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# Exploring the production of natural gas through the lenses of the ACEGES model

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HIGHLIGHTS

- We present the ‘Collective View’ and ‘Golden Age’ Scenarios for natural gas production.
- We do not observe any significant supply demand pressure of natural gas until 2035.
- We do observe ‘jumps’ in natural gas supply until 2035.
- The ACEGES-based scenarios can assess the resilience of longterm strategies.

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ABSTRACT

Due to the increasing importance of natural gas for modern economic activity, and gas's non-renewable nature, it is extremely important to try to estimate possible trajectories of future natural gas production while considering uncertainties in resource estimates, demand growth, production growth and other factors that might limit production. In this study, we develop future scenarios for natural gas supply using the ACEGES computational laboratory. Conditionally on the currently estimated ultimate recoverable resources, the ‘Collective View’ and ‘Golden Age’ Scenarios suggest that the supply of natural gas is likely to meet the increasing demand for natural gas until at least 2035. The ‘Golden Age’ Scenario suggests significant ‘jumps’ of natural gas production – important for testing the resilience of long-term strategies.



## 1. Introduction

Secure, sustainable and competitive energy is of fundamental importance to individual countries' economy, industry and citizens and a core goal of their policy. To achieve this goal, policymakers need adequate instruments to act within their borders and to promote their interests in relation to third countries.

Energy trade (particularly oil, gas and coal) is a global business. This means that countries face growing competition for fossil fuel resources, including emerging countries and energy producers themselves. Growing population and rising standards of living are likely to push global energy demand upward. Rising energy demand is pushing up global prices, bringing energy poverty to many and playing havoc with countries where fossil fuel subsidies are prevalent.

Natural gas is widely used around the world for a variety of usages such as power generation, transportation, residential use, and feedstock for chemical industries. The global natural gas market is likely to undergo a dramatic change during the 21st century. Indeed, natural gas is perhaps one of the most intriguing developments in global primary energy markets. Nearly all projections of future demand for natural gas assume a substantial increase in the coming decades, despite any likely conservation measures or gains in energy efficiency.

Whilst there are several studies that explore the outlook of crude oil production (e.g., Hallock et al., 2004; Caithamer, 2008; Nashawi et al., 2010), forward-looking outlooks of global natural gas production have not been explored with the same level of

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**Table 1**
Natural gas projections (in Trillion cubic feet – Tcf).

| Sources | EUR | Peak year | Peak production |
|---|---|---|---|
| Edwards (1997) | 1165 | 2040 | 120 |
| Al-Jarri and Startzman (1997) | 7060 | 2011 | 103 |
| Al-Fattah and Startzman (2000) | 10,000 | 2014–2017 | 99 |
| Laherrere (2002) | 10,000 | 2015 | NA |
| Aleklett and Campbell (2003) | 10,000 | 2015–2040 | 130 |
| Imam et al. (2004) | 9215 | 2019 | 88 |
| Guseo (2006) | 7332 | 2008–2014 | 100 |
| Laherrere (2007) | 10,000 | 2020 | 135 |
| Campbell and Heapes (2009) | 9886 | 2012 | 108 |
| Zhang et al. (2010) | NA | 2030–2035 | 130 |
| Mohr and Evans (2011) | 9952–17027 | 2025–2065 | 112–151 |

intensity despite the growing importance of natural gas for fuelling socioeconomic activities. Having said that, Table 1 shows several studies of long-term projections of future natural gas production, including the estimated ultimate recoverable resources (EUR), forecast peak year, and production at the peak year. Most of the studies estimate that the peak year comes before 2025 (Al-Fattah and Startzman, 2000; Al-Jarri and Startzman, 1997; Guseo, 2006; Imam et al., 2004; Laherrere, 2007). Edwards (1997), Mohr and Evans (2011) and Zhang et al. (2010) show the peak in later years.

Scenarios of natural gas production are based upon different model types such as variants of the Hubbert model, the generalized Bass model and the demand–production interaction model. However all these models belong to the general family of non-linear (parametric) regression models. The scenarios presented here are based upon the ACEGES (Agent-based Computational Economics of the Global Energy System) model proposed by Voudouris et al. (2011).

