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Partial stochastic analysis with the European Commission's version of the AGLINK-COSIMO model

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Acknowledgements

Building, maintaining and applying an integrated Modelling Platform for Agro-economic Commodity and Policy Analysis (iMAP) has since 2005 been a major project at the JRC-IPTS (AGRILIFE unit). The aim of iMAP is to deliver in-house policy support to the policy-making directorates of the European Commission.

In the process of developing the methodology described in this report, various iMAP team members have been involved. The report has also benefitted from methodological contributions from H. Gay (DG for Agriculture and Rural Development, European Commission). The authors are greatly indebted to G. Pilgrim for programming in TROLL and Microsoft VBA (Visual Basics for Applications).

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EXECUTIVE SUMMARY

Ex ante policy analysis explores the medium-term impacts of future policy changes, which are measured against a 'no-policy-change' reference scenario. The European Commission[1] publishes an annual medium-term outlook for the main agricultural commodity sectors, based on the partial equilibrium (PE) model AGLINK-COSIMO, which projects EU supply balance sheets (production, consumption, exports, and imports) 8-10 years ahead. These projections serve as the reference scenario for *ex ante* simulations of EU agricultural policy changes. Although the baseline is not a forecast, it is nevertheless often interpreted by policy makers and market analysts as an indication in its own right of the most likely future market trends. This report describes how the value of baseline information can be enhanced by setting it in a probabilistic context that recognises some of the risk and uncertainty underlying the projected values.

Projections obtained using a PE simulation model are conditional on the future values assumed for the variables that enter the model exogenously. These variables include some of the key drivers of market behaviour and are subject to considerable uncertainty. Partial stochastic analysis examines the sensitivity of future baseline projections to this uncertainty. It was already used in conjunction with the DG AGRI agricultural outlooks in 2011 and 2012 in order to assess the degree of sensitivity of the baseline projections to macroeconomic uncertainty and crop yield risk. This report presents the methodology underlying that analysis.

The approach reported here aims to quantify the extent to which the uncertainty surrounding selected exogenous variables affects the baseline projections of EU market and price developments, by providing the range of values within which medium-term outcomes may lie in a future year, given the typical uncertainty exhibited in the past by these exogenous variables. This information supplements the point estimate provided by the deterministic (non-stochastic) baseline, and allows the user to take into account the relative uncertainty of the different projected variables.

Introducing stochastic features into baseline projections has a relatively short history in large scale agro-economic models. Currently, there are only three large scale agro-economic modelling systems that have a stochastic functionality: FAPRI (FAPRI-UMC), ESIM (Hohenheim University-IPTS), and AGLINK-COSIMO (OECD-FAO). The detailed methodology described in this report and the range of applications used to illustrate it constitute the most complex and best documented account currently available of how this can be achieved.

Partial stochastic analysis can identify which baseline variables are more affected by the uncertainty relating to one or more exogenous variables (such as exchange rates or crop yield levels). It can also, in the case of a policy response that is triggered when a threshold is reached, estimate the likelihood that the trigger is activated even when the baseline value, which assumes future exogenous trends are known with certainty, may not lie in the vicinity of the policy trigger threshold. Partial stochastic analysis can also analyse the impact on the baseline of extreme, or rather unlikely, values of one or more exogenous variables. For example, the market analyst or policy maker may want to know how robust the baseline projection for medium-term grain prices is in the case of a joint occurrence of high crude oil prices and drought in major producing areas. Examples of all these policy-relevant applications of partial stochastic analysis are presented in the report. Finally, the stochastic analysis can occasionally reveal an inconsistency in model outcomes that suggest the need to re-specify one or more of the model equations themselves, thereby leading to an improved version of the deterministic baseline.

Limitations to this approach include its 'partial' nature, as it takes into account only the uncertainty in *specific external* factors as chosen by the analyst, and the fact that it ignores the uncertainty inherent in the way the model itself has been designed and parameterised. Furthermore, the applications presented in this report use estimates of the future variability in exogenous factors that are based on their variability in the past, whereas uncertainty in these variables might, for example, increase or become more correlated in the future. However, users of the methodology can provide their own prospective estimates of the future uncertainty

[1] Directorate-General for Agriculture and Rural Development (DG AGRI).

in exogenous variables. Indeed, the approach could be used to examine a range of alternative future uncertainty profiles.

The methodology used to undertake this analysis is detailed in Sections 4 and 5, with special attention to the underlying statistical assumptions, the data input used, and the software required.

In order to illustrate the technical potential of the approach and its capacity to supplement the deterministic baseline with additional information of high policy relevance, a number of simulation results are reported and analysed. The results are specific to the set of exogenous variables selected to be treated as uncertain, namely several indicators of EU macroeconomic performance (GDP, prices, exchange rate), the world crude oil price, and a large number of representative crop yields in 15 different countries worldwide. However, some results are striking and appear quite robust. First, the simulations show that crop yield uncertainty has a similar impact on EU and world producer prices, indicating a high degree of transmission of yield shocks, occurring worldwide, to EU prices via world market prices. Second, the impacts of the uncertainties analysed tend to accumulate in the projections of trade flows and in particular those of net trade, which reflects uncertainty not only in domestic supply and demand, and world market conditions, but also exchange rate variability. Third, among commodities, projections of EU production, prices and net trade for biofuels and cereals show particularly high rates of uncertainty, although the underlying reasons (analysed in the report) are different. In addition, the relative contributions of macroeconomic and yield uncertainty to total uncertain differs between these products, and across their market indicators (supply, price and so on) also show high rates of uncertainty.

The potential of the approach to provide information relating to policy or behavioural discontinuities and thresholds is illustrated by a simplified version of the EU's tariff rate quota (TRQ) arrangements for beef. According to the deterministic baseline, the TRQ is filled from 2017 onwards. However, the stochastic analysis shows that, when all the uncertainties analysed in the model are in operation, the probability that this TRQ is filled in 2017 is less than 50%, and that right up to 2022, this probability remains below 90%.

Finally, two scenarios featuring off-trend assumptions about EU economic growth are analysed. When lower-than-expected growth is combined with higher-than-expected crude oil prices, EU farm incomes are on average 16% below the level implied by the deterministic baseline. By contrast, when higher-than-expected EU growth occurs in conjunction with lower-than-expected crop yields in two major crops (EU common wheat and US maize, and hence in a greater number of crop yields that are historically correlated with these two yields), EU farm incomes are on average 7% higher than those of the deterministic baseline. The impact of these more extreme conditions on EU production reveals a mixed picture: in each scenario, supply of some products is below that of the baseline and of other products above that of the baseline. However, in the low growth scenario, EU producer prices are depressed well below baseline levels, whereas in the high growth scenario, EU prices are for the most part higher than those of the deterministic baseline by 10% or more. Thus, the impact on farm incomes of these two scenarios is dominated by price risk rather than quantity fluctuations.

The report shows the potential of this approach to enrich DG AGRI's outlook projections using information about the uncertain context in which EU agriculture operates. It is expected that increased familiarity of EU policy makers with the kind of results it can produce will further increase the policy-relevance of the uncertainties targeted and the specification of scenarios of interest. The contribution by JRC-IPTS, with results obtained by using this approach, to the 2013 OECD-FAO Outlook further demonstrates the proven interest and benefit of this approach to policy makers and stakeholders.

1. INTRODUCTION

The Directorate-General for Agriculture and Rural Development (DG AGRI) publishes an annual medium-term agricultural outlook for the main agricultural sectors (notably cereals, oilseeds, sugar, meat, dairy, and biofuels). It covers EU-wide projections of supply balance sheets (production, consumption, exports, imports, and change in stocks) for the following 8-10 years, based on the partial equilibrium (PE) model AGLINK-COSIMO (Tallard, 2006). The outlook projections serve as a reference for *ex ante* policy simulations.

Projections obtained using a PE simulation model are inevitably conditional on the values assumed for the variables that enter the model exogenously. These exogenous variables include some of the key drivers of market behaviour. Thus, such projections should not be taken as forecasts of future outcomes, but instead as a description of what may happen given a specific set of assumptions about future trends in these exogenous variables, which at the time of making the projections were judged the most plausible.

Given the uncertainty surrounding the exogenous trends that drive the model, it is very useful to conduct sensitivity analysis with respect to their assumed values. Stochastic partial analysis is one approach for doing so. This approach was used in conjunction with the DG AGRI agricultural outlooks in both 2011 and 2012 (European Commission, 2011, 2012) in order to assess the degree of sensitivity of the baseline projections to uncertainty in the macroeconomy and in crop yields. This report presents the methodology underlying that analysis.

The structure of the report is as follows. Section 2 explains how a stochastic approach to baseline modelling can be relevant for policy makers. Section 3 contains a brief review of stochastic modelling with large-scale agro-economic models. Sections 4 and 5 set out the methodology used by JRC-IPTS in order to apply stochastic concepts to DG AGRI's version of the AGLINK-COSIMO model[2] by incorporating both macroeconomic and crop yield uncertainties. Section 6 reports three applications of the methodology that illustrate the potential for this approach to add value to the traditional baseline projections by incorporating the uncertainty to which they are subject due to uncertain underlying assumptions. Section 7 contains conclusions and some caveats.

[2] The results of any analysis based on the use of the AGLINK model by parties outside the OECD are not endorsed by the OECD Secretariat, and the Secretariat cannot be held responsible for them. It is therefore inappropriate for outside users to suggest or to infer that these results or interpretations based on them can in any way be attributed to the OECD Secretariat or to the Member countries of the Organisation.

2. POLICY RELEVANCE

DG AGRI requires an annually updated, consistent set of deterministic projections of market and trade outcomes (called the 'deterministic baseline' in this report).[3] This baseline serves as the context for analysing medium-term market developments and policy changes. The baseline incorporates the assumption that current policies (of both the EU and other countries) and current international policy agreements will continue. Moreover, a single set of time series of projected exogenous macroeconomic variables and crop yields is used. For these exogenous variables, the most plausible and recent set of medium-term projections available is taken.

Although these exogenous medium-term projections are taken as given when constructing the deterministic baseline, it is recognised that they are subject to considerable uncertainty[4]. The uncertainty analysis undertaken at the JRC-IPTS aims to quantify to what extent the uncertainty surrounding these exogenous trends and assumptions affects the baseline projections of EU market and price developments.

Stochastic analysis of the deterministic baseline estimates a range of values within which a medium-term outcome may lie in a given year, given the extent of the uncertainty surrounding future values of one or more of the conditioning, exogenous variables. This information supplements the point estimate provided by the deterministic baseline, and allows the user to take into account the relative uncertainty of the different projections. For example, it shows which baseline variables are more affected by the uncertainty relating to individual conditioning values (such as exchange rates or crop yield levels).

Moreover, when the baseline is used for policy analysis, point estimates provided by the baseline may be insufficient and may even lead to inappropriate policy conclusions (Westhoff et al., 2006). This is particularly relevant if a policy is triggered when a variable exceeds or falls short of a fixed threshold (for example, a quota becomes binding when the ceiling is reached, or a farm payment becomes payable when market return falls to a given level). Although the deterministic baseline may provide a value for the variable concerned that is not in the vicinity of the policy trigger value, stochastic analysis can investigate whether, given the uncertainty affecting the exogenous variables, there is a possibility that the trigger could be activated, and what the likelihood is that this might occur.

A further interesting use of stochastic analysis is that it permits the formulation of what-if scenarios concerning the joint occurrence of specific ranges of values of exogenous variables, such as situations embodying extreme downside or upside risk, so that the consequences of these scenarios for baseline variables of interest can be examined. For example, the market analyst or policy-maker may want to know the consequences for grain prices in the medium term of a combination of high crude oil prices and drought in major producing areas. The deterministic baseline provides projections of grain prices assuming 'most plausible' future values of crude oil prices and average weather conditions. By contrast, stochastic analysis can show how different the market outcomes would be from the central value of the deterministic baseline in the more extreme scenario just described, while also providing an indication of how unlikely such a combination of events would be.

Examples of these three policy-relevant applications of partial stochastic analysis are presented in Section 6 of this report.

It is important to note that the main reason for running partial stochastic simulations is not to improve the projections of variables like macroeconomic conditions and arable crop yield trends that drive the model, but rather to investigate the degree of uncertainty in the baseline projections due to uncertainties in these underlying drivers. Moreover, from time to time, the stochastic simulations may reveal implausibilities in model outcomes that suggest the need to respecify one or more of the model equations themselves, thereby leading to a new version of the deterministic baseline. Such improvements in the properties of the behavioural properties of the model

[3] The baseline construction process is detailed in iMAP (2011). For the latest set of annual baseline results, see European Commission (2012).

[4] The projections are also conditional on the assumption that policies will remain unchanged in the medium term. Since policy changes correspond to discrete shifts in model structure and can usually be represented by a respecification of the model, it is more appropriate to analyse them using sensitivity analysis or scenario analysis rather than partial stochastic analysis.

are an additional —if occasional— benefit of undertaking stochastic analysis with a large-scale simulation model.

It should be borne in mind that there are significant limitations to partial stochastic analysis. Here, the three most important shortcomings are mentioned. First, it is 'partial' in the sense that it only takes into account the uncertainty in a chosen number of external factors. When interpreting the results, the reader should always relate the uncertainty reported for a particular baseline outcome to the uncertainty in the conditioning variables selected for the analysis. It would be erroneous to assume that all sources of uncertainty have been accounted for simultaneously, or that the range of plausible values corresponds to the maximum uncertainty present in the real world. Second, it does not analyse the consequences for the baseline outcomes of uncertainties inherent in the model, which is itself an approximation of reality. In particular, the model parameters are only estimates and some parameters may themselves be evolving over time, thereby becoming less accurate in the future. Thus, stochastic analysis is not an alternative to conducting sensitivity analysis of key behavioural parameters of the model. Third, the estimated variability in exogenous factors used for this report is based on their variability in the past, as is the extent of correlation between the variability in different exogenous variables. Both own variability and joint variability of these factors may change in the future. Of course, users of the methodology can provide their own prospective estimates of the future uncertainty in exogenous variables they are considered to be more 'realistic'. However, whatever view is taken of the future stochastic behaviour of the exogenous variables, it will inevitably be an assumption only. Given this, the approach described in this report could be used to examine a series of alternative assumptions about future uncertainty profiles.

3. LITERATURE REVIEW

The introduction of stochastic features into baseline projections and policy sensitivity analysis has a relatively short history in large scale agro-economic models. Until recently, applied partial equilibrium models of international trade in agriculture modelling were deterministic (van Tongeren and van Meijl, 1999). However, with growing instability in agricultural commodity markets and increasing uncertainty in the macroeconomy, several models have in recent years been extended so as to be able to take some of this uncertainty into account.

Currently, there are three large scale agro-economic modelling systems that have a stochastic functionality: FAPRI (FAPRI-UMC), AGLINK-COSIMO (OECD-FAO), and ESIM (Hohenheim University-IPTS).

In this section, we describe the general common approach taken in order to implement partial stochastic analysis in these three modelling systems. We also indicate a few differences between the models in the detail of their stochastic methodology.

All three models can analyse uncertainty in crop yields. In each case, deviations from trend as estimated from annual data on historical crop yields are used to represent the stochastic variability of yield. However, de-trending is performed at different levels of aggregation depending on the commodity and the coverage of the particular model.

