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How should one assess short-term economic uncertainty?

This study was prepared under the authority of the Directorate General of the Treasury (DG Trésor) and does not necessarily reflect the position of the Ministry of Economy and Finance and Ministry of Foreign Trade

- Economic activity in the major European Union countries and the United States has been heavily affected on several occasions since 2008 by the decline in confidence among economic players. Uncertainty in the financial markets, measured by market volatility indexes or government-bond spreads, rose sharply in the summers of 2011 and 2012.

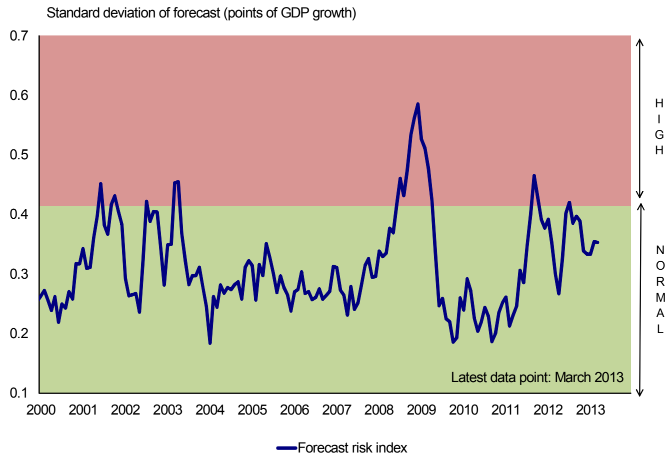
- In cyclical turnarounds, short-term economic growth is often hard to forecast with standard models, which consist of calibrations on business surveys. These models heavily underestimated the probability of very wide swings in quarterly growth at the start and end of the 2008-2009 crisis.

- This issue describes an alternative model based on quantile regressions, which captures uncertainty in real time.

- It allows a monthly assessment of the combined effects of business-climate changes and financial-market pressures not only on economic activity but also on business-cycle uncertainty.

- The model identified an uncertainty peak in July 2012. Since then, uncertainty has gradually declined-a trend probably correlated with policy-makers' response to the euro area sovereign-debt crisis.

Forecast risk index



Source: DG Trésor calculations.

MINISTÈRE DE L'ÉCONOMIE ET DES FINANCES

MINISTÈRE DU COMMERCE EXTÉRIEUR

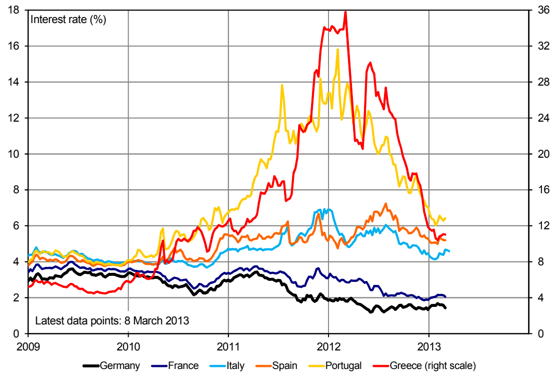
1. A cyclical context marked by strong financial uncertainty

1.1 Since summer 2011, the advanced economies have suffered a series of confidence shocks

Among the major economies, only Germany and the United States had seen their GDP growth return to its level prior to the 2008-2009 crisis by the second quarter of 2011. The upturn, whose pace varied from country to country, lost momentum in the summer of 2011. This slackening is largely attributed to the declining confidence of financial-market players regarding the containment of the debt crisis in some euro area countries and the prospects of striking a budget deal in the U.S.

The confidence shock immediately spread to the euro area sovereign-debt markets, widening the interest-rate spread between euro area member countries in summer 2011. The euro area countries that had accumulated the most negative net external positions due to persistent current-account deficits-notably Portugal and Greece-suffered a further rise in the risk premium on their public debt. Spain and Italy fell victim in turn, albeit to a lesser extent, to pressures on their sovereign debt (chart 1). Tension on government-bond yields eased in October 2012 after the European Central Bank (ECB) announced its readiness to resort to an innovative crisis-management tool: outright monetary transactions (OMTs). The program involves the repurchase of short-dated government bonds on the secondary market with no preset ceiling, subject to a EFSF/ESM financial guarantee.