The key advantage of the ACEGES model is that a high degree of heterogeneity is easily incorporated in the scenarios while the macroscopic explananda (world production of consumer-grade natural gas) emerge from bottom-up rather than predefined by the Walrasian Auctioneer in the form of a gas mountain (e.g., a symmetric bell shape for a gas production profile) with specific statistical and mathematical properties. This means that key uncertainties (such as EUR, demand growth, maximum allowable production growth and state of depletion at peak) are country specific and can be explored by (i) parametric and/or non-parametric distributions based upon historical observations and/or (ii) subjectively defined by the users based upon personal experience and 'forces in the pipeline' (e.g., upstream investment policies that have been announced but not implemented yet). To the best of our knowledge, this is the first time that the agent-based modelling and simulation (ABMS) framework has been used to explore forward-looking scenarios of natural gas production.

The ACEGES-based scenario narrative is constructed around the key information extracted from the simulated outputs. Following De Rossi and Harvey (2009) who provide a discussion on time-varying quantile and time-varying expectiles to provide information on various aspects of a time series, here we also employ expectiles (first introduced by Newey and Powell, 1987) and quantiles to provide information on plausible trajectories of natural gas production. The expectiles are estimated using the R package *expectreg*[1] and the quantiles are estimated using the highly flexible GAMLSS (Generalised Additive Model for Location Scale and Shape) framework – introduced by Rigby and Stasinopoulos (2005) – using the R package *gamlss*. Expectiles, a relatively uncommon statistical concept, are similar to quantiles except that they are defined by tail expectations rather than tail probabilities. Newey and Powell (1987) discuss the theory underlying expectiles and show how they can be applied in a regression context using least asymmetrically weighted squares (LAWS). As discussed by Schnabel and Eilers (2009), by combining LAWS with P-splines (Eilers and Marx, 1996), it is possible to estimate flexible curves in any region of the data. These flexible curves are called 'smoothed expectiles'.

To aid the interpretation of expectiles in Section 3, a particular expectile, $e_\omega$ [with $\omega$ – in the interval (0, 1) – setting the asymmetry], can be interpreted as the *asymmetrically weighted mean* with the following special cases:

- $\omega = 0.5$, the expectile is the (symmetrical weighted) arithmetic mean of natural gas production (expected frontier).
- $\omega \approx 1$, the expectile is very close to the maximum of natural gas production (asymmetrically weight upper frontier).
- $\omega \approx 0$, the expectile is very close to the minimum of natural gas production (asymmetrically weight lower frontier).

One way to explain the different types of information represented by quantiles and expectiles is to compare the information that can be extracted by the 50% quantile $q_{0.5}$, which is the median, with the information that can be extracted by the expectile $e_{0.5}$, which is the arithmetic mean. The $q_{0.5}$ of natural gas production informs us that there is 50% probability that the production of natural gas will be above a specific production level $q_{0.5}$ and 50% probability that the production of natural gas will be below a specific production level $q_{0.5}$. The $e_{0.5}$ gives us the expected production of natural gas. The difference between $e_{0.5}$ and $q_{0.5}$ gives us an estimate of the degree of (positive or negative) skeweness – a measure of the balance of risk for natural gas production. In other words, when $e_{0.5} > q_{0.5}$ the production of natural gas is positively skewed while when $e_{0.5} < q_{0.5}$ the production of natural gas is negatively skewed. To generalise, time-varying quantiles and expectiles will coincide if the shape of the distribution is constant over time. The location and scale of the distribution can vary, but not the shape (skewness and kurtosis). When there are changes in the shape of the distribution, expectiles will not match up with quantiles (De Rossi and Harvey, 2007). Therefore, the reasoning of using both time-varying expectiles and time-varying quantiles to analyse the ACEGES-based scenarios is to provide information on various aspects of natural gas production such as time-varying dispersion, asymmetry and kurtosis.

The structure of this paper is as follows. Section 2 outlines the ACEGES model, particularly the decision rule of the agents, which represent here countries (finer scale representation is also possible). Because the ACEGES model is a *realistically rendered agent-based model*, it also discusses how the model is initialised with observational data and how heterogeneity is introduced in the scenarios. Section 3 presents the results of the 'Collective View' Scenario and the 'Golden Age' Scenario. The narratives of the scenarios are summarised by the estimated time-varying quantiles and time-varying expectiles. Section 4 concludes.

## 2. Method

### 2.1. The ACEGES model

The ACEGES model, first introduced by Voudouris (2011a), is an agent-based model (ABM) for exploratory energy policy. ABM is a novel and flexible modelling framework for the computational study of socioeconomic and natural processes. ABM conceptualises, in this instance, the global natural gas market as a complex adaptive system of interacting agents (countries) who do not necessarily possess perfect rationality and information. It should be noted that the current implementation of the ACEGES: Gas

[1] Schnabel (2011) provides a detailed technical discussion on estimation methods of smoothed expectiles.

model follows the same specifications as the ACEGES: Oil model detailed in Voudouris et al. (2011).