A multivariate distribution is assumed to generate the stochastic components. For ESIM and AGLINK-COSIMO, a multivariate normal distribution of the stochastic error components is assumed and is parameterised using the variances and covariances of the historical yield deviations. In the case of FAPRI, an empirical multivariate distribution is fitted to the stochastic error components.

A number of random draws of correlated crop yields are made from these multivariate distributions using various techniques (Gaussian Quadrature[5] (ESIM), Latin Hypercube (FAPRI) and Monte Carlo (AGLINK-COSIMO)). These draws are then fed into the model, and the model is simulated the required number of times, each time with a different set of stochastic yields. In ESIM (Artavia et al., 2008), each crop yield is driven by input and output prices, but the small impact on output price caused by the stochastic yield shock does not cause any additional yield adjustment. AGLINK-COSIMO (Giner, 2011; Taya, 2012) assumes that yield trends and deviations from trend are not affected by input and output prices in their stochastic crop yield model. FAPRI's stochastic model draws on the error terms of a set of crop yield equations that do include input and output prices. Since input and output effects are relatively small, the error terms from the equations are very similar to the deviations from a simple trend. By contrast, the approach described in this report takes into account the contemporaneous impact of input and output prices (via the cost production cost index and producer prices) in the yield value, and hence allows an exogenous yield shock to have further indirect repercussions on the same yield (and other yields) that are transmitted via the endogenous variables in the yield equation.

FAPRI and AGLINK-COSIMO also perform stochastic analysis assuming uncertainty affecting other variables. The other stochastic variables in FAPRI are exogenous energy and cost variables, domestic demand and domestic stockholding, and trade in the rest of the world (captured by reduced form equations for the rest of the world trade). Having derived the joint distribution of these variables, stochastic analysis performed with FAPRI is based on joint draws from this multivariate distribution of exogenous values for prices of crude oil and natural gas, fuel costs, seed costs and labour costs. On the demand side, FAPRI has three groups of stochastic variables. The errors on key elements of domestic demand are drawn from a joint empirical distribution that maintains historical relationships unexplained by price

[5] In order to save computing capacity and time, the Gaussian Quadrature (GQ) approach is used. GQ is a convenient method to approximate multivariate integrals accurately while requiring a small number of evaluations of the integrand as compared to Monte Carlo method (Arndt, 1996).

and income movements. Stocks or carry-over quantities are drawn from joint distributions to ensure that historic relationship among crops are preserved, and are drawn separately from the other demand components. Uncertainty regarding foreign demand, which affects the reduced form trade equations, is due only to uncertain exchange rates. The equation for a given commodity —and hence its unexplained stochastic component— takes into account all variations from the world area, including yields, exchange rates, demand shocks and other factors that affect US trade in that commodity.

The macroeconomic stochastic analysis performed so far with the AGLINK-COSIMO model (Giner, 2011; Taya, 2011) was based on a simple macroeconomic model of changes in the GDP index and consumer price index of the large economies (Brazil, China, European Union, India, Japan, Russia and the US). The functional relationships in that model aim to capture how a shock in one of the above macroeconomic variables in one country is transmitted to the other macro variables across countries, and to future periods via lagged effects. The error terms of each equation were used to construct a joint distribution of these macroeconomic shocks. AGLINK-COSIMO was then run 150 times using random draws from this joint distribution in conjunction with stochastic draws of crude oil prices taken from a truncated normal distribution.

4. METHODOLOGY FOR ANALYSING MACROECONOMIC UNCERTAINTY

The Commission's annual baseline simulations are based on assumptions about macroeconomic conditions and arable crop yields[6]. The macroeconomic assumptions are derived from several sources, mainly the Commission's own macroeconomic model operated by the General Directorate for Economic and Financial Affairs (DG ECFIN) and projections made by Global Insight. The arable crop yields are assumed to evolve according to trend. The crop yield trend equations, whose empirical content has been supplied from various sources, are themselves part of the AGLINK-COSIMO model.

As with all medium-term projections, these trend projections ignore any short-term fluctuations that might be caused by unusual weather conditions, animal or plant disease outbreaks, or sudden market disruptions of any kind. Thus, the baseline projections based on these assumptions also depict rather smooth market developments, while in reality agricultural markets tend to move along a more uncertain path.

The main objective of the uncertainty analysis is to assess and quantify how uncertainty surrounding the assumptions about the general macroeconomic setting (including the crude oil price) and crop yield levels might affect the projected agricultural market developments, and in particular the extent to which this exogenous uncertainty is transmitted to various elements of the baseline projections.

'Uncertainty analysis', understood in its broadest sense, is carried out at the JRC-IPTS using four agricultural sector models, namely the Commission's updated and augmented AGLINK-COSIMO, CAPRI and ESIM, and a general equilibrium model, MAGNET. However, only AGLINK-COSIMO and ESIM can be used for partial stochastic analysis. CAPRI and MAGNET approach the analysis of uncertainty via more traditional sensitivity analysis. This report focuses on the implementation of partial stochastic analysis in AGLINK-COSIMO, in the context of preparing the annual agricultural outlook.

As part of the outlook preparation in 2011 and 2012, DG AGRI's updated and augmented AGLINK-COSIMO model was used to undertake stochastic analysis based on uncertain arable crop yields and macroeconomic variables. Yield uncertainty clearly affects the supply side of agricultural markets, and is transmitted from crop products to livestock supplies via animal feed costs. As for macroeconomic uncertainty, it is well recognised that the outlook for EU agricultural markets is subject to a number of uncertainties related to macroeconomic assumptions, which are exogenous with respect to the agricultural markets and trade flows themselves. Uncertainty from this source can affect both the demand side of agricultural markets, and also the supply side if macroeconomic conditions affect input costs.

This section outlines the stochastic analysis methodology used for exploring the implications of uncertainty regarding macroeconomic assumptions for the baseline projections, and in particular for assessing the degree of transmission of this uncertainty to the baseline projections of EU agricultural market and price projections.

4.1 EU macroeconomic variables treated as uncertain

The macroeconomic setting plays a key role in the agricultural baseline for various reasons. For example, EU competitiveness on world markets varies with exchange rates, aggregate food demand is linked to total household income and the incentive to produce biofuels partly depends on the crude oil price.

For the exercise reported here, partial stochastic analysis of the macroeconomic environment is undertaken with respect to eight key variables:

- EU-15 and EU-N12 real Gross Domestic Product (GDP), expressed as an index, which is also used as a proxy for consumer income;

[6] For more details, see European Commission (2012).

- EU-15 and EU-N12 Consumer Price Index (CPI), expressed as an index. It measures changes in the price level of consumer goods and services purchased by households and it is used to deflate nominal consumer prices;

- EU-15 and EU-N12 Gross Domestic Product Deflator, which is used as a proxy for economy-wide inflation;

- the exchange rate of the euro against the US dollar (EUR-USD), expressed as the amount of dollars bought by one euro, which reflects fluctuations in relative competitiveness; and

- the world oil price, which is the Brent crude oil price in USD per barrel.

In the analysis reported here, macroeconomic uncertainty in non-EU countries is ignored, apart from the endogenous impacts on these countries produced by different assumptions about the eight macroeconomic variables listed above. However, non-EU macroeconomic uncertainty could easily be incorporated on request.

4.2 Quantification of uncertainty in macroeconomic variables

In order to perform stochastic simulations involving uncertainty in the macroeconomic variables listed above, a joint distribution of the deviations around the projected trends for these variables is needed.

DG ECFIN publishes its main economic forecasts in the spring and autumn of each year, preceded by more concise, interim forecasts several weeks earlier[7].

We used the errors in the 18-month-ahead forecasts as the basis for calculating the variability in the macroeconomic variables listed.

Figures 1 and 2 illustrate this calculation using the Brent oil price forecast, outturn and forecast error (= outturn minus forecast) as an example. The same treatment was applied to DG ECFIN's forecasts of all the eight variables listed above, using forecast errors from 2000 to 2011.

The next step involved estimating the joint probability distributions of the forecast errors. Assuming no data or model limitations, it would be desirable to estimate the empirical probability distributions of the chosen macroeconomic variables. However, in this case it was not possible to do so because the available time series are too short (2000-2011). Therefore, it was simply assumed that the distribution of the macroeconomic forecast errors follows a known functional form, the normal (Gaussian) distribution. This means that the possible outcomes of each variable are assumed to be distributed symmetrically around a central most probable value, with those closer to the centre being more likely than those further away[8]. The extent of correlation between the forecast errors of the eight variables was also established empirically, and a multivariate normal distribution of the eight was established.

The use of empirically based correlations between forecast errors of different variables implies that some combinations of variable forecasts may be virtually impossible. For example, if the forecast errors for the GDP and CPI deflators have a high positive correlation, the probability of the occurrence of a value for the GDP deflator that is well above the central projection with one for the CPI deflator that is well below it is very small.

Figure 1. Brent crude oil price: Forecast and out-turn (USD/barrel).

Figure 2. Brent crude oil price: Forecast error (USD/barrel).

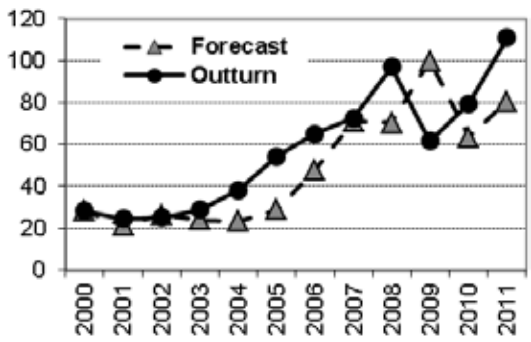

Figure 1.

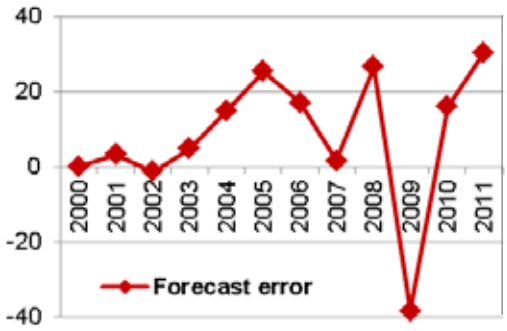

Figure 2.

[7] An index of past economic and interim macroeconomic forecast are available via the link below: http://ec.europa.eu/economy_finance/eu/forecasts/index_en.htm

[8] Statistical tests for normality were conducted. In 50 out of 54 cases, normality was not rejected at the 1% significance level, and in 43 out of 54 cases, normality was not rejected at the 5% significance level.

Table 1. Correlation matrix for stochastic macroeconomic forecast errors

	EU-15 real GDP	EU-12 real GDP	EU-15 GDP deflator	EU-12 GDP deflator	EU-15 CPI	EU-12 CPI	Brent crude oil price	EUR-USD exchange rate
EU-15 Real GDP	1.00	**0.58**	**0.41**	**0.62**	**0.62**	**0.49**	**0.66**	-0.10
EU-N12 Real GDP		1.00	-0.04	**0.41**	-0.05	0.12	0.04	-0.14
EU-15 GDP deflator			1.00	**0.47**	**0.59**	**0.39**	**0.54**	-0.20
EU-N12 GDP deflator				1.00	**0.52**	**0.80**	**0.42**	**-0.46**
EU-15 CPI					1.00	**0.81**	**0.87**	-0.19
EU-N12 CPI						1.00	**0.58**	**-0.38**
Brent crude oil price							1.00	**-0.33**
EUR-USD exchange rate								1.00

Table 1 shows the upper triangle of the 8x8 correlation matrix for the eight macroeconomic forecast errors. The correlations displayed in bold are significantly different from zero at the 30% significance level. Although 8 of the 28 correlations are not significant at the 30% level, *all* estimated correlations were used regardless of their significance level when drawing a set of correlated errors from the multivariate error distribution, since they are the 'best' estimates available. It should be noted that correlations that are insignificant at the 30% level are also relatively small, so in this case it makes little difference whether they are set to zero or not.

A 'draw' consists of a set of errors from the 8-variable multivariate normal distribution, generated in accordance with the estimated variances and covariances of the eight forecast errors, and assuming that the mean forecast error is zero (i.e. each year's forecasts are assumed to be unbiased at the time they are made).

In the next stage, stochastic terms were drawn 500 times[9] for each year of the projection period using the Latin Hypercube technique in the software programme SIMETAR, an Excel add-in developed by Texas A&M University (Richardson et al., 2008)[10]. The Latin Hypercube sampling technique divides the cumulative density function of a given probability distribution into *N* equal intervals on the probability scale between zero and one, *N* being the number of iterations to simulate. One random draw is then made from each of the *N* intervals. This stratified approach recreates the probability distribution with fewer iterations than required by Monte Carlo sampling.

Using these stochastic draws, 500 alternative projections of the eight uncertain macroeconomic variables were then generated for each year (t,..., $t+n$) of the projection period. It was assumed that the stochastic errors are independent between years, hence no serial correlation is allowed for[11]. The following calculation was used to derive the time series data for the eight macroeconomic variables over the projection period:

$$y_t = b_t + e_t \tag{1}$$

$$y_{t+1} = \frac{b_{t+1}}{b_t} y_t + e_{t+1} \tag{2}$$

$$y_{t+2} = \frac{b_{t+2}}{b_{t+1}} y_{t+1} + e_{t+2} \tag{3}$$

[9] The total number of draws, 500, follows the precedent set by FAPRI (2004, 2006). The number of runs could, of course, easily be increased.

[10] The alternative of Monte Carlo sampling was also available. These two techniques differ in the number of iterations required until sampled values approximate input distributions, with Monte Carlo sampling generally requiring a much larger number of draws to approximate a normal distribution. Therefore, the Latin Hypercube was preferred.

[11] No tests were performed, as the time series of historical forecast errors is too short. Inspection of the correlograms of all the estimated errors suggested stationarity, except possibly for the EU-N12 GDP deflator. All the stochastic errors are assumed to be stationary.

$$y_{t+3} = \frac{b_{t+3}}{b_{t+2}} y_{t+2} + e_{t+3} \quad (4)$$

and, using backward substitution,

$$y_{t+n} = \frac{b_{t+n}}{b_t} y_t + b_{t+n} \sum_{i=1}^{n} \frac{e_{t+i}}{b_{t+i}} \quad (5)$$

where y is the new exogenous macroeconomic projection, b is the baseline projection, e is the forecast error and t is the first year of the simulation period. The assumption that the expected value of the forecast error is zero means that the change in the forecast macroeconomic variable is equal to the change in the deterministic baseline. Equation (5) allows the macroeconomic forecast errors to accumulate over time in a mechanistic way to reflect that the uncertainty of long-term forecasts is greater than for short-term ones. The forecast errors of the macroeconomic variables depend on the forecast horizon. Equations (1) to (5) imply that the variable projected in a given period equals its previous value augmented by the percentage change in the deterministic baseline plus the forecast error drawn for the current period.

The above procedure resulted in a set of 500 alternative macroeconomic baseline projections that lie within the boundaries of what might be possible, given estimates of past levels of uncertainty (based on eleven years of data) and the assumption that this degree of uncertainty applies to future forecast errors.

