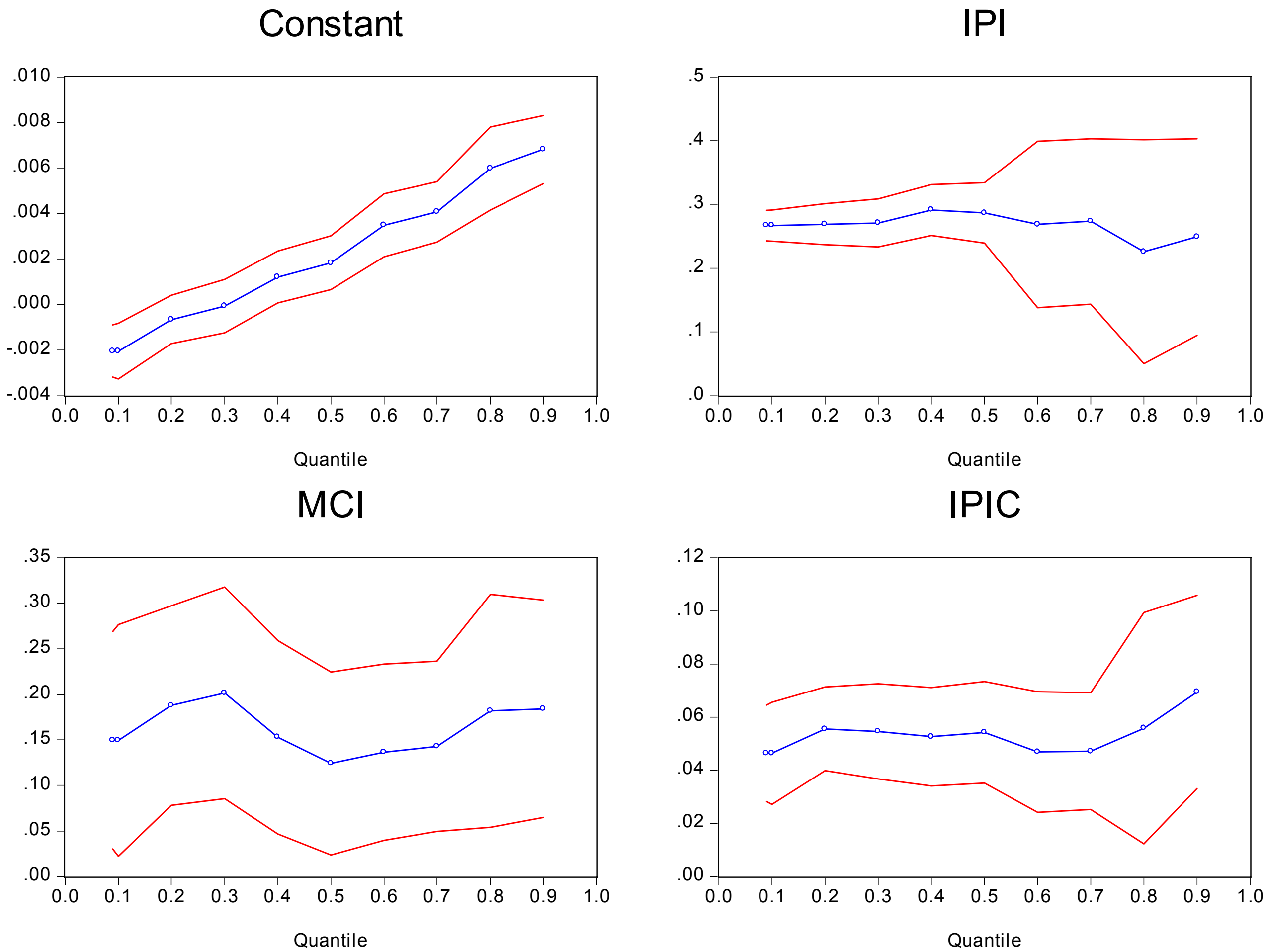
Source: OECD calculations.

Figure 6. Coefficient estimates for the German hard model



Source: OECD calculations.

Figure 7. Coefficient estimates for the German mix model



Source: OECD calculations.

Comparison with other methods of distribution forecast

24. The G-test can also be used to compare the distribution obtained via QR with the standard indicator model methodology of a normal distribution around the OLS point forecast, with standard deviation based on the RMSFE (root mean squared forecasting error). The QR method is tested against two methods of computing the RMFSE, depending on the past sample considered. Either the RMFSE is evaluated recursively between 1998 and the quarter preceding the quarter of interest (RMFSE-fixed start) or using a sliding three-year window preceding the quarter of interest. Here, the G-statistic is not used to make a formal test, but is seen as a measure of the distance between the *ex-ante* assessment of uncertainty, based on either OLS (RMSFE) or QR forecasts, and the *ex-post* GDP realisations. The comparisons of G-statistics enable to see which methodology is "closest" to the realised GDP distribution. Table 2 shows that, in most cases, QR does not improve the fit of the uncertainty measure with respect to the two RMFSE measures, of which the second (RMFSE- window) shows the best result.

Table 2. Comparison between the QR and RMFSE-based forecast distribution

Country	United States			Japan			Germany		
Model	1s0h	2s1h	3s2h	1s0h	2s1h	3s2h	1s0h	2s1h	3s2h
Quantile regression	14.81	8.71	17.05	8.20	9.76	13.01	7.55	7.89	9.90
RMFSE- fixed start	11.00	6.62	8.48	15.61	10.98	10.75	4.72	6.31	3.30
RMFSE- window	8.77	4.83	6.25	16.37	n.a.	n.a.	3.65	4.04	4.04

Country	France			United Kingdom			Italy		
Model	1s0h	2s1h	3s2h	1s0h	2s1h	3s2h	1s0h	2s1h	3s2h
Quantile regression	14.74	14.17	16.99	19.75	n.a.	13.52	n.a.	n.a.	13.38
RMFSE- fixed start	14.70	12.05	14.70	12.41	16.31	9.70	11.48	n.a.	n.a.
RMFSE- window	13.89	n.a.	11.99	12.95	14.45	7.43	17.82	24.71	12.25

Sample: 2001-2011q3. Models with lower G-statistic highlighted.

Source: OECD calculations.

25. Although disappointing, this result does not necessarily mean the QR method should be disregarded. First, this result derives partly from the way the model is estimated: the OLS estimation procedure explicitly optimises around the RMFSE concept, hence leading to better results when using RMFSE. Second, the QR method has the great practical advantage of being conditional on the current situation, and not an average of past situations, thus enabling the computation of more interesting indices of uncertainty, which are presented below. This shows a possible trade-off between the accuracy of the uncertainty measure and its interest. In fact, although RMFSE may provide a more accurate measure of uncertainty than QR, as measured by the G-test, the information provided by RMFSE is characterised by a high degree of inertia resulting from the fact that it is a moving average of past errors.