Chart 1: Interest rates on 10-year sovereign debt



Source: Global Insight.

Financial markets, especially in Europe, were hit by the shock and fell steeply in summer 2011. The shock did not simply impact stock and bond prices. It also sharply increased their volatility, generating a highly uncertain environment.

1.2 Economic uncertainty is changing behaviors

The deterioration of cyclical indicators in summer 2011 indicates that financial tensions had spread to the real economy. In France, the business climate index calculated by INSEE (the national statistical institute) dropped sharply and has been running below its historical average since September 2011.

Economic theory identifies several channels through which an uncertainty shock can influence the behavior of economic agents. In particular, according to Bloom,[1] if the launch of investment projects entails sunk fixed costs, the uncertainty level will be one of the determinants of the investment decision, even if the expected return remains constant. A rise in uncertainty incites risk-averse entrepreneurs to wait before starting new projects. Firms delay or stop hirings and defer investment.

A study by Zakhartchouk (2012)[2] finds that an uncertainty peak in France-identified by a significant rise in the monthly volatility of the CAC 40 stock-market index-would weigh heavily on manufacturing output, and that the effect would take 14 months to wear off.

1.3 As a result, the quality of forecasting models could deteriorate

If uncertainty shocks change economic agents' behavior, the statistical links between the economic variables tracked by forecasters may be altered.

Forecasters usually prepare their scenarios using statistical models. The degree of uncertainty attached to a statistical forecast will therefore depend on the quality of the chosen model. However, the uncertainty associated with standard models does not depend on current economic conditions (box 1).

Cornec (2011)[3] argues that standard models have had trouble forecasting economic activity in certain quarters, especially at the outbreak of the crisis (2008Q4) and in the later rebound (2009Q2). The same models also underestimated the probability of observing the outlier outcomes for quarterly growth. The implication is that the models do not make sufficient allowance for business-cycle uncertainty and that new tools are needed to improve the measurement of that uncertainty.

(1) N. Bloom (2009), "The impact of uncertainty shocks," *Econometrica*, vol. 77, pp. 623-685.
(2) A. Zakhartchouk (2012), "Uncertainty shocks slowing down business," "*Conjoncture*" in France, INSEE, March 2012.
(3) M. Cornec (2011), "Constructing a conditional GDP fanchart with an application to French business survey data," http://www.tresor.economie.gouv.fr/File/334878.

Box 1: **Uncertainty in standard calibrate models**

In standard practice, forecasters seek to predict the outcome of a variable of interest at a horizon h from a statistical model called calibration, which takes the following form:

$$y_{t+h} = X_t'\beta + u_{t+h}$$

y_{t+h} the variable to be forecast; X_t the vector of the leading indicators available; β is an unknown coefficient u_{t+h} is a random variable athat summarizes the set of unobserved factors.

These statistical models assume that u_{t+h} in independant of X_t and that u_{t+h} has a Gaussian distribution with a zero mean and constant variance of σ^2.

Under these assumptions, the best forecast is $\hat{y}_{t+h} = X_t'\hat{\beta}$

$\hat{y}_{t+h}$ is the forecast for the variable in $t+h$ et $\hat{\beta}$ is the estimate for coefficient β, generally obtained using the ordinary least squares (OLS) method.

This forecast is subject to an error noted e_{t+h}): $e_{t+h} = y_{t+h} - \hat{y}_{t+h} = u_{t+h} + X_t'(\beta - \hat{\beta})$ (1)

Equation (1) enables us to separate two sources of forecast error: (i) the term u_{t+h} is unobserved at the forecast date; (ii) $X_t'(\beta - \hat{\beta})$ reflects errors in the estimate for coefficient β.

Under the above assumptions, the forecast error has a Gaussian distribution with the following properties:

- The mean forecast error is zero: $E(e_{t+h}) = 0$
- The error variance is: $V(e_{t+h}) = \sigma^2[1 + X_t'(X'X)^{-1}X_t]$ where X is the matrix of the set of leading-indicator values observed during the model's estimation period.