Inspection of the simulated marginal distributions of stochastic forecast errors (see Appendix A) shows that the distributions for real GDP deflator, GDP deflator and the CPI are relatively small compared to those of the exchange rate and the Brent crude oil price. Consequently, the spread of (future) possible projected values of the EUR-USD exchange rate and the oil price, or in other words, the uncertainty inherent in the exogenous projections of these variables, is much larger than the uncertainty relating to real GDP, the GDP deflator and the CPI.

Forecasting exchange rate fluctuations and oil prices is very difficult. Meese et al. (1983) showed that fundamentals-based exchange rate models fail to outperform random-walk models. Similarly, oil market forecasting is fraught with problems. In relation to forecasting oil supply, Lynch (2002) highlighted the inability of forecasters to perceive, let alone correct, their errors. He considers that this partly reflects the self-interest and wishful thinking of practitioners. Chen et al. (2008) and Rogoff and Stavrakeva (2008) provide more recent evidence on the difficulty of forecasting these complex and volatile variables. Given this background, it is not surprising that in the work reported here the variance of forecast errors for the Brent crude oil price and EUR-USD exchange rate are considerably larger than those of the GDP deflator, real GDP and CPI.

The main statistic used here for assessing the impact of uncertainty on a particular simulated variable over the entire projection period is its average coefficient of variation (ACV). To obtain this statistic, a coefficient of variation (CV)[12] is calculated, for each year, based on the simulated values between the 10th and 90th percentiles, i.e. over the 80% 'central' values out of the total number of simulation runs for which the model solved[13], and ignoring the lowest and highest 10% of the spread of values in order to eliminate extreme outliers. These annual CVs measure the variability of the variable relative to its mean in the corresponding year. The average annual coefficient of variation (ACV) is calculated as the average of these annual CVs over all years within the projection period.

This statistic can be used both to measure the average intra-year variability of the exogenous variables over the entire period and the extent to which, during the period, uncertainty introduced into the baseline by these variables is transmitted to specific endogenous baseline variables that are simulated within the model.

The ACV should not be compared with the CV of the actual forecast errors during the period 2000-2011. The ACV is the average of a number of CVs, each based on *cross sectional* data between the 10th and 90th percentiles of the distribution in series of years, whereas the CV of the past forecast errors is based on one realisation per year over a given time period. The ACV contains no information about volatility (that is, fluctuations around trend *over time*), since no information on year-to-year movements has been used to construct it. Although the spread of the cross-sectional distribution of errors contains information about the potential *amplitude* of fluctuations in a volatile series, information about the cyclical behaviour of the variable in the time dimension would also be needed to establish the extent of volatility.

[12] The coefficient of variation is the standard deviation divided by the mean. As our analysis assumes the forecast errors follow a joint normal distribution, the marginal distribution of each forecast error is fully described by its first two moments, mean and variance.

[13] This may be less than 500.

Table 2. ACVs for macroeconomic projections, 2012-2022

	EU-15 real GDP	EU-12 real GDP	EU-15 GDP deflator	EU-12 GDP deflator	EU-15 CPI	EU-12 CPI	Brent crude oil price	EUR-USD exchange rate
ACV (2012-2022)	5.6	4.8	0.6	3.0	0.9	1.7	25.0	13.5

Table 2 summarises the ACVs of the eight macroeconomic variables projected over the period 2012-2022 according to equations (1) to (5).

The outer extremes of the spread of a simulated variable in each year indicate the range of possible values in that year, given the uncertainty involved. Figures 3 to 7 depict these ranges for the eight exogenous macroeconomic variables that are treated as uncertain in this study, where the most extreme lower and upper values have been removed and the spread between the 10th and 90th percentiles is shown[14].

In most cases, the 10th and 90th percentiles evolve over the projection period in a way that is symmetric around the deterministic baseline. However, in Figures 3 and 4, which show the spread of uncertain values for the Brent crude oil price and the EUR-USD exchange rates, the 10th and 90th percentiles are not equidistant the from deterministic baseline. This asymmetry reflects the fact that in the historical period, from which the forecast errors used to derive the stochastic distributions are taken, these two variables tended to be underestimated. Thus, in both cases, there is greater uncertainty concerning possible values above the value used in the deterministic baseline than for values below.

By 2022, the 90th percentile of the world oil price projections reaches 190 USD per barrel whereas the 10th percentile is below 50 USD per barrel (see Figure 3). This wide spread reflects the extreme uncertainty about this variable, which cumulates over time thereby creating a widening distribution of plausible crude oil prices.

Regarding the EUR-USD exchange rate, the 90th percentile in 2022 of 2.1 indicates a very large appreciation of the Euro relative to the US dollar (Figure 4). This would lead to a worsening of the terms of trade, higher commodity imports, lower exports from the EU, and hence a deteriorating trade balance. However, the value of the 10th percentile (1.00) would mean a significant depreciation of the Euro relative to the USD, which would improve EU competitiveness. It is interesting to note that over the entire period, parity between the US dollar and the Euro does not fall within the 80% central values of the simulations for 2013-2021, and occurs with a probability of just 10% only in 2022.

The spread of possible values around the baseline for the other six macroeconomic variables treated as uncertain in this study is in each case much narrower and evolves in a way that is symmetric around the baseline (Figures 5 to 7).

The 500 sets of macroeconomic projections are then run through the AMI (AGLINK-COSIMO Model Interface), a graphical user interface developed at the UK Department for Environment, Food and Rural Affairs (DEFRA) for documenting and simulating models written in TROLL[15] in order to perform stochastic simulation of the baseline[16].

Typically, the model will not solve for every one of the 500 macroeconomic data sets input into AGLINK-COSIMO[17]. In the present study, when the only source of uncertainty injected into the baseline concerned the macroeconomic projections, the model solved in 495 (99%) of the 500 runs. When only uncertainty in yields was analysed, the solution rate was 94.4% (472 runs). When the 500 sets of macroeconomic projections were combined with the 500 sets of projected yields in order to analyse macroeconomic and yield uncertainty together, the model solved in 93.4% (467) of the 500 runs.

[14] Future work will consider whether it makes any difference if potential outliers are dealt with by assuming the stochastic deviations follow truncated joint normal distributions. Clearly, the extent of the truncation assumed will affect the results.

[15] TROLL is an integrated software system for econometric modelling and statistical analysis.

[16] JRC-IPTS has adapted and extended this software to enable the stochastic simulations presented in this report.

[17] When uncertainty is allowed for and an extreme exogenous values is used, there is a possibility that the model is pulled right outside the solution space for one or more years, and hence the simulation does not complete.

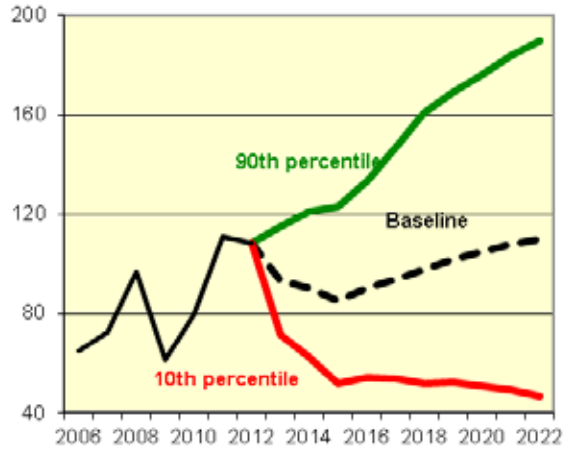

Figure 3. Brent crude oil price, USD per barrel

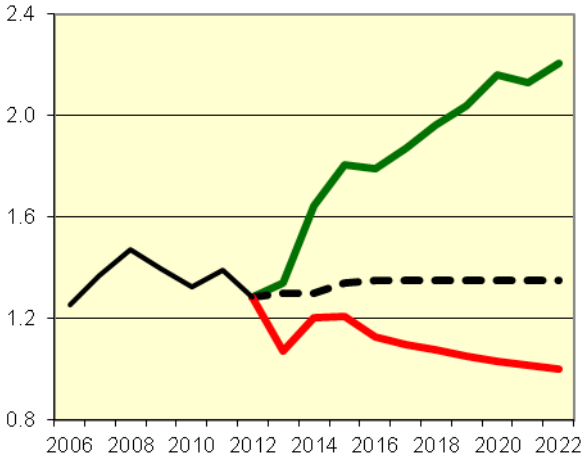

Figure 4. EUR-USD exchange rate

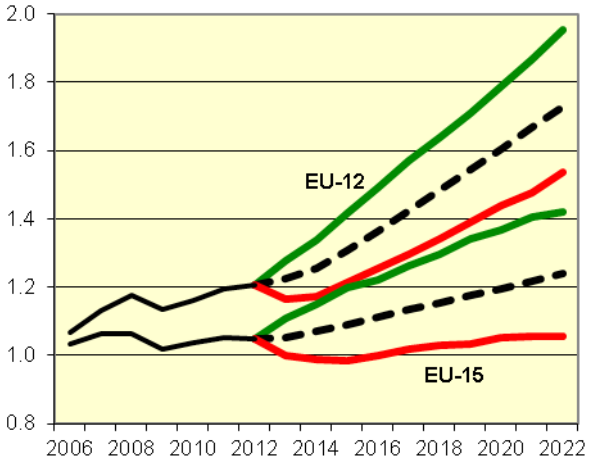

Figure 5. EU real GDP index (2005=1)

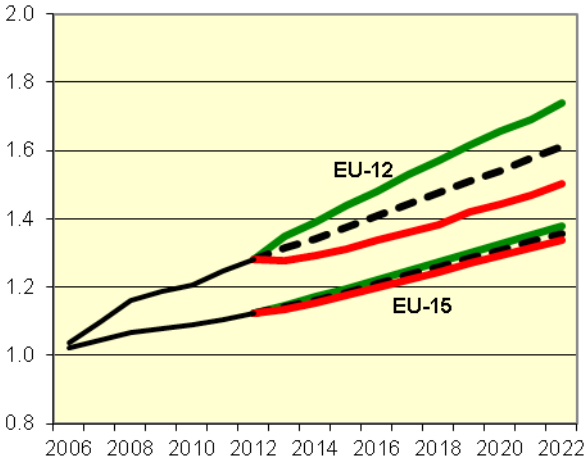

Figure 6. EU real GDP deflators (2005=1)

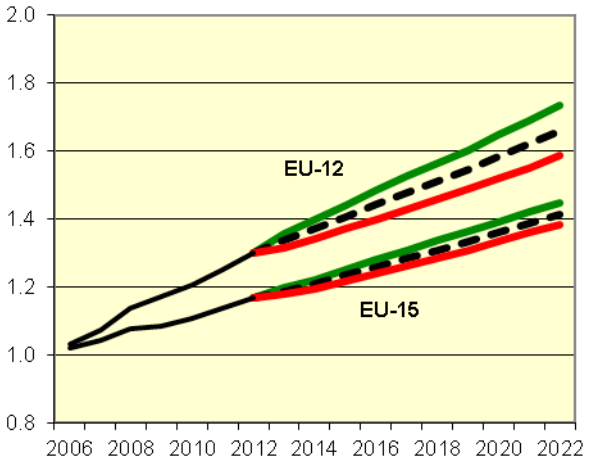

Figure 7. EU Consumer price index (2005=1)

5. METHODOLOGY FOR TREATING UNCERTAINTY IN ARABLE CROP YIELDS AROUND THE WORLD

Much of the variation around trend in crop production and market prices observed in the past can be explained by variations in crop yields, a significant part of which is due to weather fluctuations. Partial stochastic simulation translates crop yield uncertainty into uncertainty regarding projected market supplies and prices. Analysis of past crop yield fluctuations around the estimated trend in crop yields, together with the assumption that this pattern of variation will persist in the future, permits probabilistic limits to be fixed around the European Commission's agricultural baseline projections of production and prices that take uncertainty in yields into account.

5.1 Quantification of uncertainty in arable crop yields

The cereals sector in AGLINK-COSIMO covers supply, demand, net trade, stocks and price linkages between biofuel feedstocks and biofuel production. Crop production is the product of area harvested and yield per hectare. For each crop, the area harvested is a function of return per hectare, return per hectare of competing and joint crops, cost of production index, government policies and a trend. Crop yields, which are modelled by double-log functions[18]. depend on lagged own price, cost of production index, government payments and trend. Following FAPRI (2006) and Strauss and Meyer (2010), JRC-IPTS has augmented the European Commission's version of the AGLINK-COSIMO model, developed and maintained by OECD and FAO, to enable partial stochastic simulation of the crops discussed above.

The first step in performing stochastic simulations of crop yield uncertainty involves separating the stochastic and non-stochastic elements of crop yields. There are three approaches for separating out the stochastic components of a random variable: (a) when the series is stationary: take deviations from the mean or, when it is trended, take deviations from a time trend; (b) when some of the total variation in the variable can be explained by other variables: use regression or time series techniques that identify this systematic variability and remove it from the observations; (c) when equations for yield already exist as part of a simulation model: calculate the deterministic component using these equations and subtract it from the observations. The third approach is adopted here, using elasticities from the AGLINK-COSIMO database.

In AGLINK-COSIMO, production of each commodity is modelled as area harvested x yield, and a typical yield equation is specified as in (6):

where *PP* is producer price per ton, *EPA* (also in money units per ton) reflects all government payments based on yield, *CPCI* is the commodity producer cost index for the crop concerned, *t* is a time trend, and *r* is a calibration term. The subscript *c* identifies each crop and the superscript *i* represents the country or region. The parameters $(\beta^i_{1c}, \beta^i_{2c}, \beta^i_{3c}, \beta^i_{4c})$ are derived from a variety of sources.

The stochastic component in yield is calculated as

$$\ln(e^i_{c,t}) = \ln(YLD^i_{c,t}) - \ln(\hat{YLD}^i_{c,t}) \qquad (7)$$

where the error term, *e*, picks up the deviation between observed yield and the modelled yield (corresponding to the expected yield in normal weather conditions). This variable measures the historical forecast error, capturing the impact on yield of unusual weather conditions and any other random factors that cause yield to deviate from the value given by the deterministic yield equation plus calibration term.

$$\ln(\hat{YLD}^i_{c,t}) = \beta^i_{1c} + \beta^i_{2c}\ln((PP^i_{c,t-1} + EPA^i_{c,t}) / (\beta^i_{3c}\ln(CPCI^i_{c,t}) + (1-\beta^i_{3c})\ln(CPCI^i_{c,t-1})) + \beta^i_{4c}t + \ln(r^i_{c,t}) \qquad (6)$$

[18] Hence the parameters in the yield equation are elasticities. Our approach assumes that these elasticities are known with certainty, thus ignoring that they are estimates.

A set of time series for *e*, for each crop and country or region in AGLINK, was calculated for the period 1993-2011 using data on yields, producer prices, commodity production cost indices and policy instruments for 54 country and commodity combinations provided by DG AGRI's updated and augmented AGLINK-COSIMO model[19]. The yield deviations derived in this way take into account endogenous input and output price effects for each crop, whereas the approach used by the OECD (Giner, 2011; Taya, 2012) measures the errors as deviations from a deterministic trend only.