Potential applications to assess uncertainty

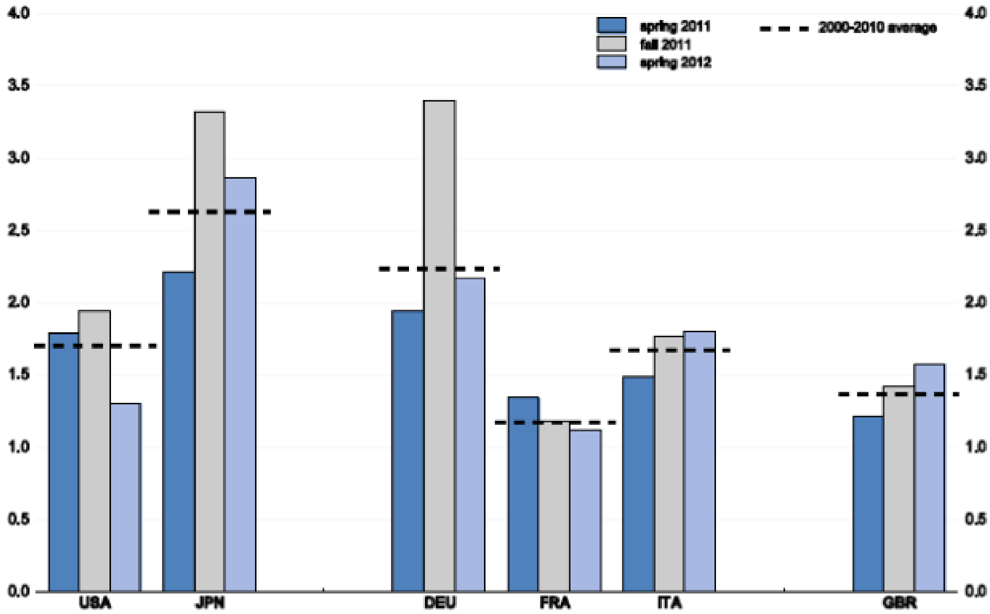
26. A probability distribution around the forecasts can be build from the QR methodology even if the raw output of the quantile regression is not the distribution itself but its 99 centiles. While the centiles or the distribution drawn from them convey a lot of information,[10] it may not be easy to read, interpret or compare to a benchmark (drawn from the past or other countries). This raises the need for a synthetic presentation of the results, focused on conveying the most useful information in the clearest way. Several one-dimensional indicators and graphical representations, which are illustrated for the German model, have been considered, with focus kept on two preferred indicators. Finally, a relatively common way to present uncertainty surrounding forecasts (conditional fan charts) is discussed.

27. The first potential presentation method is the standard deviation around the forecast. It has the advantage of being fairly simple and is a commonly used measure of dispersion, making readability straightforward. For example, in Figure 8, the contemporaneous measure for forecasts as of March 2012 is

10. Even more since the estimated distributions are non parametrical, and cannot be reduced to a small set of values.

compared with the level of uncertainty observed in the past,[11] which enable the assessment of the evolution of uncertainty. Here the uncertainty is clearly receding in the three largest G7 economies.

Figure 8. Standard deviation around GDP forecasts (% of GDP, annualised rates), IPC spring 2012 handout

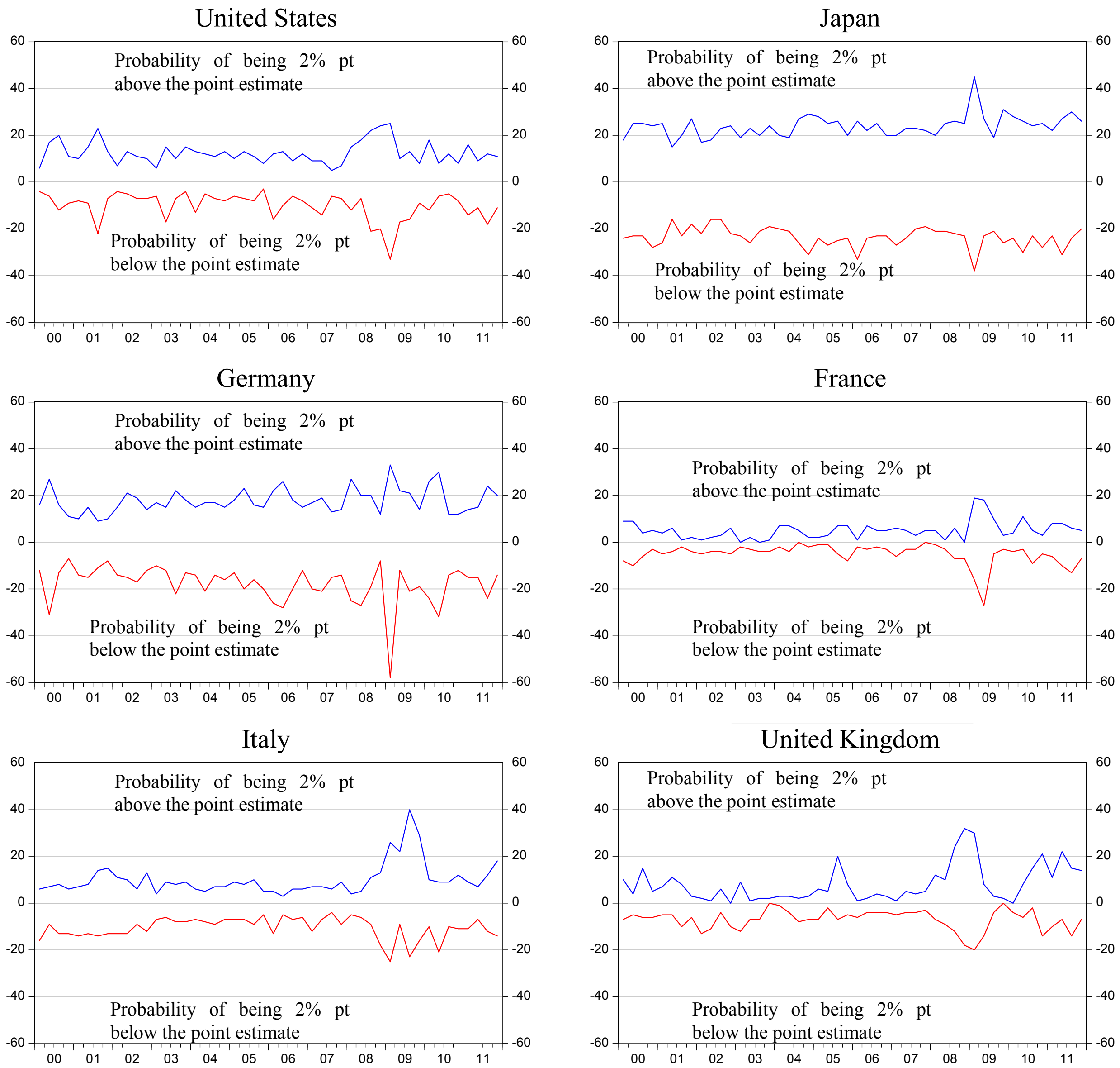


1. The standard deviation combines two sources of uncertainty. First, uncertainty due to differences in forecasted GDP between the three models (soft-, hard- and mixed-indicator models) that are used to make the projections. Second, uncertainty around the GDP forecasts of each individual model is derived using quantile regressions, which allows some explanatory variables to have more weight in explaining GDP during a sharp downturn (or recovery) than in more normal times.
Note: See Appendix for a more detailed description of the methodology.
Source: OECD