In other words, the uncertainty of the forecast obtained by calibration depends on the size of the unobserved shocks (first term of equation (1)) and the precision of the estimates (second term of equation (1), which depends on the size of the estimation sample).

2. INSEE business and consumer surveys yield information on the level of economic activity, but also on the level of uncertainty

The business and consumer surveys published by INSEE are one of the most useful information sources for preparing short-term forecasts. The results are available very quickly-around the 20th of every month-whereas the main quantitative indicators ("hard data") for the same month are released two months later (household consumption of goods, industrial production, and external trade) or even three months later (retail sales). Moreover, the balances of opinion undergo minimal revision after initial publication. This prevents forecast errors that are merely due to an inaccurate measurement of current conditions (box 2).

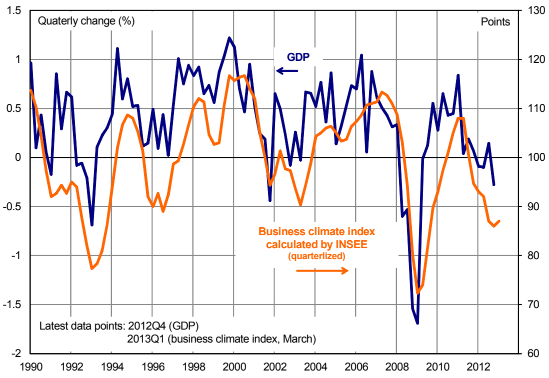
2.1 The INSEE business climate index is correlated with actual economic activity

The INSEE business climate index (Index du Climat d'Affaires, ICA), published with the monthly business and consumer surveys, is a quality leading indicator for forecasting economic activity, as Bardaji, Minodier, Clavel, and Tallet have shown (2008)[4] (chart 2). The correlation between GDP growth and the quarterly average of the index is 0.63.

In the period 1990-2009, French GDP grew at an average quarterly pace of approximately 0.4% (table 1). The ICA's position relative to its long-term average gives a more precise estimate of growth. When the index is running above its average, GDP is growing at an average pace of approximately 0.6%, versus 0.1% or so if the index is running below its average,. This simple example shows an apparently increasing link between the ICA and quarterly GDP growth.

Quarterly growth depends not only on the level of the index but also on its rate of change. An index above 100 suggests high GDP growth ahead, especially if the index is trending up: in such cases, quarterly GDP growth averages around 0.7%. In contrast, when the index is under 100 and trending down, GDP growth rates are often negative. When the signals display opposite signs, GDP growth is likely to run close to its long-term average.

Chart 2: INSEE French business climate index (ICA) and quarterly GDP growth



Source: INSEE, DG Trésor calculations.

(4) J. Bardaji, C. Minodier, L. Clavel, and F. Tallet (2008), "Two New Indicators to Help Analyse the Economic Outlook in France," "*Conjoncture*" in France, December 2008, pp. 23-44, http://www.insee.fr/en/indicateurs/analys_conj/archives/december2008_d1.pdf

Table 1: Descriptive statistics for GDP (1990-2009) as a function of the business climate index (ICA)