In the AGLINK-COSIMO simulations, production of a particular crop is generated by multiplying yield per hectare (equation 6) and area harvested. The model generates internal market clearing prices for each commodity at country level (apart from Europe where prices clear at EU-27 level). Once these equations are expanded by adding the stochastic component *s*, uncertainty in crop yields is transmitted directly to internal market prices and indirectly to world price via changing trade flows. Each yield error also transmits uncertainty to output and prices the following year via lagged output prices in the yield equation.

Table 3. Normality tests for arable crop yield deviations, 1993-2011

Country/region	Commodity coverage and normality test[1] result	Correlated regional weather blocks
EU-15	Common wheat, durum wheat, barley, maize, oats, rye, rapeseed, sunflower seed** and sugar beet	European Union
EU-N12	Common wheat, durum wheat* barley, maize*, oats, rye, rapeseed, sunflower seed and sugar beet	
Kazakhstan	Common wheat and oilseeds	Black Sea
Russia	Common wheat, sunflower seed and sugar beet	
Ukraine	Common wheat**, coarse grains and oilseeds	
Argentina	Common wheat, barley, maize, sunflower seed, sugar beet and sugar cane	South America
Brazil	Common wheat, maize and sugar cane	
Uruguay	Common wheat** and coarse grains	
Paraguay	Common wheat, coarse grains and oilseeds**	
Mexico	Common wheat and maize*	North America
USA	Common wheat, maize, soybean, sugar beet, sugar cane*	
Indonesia	Palm oil	South East Asia
Malaysia	Palm oil	
Thailand	Sugar cane*	
Australia	Common wheat, barley, rapeseed* and sugar cane	Oceania

[1] Unless otherwise stated, the null hypothesis that these values come from a normal population is not rejected at the 5% significance level.

** The null hypothesis that these values come from a normal population is rejected at the 5% significance level but not at the 1% significance level.*

*** Null hypothesis that these values come from a normal population is rejected at the 1% significance level.*

The yield errors were adjusted so that they sum to zero over the historical period on which they are based (1993-2011). They were found to be uncorrelated from year to year[20]. In a few cases, yield errors were found to be trended. Where this occurred, the coefficient on the trend term (β^{i}_{4c}) was adjusted to make the forecast errors stationary. The constant term for each equation was then re-estimated to ensure that the left-hand side and the right-hand side of the yield equation are equal to each other.

[19] When data on a variable needed to calculate crop yield were not available for the entire historical period, they were replaced by an extrapolated linear time trend. In particular, this strategy was used for the cost of production commodity index for some arable crops.

[20] The Lagrange multiplier test was used to test for serial correlation. The Breusch-Pagan-Godfrey test failed to find evidence of heteroscedasticity.

Appendix B reports detailed statistics of annual global crop yields between 1993 and 2011. Based on a simple average of the annual interquartile range divided by the mean, North America and EU-27 have the least uncertainty in crop yields over the period, whereas the Black Sea region and South East Asia have the highest level of uncertainty. This may reflect regional differences in the prevalence of climatic shocks like floods, droughts and El Niño cycles in arable crop production as well as in their ability to implement strategies for mitigating such shocks.

Table 3 reports the results of tests for normality of the yield errors for the 54 area-specific crop yields that are treated as uncertain for this study. The table also shows the country and commodity coverage used in the global crop yield uncertainty analysis.

The selection of crop yields to treat as stochastic reflects the needs of the policy analyst or the subjective criteria of the modeller. It should be borne in mind when interpreting the illustrative examples given in the following sections that the selection made in this study ignores uncertainty in Canadian crop yields and some of the yield uncertainty affecting biofuel feedstocks (in particular, US, Brazilian and Argentine soybeans as well as Russian rapeseed[21]).

The vast majority of historical yield deviations were found to be normally distributed. However, EU-15 sunflower seed, Ukrainian and Uruguayan common wheat and Paraguayan oilseeds data do not support the hypothesis that the values come from a normal population. It should be noted that in all cases where normality is rejected, the volume of production for that commodity and country is less than five per cent of global production. For simplicity, therefore, it is assumed that crop yields are normally distributed in the projection period for all arable crops.

Contemporaneous correlation between the stochastic component of yields is allowed for within regional blocks (EU, Black Sea area, South America, North America, South East Asia and Australia) but not between these blocks. As with the macroeconomic stochastic elements, these correlations are based on past observed correlations between the deviations from 'expected values' in the series. Appendices C-H present these correlation matrices for yields within each of the six regional blocks. Whether or not the estimated correlation coefficient is significant at the 5% significance level is also indicated. For making the correlated draws, all estimated correlations are used regardless of their significance (that is, when the coefficient is not significantly different from zero at 5%, its estimated value is used rather than zero). As was done for the macroeconomic stochastic elements, the stochastic components of yield are assumed to be uncorrelated between time-periods.

5.2 Incorporating yield uncertainty into the baseline

After making the above adjustments, the software programme Simetar is used to obtain 500 independent draws per year of correlated values for the 54 stochastic crop yield variables. Given the assumptions made, it is not surprising that the level of crop yield uncertainty remains unchanged over the period up to 2022.

Two examples (EU common wheat and US maize) are reported below (Figures 8 and 9). The results indicate that the projected EU-15 common wheat yield is relatively more certain than that of US maize.

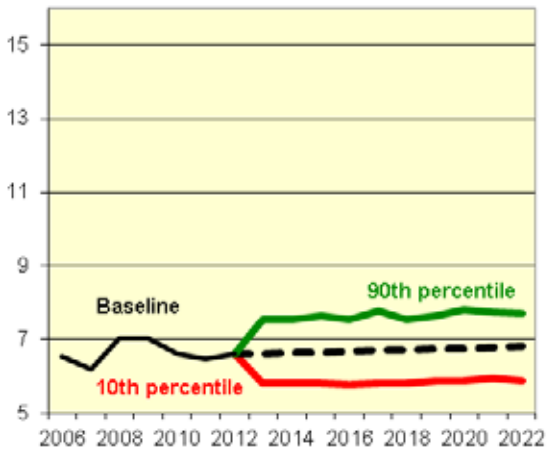

Figure 8. EU-15 Common wheat yield (t/h)

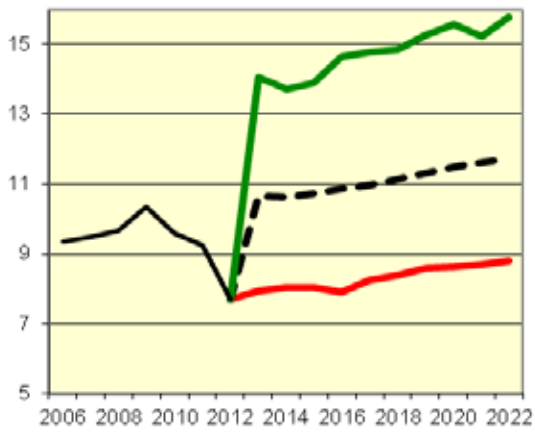

Figure 9. US Maize yield (t/h)

[21] By request, US, Brazilian and Argentine soybeans and Russian sunflower seed were treated as stochastic in the applications prepared by the authors for the 2013 OECD-FAO Agricultural Outlook.

The greater uncertainty in projected US maize yields could already be expected on the basis of the marginal distributions of the forecast errors for these two crops, which are displayed in Figures 10 and 11. Note that in Figure 11, the horizontal axis uses a smaller scale than in Figure 10. Both forecast errors are quite symmetrically distributed around their zero means, as is expected given the normality assumption. However, the tails of the US maize yield error distribution extend about twice as far either side of zero than those of the EU-15 wheat yield.

Table 4 summarises the ACVs for the 54 country-specific crop yield projections for the period 2013-2022. The projected yield uncertainty is much greater for most crops (the exceptions are rye and sugar beet) in EU-N12 than in EU-15. However, definitive conclusions on this cannot be drawn since not all major crops are shown. Crop yield uncertainty is on average very high in Australia for the crops shown. At first sight, yield uncertainty appears to be higher in the USA than in EU-15. However, projected uncertainty in these crops yields across all 27 EU Member States (a geographical area that is more comparable with the US in size) is probably similar to that of the US.

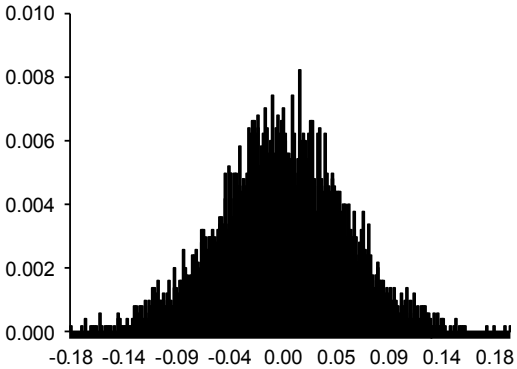

Figure 10. Marginal distribution of the forecast error for EU-15 common wheat yield[1]

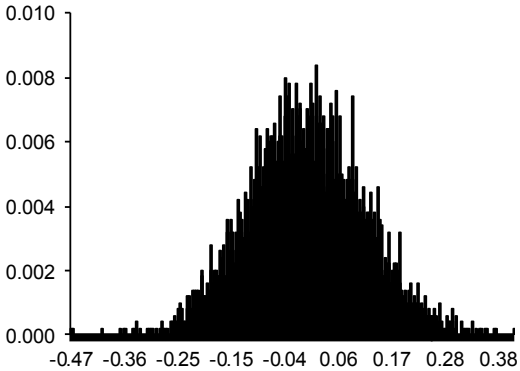

Figure 11. Marginal distribution of the forecast error for US maize yield[1]

[1] *The forecast errors are expressed in terms of the proportionate deviation of the forecast from the trend yield as used in the deterministic baseline.*

Table 4. ACVs of yield projections, 2013-2022

	Barley	Coarse grains	Common wheat	Durum wheat	Maize	Oats	Oilseeds
Argentina	30.7	6.2	13.9		14.4		9.4
Australia	58.0	20.5	69.8				11.9
Brazil		6.0	29.6		12.6		1.6
EU-15	6.6		7.0	12.2	8.1	6.7	3.6
EU-N12	10.9		15.3	19.3	26.4	12.5	9.0
Indonesia		0.4	0.4				0.5
Kazakhstan		0.3	30.4				37.0
Malaysia		0.5	0.4				0.5
Mexico	1.3	6.9	12.7		17.4		0.0
Paraguay		22.4	60.4				18.7
Russia	0.2	0.2	20.6		0.2	0.2	7.5
Thailand		0.5	0.4				0.4
Ukraine		22.0	33.0				25.1
Uruguay		27.2	39.6				0.4
USA	1.5	7.2	10.2		14.9	0.1	5.1

	Palm oil	Rapeseed	Rye	Sugar beet	Sugar cane	Sunflower seed
Argentina					25.7	17.3
Australia		39.0			14.1	
Brazil					4.8	
EU-15		9.4	16.0	9.3		11.5
EU-N12		14.4	10.9	5.2		34.3
Indonesia	11.8			0.1	0.2	
Kazakhstan				0.1		
Malaysia	6.6			0.1	0.2	
Mexico						
Paraguay				0.1	0.2	
Russia		0.1	0.1	21.4		20.7
Thailand				0.3	45.9	
Ukraine				0.1		
Uruguay				0.1	0.2	
USA				15.3	8.6	0.8

Five hundred draws of the yield errors from the region-specific multivariate distributions were incorporated into the yield equations of the model, and the model was solved for each configuration of yields. This yielded a set of 472 alternative sets of model solutions (for 28 draws, the model did not solve), which span the possibilities consistent with past levels of uncertainty.

In most cases, the 10th and 90th percentiles of the variables of interest evolve over the projection period in a way that is similar to their deterministic baseline. However, in some cases the introduction of stochastic yields leads to a spread of values between the 10th and 90th percentiles that is asymmetric with respect to the deterministic baseline. This occurs because of a regime-switching mechanism (i.e. moving between non-binding and binding biofuel mandates and tariff rate quotas), such that the 10th and 90th percentiles are not equidistant from deterministic baseline.

6. POLICY-RELEVANT APPLICATIONS OF PARTIAL STOCHASTIC ANALYSIS

This section presents a series of applications of partial stochastic analysis that supplement and add value to the deterministic baseline projections provided for DG AGRI's annual agricultural market outlook. The first application consists of a comparison of the consequences of EU macroeconomic and worldwide arable yield uncertainty, by projected outcome and by source of uncertainty, summarised for the entire projection period. This enables policy makers to see which variables and outcomes are more sensitive to the uncertainties analysed.

The second application illustrates how partial stochastic analysis can give a deeper and more nuanced account of likely market developments when markets are subject to limits, thresholds or discontinuities (often introduced by policies) that act as triggers for different behaviour or consequences depending on which side of the threshold the outcome falls. The example chosen concerns the likelihood of various TRQs for policy-sensitive commodities being filled during the projection period.

The third application looks at what-if scenarios involving combinations of several sources of uncertainty. A subset of the AGLINK simulations corresponding to specific situations concerning the underlying uncertain factors are analysed. Both of these scenarios involve off-trend assumption about EU growth; in the first, lower growth than expected in the EU is combined with a higher than expected oil price, whereas in the second, higher-than-expected EU growth is combined with yield-reducing drought in the EU and the US.

6.1 Relative impact of uncertainty on market outcomes by commodity and uncertainty source for EU-27

Table 5 summarises for the whole 2013-2022 period the average uncertainty in the projections of EU-27 yield, area harvested, production and use that is due to uncertainty in EU macroeconomic and global arable crop yield assumptions. In all cases, the total uncertainty from all these sources is less than the sum of the uncertainty due to macroeconomic factors and crop yields taken separately, which implies some netting-out of uncertainty impacts. At the same time, in most cases, the uncertainty from all sources is greater than that from macro or crop yields considered alone. It should be noted that with a relatively small sample size of 500 simulations there may be some anomalous results.

Arable crop yield: Macroeconomic uncertainty has virtually no impact on arable crop yield uncertainty. EU-27 milk yields are affected by both macroeconomic and arable crop yield uncertainty through variations in production cost, which is linked to oil price and producer price uncertainty, and uncertainty in ruminant feed costs via feed cost prices and depending on the proportions of different crops in ruminant feed rations. The degree of uncertainty in milk yields is relatively small compared to arable crops.

Area: The transmission of the uncertainty from macroeconomic assumptions is generally lower than transmission of arable crop yield uncertainty for area harvested. This is because returns per hectare to arable crops are more sensitive to yield-induced fluctuations (coming through both production volumes and producer prices) than to variations in costs triggered by macroeconomic uncertainty. The simulations suggest that adding macroeconomic uncertainty to arable crop yield uncertainty only marginally raises area harvested uncertainty, and that coarse grains is the least sensitive to macroeconomic uncertainty.