The demand function within the ACEGES model can be a deterministic function or a stochastic function with explanatory variables. Although here we use a deterministic function, a stochastic formulation can be formulated as a GAMLSS-based model (see below for a outline of the GAMLSS framework):

$$\begin{aligned} &g_{a_t}|\mu_t,\sigma_t,\nu_t,\tau_t \sim SST(\mu_t,\sigma_t,\nu_t,\tau_t)\\ &\quad \log(\mu_t) = s(gdp_{a_t}/population_{a_t}) + s(price_t) + efficiency_{a_t}\\ &\quad \log(\sigma_t) = s(time)\\ &\quad \log(\nu_t) = s(time)\\ &\quad \log(\tau_t) = s(time), \end{aligned}$$

where $g_{a_t} = \log(demand_{a_t}/demand_{a_{t-1}})$, $gdp_{a_t}$ is the country-specific gdp growth rate, $population_{a_t}$ is the population growth rate, $price_t$ is the (regional) price of gas and $efficiency_{a_t}$ is a country-specific energy efficiency.

Alternatively, the deterministic function, which is used here, is given by

$$demand_{a_t} = (1+g_a) * demand_{a_{t-1}}, \tag{1}$$

where $demand_{a_t}$ is the demand of agent $a$ at time $t$. The specification of $g_a$ (country-specific demand growth rate) is used to capture a range of factors (e.g., prices, energy efficiency measures, technological innovation) that can affect the growth rate of the country-specific demand for natural gas. Therefore, $g_a$ can be a (parametric or non-parametric) regression function with explanatory variables (including time). For this analysis, the $g_a$ is exogenously specified based upon the World Energy Outlook (WEO) 2011 by the International Energy Agency (IEA) (IEA, 2011). Therefore, by fixing the demand based upon the three scenarios (Current Policies, New Policies and 450 Scenario) of WEO 2011, we can explore the supply dynamics of the natural gas market and compare the results of the ACEGES model with the results of WEO 2011 and other studies that are based upon WEO 2011.

One way to make Eq. (1) stochastic is to model the demand growth rate $g_a$ as a semi-parametric econometric model (i.e. explanatory variables: GDP growth, population growth, energy efficiency and prices) using the GAMLSS framework, which has been implemented within the ACEGES model. Effectively, each agent assumes that, for $i = 1, 2, \dots, n$, observations $Y_i$ (country-specific demand growth rate for natural gas) have the probability density function $f_Y(y_i|\theta^i)$ conditional on $\theta^i = (\theta_{1i}, \theta_{2i}, \theta_{3i}, \theta_{4i}) = (\mu_i, \sigma_i, \nu_i, \tau_i)$ a vector of four distribution parameters, each of which can be a function to the explanatory variables. This is denoted by $Y_i|\theta^i \sim D(\theta^i)$, i.e. $Y_i|(\mu_i,\sigma_i,\nu_i,\tau_i) \sim D(\mu_i,\sigma_i,\nu_i,\tau_i)$ independently for $i = 1, 2, \dots, n$, where $D$ represent the distribution of $Y$. Let $\mathbf{Y}^\top = (Y_1, Y_2, \dots, Y_n)$ be the $n$ length vector of country-specific demand growth rate for natural gas. For $k$=1, 2, 3, 4, let $g_k(\cdot)$ be a known monotonic link function relating the distribution parameter $\theta_k$ to predictor $\eta_k$:

$$g_k(\theta_k) = \boldsymbol{\eta}_k = \mathbf{X}_k\boldsymbol{\beta}_k + \sum_{j=1}^{J_k} \mathbf{Z}_{jk}\gamma_{jk},$$