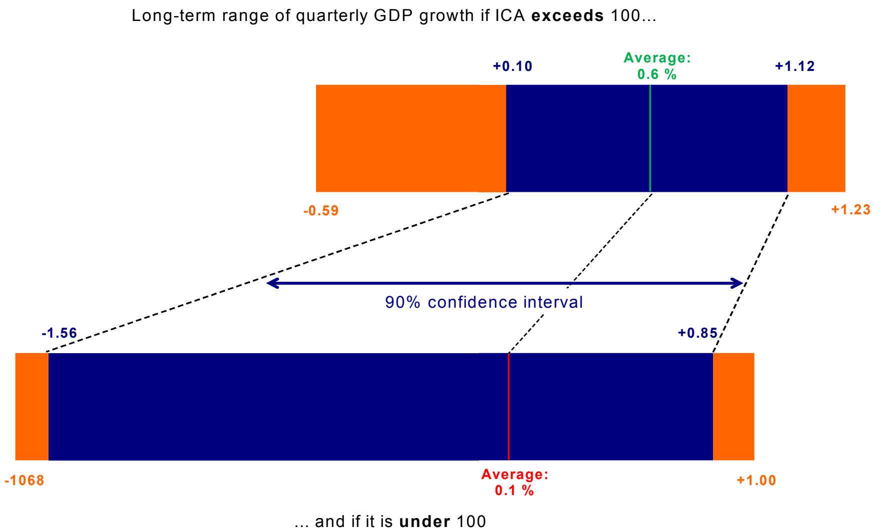
	Observations	Average	Standard deviation	Inter-quartile deviation
GDP	80	0.38	0.52	0.58
if the ICA is running at or above its long-term average...	***44***	***0.60***	***0.35***	***0.43***
... and its variation is positive or zero	26	0.73	0.26	0.35
... and its variation is negative	18	0.43	0.38	0.39
if the ICA is running below its long-term average...	***36***	***0.11***	***0.58***	***0.61***
... and its variation is positive or zero	17	0.42	0.30	0.52
... and its variation is negative	19	–0.18	0.63	0.67

Source: INSEE.

2.2 However, the ICA-GDP link varies according to the position in the cycle

While the ICA provides a signal on economic activity, the link's precision varies according to the index level. When the index exceeds its long-term average, quarterly growth lies in a 1.8-point range between a negative 0.6% and a positive 1.2%. When the index is running below its long-term average, the range widens to 2.7 points, from a negative 1.7% to a positive 1.0%. In other words, the link between quarterly GDP growth and the business climate index seems weaker when the economy is in a downswing (chart 3).

Chart 3: Range of quarterly GDP growth (1990-2009) as a function of INSEE French business climate index (ICA)



How to read this chart: When the ICA was running above 100 between 1990 and 2009, GDP quarterly growth ranged between a negative 0.59% and a positive 1.23%. For 90% of the time, it ranged between 0.10% and 1.12%.

Source : INSEE.

2.3 By analyzing several survey waves, we can identify shocks on economic activity

The business climate index provides initial information on the level of activity at a given point in time. However, the ICA merely summarizes a larger information set. Business owners surveyed by INSEE give qualitative answers[5] to a very broad range of questions on variables such as recent business, business outlook, and order intake. To make the most of this information-particularly with regard to measuring short-term economic uncertainty-we can test whether business owners' responses are consistent over time. Specifically, the published balances of opinion make it possible to determine if the level of business reported by firms is in line with their earlier forecasts.

The opinion balance on recent business is strongly correlated with the personal outlook expressed in the past. This suggests that business owners are very good at predicting their business activity one quarter ahead[6] (in manufacturing, the correlation is 0.85). We can thus interpret the gaps observed as unexpected shocks, which can be described as "business-cycle surprises." Their magnitude is significant in cyclical turnarounds, whether at the start of a downswing (2001 and 2008) or at the start of an upswing (2010).

(5) More specifically, their responses fall into one of three categories: positive, neutral or negative. From these responses, INSEE calculates the difference between positive and negative opinions and publishes the balances.

(6) E. Michaux (2005), "Les anticipations des entrepreneurs industriels de la zone euro sont-elles rationnelles?," *Économie et prévision*, no. 168, shows that French manufacturers' personal forecasts are slightly biased. The inclusion of order intake would improve the forecasts of future production and provide a more accurate measure of the business-cycle surprise.

3. Quantile regressions allow a measurement of the effect of current economic conditions on the growth forecast

To quantify the level of uncertainty month by month and track its variation over time, we should:

1. use models whose forecasts are comparable month after month. This means that the data available at the end of the quarter should not be intrinsically more informative that those available at more distant horizons. As a result, any change in the forecast should be solely due to changes in the leading indicators (box 2).
2. use a modeling method whose estimate of uncertainty depends on the total information available-a condition that standard forecasting methods do not meet (box 1).

Box 2: **Constructing a calibrated model comparable month by month**

To obtain models supplying comparable information month by month, the first prerequisite is that the same variables must be used each month.