Table 5. Average coefficient of variation (%) (2013-2022) of EU-27 yield, area harvested, supply and use due to uncertainty in macroeconomic and global crop yield assumptions

	Yield			Area harvested			Production			Total use			Food use			Feed use			Biofuel use		
	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield
Cereals	3	0	3	1	0	0	3	1	3	1	1	0	1	0	0	2	2	1	7	3	6
Wheat	3	0	3	1	1	1	4	1	4	2	1	1	1	0	1	5	3	4	10	4	8
Coarse grains	3	0	3	0	0	0	4	0	4	1	1	1	1	0	1	1	1	1	8	3	6
Barley							3	0	3	2	0	2									
Maize							6	0	6	3	1	3									
Oilseeds	5	0	4	1	0	1	5	0	5	2	0	2	1	0	0						
Protein meal							2	0	2	1	1	1				1	1	1			
Vegetable oils							2	0	2	3	3	1	2	2	1				5	5	1
Ethanol							5	2	4	7	7	3									
Biodiesel							5	5	1	5	5	1									
White sugar																					
Meat							1	0	1	1	1	0	1	1	0						
Beef and veal							1	0	1	1	1	0	1	1	0						
Sheet and goat							1	1	0	1	1	0	1	1	0						
Pork							1	0	1	1	1	0	1	1	0						
Poultry							1	1	1	2	2	0	2	2	0						
Milk	1	0	1				1	1	1												
Butter							2	1	1	1	1	0	1	1	0						
Cheese							1	1	0	2	2	0	2	2	0						
SMP							7	6	3	1	1	0	0	0	0	1	1	1			
WMP							7	5	3	1	1	0	1	1	0						
Average	3	0	3	1	0	1	3	1	2	2	1	1	1	1	0	2	1	1	7	4	5

Production: Given that yields heavily influence production, crop production is more sensitive to global yield uncertainty than to macroeconomic uncertainty in Europe. The opposite is true for biodiesel, where the transmission of macroeconomic uncertainty (which includes uncertainty in the Brent crude oil price and exchange rate) to projected production is much greater than that of yield uncertainty since the incentive to produce biofuels depends strongly on the crude oil price. However, the ethanol results tell a different story. The EU is a major importer of wheat and maize as demand continues to outstrip domestic production. Given the strong transmission of uncertainty from arable crop yields to cereal producer prices, ethanol production is more sensitive to global arable crop yields than to EU macroeconomic uncertainties (and including uncertainty in the Brent crude oil price).

In the livestock sector, the picture is mixed. Beef and veal, and pork are more sensitive to crop yield uncertainty than to macroeconomic uncertainty, although even the yield uncertainty impact is very small. Sheep meat is more sensitive to macroeconomic factors than yield uncertainty because the feeding system is based on grass, whereas poultry is as sensitive to macroeconomic uncertainty as it is to that of arable crop yields. In all cases, the combined effect of macroeconomic and arable crop yields uncertainty is only marginally higher than that from each source separately.

In the dairy sector, the effect of macroeconomic uncertainty outweighs that of arable crop uncertainty. Skim milk powder (SMP) and whole milk powder (WMP) production are projected to have a higher level of uncertainty than the other dairy products. The simulations suggest that the uncertainties from the two sources are independent.

Total use: Total use of agricultural products consists of human consumption, animal feed and biofuel processing. The most uncertain baseline results are for biofuels and cereals followed by meats and dairy. The relative impact of the two sources of uncertainty on total use differs

according to the product. For broad commodity groups, with the exception of cereals, total use is more sensitive to macroeconomic uncertainty than to crop yield uncertainty. The uncertainty in total use can be broken down into food use uncertainty and feed use uncertainty. Less of the uncertainty from both sources is transmitted to food use than to feed use, given very low elasticities of food demand. Feed use is more sensitive than food use because there is more price-driven substitutability between animal feed ingredients than is the case for human consumption patterns. Most of the high level of uncertainty in biofuel use comes from macroeconomic factors (which in this study include the crude oil price). In the meat sector, poultry is the most sensitive to both macroeconomic uncertainty and uncertain crop yields, reflecting higher combined own-price, cross-price and income elasticities in the consumption equation compared to the other meats.

Table 6 summarises the implication of uncertainty from the two sources for baseline projections of EU trade flows, stock changes and prices over the whole projection period.

Exports and imports: Trade flows in both directions tend to be more sensitive to uncertain crop yields that to uncertainty in the macroeconomic factors analysed, the exceptions being poultry and dairy products, where the reverse is true. In the arable crop sector, exports and imports are more uncertain than production and total use. The story is mixed for biofuels. Biodiesel exports are less affected by uncertainty than their production and total use. However, biodiesel imports and both trade flows for ethanol are more uncertain than their production and total use. In the livestock sector, the small impact of uncertainty regarding sheep and goat trade flows reflects the fact that exports are to niche markets and imports are largely within TRQs. The transmission of uncertainty to world market prices for these products is also low.

Table 6. Average coefficient of variation (2013-2022) of EU-27 trade flows, stocks and prices due to uncertainty in macroeconomic and global crop yield assumptions

	Exports			Imports			Net trade[1]			Stocks			Consumer price			Producer price			World price in USD		
	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield	Macro & Yield	Macro	Yield
Cereals	23	5	22	28	11	26	79	16	80	3	1	3				16	12	11	11	4	10
Wheat	25	6	24	24	7	23	50	10	48	5	2	4	7	6	5	17	13	11	11	4	10
Coarse grains	26	6	23	37	16	33	89*	6	19	3	1	3				16	11	12	13	5	12
Barley	26	6	22	8	2	7	n.c.	n.c.	n.c.	3	1	3				17	11	12	13	5	11
Maize	27	9	25	39	17	35	n.c.	n.c.	n.c.	3	1	3				16	10	12			
Oilseeds	41	7	40	7	1	6	8*	1*	8*	1	0	1				16	12	11	13	5	12
Protein meal	5	2	5	3	1	3	3*	1*	3*	2	1	2				15	13	8	9	4	8
Vegetable oils	5	4	2	7	6	3	8*	7*	3*	2	1	1	8	7	3	12	12	4	5	4	3
Ethanol	10	9	3	25	20	13	26*	20*	14*				6	6	2	12	12	3	12	12	3
Biodiesel	3	2	1	10	9	4	11*	10*	4*				8	7	3	12	11	4	8	7	4
White sugar	24	10	20	10	5	8	50	23	40				4	3	2	12	10	6	5	4	3
Meat	8	7	4	6	6	3	17	14	8	1	1	1				12	11	5			
Beef and veal	4	2	3	10	7	7	35*	16*	33*	2	2	2	3	3	2	16	14	8	3	2	3
Sheep and goat	0	0	0	8	8	2	10*	9*	3*	0	0	0				12	12	2	3	2	2
Pork	7	4	5	8	7	4	7	4	6	0	0	0	3	3	2	10	9	5	6	3	5
Poultry	15	14	4	8	8	3	56	53	15	0	0	0	5	4	2	12	11	4	5	3	4
Milk																10	9	4			
Butter	19	17	8	16	11	10	29	26	13				6	6	3	9	8	4	5	4	3
Cheese	10	9	5	8	7	5	12	10	5	0	0	0	3	3	1	10	9	4	5	3	3
SMP	14	13	6	0	0	0	14	13	6				11	10	3	11	10	3	5	4	3
WMP	13	11	6	0	0	0	13	11	6				10	10	3	10	10	3	4	4	2
Average	15	7	11	13	7	10	8	7	10	2	1	2	6	6	2	13	11	7	8	5	6

n.c. Not calculated.

[1] *An asterisk in the net trade column indicates that the EU is on average a net importer of the product. Therefore, the uncertainty shown is relative to average net imports. Otherwise it is relative to average net exports.*

Net trade: The uncertainty in production and total consumption has implications for net trade, which is the difference between these two large aggregates, net of stock changes. Production of agricultural commodities is more affected by uncertainty than consumption; this is transmitted to the net trade figures, where it is magnified by being related (in the CV calculations) to the much smaller net trade average. For a number of commodities, when the full range of possible values around the deterministic baseline is taken into account, it is observed that EU-27 may be a net importer *or* a net exporter, both with non-zero probability. For example, for coarse grains, EU-27 is a net importer up to the 30th percentile of uncertain outcomes in 2014 and 2015, and again in 2017, whereas in 2016 EU-27 is still a net importer at the 40th percentile. In 2019 and 2020, EU-27 is still a net importer at the 60th percentile but not from the 70th percentile on, indicating that in these years there is still a probability of 30-39% of net-exporter status. In 2021 and 2022, this probability is 40-49%. By comparison, the deterministic baseline reports that EU-27 has net exporter status from 2013 to 2017, and net importer status from 2018 up to 2022. Moreover, the deterministic baseline figures for net trade are not close to zero in these years (which might otherwise signal caution in drawing conclusions from the baseline figures)[22].

The greatest implications for the baseline of the uncertainties studied here occur for net trade. The dominant source of uncertainty in the net trade projections depends on the product and on the direction of the flow. However, a simple average of the AVCs shows that the uncertainty transmitted from macroeconomic factors and crop yields is roughly the same. Combining the two sources of uncertainty is greater than the individual sources of uncertainty. Oilseeds are the most sensitive followed by cereals, white sugar and meats.

The degree of uncertainty in the 2013-2022 baseline of net trade is in some cases very large. For example, the variability of simulated net trade in coarse grains and poultry due to both sources of uncertainty is 89% and 56%, respectively. Poultry net trade is the most uncertain due to macroeconomic uncertainty alone, whereas net trade in common wheat is the most sensitive to global crop yield uncertainty alone.

In summary, the net trade uncertainty reported in the table reflects not only the cumulative uncertainty of projected supply and demand between 2013 and 2022 for each product but also the volume of average net trade itself, since the variability in the net trade flow is expressed relative to its mean. A strong conclusion can be drawn here: although the uncertainty in the macroeconomic and yield assumptions imparts a degree of uncertainty to virtually all the baseline projections, it is the trade flows and particularly the net trade projections that are the most uncertain as a result of uncertainty in these underlying assumptions.

Prices: For all the crops analysed, EU producer prices in euros and world market prices in US dollars have comparable levels of uncertainty due to crop yield uncertainty. This indicates that most of the global crop yield uncertainty is transmitted from world markets to EU market. However, this is not the case for macroeconomic uncertainty, which for this study has been limited to just eight variables, and ignores income uncertainty outside the EU. Not surprisingly, therefore, macroeconomic uncertainty has a greater impact on EU producer prices than on world market prices, especially since exchange rate uncertainty is allowed for. Therefore, yield variability is more important as a source of uncertainty for world market prices.

In general, EU producer prices for arable crops are more sensitive to uncertainty from both sources than are prices for other commodities. However, the relative importance of macroeconomic and yield uncertainty depends on the product. On average, the baseline price projections are more sensitive to macroeconomic uncertainty than to crop yield uncertainty. There is also greater differentiation between commodities regarding the transmission of uncertainty from crop yields compared with from macroeconomic factors, with arable crops having the largest uncertainty from this source, as would be expected.

For cereals, both sources of uncertainty are about equal. However, prices for oilseeds, biofuels, meats and dairy products experience greater uncertainty with respect to uncertain macroeconomic factors relative to arable crop yields.

The greater part of the uncertainty characterising EU producer prices for cereals, whether arising from uncertain macroeconomic assumptions or uncertain yield assumptions, is transmitted to animal feed costs[23] (see Table 7).

[22] The baseline figures for net trade for 2018-2022 inclusive are -1,762, -2,642, -3,093, -2,749 and -2,356 thousand tons, respectively, with the negative sign indicating net *imports*.

[23] In AGLINK-COSIMO, the feed indices cover compound feed only. The cost of feed components such as fodder and grass is disregarded in the production cost indices, although they are partly reflected, indirectly, in energy and labour costs.

Table 7. AVCs (2013-2022) of projected EU feed cost indices due to uncertainty in macroeconomic and global crop yield assumptions

	Macro & Yield	Macro	Yield
Non-ruminant feed			
EU-15	15	12	9
EU-N12	15	11	10
Ruminant feed			
EU-15	15	12	10
EU-N12	15	11	10

Yield-induced uncertainty in feed costs is greater for EU-N12 than for EU-15 because the degree of uncertainty in the yield assumptions themselves was estimated to be higher for EU-N12.

6.2 Thresholds, targets and discontinuities

Stochastic analysis of baseline projections can provide valuable supplementary information to the policy maker in situations where there are discontinuities, switching points or other kinds of threshold in the policy environment. Examples are policies that are triggered when a variable exceeds or falls short of a fixed threshold (such as a farm payment that becomes payable when market return falls to a given level) or measure whose parameters change beyond a fixed ceiling (such as a marginal tariff rate that changes from a lower in-quota rate to the higher MFN (most favoured nation) rate when a TRQ limit is reached). Although the deterministic baseline may provide a value for the variable concerned that is not in the vicinity of the policy trigger value, stochastic analysis can investigate whether, given the uncertainty affecting the exogenous variables, there is a possibility that the trigger could be activated, and what the likelihood is that this might occur.

With the abolition of EU milk and sugar quotas scheduled for 2015, there are currently no major EU policies that will be in operation for the entire projection period with which we can easily illustrate the potential for stochastic analysis to enrich the interpretation of the deterministic projections in such circumstances. This type of application is illustrated here using the example of EU market access for beef imports. However, it must be made clear from the outset that this example is for illustrative purposes only, as explained in the next paragraph.

The situation regarding preferential EU market access for beef is complex, characterised by a number of bilateral and multilateral TRQs, many of which are restricted to very specific grades or cuts of beef. This complexity is not modelled in AGLINK-COSIMO. Rather, ‚beef and veal' is treated as a homogeneous product both in domestic markets and in external trade. Moreover, AGLINK-COSIMO does not distinguish bilateral trade flows. Therefore, the beef TRQ as specified in AGLINK-COSIMO is merely the sum of the total quota volumes allocated for different kinds of meat and to various countries under existing TRQ arrangements. This simplified approach is adequate when the objective is to obtain an overview of market developments generally, but may be considered insufficiently rich in pertinent detail for an in-depth study of the EU's beef trade.

Nevertheless, the example is well chosen for illustrative purposes for another reason: given the very high out-of-quota (MFN) tariffs for beef generally, which have been sufficiently high to deter all out-of-quota imports of beef into the EU in recent years, it is plausible to assume that simulated EU imports of beef will enter only under a TRQ (and hence liable for a much lower rate of tariff) until the TRQ ceiling is reached. The question arises as to whether during the projection period this ceiling will be reached, and how certain the policy maker can be about it.

AGLINK-COSIMO models the aggregate of beef and veal meat (live animals not included), which we hereafter refer to as 'beef' since the veal component is very small. Figure 12 compares the simulated baseline projection for EU beef imports over the period 2013 to 2022 with the TRQ ceiling of 313 thousand tons. According to the deterministic baseline, the TRQ will not be filled up to and including 2016, but from 2017 onwards, the EU will import beef in excess of the TRQ ceiling, with the quantity of out-of-quota imports reaching 45 thousand tons in 2022.