where $\boldsymbol{\theta}_k$ ($k$=1, 2, 3, 4) the vector representing the four distribution parameters, $g_k$ is a known link function (e.g., identity or log link function), $\boldsymbol{\beta}_k$ is a parameter vector of length $p_k$ and the $\mathbf{x}_{k,t}$ are the explanatory terms (exogenous variables). Note that $\mathbf{Z}_{jk}$ is a fixed known $n \times q_{jk}$ design matrix and $\boldsymbol{\gamma}_{jk}$ is a $q_{jk}$ dimensional random variable which is assumed to be distributed as $\boldsymbol{\gamma}_{jk} \sim N_{q_{jk}}(\mathbf{0}, \mathbf{G}_{jk}^{-1})$, where $\mathbf{G}_{jk}^{-1}$ is the (generalised) inverse of a $q_{jk} \times q_{jk}$ symmetric matrix $\mathbf{G}_{jk} = \mathbf{G}_{jk}(\boldsymbol{\lambda}_{jk})$ which may depend on a vector of hyperparameters $\boldsymbol{\lambda}_{jk}$, and where if $\mathbf{G}_{jk}$ is singular then $\boldsymbol{\gamma}_{jk}$ is understood to have an improper prior density function proportional to $\exp\left(-\frac{1}{2}\boldsymbol{\gamma}_{jk}^\top \mathbf{G}_{jk}\boldsymbol{\gamma}_{jk}\right)$, while if $\mathbf{G}_{jk}$ is nonsingular then $\boldsymbol{\gamma}_{jk}$ has a $q_{jk}$ dimensional multivariate normal distribution with mean $\mathbf{0}$ and variance-covariance matrix $\mathbf{G}_{jk}^{-1}$.

The model above allows the agent to model each distribution parameter as a linear or non-parametric functions of explanatory variables. Furthermore, each agent not only develops regression-type of models for the distribution parameters $\mu$, $\sigma$, $\nu$ and $\tau$ but also selects the distribution $D(\theta^i)$ that best approximates the country-specific demand growth rate such as the two-parameter Normal distribution or the four-parameter SHASH distribution used by Voudouris et al. (2011). In the ACEGES model, agents are not restricted to develop a single identical model. In fact, using a reinforcement learning algorithm (see Sutton and Barto, 1998), agents can learn to select the best $D(\theta^i)$ over time.

One of the key features of agent-based models is the agent's decision rules to select actions (i.e. production of natural gas). A basic feature of the decision rule is to respond to changes in the environment such as cumulative production, remaining reserves and world net demand for natural gas. Fig. 1 shows the decision rule for natural gas production of the agents in the ACEGES model representing 216 countries.

The mathematical description of the actions of the decision rule of Fig. 1 is given by

$$production_{a_t} = production_{a_{t-1}} + g_a * demand_{a_{t-1}} + wd_{a_t}, \tag{2}$$

$$production_{a_t} = production_{a_{t-1}} + g_a * demand_{a_{t-1}}, \tag{3}$$

$$production_{a_t} = production_{a_{t-1}} - (production_{a_{t-1}} * (production_{a_{t-1}}/y_{a_{t-1}})), \tag{4}$$

where

- $production_{a_t}$ denote the annual oil production of $a_t$.
- $y_{a_t}$ denote the oil yet to be produced of $a_t$ before $production_{a_t}$.
- $prenp_{a_t}$ is a boolean attribute that denote if $a_t$ is a pre-peak net producer.
- $wd_{a_t} = (nwd_{t-1}/nppnp_{t-1}) * (production_{a_{t-1}}/mp_{t-1})$ is the share of world demand to be satisfied by $a_t$ if it is a net producer. It is assumed that agents with larger production would be able to increase production more to meet the net unmet world demand.
- $nwd_t$ is the net world demand at time $t$.
- $nppnp_t$ is the total number of pre-peak net producers at $t$.
- $mp_t$ is the mean production from the pre-peak net producers at $t$.

Effectively, Eq. (3) allows those pre-peak net producing agents (countries) to respond to the changes in the global environment given by $nwd_t$. The assumption in the ACEGES model is that agents are ‘market-friendly’ decision-making entities producing natural gas in order to fulfill the net unmet world demand for natural gas (world demand–world production). We consider that this assumption is realistic given that (i) the key natural gas exporters will not like to cause a permanent damage in the world demand for natural gas and (ii) the key natural gas exporters still complete to enhance their market shares. This is an approximation of the ‘consumers logic’ first developed by Royal Dutch Shell in the 1970s. Pre-peak net producers are countries with large resources (compared with their cumulative production) and production greater than their domestic demand. The group of pre-peak net producers (e.g., Russia, Qatar) is the key players in the global export market for natural gas. By way of an example, Fig. 2 shows the decision pathway of Qatar, which is a country with large resources (relative to the cumulative production) and a domestic production of natural gas greater than the domestic demand of natural gas.