28. The second choice is a synthetic indicator conveying information on both the extent of the uncertainty and the asymmetry of risk, using two time series. While constructing this uncertainty index, several desired features were examined. The distribution of risk around the forecast had to be reduced to the two dimensions of interest, namely the balance of risks and the extent of the uncertainty. Focus was put on the large forecast errors, which, while less likely than small errors close to the forecast point, are more serious and could be more costly. On this basis, the proposed set of uncertainty indices measure the probability of being more than 2 percentage points (annualised) above or below the central point estimate forecast of GDP growth, see Table 3 and Figure 9 (both relate to projections made in early January 2012). In Figure 9, the distance between the two lines gives an indication on the uncertainty around the point estimate (the further apart, the more uncertainty), while the comparison of the distance of the two lines from the zero axis gives an indication of the balance of risks. Table 3 summarises this information by quantifying the current uncertainty relative to "normal times" over the period 2000-07 (*i.e.* excluding the recent crisis) and showing the highest values of the index recorded during the financial crisis during 2008Q4-2009Q4 (see Figure 9).

11. Uncertainty is evaluated using the data available at the time the individual forecasts are made (without following revisions), while the 2000-10 average is computed with data available in spring 2011.

Figure 9. Probability of large forecast errors for the current quarter (+/- 2% around the point estimate)



Note: Probability of large negative errors is given on the negative scale (*i.e.* –P) for presentational reasons. The lines show the probability of being 2% points above or below the point estimate for the same set of monthly information in forecasting the current quarter.

Source: OECD calculations.

29. Figure 9 shows that the average uncertainty varies greatly between countries with the United Kingdom and France showing much lower figures than Japan or the United States. To the extent there is greater interest in comparisons across time in a given country rather than across countries, and as the cross-country dimension should be handled carefully as the country models are different, a normalisation of the uncertainty index has been made, taking the average value during the 2000-07 as a denominator, for each country separately and are presented in Table 3.

Table 3. Uncertainty around the “current” quarter projection (2011Q4)

	January 2012		Average 2008Q4-2009Q4	
	Downside	Upside	Downside	Upside
United States	1.1	1.1	1.9	1.6
Japan	0.9	1.1	1.1	1.3
Germany	0.8	1.2	1.5	1.2
France	1.8	1.3	3.0	2.5
Italy	1.6	2.1	2.1	3.1
United Kingdom	1.3	2.5	2.0	2.7

Note: A value of one corresponds to the average probability of being above or below the point estimate by 2 % point in "normal times". An index above 1 shows that uncertainty is higher than in "normal times".

Source: OECD calculations.

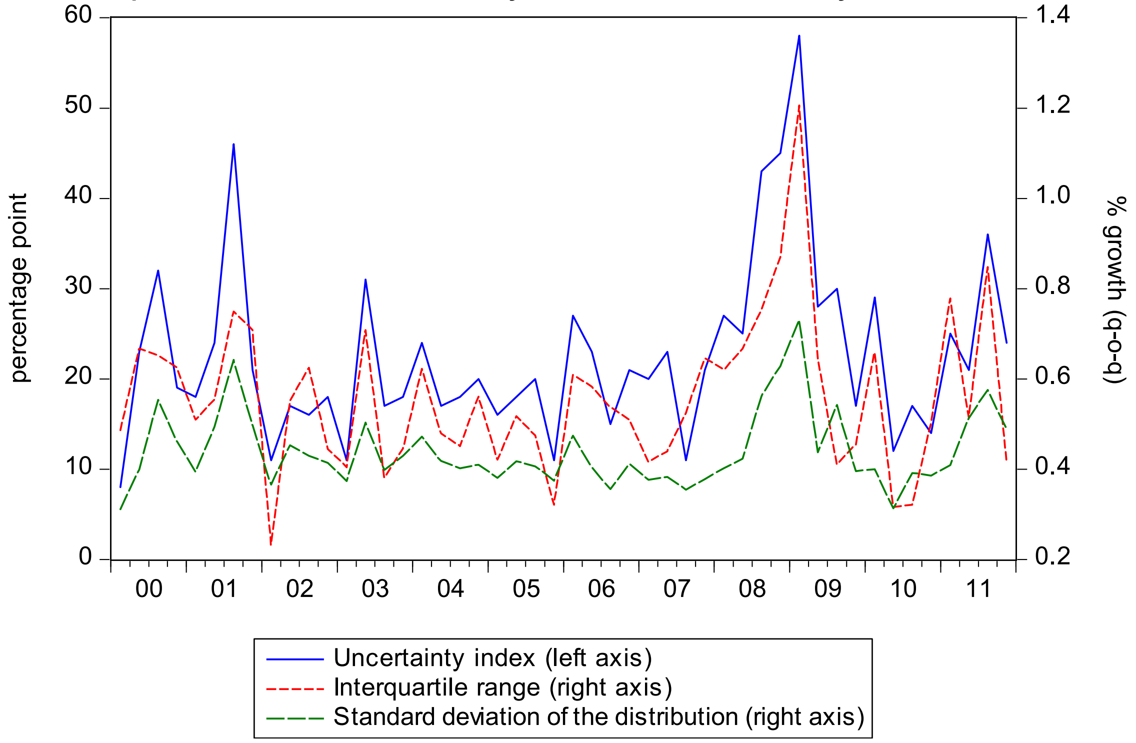
30. All measures show an increase in uncertainty around the financial crisis. Over 2011 there has been a slight overall widening in uncertainty around the forecast of Q2 and/or Q3, mainly due to increased disagreement between models (the *between effect*), which seems to have recently abated for the current forecast of Q4.

Comparison of the uncertainty and asymmetry indexes with other internal or external proxies

31. The proposed uncertainty index (the probability of being 2 annualised percentage points away from the forecast) and other uncertainty measure drawn from the forecast distribution, like the interquartile range (the different between the 75^{th} quartile and the 25^{th} percentiles) or the standard deviation, follow very similar patterns (Figure 10).