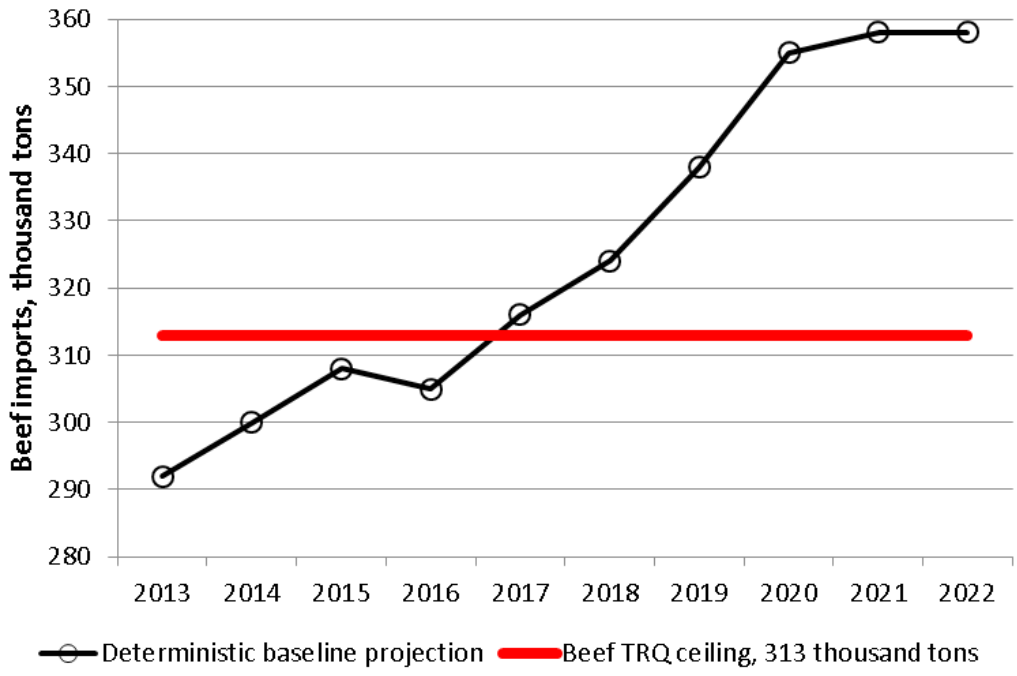

Figure 12. Beef imports 2013-2022: Deterministic baseline and TRQ ceiling.

However, once the uncertainty surrounding the eight macroeconomic variables and the 54 arable crop yields considered as uncertain in this study is taken into account, the picture becomes more nuanced.

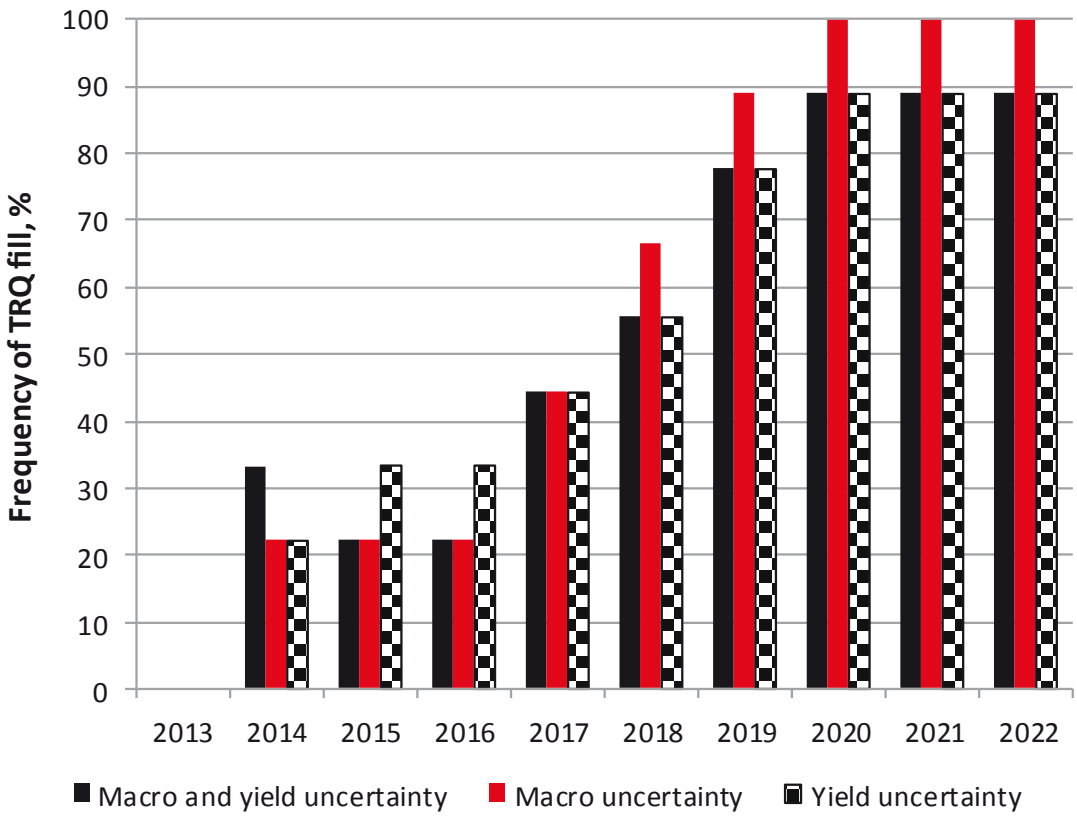

Figure 13. Annual frequency with which the EU beef TRQ is filled, 2013-2022.

Figure 13 shows the frequency with which the TRQ is filled year by year, given the distribution of possible market outcomes in each year. It indicates that in 2013 (when according to the deterministic baseline imports fall short of the quotas ceiling by 21 thousand tons), there is zero probability of the TRQ being filled, even when all uncertainties are taken into account. Thereafter, the probability of complete fill is never below 20%, and increases to nearly 90% in the last three years of the projection period. Interestingly, in 2017, the first year in which the baseline projection is above the quota, the probability of this occurring, once uncertainty is accounted for, is still below 50%.

It is curious that, in 2014, the two different types of uncertainty reinforce each other, in the sense that the probability of an outcome whose message is different from that of the deterministic baseline (i.e. TRQ not filled) is greater when both types of uncertainty are present than for one or the other type of uncertainty alone. In 2015 and 2016, however, this situation is reversed: the macroeconomic uncertainty offsets some of the crop yield uncertainty. From 2018 onwards, the probability of filling the quota is higher when only macroeconomic uncertainties are taken into account than when only yield uncertainty is considered. When both types of uncertainty are in play together, the probability of complete TRQ fill is lowered to the level characterised by yield uncertainty alone. Even in 2022, when according to the deterministic baseline, out-of-quota beef imports bring total imports to a level that is more than 14% above the TRQ, there is nevertheless a 10% possibility that the TRQ will not be filled.

This illustrative example shows how partial stochastic analysis can be used by the policy maker to attach a degree of uncertainty to the position of the deterministic baseline value with respect to a policy-sensitive threshold or limit.

6.3 Combinations of 'less likely' conditions

This section illustrates how partial stochastic analysis can be used to investigate the consequences for the deterministic baseline of particular configurations of uncertain underlying conditions. The deterministic baseline is conditional on assumptions that the most likely yields will prevail in future time periods. As far as yields are concerned, 'most likely' means yields as predicted by past trends. For the macroeconomic conditions, values representing 'most likely' conditions are based on the forecasts of a reputable forecasting organisation. It should be noted that these forecasts do not necessarily represent conditions that would be considered 'normal' based on past trends; for example, if the world is expected to remain in recession some years into the future, this —rather than what was considered 'normal growth' in the past— will be reflected in the 'most likely' assumptions used for the deterministic baseline.

Users of the baseline projections may want to know how the projected values would change if GDP in the EU turned out to be lower than expected, or if the crude oil price rose considerably higher than was assumed in the deterministic baseline. Moreover, they may be interested in the implications of certain combinations of conditions occurring together, such as lower than expected EU GDP *and* a higher than expected EUR-USD exchange rate (which could arise, despite lower growth in the EU, due to a worsening financial situation in the US).

Here, we examine two scenarios, each defined by a combination of 'less likely' circumstances: (i) lower growth than expected in the EU combined with a higher than expected oil price and (ii) higher growth than expected in the EU but drought in the northern hemisphere, particularly affecting crop yields in the EU and the US.

To perform this analysis, several additional steps are required. First, the hypothesised situation has to be translated into clearly defined ranges for the variables used to characterise it. Then, using the European Commission's AMI software, those draws for which the conditioning variables fall within the defined ranges are extracted from the full set of draws used for the main stochastic analysis (in which the stochastic exogenous variables may take any values generated by the joint probability distribution). This subset of draws, and corresponding simulation runs, are analysed and used to examine the extent to which the less likely combination of events would affect the values of various key variables in the deterministic baseline.

Several points need to be made about this procedure. First, if the ranges within which the 'criterion' variables can lie are made too narrow, or if many criteria are chosen to define jointly the what-if situation, then the number of draws corresponding to these specific conditions (for a given number of draws in the main experiment) will be smaller. Care has to be taken that the subset of simulation runs identified in this way is large enough to avoid the results being distorted by one or two very unusual runs. Clearly, the more narrowly the defining ranges are specified and/or the greater the number of uncertain conditioning variables that are selected to define the situation of interest, the larger the initial number of simulation runs that may be needed to ensure a sufficiently large subset of runs for analysis. Second, since only some of the stochastic variables are selected to define the 'what-if' situations examined here, the values of the remaining stochastic variables are treated as random and are allowed to vary over their entire range. In other words, they are not fixed equal to the values assumed — or generated— for them in the deterministic baseline. This means that the correlations embedded in the joint probability distribution between the variables whose range has been

fixed by the analysis and those whose values are free to vary over their entire range will still be in play, and this may pull them away from their baseline value. For example, given the positive correlations between crop yields within geographical blocks, if the yield range for one crop is specified to be below the level assumed in the deterministic baseline, other crop yields in the subset will also tend to be below their trend values even though this has not been imposed by the analyst.

Table 8 reports the criteria used to define the two what-if experiments already specified qualitatively above, namely 'low EU growth + high oil price' and 'high EU growth + poor crop harvests in the EU and the US'. These criteria are applied to the relevant conditioning variables in 2022 only. It would be possible to specify low growth in, for example, each of the three years 2020, 2021 and 2022. If this were done, however, it would greatly restrict the number of runs selected and would require a much larger number of initial draws than the 500 per year used in this study.

Table 8. Selection criteria defining two 'what-if' scenarios

	Scenario 1	Scenario 2
	Low EU growth, high oil price in 2022	High EU growth, low yields in 2022
Selection criteria	Values lying between	
EU-15 real GDP	10th and 50th percentiles	50th and 90th percentiles
Brent crude oil price	60th and 90th percentiles	
EU-15 common wheat yield		10th and 50th percentiles
US maize yield		10th and 50th percentiles
Number of draws	43 (9.2%)	25 (5.4%)
Key variables	Percentage difference from the deterministic baseline	
EUR/USD exchange rate	-4.9	6.0
EU-15 real GDP	-4.2	7.5
Oil price (USD)	35.0	9.5
EU-27 common wheat yield	-1.5	-6.1
EU-27 barley yield	-0.2	-5.0
EU-27 maize yield	0.2	-4.1
US maize yield	5.3	-11.1
US wheat yield	0.6	-1.6
US soybean yield	4.2	-7.8
US sugar beet	3.0	-9.0

Given the criteria defined for the two scenarios in Table 8, 9.2% and 5.4%, respectively, of the total number of runs (467 out of 500) for which the model solved, were selected. The size of these subsets of runs gives an idea of the relative likelihood of each of the two situations occurring, once underlying uncertainty is taken into account.

The lower half of Table 8 reports the average values of some of the key variables driving agricultural markets in these two situations. The values shown in bold correspond to those variables whose range has been limited by the criteria defining the scenario. It shows that the average oil price corresponding to the range specified in the two scenarios is 34.3% and 9.5%, respectively, above the one used in the baseline. Thus, although the second scenario does *not* constrain the values that can be taken by the oil price, its correlations with variables that have been constrained (namely, EU-15 real GDP, EU-15 common wheat yield and US maize yield) push its average above the 'most likely' value used in the deterministic baseline. It is important to remember, when interpreting the results of these scenarios where the oil price plays a key role, that the EU mandate requiring 8.6% of transport sector fuel to consist of first-generation biofuels (ethanol and biodiesel) remains in force in both of them.

In the drought scenario, we note also that, although only the EU common wheat yield and the US maize yield have been forced below their 'most likely' values by the selection criteria, the

correlations in the joint probability distribution of yields have dragged down the average values of most other competing crops in the EU and the US. The exchange rate (price of one euro in dollars) was not constrained in either scenario. However, because of its correlations with other key variables, it is on average about 5% below the value assumed in the deterministic baseline in the low growth-oil price scenario, and 6% above the value underlying the deterministic baseline in the high growth-low yield scenario.

Having defined the scenarios, the next stage is to take the average values of the simulated outcomes within the subset of selected runs, and to compare these averages with those of the deterministic baseline. Table 9 summarises the percentage deviations of these averages from the simulated value in the deterministic baseline.

Table 9. Differences from the deterministic baseline in two 'what-if' scenarios

	Low EU growth, high oil price in 2022						High EU growth, low crop yields in 2022					
	Percentage difference from the deterministic baseline											
	Supply	Consumption	Imports	Exports	Producer price (EUR)	World price (USD)	Supply	Consumption	Imports	Exports	Producer price (EUR)	World price (USD)
Common wheat	-2.0	-1.3	10.4	-3.3	-2.1	-1.4	-3.0	1.4	40.3	-24.0	17.1	5.1
Durum wheat	0.8	1.2	2.5	-0.3	-4.7		-2.0	3.1	18.0	-12.5	12.0	
Coarse grains	0.0	-0.3	-18.5	8.8	-2.8	0.7	-1.5	-0.1	13.4	-4.7	17.9	11.2
Barley	-0.1	-0.8	1.4	12.6	-2.9	n.a.	-2.1	-1.1	6.4	-7.6	19.7	n.a.
Maize	1.4	-0.5	-19.6	2.3	-3.2	n.a.	-1.2	0.8	13.9	0.1	16.9	n.a.
Other cereals	0.0	-0.3	-13.9	0.0	0.0	n.a.	0.2	0.5	9.3	0.0	0.0	n.a.
Milk	-1.0				-2.0		0.8				11.2	
Butter	-1.2	-0.5	10.4	-6.4	-0.5	3.5	-0.1	0.3	17.1	-1.2	8.1	2.8
Cheese	-1.0	-1.3	0.9	2.0	-2.7	1.7	1.2	2.1	13.3	-6.4	11.9	3.4
SMP	-0.7	0.2		-1.5	-3.4	1.8	-5.8	-0.1		-11.2	11.2	4.4
WMP	0.0	-0.2		-0.1	-2.4	2.3	-4.0	0.3		-8.0	10.1	3.2
Beef	-0.4	-0.4	3.0	4.5	-6.3	0.6	0.7	1.4	15.9	2.4	4.6	1.8
Pork	0.1	-0.4	0.4	4.9	-4.7	1.6	0.8	0.8	5.1	1.1	7.1	3.0
Poultry	-0.9	-1.0	-3.2	-1.1	-4.2	0.7	0.1	1.1	0.5	-8.7	10.5	3.7
Ethanol	-4.4	-13.3	-35.0	17.0	0.7	15.0	-5.2	3.0	23.7	-1.0	9.9	5.9
Biodiesel	3.8	3.0	-3.2	1.5	-1.0	6.0	3.8	4.6	9.8	-1.6	10.5	6.2
EU farm income	-15.8						7.1					

The results show that the biofuel sector is particularly sensitive to the uncertainty analysed. It is striking that in both the what-if scenarios EU production of ethanol is below the deterministic baseline and EU biodiesel production is above the baseline. However, the underlying market behaviour is quite different in the two cases. In the first scenario, EU biofuel prices are lower than in the baseline (despite the higher world market prices for biofuels that follow the oil price upwards) because of lower EU prices for feedstocks and lower demand due to lower EU GDP. However, since ethanol is used in the transport sector only when blended with fossil petrol, the high price of crude oil has a direct negative impact on demand for ethanol blends. This combination of lower demand and higher world market price reduces ethanol imports far below the deterministic baseline in relative terms, while boosting its export. By contrast, biodiesel is used in unblended form, and EU demand for it as a fossil fuel substitute increases.