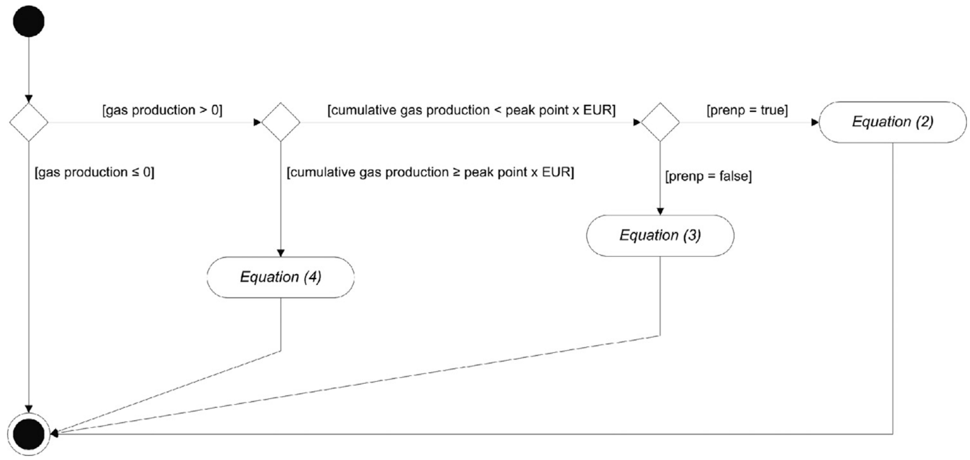


**Fig. 1.** Simplified behavioural rule for natural gas production.
(Source: Voudouris et al., 2011).

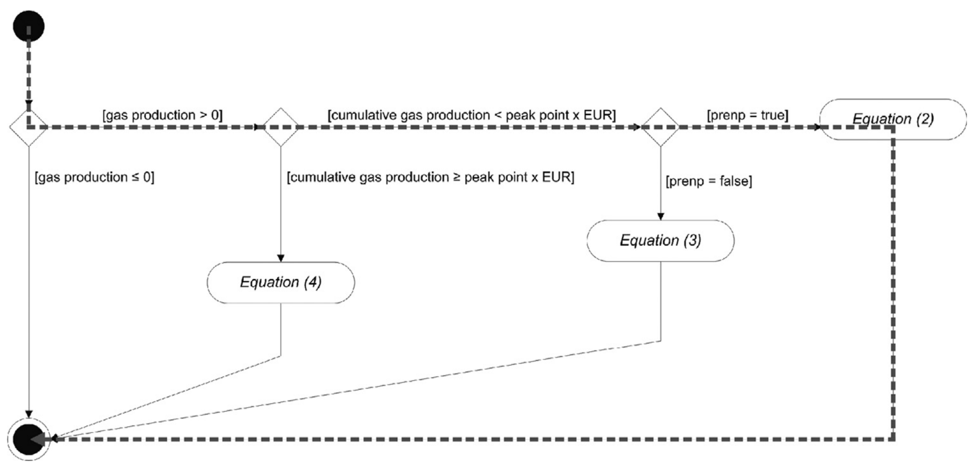


**Fig. 2.** Decision pathway of Qatar (pre-peak net producer).

The action of Eq. (4) is selected by agents who can meet their internal demand growth but cannot make a net contribution towards $nwd_t$. The action of Eq. (5) is selected by the agents whose environment is dominated by 'geology' rather than by economic/technological forces. The second decision point of the decision rule in Fig. 1 determines the *balance* between 'geological' and 'economic/technological' forces (see also Benes et al., 2012 for an alternative geologic–economic model).

Although the process of developing scenarios is primarily a non-mechanistic mental process, the ACEGES model can facilitate the exploration of plausible developments in the future by means of computational experiments using a graphical user interface (GUI), which is shown in Fig. 3. The 'Model' tab enables the scenario team to set-up the key driving forces of the natural gas scenarios such as allowable production growth, demand growth, peak/decline point and estimated volumes of natural gas originally present before any extraction. The graphic representations show the simulated scenarios of a single run (each run can simulate, for example, 100 years). The GUI gives access to model data, plays, stops, pauses and steps the simulation. Once the user runs a large number of simulations, say 10,000 simulations, the results can be summarised using time-varying quantiles and expectiles as discussed in the introduction.

Furthermore, the ACEGES model can be used for thought experiments by interactively adjusting the most important and uncertain parameters of the model. By way of an example, Fig. 4 shows that the key uncertainties are not necessarily restricted to a limited set of values (usually three) but are defined by highly flexible probability distributions. Using the simulation engine of the ACEGES model, these country-specific distributions are used to explore the full uncertainty space of the scenarios.