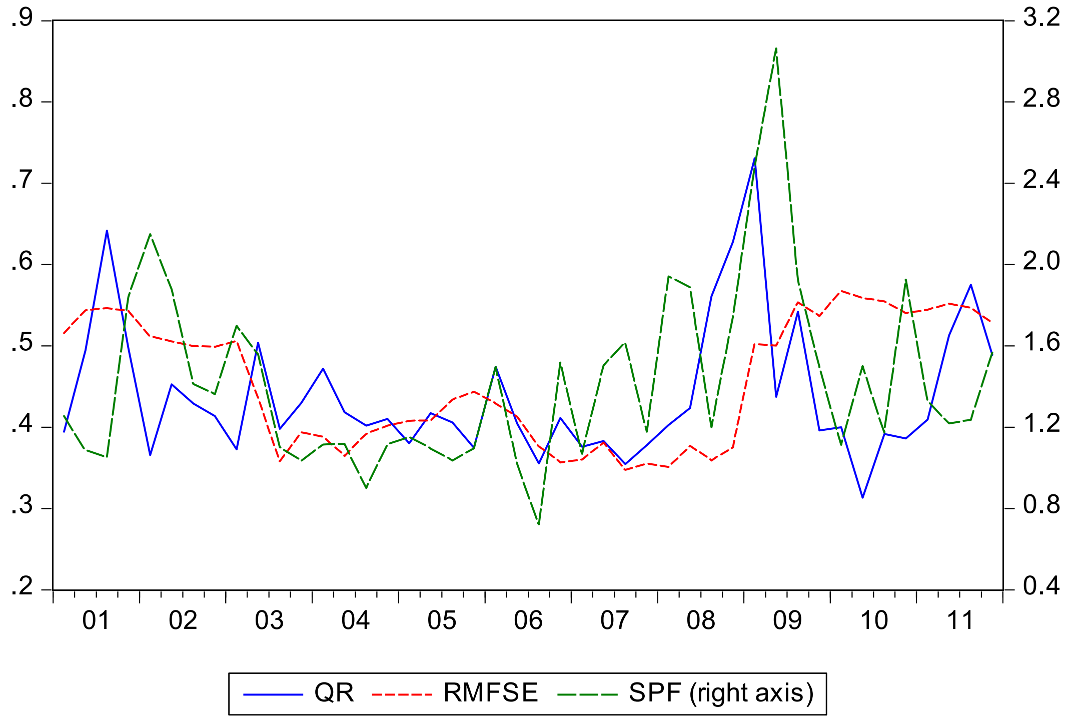
32. The comparison of the uncertainty as measured by the QR (here the standard deviation of the forecast distribution) and other uncertainty measures (Figure 11) leads to interesting insights: comparing the QR index and the standard deviation as computed by the RMFSE method shows that the QR is much more reactive than the RMFSE, as this last measure, being a historical moving average, lags behind and is very inertial. Moreover the QR measure tends to lead the Survey of professional forecaster (SPF) measure of uncertainty, made by the Philadelphia FED (a common benchmark for the uncertainty of the GDP forecast), at least during the 2001 and 2008-09 downturns.

Figure 10. Comparison between three uncertainty measures drawn recursively from the US QR 2s1h model



Note: The measures of uncertainty are one-period ahead, estimated recursively over the period 2000Q1-2011Q3.
Source: OECD calculations.

Figure 11. Comparison among the QR uncertainty measures drawn from the US QR 2s1h and other uncertainty indexes



Source: OECD calculations.

33. The uncertainty index is then compared to several financial indexes, which are often taken as good predictor of uncertainty (Figure 12). This includes the volatility index of the American stock market (VIX); the financial condition indicator (FCI) which is an indicator produced by the OECD and the spread between long term and short term interest rates. While the new measure of uncertainty may appear to lead the surveys of professional forecasters it tends to lag financial indicators such as stock volatility indices and FCI (even more since, for a given date, they are available sooner than economic indicators) in signalling the 2008-09 crisis. There seems to be less relation between the yield curve and the QR uncertainty index. In the most recent quarters, a divergence appears between FCI and the QR uncertainty, which reflect the fact that the economic environment is still very much affected by the difficulties in both the United States and Europe, despite exceptionally accommodative monetary policy that drive the FCI down. This shows the caveat of relying on one aspect of the economic climate (financial conditions) that, while having been majorly linked to the last crisis, may not been that relevant to assess current climate of uncertainty.

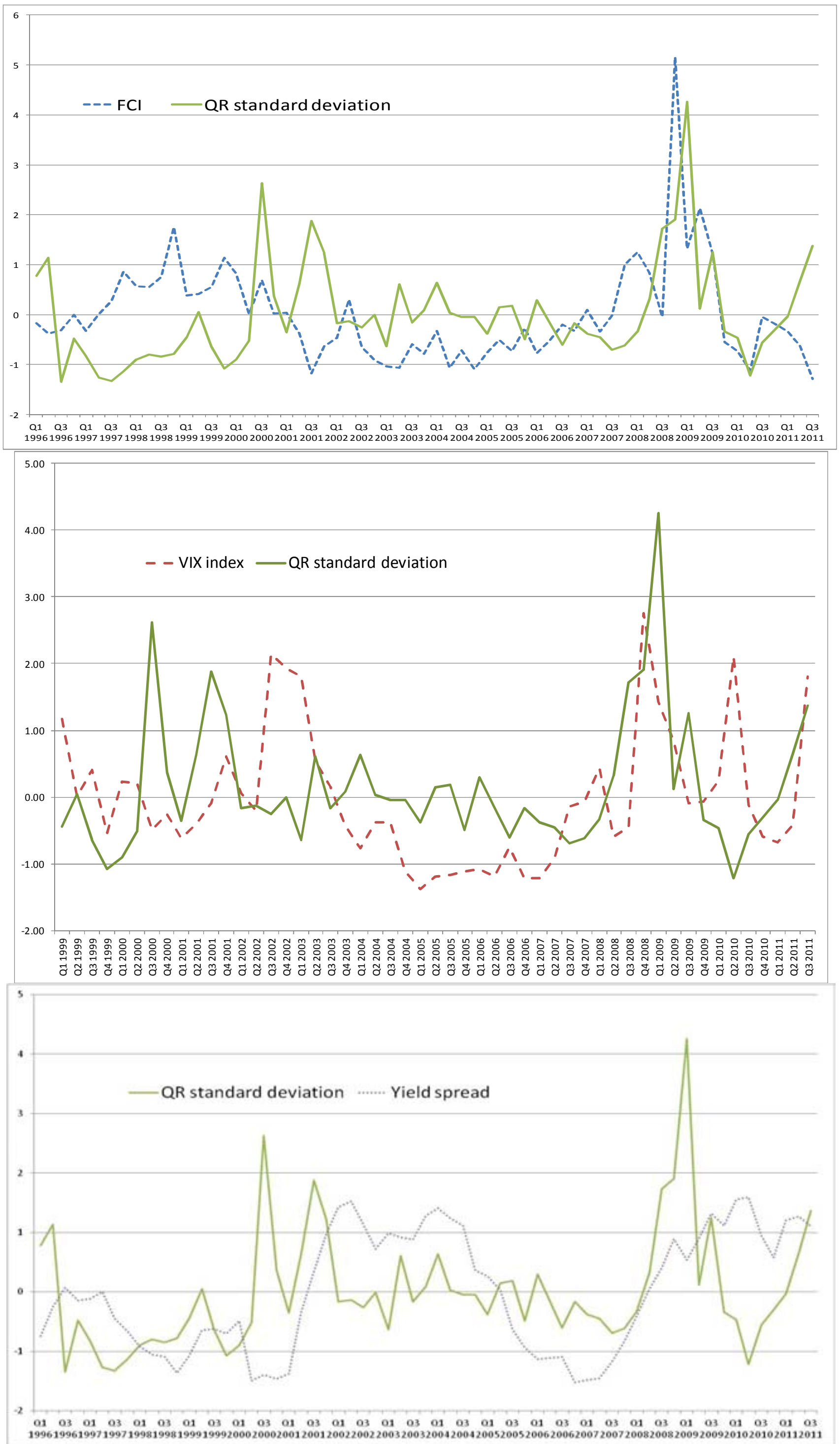
34. Another way to assess and represent the balance of risk is to present the difference between the mean forecast, made by OLS, and the median of the forecast distribution, estimated with QR. Figure 13 presents an example of this indicator with the US 2s1h model. When the mean is above the median, the GDP is more likely to be below the indicator model point forecast (the mean). The drawback of this very simple measure is that it gives no information about the size of the deviation from the mean or the median. Actually, a mean higher than the median can indicate that there are large positive outliers, which makes this measure sometimes counter-intuitive.