In the second scenario, EU demand for both biofuels is above that of the deterministic

baseline because of higher GDP, and this occurs despite the considerable price rise (which is in fact very close to the rise in the crude oil price in this scenario). The result is that considerably more biofuel imports, particularly those of ethanol, are sucked into the EU transport fuel market. Interestingly, the drought-induced rise in the world price of coarse grains is not fully transmitted to the world price of ethanol, as the market remains dominated by low-cost, sugar-cane-based Brazilian ethanol. However, the increase in world market prices for these grains has implications for low-income food-importing countries.

Production of cereals is on average lower than in the baseline in both scenarios. In the first scenario, this is due to a combination of higher energy costs, loss of international competitiveness and lower demand in reaction to higher prices, whereas in the second scenario, lower production is due largely to lower yields, which —together with much higher food demand— leads to higher producer prices than in the deterministic baseline.

In the first scenario, market outcomes are less susceptible in the livestock sector to the uncertainties analysed than they are in the crop sector. Divergences from the deterministic baseline are relatively small, the greatest impact being to reduce average EU producer prices, which is partly due to lower feed prices. In the second scenario, by contrast, livestock market outcomes are more sensitive to the shocks assumed in the factors analysed than was the case in the first scenario. It is interesting to observe that the milk price is 11% above its deterministic baseline value in the 'high growth + low yield' scenario, despite lower exports of the main traded dairy products, especially the high-value products cheese and WMP. This boost to the EU dairy sector, coming especially from domestic cheese consumption, is clearly generated by buoyant conditions in domestic markets rather than being a response to a world market boom in dairy products.

Table 9 also reports the implications of these two hypothetical scenarios for the baseline value of agricultural sector income. In the first scenario, real agricultural sector income is on average 15.8% below that of the deterministic baseline. However, in the second scenario, and despite lower production of many commodities due to lower yields, market-driven price increases, which are due more to yield-induced scarcity rather than higher consumer demand, boost average agricultural sector income 7.1% above the level of the deterministic baseline.

A variety of combinations of 'less likely' conditions could be specified and their implications for the baseline examined using this approach. In these illustrative examples, the criteria specified concerned the values taken by exogenous values in 2022 only, and the results are given for 2022. However, it would be possible to specify a range for a variable over several time periods (e.g. lower EU-27 GDP than expected for each year of the period 2020-2022) to examine the cumulative effect of this on the 2022 value, thereby exploiting the recursive-dynamic property of AGLINK-COSIMO. We remind the reader that, for this exercise, no year-to-year correlation in the uncertain exogenous variables has been assumed. Thus, it is likely that once scenarios are specified in terms of conditions that are sustained over several periods, a greater number of runs would have to be performed in order to obtain a large enough subset of qualifying runs.

7. CONCLUSIONS

This report describes the methodology used in recent years by JRC-IPTS for performing partial stochastic simulation using DG AGRI's updated AGLINK-COSIMO model. The information generated in this way supplements the deterministic baseline by incorporating the uncertainty inherent in the values assumed for various key drivers over the projection period and indicating to the user of the baseline the extent to which this uncertainty is transmitted to various key endogenous projections of interest.

The report describes the data required, the various steps undertaken and the additional software used in order to perform partial stochastic analysis with the AGLINK-COSIMO model in the context of the Commission's annual agricultural outlook process.

The report illustrates three ways in which the results of partial stochastic analysis can add value to the deterministic baseline for the user. First, it provides a range of values within which a medium-term outcome may lie in a given year, given the uncertainty surrounding future values of one or more of the conditioning, exogenous variables. The choice of which uncertainties to take account of can depend on the user. In the work presented in this report, we have considered uncertainty surrounding a set of exogenous EU macroeconomic variable *plus* uncertainty in the price of the Brent crude oil and the EUR-USD exchange rate (together labelled 'macroeconomic uncertainty'), and the uncertainty inherent in future values of 54 country-specific crop yields ('yield uncertainty'). The implications of uncertainty from these sources are analysed for the projection period 2013 to 2022. However, projections of other key conditioning variables, which are also subject to uncertainty (for example, GDP growth in the US and China), have been treated as given and their potential variability has not been taken into account. Thus, the *partial* nature of the stochastic analysis reported here must always be borne in mind.

Results are presented in the report in such a way as to highlight the relative contribution of uncertainty from these two groups of conditioning variables to the total uncertainty implied by them for various baseline results. Clearly, this comparison partly reflects the relative degrees of uncertainty assumed for the macro variables and crop yields. However, it should be borne in mind that this assumption is not completely arbitrary. Rather, it is based on deviations from forecasts or trends in a recent historical period. This information on how uncertainty in underlying exogenous conditions impacts on model outcomes supplements the point estimate provided by the deterministic baseline, and allows the user to take into account the relative uncertainty of the different projections. The breakdown of uncertainty according to source could be taken further in order to assess, for example, which baseline variables are more affected by the uncertainty relating to individual conditioning variables (such as the exchange rate or the oil price). The uncertainty implied for baseline projections by the uncertainty in the conditioning variables can be assessed either for a particular year in the projection period, or summarised for the entire period (in this report, by using the average coefficient of variation of the variable of interest).

Second, when the policy maker wants to know whether or not a particular variable will exceed or fail to reach a given threshold or target value during the projection period, partial stochastic analysis can be used to gauge the probability with which this may happen. Although the deterministic baseline may provide a value for the variable concerned that is not in the vicinity of the threshold value, stochastic analysis can show the likelihood of the value being met once the underlying uncertainties are taken into account. The illustration presented in the report concerns the TRQ for EU beef imports, and the likelihood it will be filled during the projection period. The straightforward message of the deterministic baseline (namely, that it will be underfilled up to and including 2016 and filled thereafter) is considerably nuanced once the underlying uncertainty in these projections is taken into account.

Third, stochastic analysis permits the formulation of user-specified, what-if scenarios concerning the joint development of exogenous variables, so that the consequences of these scenarios for baseline variables of interest can be examined. For example, the market analyst or policy-maker may want to know the consequences for grain prices in the medium term of a combination of high crude oil prices and drought in major producing areas. The

deterministic baseline provides projections of grain prices assuming 'most plausible' future values of crude oil prices and average weather conditions. By contrast, stochastic analysis can show how different the market outcomes would be from the central value of the deterministic baseline in scenarios characterised by less plausible ranges of assumed values for these variables.

In the report, this type of application is illustrated by examining two what-if scenarios: low EU GDP growth plus higher than expected oil prices, and stronger than expected EU GDP growth together with lower crop yields in the EU and the US. By focusing in turn on the two subsets of stochastically generated results corresponding to these underlying 'states-of-the-world', and examining how the average outcomes within these subsets differ from those of the deterministic baseline, interesting insights can be drawn that greatly enrich the user's understanding of the functioning of the markets concerned. In particular, much can be learnt from analysing such 'worst-case' or 'best-case' scenarios that —because they are considered less likely to happen— are never analysed in the deterministic baseline, but they could occur with non-zero probability.

The use of this methodology is subject to a number of caveats. First, it is 'partial' in the sense that it only takes into account the uncertainty in a chosen number of external factors. When interpreting the results, it should always be borne in mind that the uncertainty whose implications are studied is coming from specific conditioning variables selected for the analysis. It should not be assumed that all sources of uncertainty that characterise the real world have been accounted for.

Second, the methodology does not take into account the uncertainties inherent in the model itself, such as the fact that model parameters are only estimates and that the underlying parameters describing the behaviour of economic agents and markets may be drifting over time.

Third, the estimated variability in exogenous factors that is projected into the future is based on their variability in the past, as is the assumed correlation between of the variability in different exogenous variables. Both own variability and joint variability of these factors may change in the future. The possibility of what has become known as a 'black swan' event (that is, a highly improbable event with an extreme impact, characterised by ex post —but not *ex ante*— predictability) is inevitably not taken into account at all. Nonetheless, by making use of the information we *do* have about the inherent variability in underlying model drivers and about actual deviations from what was considered 'most likely' in the recent past, a more realistic and nuanced picture can be given of future developments than that provided by the deterministic baseline alone.

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9. APPENDICES

Appendix A. Simulated marginal distributions of stochastic forecast errors

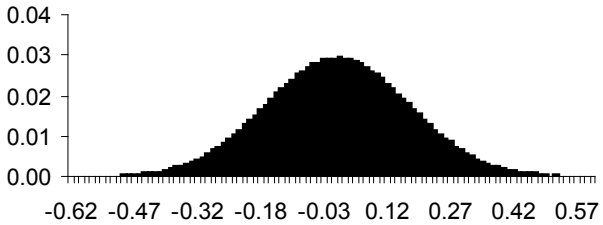

Figure A1. Brent crude oil price.

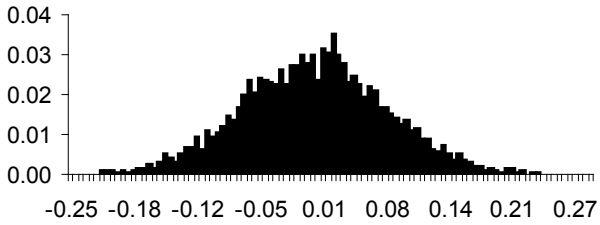

Figure A2. EUR-USD exchange rate.

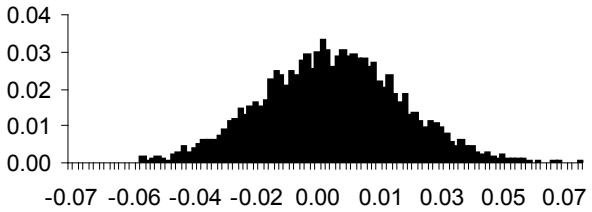

Figure A3: EU-15 Real GDP.

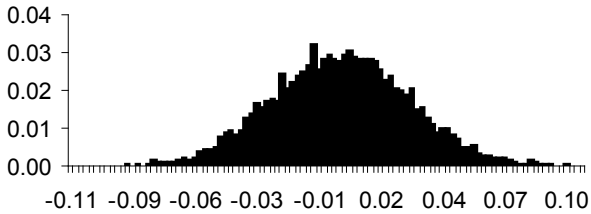

Figure A4: EU-N12 Real GDP.

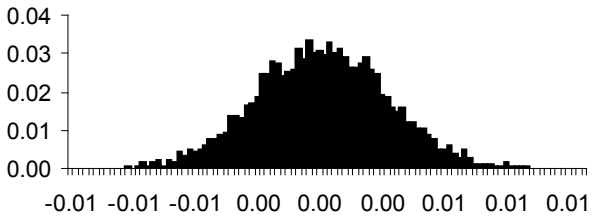

Figure A5: EU-15 GDP deflator.

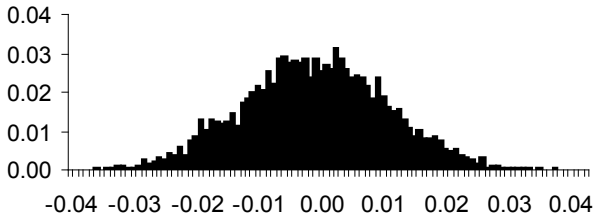

Figure A6: EU-N12 GDP deflator.

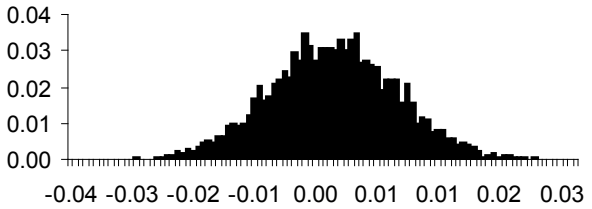

Figure A7: EU-15 Consumer price index.

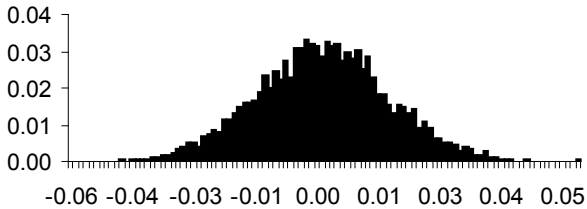

Figure A8: EU-N12 Consumer price index.

Appendix B. Summary statistics of crop yields around the world

Country	Commodity	Mean	Std Dev	Skewness	Kurtosis	Normality test of forecast errors	Min	Max	Range	1st quartile	3rd quartile	Interquartile range	Interquartile range/mean	Arithmetic average of interquartile range/mean
		t/h	t/h				t/h	t/h	t/h	t/h	t/h	t/h	%	%
EU-15	Common wheat	6.5	0.4	0.1	-0.6	Y[1]	6.0	7.2	1.2	6.2	6.7	0.5	8	
EU-N12		3.4	0.4	0.5	0.0	Y	2.8	4.2	1.5	3.2	3.6	0.4	13	
EU-15	Durum wheat	2.7	0.4	0.0	-1.6	Y	2.2	3.3	1.0	2.4	3.0	0.7	25	
EU-N12		3.0	0.5	0.2	-0.7	Y	2.0	3.9	1.9	2.7	3.5	0.8	26	
EU-15	Barley	4.5	0.3	-0.5	0.0	Y	4.0	5.0	1.1	4.4	4.7	0.3	6	
EU-N12		3.0	0.3	0.7	-0.1	Y at 1%	2.5	3.6	1.1	2.8	3.1	0.3	11	
EU-15	Maize	8.8	0.7	-0.4	-0.1	Y	7.6	10.1	2.5	8.6	9.2	0.6	7	
EU-N12		4.1	0.9	-0.2	-1.2	Y at 1%	2.5	5.3	2.8	3.5	4.8	1.3	31	
EU-15	Oats	3.3	0.2	0.1	-1.3	Y	3.0	3.6	0.5	3.1	3.4	0.3	9	
EU-N12		2.2	0.2	-0.2	0.4	Y	1.7	2.6	0.9	2.1	2.3	0.2	9	
EU-15	Rye	4.4	0.4	0.3	-0.6	Y	3.7	5.2	1.5	4.0	4.6	0.5	12	
EU-N12		2.4	0.2	0.0	0.4	Y	1.9	2.8	0.9	2.3	2.5	0.2	9	
EU-15	Rapeseed	3.1	0.3	0.1	-0.3	Y	2.5	3.8	1.3	3.0	3.4	0.4	13	
EU-N12		2.2	0.3	0.3	1.0	Y	1.6	2.9	1.2	2.0	2.3	0.3	14	
EU-15	Sunflower seed	1.6	0.2	-1.4	2.2	N	1.1	1.9	0.8	1.6	1.8	0.2	11	
EU-N12		1.5	0.3	0.4	-1.4	Y	1.1	1.9	0.9	1.3	1.8	0.5	36	
EU-15	Sugar beet	61.7	6.9	0.5	-0.7	Y	53.5	76.2	22.7	55.6	66.5	10.9	18	
EU-N12		39.9	8.3	0.0	-1.3	Y at 1%	26.8	53.4	26.7	33.7	46.5	12.8	32	
EU														16
Kazakhstan	Common wheat	1.0	0.3	0.7	0.6	Y	0.6	1.6	1.0	0.8	1.1	0.4	36	
Kazakhstan	Oilseeds	0.8	0.3	0.0	-0.9	Y	0.3	1.3	1.0	0.5	1.0	0.4	53	
Ukraine	Common wheat	2.8	0.6	-0.6	1.5	N	1.4	3.8	2.4	2.5	3.1	0.6	20	
Ukraine	Coarse grains	2.4	0.5	0.8	0.6	Y	1.8	3.7	1.9	2.0	2.7	0.7	28	
Ukraine	Oilseeds	1.3	0.3	0.8	0.0	Y	0.8	2.0	1.2	1.0	1.4	0.4	32	
Russia	Common wheat	1.8	0.4	0.0	-0.6	Y	1.0	2.5	1.4	1.5	2.0	0.5	29	
Russia	Sunflower seed	0.9	0.2	0.4	-1.0	Y	0.7	1.3	0.6	0.8	1.1	0.3	30	
Russia	Sugar beet	22.4	7.4	0.6	-0.7	Y	12.0	36.2	24.3	17.6	26.9	9.3	42	
Black Sea														34