However, this condition does not suffice to ensure comparable forecasts. According to the survey methodology published by INSEE,[a] the questions asked in business surveys generally concern trends observed in the past three months. For instance, in the third month of the quarter, the balances used to construct the business climate index concern questions confined to trends observed in the quarter to be forecast. In the first month of the quarter, instead, the responses theoretically contain one month of information on the target quarter and two months of information on the previous quarter.

In this study, we assess models that comprise the following explanatory variables: the overall business climate index calculated by INSEE; its quarterly change; the "business-cycle surprise" for production deduced from the lagged opinion balances on the business outlook and the opinion balances on past production from INSEE's monthly survey of manufacturing; and the volatility of the CAC 40 (French blue-chip stock index).

If the wording of the questions modifies the scope of information available for each survey, then we could assume that the three monthly models shown in table 2 have predictive capacities that improve with each new published survey:

$$\Delta\ln(PIB)_t = \alpha_i + \beta_i ICA_t^i + \gamma_i \Delta ICA_t^i + \delta_i Surprise_t^i + \theta_i Volatilite_t^i + \varepsilon_t^i \quad \text{is month } i \text{ of } t$$

However, this intuition is invalidated by the test developed by Diebold and Mariano, which compares the quality of forecasts produced from these three models: empirically, the hypothesis that the three models have equal predictive performance cannot be rejected at a 95% confidence limit (table 2).

Table 2: Comparison of predictive performance of standard calibration described above at different forecast horizons

<table>
<tr><th></th><th>Month 1</th><th>Month 2</th><th>Month 3</th></tr>
<tr><td>Average (1)</td><td>−0.29</td><td>−0.34</td><td>−0.30</td></tr>
<tr><td>Standard deviation(2)</td><td>0.46</td><td>0.44</td><td>0.41</td></tr>
<tr><td>RMSE (3)</td><td>0.54</td><td>0.55</td><td>0.50</td></tr>
<tr><td>MAE (4)</td><td>0.39</td><td>0.39</td><td>0.38</td></tr>
<tr><td rowspan="2">Predictive capacity (5)</td><td colspan="2">−0.10</td><td></td></tr>
<tr><td></td><td colspan="2">0.30</td></tr>
</table>

Source : INSEE.

How to read this table: Statistics on predictive performance outside estimation period (1990-2005): (1) mean error; (2) standard deviation of errors; (3) square root of mean of quadratic errors; (4) mean of absolute errors; (5) statistic of test for equality of the models' predictive capacity. The capacity is deemed equivalent at a 95% confidence level if the absolute value of the statistic is under 1.96.

To ensure that any difference in the forecast can be explained by the short-term innovation of the leading indicators, we must also make sure that the parameters $\alpha_i, \beta_i, \gamma_i, \delta_i, \theta_i$ are equal in all months of the quarter. We verify this using a Wald test, which-with a 95% probability-does not reject the hypothesis of parameter equality.

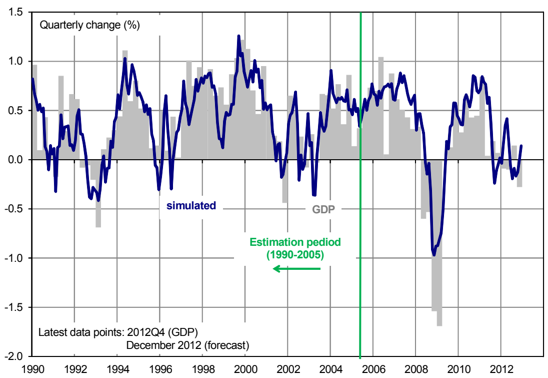
a. For example, for the survey of goods-producing industries: http://www.insee.fr/en/indicateurs/ind11/method_idconj_11.pdf

3.1 Forecasting models comparable month by month

We can construct a monthly model to forecast current-quarter growth from three explanatory variables: (i) the INSEE business climate index for France (level and quarterly changes), (ii) the "business-cycle surprise" observed in manufacturing, and (iii) the monthly volatility of the CAC 40. These explanatory variables are strongly correlated with economic activity, cyclical swings, and economic uncertainty (§2).