Conditional fan charts

35. A relatively standard way to represent information obtained through the QR distribution forecast is to graph conditional fan charts. Fan charts are mainly used for visual presentation, mainly of the asymmetry of uncertainty, but unless the asymmetry of the distribution is large, it is unlikely to be visible at first glance. Moreover, assessing the balance of risks based on fan charts may lead to confusion.[12] The standard presentation of fan charts (around the most recent forecasts) makes it difficult to assess the level of uncertainty, *i.e.* make a comparison with historical variance (or uncertainty), while presenting a set of historical (recursive) fan charts is likely to be overloaded. Figure 14 presents these types of graphs, for various dates of the German 2s1h model. The central, dark blue band represents the interval between the 4th and the 6th decile, and the three lighter bands additional deciles. Thus each shade of blue represents 20% of the probability (the remaining 20% being outside the fan. The solid red line is the historical GDP, as of 2011 Q2. The solid blue line is the OLS consensus forecast for current and next quarter.

12. Issues regarding the interpretation of fan charts are discussed in Annex II.

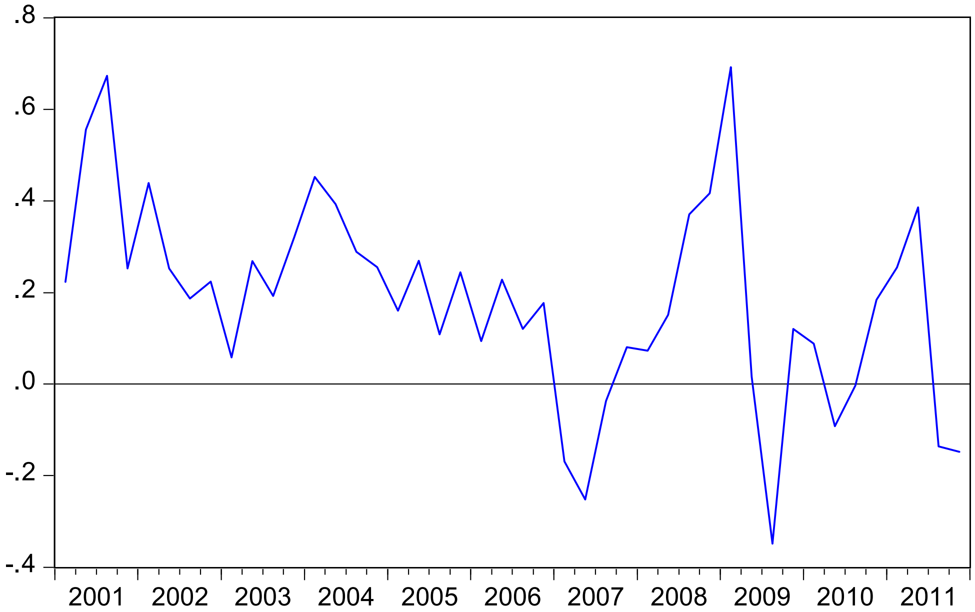
Figure 12. Comparison of the QR forecast standard deviation with financial measures of uncertainty for the United States



Notes: Comparisons of US QR 2s1h model with the Financial Conditions Index (Panel A), VIX index (Panel B) and slope of the Yield Spread curve (Panel C).

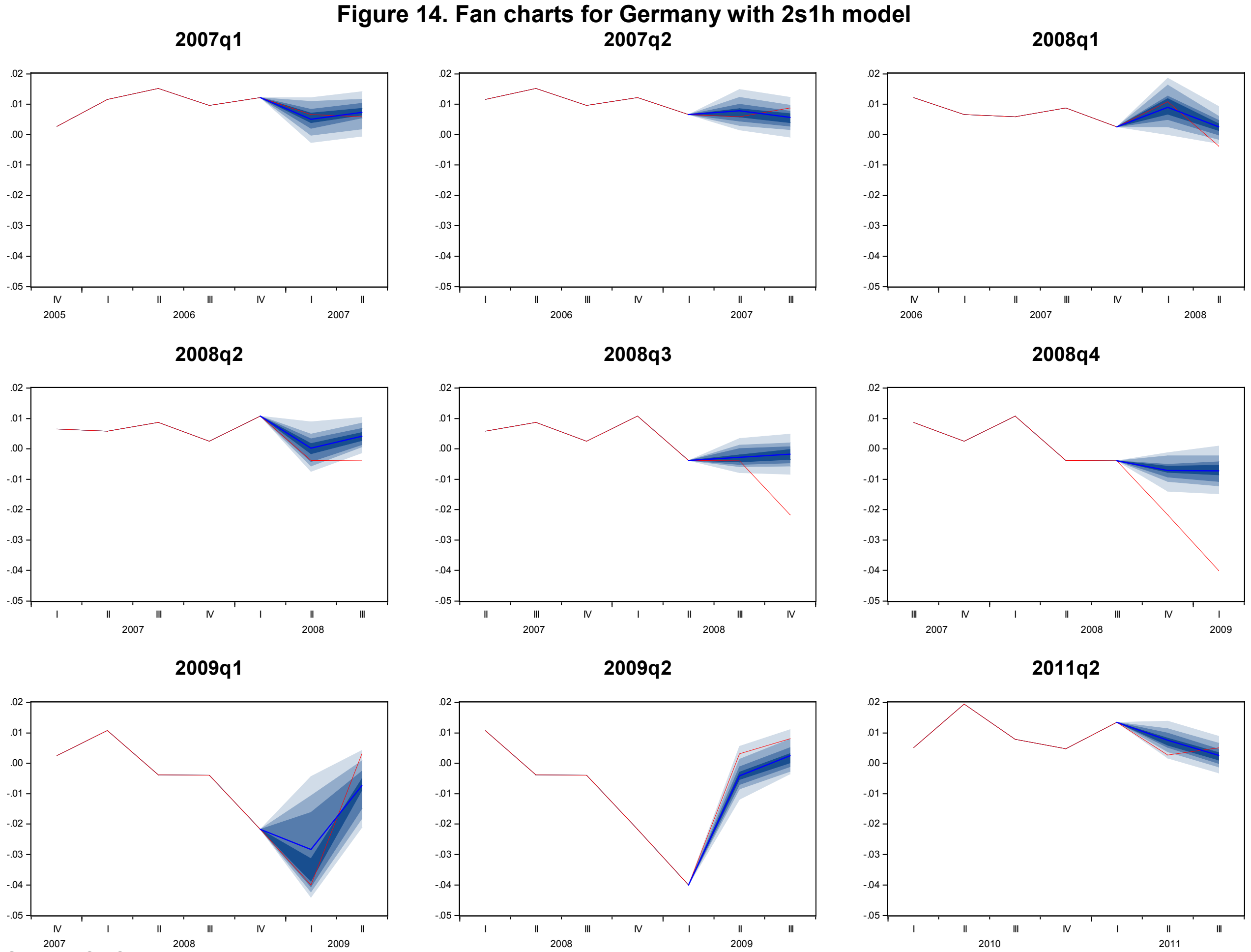
Source: OECD calculations.