It is important to clarify that here we are proposing a way of developing continuous scenarios of the natural gas market using the ACEGES model. Scenarios are not forecasts or predictions. Scenarios are coherent and credible alternative stories about the future based upon the identified driving forces. Following DuMoulin and Eyre (1979), scenario is a planning technique (a) to examine future plausibility and (b) to learn the plausible forms which energy crises may take in the future. As discussed by Jefferson and Voudouris (2011), the ACEGES model supports the development of scenarios by means of computational experiments in order to portray plausible futures. The key advantage of the ACEGES model is the explicit modelling of 216 countries and the high degree of complexity (but not complication) that can be introduced to explore the uncertainties of the natural gas market outlooks. This high degree of complexity is very difficult to be introduced with conventional models (see also Tesfatsion, 2001).

### 2.2. Data for natural gas

Natural gas is a gas consisting primarily of methane found naturally in basins around the world. There are two categories of natural gas, namely conventional and unconventional natural gas. Conventional natural gas is extracted from oil fields (associated

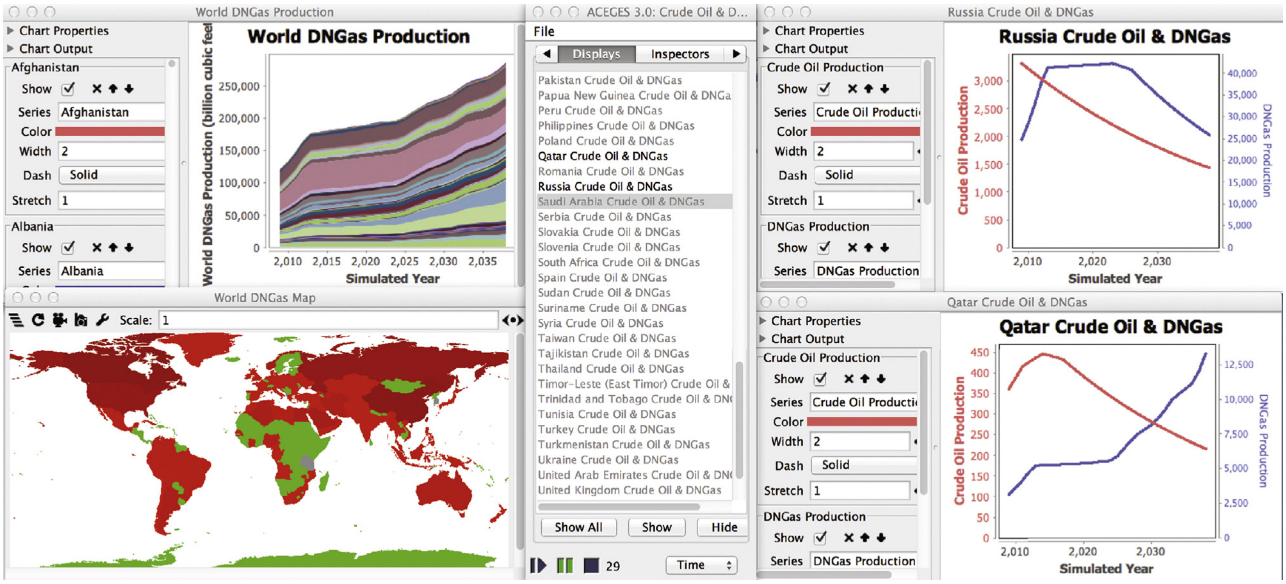


**Fig. 3.** GUI of the ACEGES model.

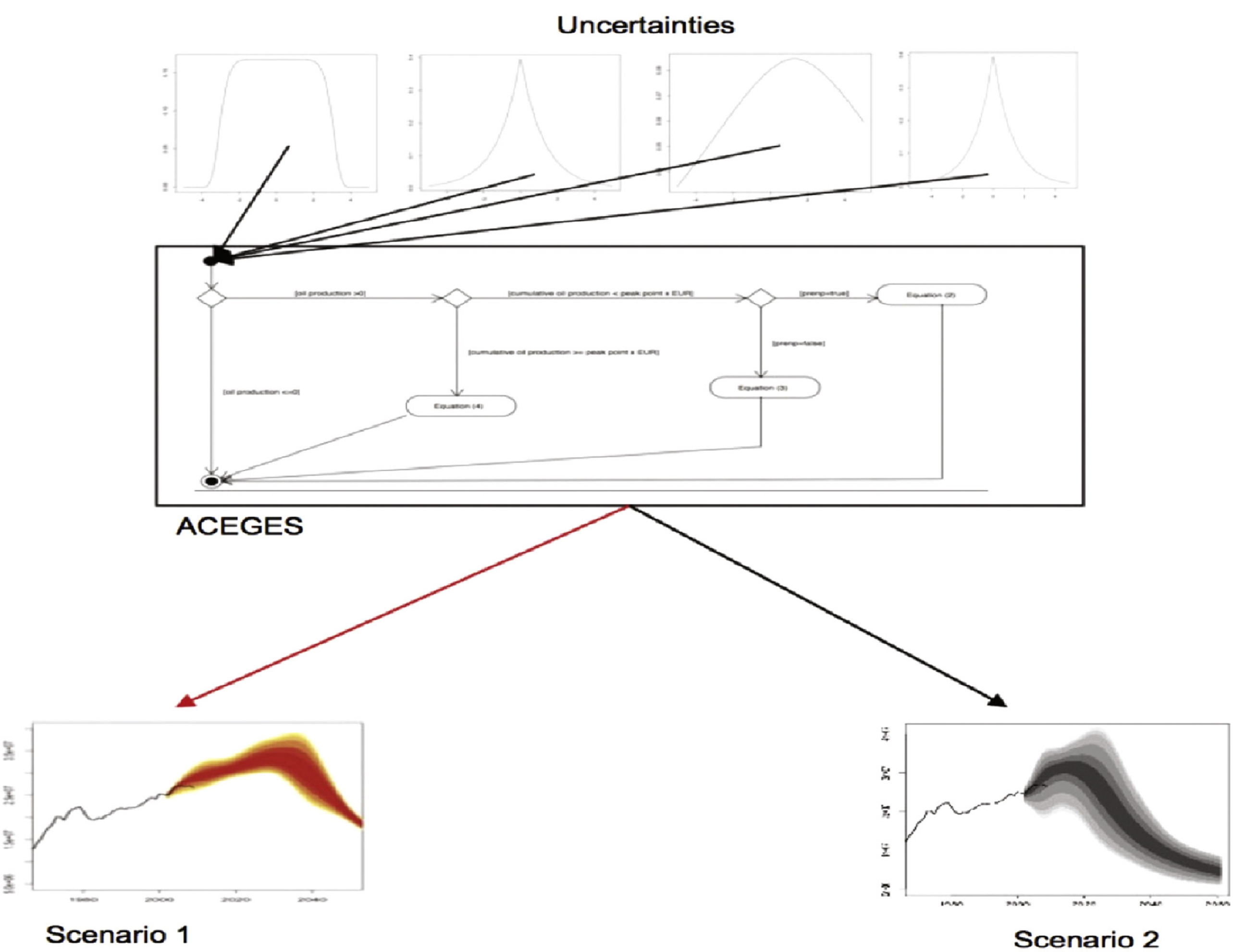


**Fig. 4.** Scheme of ACEGES-based scenarios.

gas) and gas fields (non-associated gas). Unconventional natural gas is the gas produced from the places where conventional gas is not produced, and includes tight-sand gas, coal-bed methane, shale gas, biogas and methane hydrates.

Because the ACEGES model is a realistically rendered agent based model, the model requires setting a base year which in this paper is 2008. This means that each of the 216 countries modelled in the ACEGES model is initialised with the real-world data as of 2008.

The ACEGES model is initialised with the following data for each country depending on the requirements of the scenario:

(i) The domestic demand of dry natural gas (billion cubic feet) in 2008 from the US Energy Information Administration (EIA, 2011). Dry natural gas is known as consumer-grade natural gas.