The coefficients' sign is consistent with intuition, as quarterly growth depends positively on the business climate and its quarterly change. A positive business-cycle surprise improves the growth forecast. By contrast, a rise in CAC 40 volatility cuts quarterly growth.

Chart 4: Fit of quarterly-growth forecast model



Source: INSEE, DG Trésor calculations.

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The model's statistical fit (chart 4) is satisfactory given the criterion chosen to select the variables.[7] This simple model explains 60% of the quarterly-growth variance. By comparison, Bessec (2010)[8] presents models that optimize the information content and explain 53% of growth variability in the first month of the quarter and 74% in the last month.

3.2 Models that can be extended to take better account of uncertainty

In recent years, statistical advances, greater data availability, and the improvement in computer processing power have fostered the emergence of a new modeling paradigm that makes it possible to estimate all plausible outcomes of a variable as a function of an information set. In particular, the quantile regression method (box 3) enables us to estimate all quantiles of quarterly growth distribution under fairly unrestrictive assumptions.

Box 3: **Quantile regressions**

The quantile regression method, developed from the seminal article by Koenker and Basset (1978),[a] provides information on the set of quantiles of a variable Y_t conditional upon the values taken by X_t.

The conditional quantile of order τ of the variable Y_t is defined as the value y for which there exists a probability τ of observing a lower value:

$$Q_\tau(Y_t|X_t) = inf(y; F_y(y|X_t) \geq \tau)$$

This quantity can be obtained from the following minimization problem (for a detailed technical discussion, see Koenker [2005]):

$$Q_\tau(Y_t|X_t) = \arg min E[\rho_\tau(Y_t - q(X_t))]$$

Where $\rho_\tau(u)$ is a function, called check function, that assigns asymmetrical weights to the errors, whether positive or negative:

$$\rho_\tau(u) = 1(u > 0) \cdot \tau \cdot |u| + 1(u \leq 0) \cdot (1 - \tau) \cdot |u|$$

However, this minimization exercise can prove complex if i X_t comprises many variables or if they are continuous. To simplify the procedure, the literature usually replaces $q(X_t)$ by a linear model that reduces the problem's dimensionality:[b]

$$\beta_\tau = \arg min_b E[\rho_\tau(Y_t - X_t'b)]$$

The estimator of $\hat{\beta}_\tau$ qthat minimizes the problem in the data sample available is obtained from the solution of a linear programming problem that is easy to achieve with current computing tools.[c]

Once all the conditional quantiles are known, we can thus find the conditional distribution thanks to the relationship linking the quantiles to a variable's distribution function:

$$F[Q_\tau(Y_t|X_t)] = \tau$$

a. R. Koenker and G. Basset (1978), "Regression quantiles," *Econometrica*, vol. 46, pp. 33-50.
b. J. Angrist, V. Chernozhukov, and I. Fernández-Vial (2006) show that this formulation will supply the best linear approximation available even in the presence of a specification error, i.e., when the "real" process linking the conditional quantile to X_t is not properly summarized by $q(X) = X\beta$.
c. The most commonly used statistical applications have a command for performing quantile regressions (for SAS, proc qreg; for Gauss, the Qreg library; for Stata, the qreg function).

The impact of the business climate index changes with the quantile. All other things being equal, the lowest growth outcomes are more sensitive to this variable than the higher-order quantiles. In other words, a decline in the ICA reduces the lower quantiles more steeply than the higher quantiles. This widens the range of possible growth outcomes, signaling a rise in uncertainty (table 3). This result is consistent with the findings of Bachmann, Elstner, and Sims (2010)[9] obtained from U.S. and German survey data, namely, that shocks on the economic activity level are associated with shocks on the uncertainty level. Similarly, stock-market volatility weighs more heavily on the low end of the distribution than on the top end, demonstrating that the risk of weak growth increases in periods of financial tension.