Figure 13. Difference between the OLS point forecast and the median of the distribution forecast, for the United States 2s1h model (% of GDP)



Sample 2001-2011.
Source: OECD calculations.

Figure 14. Fan charts for Germany with 2s1h model

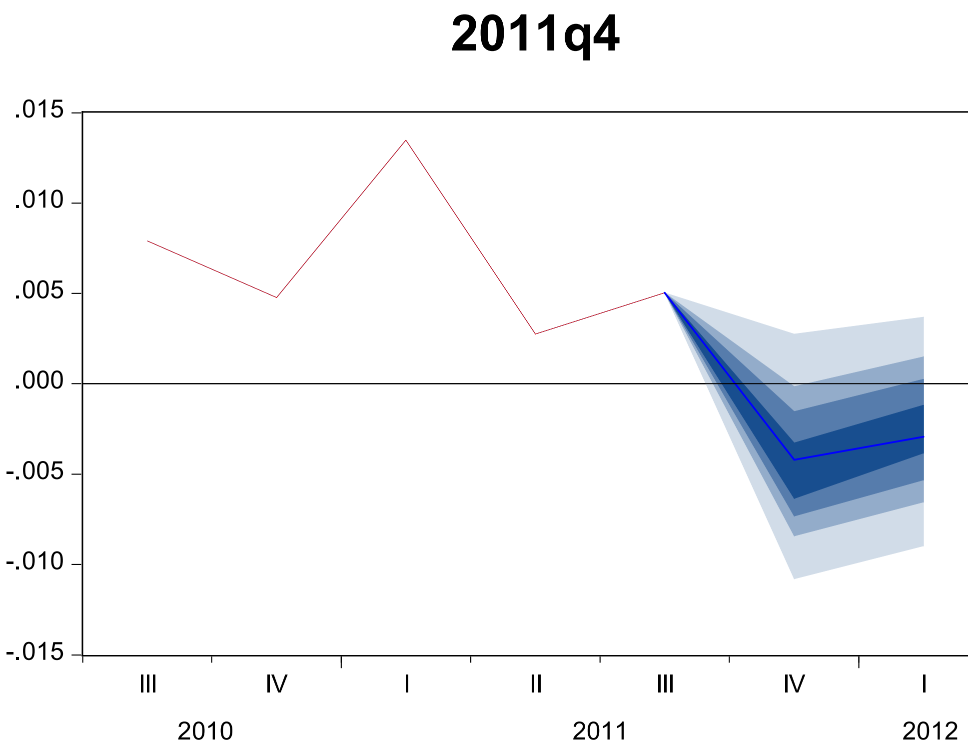


Source: OECD calculations.

36. For illustrative purpose, Figure 15 shows the forecast and fan charts for current and next quarter, with information available at the time (survey data for October and no hard data). The following (illustrative) statements can be drawn from the fan charts:

- There is a 20% chance of avoiding negative growth in the 4th quarter of 2011.
- There is 60% chance of having GDP growth between 0 and -0.8% (q-o-q rates) in the following quarter. Finally, the (provisional) GDP figure turns out to be -0.7%, so inside our 60% bracket.

Figure 15. Fan chart for the forecast based on most recent data for Germany



Source: OECD calculations.

Conclusion

37. The QR methodology presented here captures some of the uncertainty inherent to the forecasting exercise. This incorporation is made possible by the introduction of different elasticities between GDP and the indicators, depending on the position in the forecast distribution, thus enabling the indicators to have a contemporaneous impact on the width and symmetry of the uncertainty. The uncertainty indices drawn from this methodology can help to assess the extent of uncertainty conditional on the current state of the economy, in a model-based and judgment-free way.

38. While one advantage of this method is its simplicity and its closeness to the set-up of the IM model, the fit of the model is not totally satisfactory. Improvements, presented in Annex I, based on the addition of variables that seem to be related to uncertainty are presented, and the "squared indicators" approach seems the more convincing. An attempt to select a better model by LASSO gives disappointing results, which point to the fact that it is difficult to optimise a prediction of uncertainty, as uncertainty itself is not observed.

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ANNEX I. EXPLORED VARIANTS OF THE QR MODEL

39. This section presents some variants of the main methodology, aiming at extending and improving it. In order to improve the fit of the baseline specification, two directions are explored. First, the selection of variables is made specific to each quantile. Second, additional variables are added, to try to capture specific relations with the level of uncertainty.

Automatic selection of the lags

40. The models used so far are based on the OECD indicator model OLS equations, and the associate preferred lagged structure (resulting from standard information criteria). A further step would be to allow the indicator and lag selection to vary across quantiles. To do so, a criterion to discriminate between models is needed. This criterion must select a model that fulfils two objectives: maximises the fit and avoids large dimensions and over-fitting. Following Koenker, Ng and Portnoy (1994) and Machada (1993), a Schwarz information criterion is used for penalising high-dimension models:

$$SIC = \mathrm{T}\ln\left(\frac{1}{T}\sum_{i=1}^{T}\rho_{\theta}(y_i - Z'_i\,\beta)\right) + \frac{1}{2}k\ln T$$

where T is the sample size and k the number of independent variables. This criterion is applied for each centile, thus estimating 99th different models[13] and multiplying the computation time consequently.

41. Applied to the German case, this criterion allows the selection, for each quantile, of the optimal number of lags, instead of estimating the same model for all quantiles. Comparisons of the G-statistics with selection and without (Table A1) show that the selection process yields some improvement. But because of the much greater computation time this approach was not pursued.

Table A1. Comparison between the models with and without lag selection for QR

Country	Germany		
Model	1s0h	2s1h	3s2h
No lag selection	10.91	6.55	9.11
Lag selection	5.65	7.55	3.85

Source: OECD calculations.