(ii) The projected growth rates of natural gas demand using the three scenarios (i.e. the Current Policies, New Policies and 450 Scenarios) of WEO 2011 (IEA, 2011).
(iii) The volume of natural gas that originally existed before any extraction (i.e. EUR) from (a) Campbell and Heapes (2009): data available for 62 countries with global EUR of 9649 Tcf; (b) US Geological Survey (USGS, 1995, 2002, 2011) World Petroleum Assessment 2000 and National Oil and Gas Assessment: data for 97 countries with global EUR of 9228 (95% likelihood)–17855 (5% likelihood) Tcf (including reserves growth); (c) Federal Institute for Geosciences and Natural Resources (BGR, 2009) Reserves, Resources and Availability of Energy Resources 2010: Data for 132 countries with global EUR of 18553 Tcf; and (d) sum of the cumulative production (see (v) below) and the latest proved reserves from EIA (2011) for countries not included in the above sources. These values are almost in the range of the estimates in the literature as discussed in Section 1. Note that EUR estimated by the method (d) does not include the undiscovered natural gas. However, this process is essential to take into account the production aspect of as many countries as possible in the model. That is to say, the model has a more accurate picture of the net demand for imports, which is what is being apportioned among the pre-peak net producers, by modelling more countries in the world, and having both production and demand for them. Having said that, this estimate should not be used alone since it is potentially a large underestimate of actual EUR.
(iv) The dry annual production of natural gas (in billion cubic feet) in 2008 from EIA (2011).
(v) The cumulative production at the beginning of 2008. The cumulative production (1900–2001), although the starting point is different by country because of the data availability, are based on (a) Mitchell (1998a,b,c) from 1900 to 1979; and (b) EIA (2011) from 1980.
(vi) Estimates of natural gas remaining at the beginning of 2008 ((iii)–(v)).
(vii) The maximum allowable projected growth rates of natural gas production. This defines the constrained natural gas production from $t$ to $t+1$. This is defined based on literature review and our own calculations.
(viii) Assumed peak/decline point of natural gas production (e.g., 0.5 of EUR). This is defined based on the literature review and our own calculations for post-peak countries.