(7) Recall that the variables were chosen not to maximize the use of information obtained from surveys but to build efficient models whose forecasts are comparable across all forecast horizons.
(8) M. Bessec (2010), "Étalonnages du taux de croissance du PIB français sur la base des enquêtes de conjoncture," *Économie et prévision*, no. 193.
(9) R. Bachmann, S. Elstner, and E. Sims (2010), "Uncertainty and economic activity: evidence from business survey data," *NBER working paper*, no. 16143, June.

Table 3: Results of standard calibration estimates and quantile regressions for selected predetermined quantiles

	Standard calibration	Quantile 5	Quantile 50	Quantile 95
French business climate index (ICA)	0.26	0.35	0.21	0.20
	9.81	10.96	19.97	5.10
Quarterly change in ICA	0.43	0.60	0.35	0.25
	8.24	3.64	3.37	19.52
Business-cycle surprise (manufacturing)	0.04	0.04	0.06	0.03
	1.97	0.79	8.22	1.11
CAC 40 volatility	−0.02	−0.02	−0.01	−0.01
	−2.11	−1.01	−5.29	−29.34
Intercept	0.43	−0.13	0.42	0.89
	16.14	−12.85	10.35	39.84
R^2	0.60			
Observations	252 (1990Q1 - 2010Q4)			

Source: INSEE.

How to read this table: The value on the row of the variable name is the variable's coefficient in the equation. The value on the row below is the t-statistic of the coefficient's significance test. If the absolute value of t exceeds 1.96, the coefficient differs significantly from 0 with a 95% confidence interval.

4. An indicator to forecast uncertainty

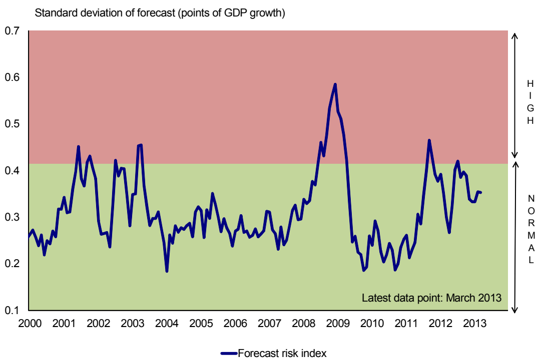
The information provided by the total probability distribution of quarterly growth is difficult to interpret as such, and it needs to be summarized. Following Cornec (2011), we choose to do so using the standard deviations of potential quarterly-growth outcomes obtained with quantile-regression estimates.

4.1 An indicator that supplements other measures of cyclical risk

During the model's estimation period (1990-2010), the indicator thus obtained displays a mean value of 0.31, a figure slightly higher than the uncertainty associated with the best forecast models in standard use. However, unlike the standard deviation of calibration-based forecasts, our indicator exhibits substantial fluctuations in response to current business conditions (chart 5).

The risk indicator's variations are correlated with other uncertainty indicators, particularly for the financial sector. For example, its contemporaneous correlation with the VIX stock-market volatility index is 0.56. However, stock-market volatility seems to precede the uncertainty estimated from the simple model. Under the often corroborated rationality assumptions, financial markets respond immediately to the news, whereas survey responses may be somewhat lagged, partly owing to the delay in transmission of shocks to the real economy.

Chart 5: Change in standard deviation of forecast, 2000-2012



Source: DG Trésor calculations.

How to read this chart: The forecast risk index measures the standard deviation of the distribution of plausible quarterly-growth outcomes obtained from quantile regressions. The index is regarded as moving into a high-uncertainty zone if it significantly exceeds its long-term level (0.31).

Moreover, the uncertainty indicator seems to anticipate the variations in yield spreads on ten-year government bonds between France and Germany. The economic uncertainty index for France constructed by Baker, Bloom, and Davis (2011)[10] responds with a three-month lag to changes in the uncertainty index derived from business surveys.