13. There is 99 percentiles lines, from 1% to 99%, separating 100 quantile intervals

Adding new indicators

42. As shown above, a disappointing feature of the estimated model is that no indicators have a significantly different impact on the top or the bottom of the distribution, which may explain the inability to forecast extreme values. Incorporating new variables that may have different effect on different quantiles could improve the model. Possible candidates are squared values of the currently used indicators, which can take advantage of non-linearity in the model and financial variables, either stock market volatility indices or commonly used leading indicators of downturns such as the yield spread. In the absence of selection criteria, the candidate variables are added to the QR equation, either one-by one or in combination. The new constructed models can then be tested against the original one.

Squared indicators

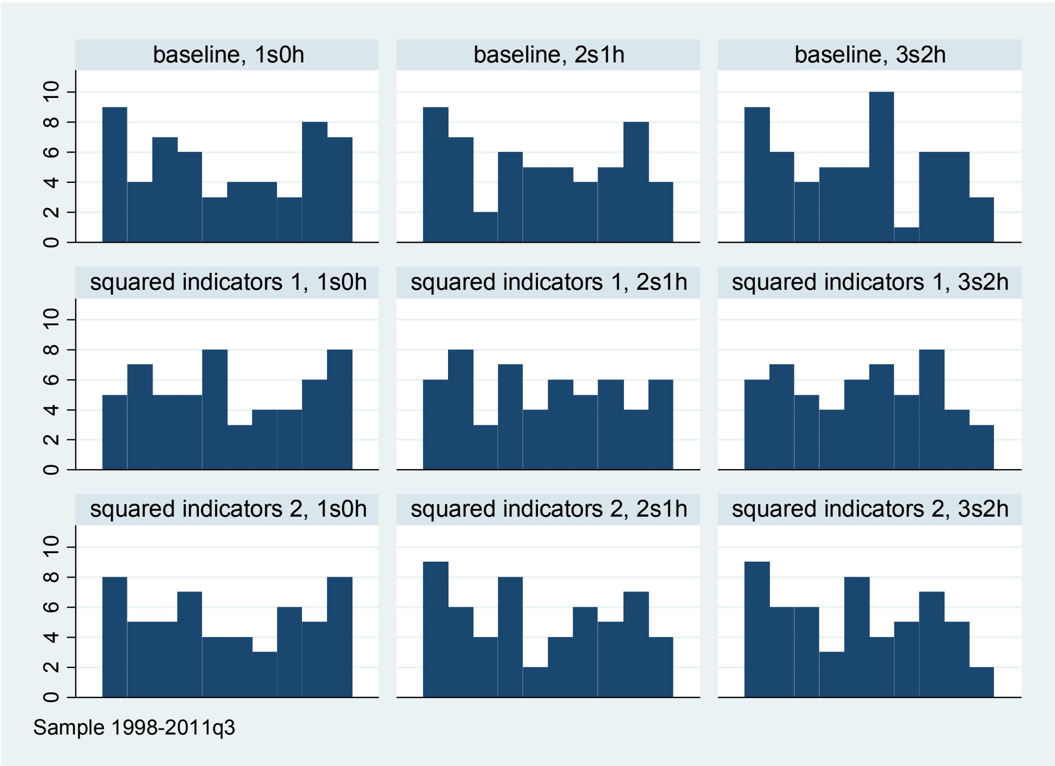
43. The idea being this technique is that large movement of the indicators may point to extreme events, and that, as movement get stronger, the link between the indicators and GDP stop being linear. The latest crisis showed an extreme example of that, with GDPs falling well below what the indicators were pointing to. The method is thus to keep the OLS mean estimation unchanged, and to add the squared value of the indicators, with the same number of lags, to the QR equations. Two alternative specifications are tested: one with the squared indicators, thus with only positive values (X^2) and a version retaining the same sign as the original variable ($X|X|$). Table A2 shows the results for Germany, France and the United States, the accuracy being estimated by the G-statistics, and compared with the baseline QR equation. Looking at Germany, while the two variants improve the fit of the distribution forecast, it seems that the first version offers the best fit. For France and the United States, the results are more disappointing, with only a marginal improvement of the fit of the models.

Table A2. Comparison of the baseline and squared indicators models for Germany, France and the United States

Country		Germany			France			United States		
Model		1s0h	2s1h	3s2h	1s0h	2s1h	3s2h	1s0h	2s1h	3s2h
Baseline	G statistic	7.73	7	11.36	9.91	11.29	13.61	22.92	7.02	5.76
	P-value	0.56	0.64	0.25	0.36	0.26	0.14	0.01	0.63	0.76
X^2	G statistic	4.82	3.86	4.2	15.39	13.08	15.01	22.49	6.94	8.42
	P-value	0.85	0.92	0.9	0.08	0.16	0.09	0.01	0.64	0.49
$X\|X\|$	G statistic	4.82	7.68	8.19	10.65	9.49	10.58	n.a.	9.28	4.60
	P-value	0.85	0.57	0.52	0.30	0.39	0.31	n.a.	0.41	0.87

Source: Sample 1998-2011Q3.

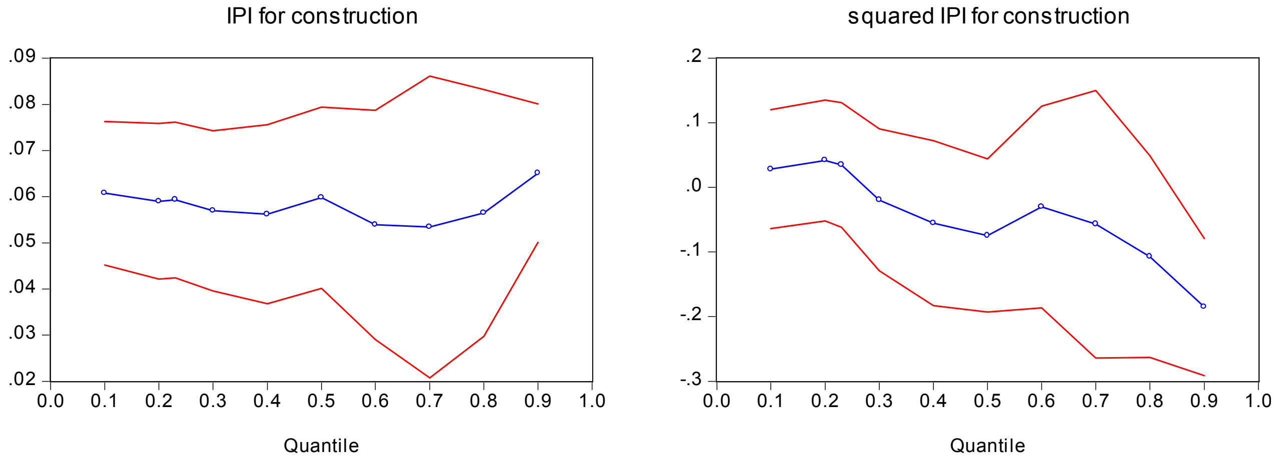
Figure A1. Talagrand diagrams comparing QR with and without squared indicators on various German models



Source: OECD calculations.