Summary statistics of crop yields around the world (continued)

Argentina	Common wheat	2.4	0.4	0.9	2.0	Y	1.9	3.5	1.6	2.2	2.6	0.4	18	
Argentina	Barley	2.6	0.6	0.5	-0.6	Y	1.8	3.8	2.0	2.2	3.0	0.8	32	
Argentina	Maize	6.1	1.2	-0.1	-0.8	Y	4.1	8.1	4.0	5.3	6.7	1.4	23	
Argentina	Sugar beet	2.5	0.4	-0.4	-0.8	Y	1.7	3.1	1.4	2.1	2.8	0.6	25	
Argentina	Sunflower seed	1.7	0.2	-0.2	0.7	Y	1.2	2.2	0.9	1.7	1.9	0.2	11	
Argentina	Sugar cane	71.8	10.0	0.2	-1.8	Y	59.3	85.7	26.4	63.5	82.1	18.6	26	
Paraguay	Common wheat	2.3	1.0	0.8	-0.4	Y	1.0	4.2	3.2	1.6	2.5	0.9	40	
Paraguay	Coarse grain	2.4	0.4	0.2	-0.7	Y	1.7	3.1	1.4	2.2	2.6	0.5	20	
Paraguay	Oilseed	2.2	0.3	0.2	-0.1	N	1.6	2.8	1.2	2.1	2.4	0.4	17	
Uruguay	Common wheat	2.5	0.6	-0.9	-0.1	N	1.2	3.3	2.2	2.2	3.0	0.8	31	
Uruguay	Coarse grain	2.8	0.6	-0.2	-1.5	Y	1.8	3.5	1.7	2.2	3.3	1.0	37	
Brazil	Common wheat	1.9	0.6	0.5	-0.6	Y	1.1	3.1	2.0	1.5	2.3	0.8	42	
Brazil	Maize	3.2	0.7	0.2	-1.1	Y	2.1	4.4	2.2	2.7	3.7	1.1	33	
Brazil	Sugar cane	71.3	4.6	0.3	-0.9	Y	63.3	79.3	16.0	67.9	74.4	6.5	9	
South America														26
Mexico	Common wheat	4.7	0.5	-0.2	-0.5	Y	3.7	5.6	1.8	4.4	5.1	0.7	15	
Mexico	Maize	2.7	0.4	0.3	-1.3	Y at 1%	2.2	3.3	1.1	2.4	3.0	0.6	21	
USA	Common wheat	2.8	0.2	-0.3	-1.1	Y	2.4	3.1	0.7	2.6	2.9	0.3	12	
USA	Maize	8.7	1.0	-0.6	0.4	Y	6.3	10.3	4.0	8.1	9.4	1.3	15	
USA	Soybean	2.7	0.2	-0.6	-0.4	Y	2.2	3.0	0.8	2.5	2.8	0.3	11	
USA	Sugar beet	51.2	5.8	0.4	-0.8	Y	41.7	62.1	20.4	46.7	55.2	8.5	17	
USA	Sugar cane	71.6	4.2	-1.0	2.4	Y at 1%	60.1	78.6	18.5	70.1	74.0	3.9	6	
North America														14
Indonesia	Palm oil	4.1	0.4	-1.0	1.5	Y	3.1	4.8	1.7	3.9	4.3	0.4	10	
Malaysia	Palm oil	4.1	0.4	-0.1	-1.2	Y	3.4	4.7	1.4	3.8	4.4	0.6	16	
Thailand	Sugar cane	59.0	9.3	-0.1	-0.6	Y at 1%	40.2	73.3	33.1	53.0	66.2	13.3	22	
South East Asia														16
Australia	Common wheat	1.7	0.4	-1.0	-0.2	Y	0.9	2.1	1.2	1.6	2.0	0.4	25	
Australia	Barley	1.8	0.4	-0.9	0.1	Y	1.0	2.3	1.3	1.6	2.0	0.4	22	
Australia	Rapeseed	1.2	0.3	-0.6	0.2	Y at 1%	0.5	1.7	1.2	1.1	1.4	0.3	23	
Australia	Sugar cane	86.9	8.6	-0.3	-0.8	Y	69.8	99.6	29.8	80.4	94.2	13.8	16	
Australia														22

[1] *'Y' means that the null hypothesis of normality is accepted at the 5% significance level; 'Y at 1%' means that normality is not accepted at the 5% significance level but is accepted at the 1% level; 'N' means that normality is rejected at the 1% significance level.*

Appendix C. Correlation matrix[1] for the stochastic element of arable crop yields in Europe

	EU-15 Common wheat	EU-N12 Common wheat	EU-15 Durum wheat	EU-N12 Durum wheat	EU-15 Barley	EU-N12 Barley	EU-15 Maize	EU-N12 Maize	EU-15 Oats	EU-N12 Oats	EU-15 Rye	EU-N12 Rye	EU-15 Rapeseed	EU-N12 Rapeseed	EU-15 Sunflower seed	EU-N12 Sunflower seed	EU-15 Sugar beet	EU-N12 Sugar beat
EU-15 Common wheat	1.0	0.0	0.3	0.0	**0.7**	0.0	0.3	0.1	0.2	0.0	**0.8**	0.3	0.3	0.3	0.4	-0.4	-0.3	**0.6**
EU-N12 Common wheat		1.0	0.2	**0.7**	-0.2	**0.9**	0.3	**0.7**	0.0	**0.7**	0.0	**0.5**	0.3	**0.7**	-0.2	**0.6**	**0.5**	-0.1
EU-15 Durum wheat			1.0	0.3	0.4	0.1	0.0	-0.1	0.2	-0.1	0.0	0.0	0.1	0.3	0.0	0.2	0.4	0.1
EU-N12 Durum wheat				1.0	-0.2	**0.5**	0.3	**0.5**	0.0	0.3	0.0	0.1	0.2	**0.7**	-0.1	0.4	0.4	0.0
EU-15 Barley					1.0	0.0	0.5	-0.2	**0.5**	0.0	**0.5**	0.1	0.1	0.1	**0.5**	-0.4	-0.2	0.3
EU-N12 Barley						1.0	0.2	**0.7**	0.1	**0.9**	0.1	**0.7**	0.3	**0.7**	-0.1	**0.5**	0.4	0.1
EU-15 Maize							1.0	0.1	0.4	0.3	0.3	0.1	0.0	0.3	**0.5**	-0.4	0.1	0.2
EU-N12 Maize								1.0	-0.3	**0.6**	0.2	0.4	0.4	0.4	0.0	**0.5**	0.2	-0.1
EU-15 Oats									1.0	0.1	-0.1	-0.1	-0.3	-0.2	0.2	-0.1	0.1	0.2
EU-N12 Oats										1.0	0.1	**0.8**	0.3	**0.5**	-0.1	0.4	0.3	0.1
EU-15 Rye											1.0	0.4	0.4	0.4	0.4	-0.4	**-0.5**	**0.6**
EU-N12 Rye												1.0	0.4	**0.6**	-0.1	0.2	0.0	**0.5**
EU-15 Rapeseed													1.0	**0.6**	-0.2	0.1	0.2	0.4
EU-N12 Rapeseed														1.0	-0.1	0.2	0.2	0.3
EU-15 Sunflower seed															1.0	**-0.5**	-0.3	0.2
EU-N12 Sunflower seed																1.0	**0.6**	-0.3
EU-15 Sugar beet																	1.0	-0.1
EU-N12 Sugar beat																		1.0

[1] The table contains the estimated correlation coefficients of the deviations from trend yield over the period 1993-2011. Bold typeface indicates that the coefficient is significantly different from zero at the 5% significance level.

Appendix D. Correlation matrix[1] for the stochastic element of arable crop yields in the Black Sea region

	Kazakhstan wheat	Kazakhstan oilseeds	Ukraine wheat	Ukraine coarse grains	Ukraine oilseeds	Russia wheat	Russia sunflower seed	Russia sugar beet
Kazakhstan Wheat	1.0	0.4	-0.1	0.1	-0.3	0.4	0.2	0.3
Kazakhstan Oilseeds		1.0	**-0.5**	0.0	0.1	0.0	-0.3	-0.3
Ukraine Wheat			1.0	**0.7**	0.1	**0.5**	0.4	**0.6**
Ukraine Coarse grains				1.0	0.3	**0.8**	**0.5**	**0.6**
Ukraine Oilseeds					1.0	0.1	0.3	0.2
Russia Wheat						1.0	0.4	**0.6**
Russia Sunflower seed							1.0	**0.9**
Russia Sugar beet								1.0

[1] *The table contains the estimated correlation coefficients of the deviations from trend yield over the period 1993-2011. Bold typeface indicates that the coefficient is significantly different from zero at the 5% significance level.*

Appendix E. Correlation matrix[1] for the stochastic element of arable crop yields in South America

	Argentina wheat	Argentina barley	Argentina maize	Argentina soybean	Argentina sunflower seed	Argentina sugar cane	Paraguay wheat	Paraguay coarse grains	Paraguay oilseeds	Uruguay wheat	Uruguay coarse grains	Brazil common wheat	Brazil maize	Brazil sugar cane
Argentina Wheat	1.0	-0.4	-0.2	0.2	0.3	**-0.6**	-0.1	0.2	0.1	0.1	0.0	0.2	0.0	-0.3
Argentina Barley		1.0	0.2	0.1	**-0.5**	**0.6**	-0.1	0.1	0.0	0.1	0.0	**-0.5**	-0.4	0.3
Argentina Maize			1.0	0.3	-0.3	0.4	-0.1	0.0	0.1	-0.1	0.1	-0.3	-0.3	0.4
Argentina Soybean				1.0	0.3	-0.3	**-0.5**	-0.2	**0.5**	-0.3	-0.3	-0.2	-0.2	-0.4
Argentina Sunflower seed					1.0	**-0.5**	-0.3	-0.1	0.1	-0.1	-0.3	0.2	0.4	**-0.5**
Argentina Sugar cane						1.0	**0.5**	0.3	0.2	0.3	0.4	-0.3	-0.4	**0.7**
Paraguay Wheat							1.0	**0.6**	0.2	**0.5**	**0.7**	0.2	-0.2	**0.5**
Paraguay Coarse grains								1.0	0.4	0.5	**0.7**	0.1	-0.3	**0.6**
Paraguay Oilseeds									1.0	0.2	0.2	-0.3	-0.3	0.1
Uruguay Wheat										1.0	**0.7**	0.0	-0.4	0.4
Uruguay Coarse grains											1.0	0.0	-0.4	**0.6**
Brazil Common wheat												1.0	0.2	-0.3
Brazil Maize													1.0	-0.3
Brazil Sugar cane														1.0

[1] *The table contains the estimated correlation coefficients of the deviations from trend yield over the period 1993-2011. Bold typeface indicates that the coefficient is significantly different from zero at the 5% significance level.*

Appendix F. Correlation matrix[1] for the stochastic element of arable crop yields in North America

	Mexico wheat	Mexico maize	US wheat	US maize	US soybean	US sugar beet	US sugar cane
Mexico Wheat	1.0	**0.7**	0.4	**0.6**	**0.6**	**0.6**	0.1
Mexico Maize		1.0	**0.6**	**0.7**	**0.6**	**0.8**	0.0
US Wheat			1.0	**0.6**	0.3	**0.7**	0.2
US Maize				1.0	**0.9**	**0.8**	0.1
US Soybean					1.0	**0.7**	0.0
US Sugar beet						1.0	0.3
US Sugar cane							1.0

[1] *The table contains the estimated correlation coefficients of the deviations from trend yield over the period 1993-2011. Bold typeface indicates that the coefficient is significantly different from zero at the 5% significance level.*

Appendix G. Correlation matrix[1] for the stochastic element of arable crop yields in South East Asia

	Indonesia palm oil	Malaysia palm oil	Thailand sugar
Indonesia Palm oil	1.0	0.2	-0.4
Malaysia Palm oil		1.0	0.0
Thailand Sugar			1.0

[1] *None of the estimated correlation coefficients in the table is significant at the 5% significance level.*

Appendix H. Correlation matrix[1] for the stochastic element of arable crop yields in Australia

	Australia wheat	Australia barley	Australia rapeseed	Australia sugar cane
Australia Wheat	1.0	**1.0**	**0.8**	-0.2
Australia Barley		1.0	**0.8**	-0.2
Australia Rapeseed			1.0	0.0
Australia Sugar cane				1.0

[1] *The table contains the estimated correlation coefficients of the deviations from trend yield over the period 1993-2011. Bold typeface indicates that the coefficient is significantly different from zero at the 5% significance level*

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Abstract

This report describes the methodology for performing partial stochastic analysis of the European Commission's annual outlook projections for agricultural markets. The simulation model used is AGLINK-COSIMO, which is developed and maintained jointly by the OECD and FAO.

Partial stochastic analysis quantifies the extent to which future uncertainty surrounding selected exogenous market drivers, which underlie the projections, affects the projected outlook for markets and prices. It does so by providing the range of values within which medium-term outcomes may lie in a future year, given the unforeseen variability exhibited by these exogenous variables in the past. This information supplements the point estimates provided by the outlook projections and allows the user to take into account the relative uncertainty of the various projected outcomes.

The report details the statistical underpinnings of the methodology and the sequence of operational steps involved, as well as the additional software required. It then applies the methodology to the Commission's 2012 outlook projections, providing information on how the projected agricultural market outcomes are affected by the uncertainty surrounding key macroeconomic variables (including exchange rates and the crude oil price) and agricultural crop yields. The potential of the approach to provide information relating to policy or behavioural discontinuities and thresholds, and for analysing specific 'less likely' situations, is also illustrated.

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