Table 4: Correlation of forecast risk index with other uncertainty indicators, 1997-2012

	Q-3	Q-2	Q-1	Q	Q+1	Q+2	Q+3
VIX (US)	0.35	0.47	**0.56**	**0.56**	0.50	0.45	0.41
CAC 40 volatility	0.35	0.44	**0.46**	0.44	0.27	0.22	0.22
France-Germany spread (10-year)	0.25	0.29	0.32	**0.34**	**0.34**	**0.34**	0.33
Spain-Germany spread (10-year)	0.16	0.19	**0.20**	**0.20**	0.19	0.18	0.16
France Uncertainty Index (Bloom et al.)	0.17	0.22	0.29	0.34	0.34	0.37	**0.40**

Source: INSEE.

How to read this table: The VIX index for Q-3 has a correlation of 0.35 with the uncertainty index for French GDP forecasts for quarter Q calculated from quantile regressions for Q.

4.2 Need for comparison with other indicators

While the forecast risk indicator obtained from business surveys is correlated with existing indexes, it offers the advantage of identifying uncertainty shocks on the real economy in real time. When we apply Zakhartchouk's method,[11] the shocks identified by our indicator are not identical to those captured by indexes responding only to financial-market tensions (table 5).

(10) For details on the construction of this indicator, see S. Baker, N. Bloom, and S. Davis (2011), "Measuring economic policy uncertainty," http://www.stanford.edu/~nbloom/PolicyUncertainty.pdf. The monthly observations for France are available at www.policyuncertainty.com.

(11) An episode is identified as an uncertainty shock if (1) the standard deviation exceeds a limit c chosen to reflect a historically rare level (5% significance limit) and (2) no episode of this kind has been observed in the past three months.

In particular, the indicator captures more uncertainty peaks than the financial variables do. Between 1990 and 2009, the indicator identifies twenty-nine months of uncertainty, versus only thirteen for the financial-market indicator. Moreover, these uncertainty peaks are more often associated with large forecast errors. For example, among the 10% largest forecast errors in absolute terms obtained with the calibration described in §3, the survey-based indicator would have flagged the high forecast risk in ten cases out of twenty-four, whereas the CAC 40 volatility would have done so only four times.

By contrast, our indicator identifies some shocks, such as the 2003 Iraq crisis, with a certain lag. According to the CAC 40 volatility index, the crisis impacted stock prices as early as January, whereas the indicator based on business surveys captures the shock in March. We observe the same lag when certain euro area countries experienced new financing difficulties in summer 2011.

During the 2008 crisis, the financial-market tension indicators fluctuated sharply in October. By contrast, the indicator described here identified the rise in uncertainty as early as June. The survey data were deteriorating since January. By June, the business climate index (ICA) was no longer running above its long-term average. The worsening of qualitative data is thus reflected in the identification of an uncertainty peak in June. Moreover, the indicator stayed in a high-uncertainty zone continuously between June 2008 and April 2009, signaling the persistence of economic tensions during the period.

More recently, the model estimated from quantile regressions flagged a steep rise in uncertainty in July 2012, followed by a gradual easing.

Table 5: Uncertainty shocks identified by each method, 1990-2011

DG Trésor using INSEE business and consumer surveys	INSEE "Conjoncture in France" using CAC 40 volatility	Cause	Type
	Aug. 1, 1990	Gulf War	Geopolitical
Oct 1, 1990		Social unrest (France)	Political
Feb. 1, 1991		Demonstrations in former Eastern Bloc countries	Geopolitical
Aug. 1, 1992		Monetary tension in Europe	Financial
Oct. 1, 1995		Start of social unrest (France)	Political
	Sept. 1, 1998	Russian crash	Financial
May 1, 2001		NASDAQ downswing	Financial
Sept 11, 2001	Sept 11, 2001	Terrorist attacks in U.S.	Geopolitical
July 1, 2002	July 1, 2002	Worldcom crisis	Financial
	Jan. 1, 2003	Iraq crisis	Geopolitical
March 1, 2003		Iraq crisis, social unrest	Geopolitical
	Oct 1, 2008	Brent crude oil hits $100/barrel	Oil
June 1, 2008		Fears of U.S. recession	Financial
	Oct 1, 2008	Lehman Brothers failure	Financial
	July 1, 2009	Uncertainty over recession	Financial
Sept. 1, 2011	Aug. 1, 2011	Euro area sovereign-debt crisis	Financial

Source: INSEE

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