44. Looking at the Talagrand diagrams for Germany (Figure A1), the better fit for all variables seems also to be using the first alternative of the squared indicators (middle row of Figure A1). Moreover, this specification seems quite effective in capturing the bottom of the distribution, which is where the baseline specification is weakest. The estimated coefficients at the top and the bottom of the distribution are also not the same for some squared variables (Figure A2). For example, the squared IPI for construction displays a clear decreasing pattern, implying that high absolute value of the IPIC mean higher bottom quantiles and lower upper quantiles, thus narrowing the distribution. In this setting, the elasticity between GDP and the IPIC is positive and doesn't vary significantly between the top and the bottom of the distribution, so that high or low values of the IPIC move the forecast distribution up or down without altering it, at first order. The elasticity between the squared IPIC and the GDP is decreasing across the distribution, positive at the bottom and negative at the top, meaning that large movements in the IPIC (large positive value of the squared indicator) tend to narrow the distribution, raising the bottom of the distribution and decreasing the top. So IPIC has a first order impact on the level of GDP and a second order one on the width of the uncertainty.

Figure A2. Coefficients estimated for the 9th deciles by QR, for the mixed model with squared indicators



Sample 1991-2011

Source: OECD calculations.

Financial variables

45. Another alternative is to add financial variables to the QR equations. Two financial indicators are tested for the German level, the growth of the DAX index and its volatility (measured as the standard deviation of the daily levels of the index over the considered period). The two indicators are taken quarterly, and for the current quarter, the data is prolonged as if the growth will keep at the same pace and the volatility will remains the same (so, with two months of information, the growth indicator is projected as 3/2 of the first two months growth, whereas the volatility is the volatility of the first two months.) The indicators are added to the QR equations, for all three models (soft, hard and mix), with the number of lags selected for the other variables. As usual, this model is tested against the baseline one, without financial indicators, by comparing the G-statistics (Table A3).

Table A3. G-tests comparing QR with and without financial indicators on various German models

Country		Germany		
Model		1s0h	2s1h	3s2h
Financial indicators	G statistic	13.81	9.18	10.56
	P-value	0.13	0.42	0.31
Baseline	G statistic	7.73	7.00	11.36
	P-value	0.56	0.64	0.25

Source: Sample: 1998-2011Q3.

The results are quite disappointing, with only the more complete model (3S2H) showing a marginally lower G-statistic.

Model selection via a LASSO routine

46. As adding new variables with no theoretical backing or selection criteria can amount to data-mining, a way to correctly select the model is tested, using a LASSO-type (Tibshirani, 1996) estimating algorithm to select the model. The principle of this estimator is to add to the minimising function a term dependent on the L1-norm of the vector coefficient (the sum of the absolute value of the coefficients):

$$\beta_\theta = Arg\ min \sum_{i=1}^{t} [\rho_\theta(y_i - Z'_i\,\beta)] + \lambda||\beta||_1$$

47. This penalty allows for the selection of sparse models, by setting the betas of the less relevant variable to 0, through the minimization process. Its great advantage is that it selects and estimates the model in one minimisation, which allows for considerable gains in computing time. The caveat is that there is no theoretical value for the lambda coefficient, on which the estimation crucially depends: a low value will fail to discard any possible predictors, while higher values will discard all predictors but the constant.

48. This technique has been tested on the German model, first with the original set of predictors with the three models and then adding their squares to the set of predictors (see above for a description of the squared indicators). The estimator is applied on the normalised set of predictors, in order to have betas of comparable size. After some test, a lambda of 2 seems to provide the best estimation, but none of them beat the fit of the original setting, where the quantile models are identical to the mean prediction model.

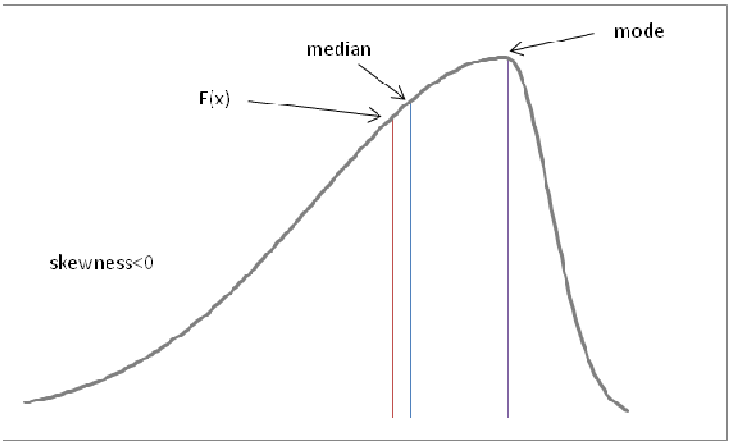
ANNEX II. INTERPRETING FAN CHARTS

Interpreting fan charts and distribution forecasts in light of risks

49. Fan charts have become an increasingly popular way of presenting uncertainty around forecasts. Still, their use for describing the balance of risks can lead to confusion.

50. Ideally, one would like to associate the fan chart shape (asymmetry) with the distribution of risks to the forecast. The most straightforward way, used by central banks including the BoE is based on the skewness of the forecast distribution. Negative skewness (for example under a two-piece normal distribution, as in Figure A3) implies E(x)<median<mode and is associated with a negative balance of risks to the central forecast, being implicitly the mode ("downside risks"). In other words, given the most likely outcome (mode), E(x)<mode and Pr(x<mode)>0.5.

Figure A3. A negatively skewed distribution



Source: OECD calculations.

51. The situation becomes somewhat more complicated when the published point forecast is not the mode but rather the mean (expected value) or median. In case of the mean, a negative skewness, as above, is sometimes interpreted as an illustration of upside risks to the expected forecast -- as Pr(X>E(x))>0.5. This is somewhat misleading, as while Pr(X>E(x))>0.5 the distribution can be characterised as having a large probability of slightly higher outcomes (not very interesting from a policy maker point of view) while the probabilities of large negative errors to the forecast dominate the probability of large positive errors (much more interesting for a policy maker, a fact that may be hard to see if labelled as upside risks).

52. In practice, the EC and the IMF seem to be somewhat confused in this respect. In both cases, the aggregate GDP forecasts (euro-area in case of the EC, world in case of the IMF), are constructed by aggregating individual country-desk forecasts. This is then assumed as the mode (euro-area or global) forecast, around which they construct a distribution based on some subjective assessment of risks to the forecast. However, it is not clear what the desk central forecasts represent: if they are actual modes of desk forecasts (most likely values), then the aggregation does not guarantee one obtains the mode of the aggregate distribution. Alternatively, if they were to be means (expected values), treating the aggregated number as the mode of the aggregate forecast (for the risk interpretation) would not be correct.

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