We use two different data sets to obtain the cumulative production. By comparing the overlapping period between EIA (2011) and Mitchell (1998a,b,c) (i.e. 1980–1993), some differences are observed. These differences might also be attributed to semantics. Therefore, we adjust the Mitchell's data based upon the data provided by EIA. We calculate the country-specific conversion factor as follows:

$$cf_i = \frac{\sum_{t=1980}^{1993} prodE_{it}}{\sum_{t=1980}^{1993} prodM_{it}}, \tag{5}$$

where $cf_i$ is the country-specific conversion factor, $prodE_{it}$ is production data from EIA of country $i$ at time $t$, and $prodM_{it}$ is the country-specific production data from Mitchell at $t$.

The data above is just an indication of how the model can be empirically initialised and standardised. It is important to note that because of the use of dry natural gas, we are really testing whether the EUR estimates, in the form of dry natural gas, generate results consistent with the empirical data.

## 3. Results

Here we present two scenarios, namely:

- *The 'Collective View' Scenario*: A Monte Carlo process is used for all the four key uncertainties: (i) EUR, (ii) demand growth, (iii) maximum allowable production growth and (iv) peak/decline point. The result of this scenario is interpreted as the 'equally weighted collective view' of the agencies of the data sources reported in Section 2.2.
- *The 'Golden Age' Scenario*: This scenario assumes the demand growth rates of the Current Policies Scenario from WEO 2011 (IEA, 2011). The Golden Age scenario also assumes the high EUR estimates of BGR (2009). Both the maximum allowable production growth rate per year and the peak point are selected from a Monte Carlo process with the exception that the production growth is assumed to be a random number between 10% and 15% because of the favourable investment conditions for upstream operations.

It is important to note that by using the ACEGES model with expectiles and quantiles we suggest a move from the multi-pathway scenarios, a key innovation from 1971 when Shell's Group Planning shifted away from single-line forecasting (Jefferson and Voudouris, 2011; Jefferson, 2012), to continuous scenarios as a way of emphasising key features of natural gas production over time such as time-varying dispersion, asymmetry and kurtosis. Following Voudouris (2011b) and Jefferson and Voudouris (2011), continuous scenarios address the following limitations of the multi-pathway scenario approach.

- *Continuous scenarios* quantify the uncertain within each scenario narrative. This is demonstrated schematically by Fig. 4. Therefore, technically speaking, instead of selected four different values for the key uncertainties, continuous scenarios rely on the construction of continuous distributions.
- *Continuous scenarios* avoid having a proliferation of scenarios by acknowledging that different values for the key uncertainties do not qualify for the generation of a new scenarios. Different scenarios must outline significantly different narratives about the future.

Based upon the work of MacGillivray (1986) for quantile-based skewness and Andrews et al. (1972) for quantile-based kurtosis, we have the following measures of quantile-based measures of dispersion, symmetry and kurtosis:

$$d_p(t) = q_{1-p}(t) - q_p(t), \tag{6}$$

$$s_p(t) = \frac{[q_p(t) + q_{1-p}(t)]/2 - q_{0.5}(t)}{[q_{1-p}(t) - q_p(t)]/2}, \tag{7}$$

$$k_p(t) = \frac{[q_{1-p}(t) - q_p(t)]}{[q_{0.75}(t) - q_{0.25}(t)]}, \tag{8}$$

where $d$ is a measure of dispersion, $k$ is a measure of kurtosis,[2] $s$ is a measure of skewness,[3] $p$ is probability[4] and $t = 1.., T$ is time. The reason for using quantile-based measures of dispersion, symmetry and kurtosis is because moment-based measures of dispersion,

[2] $k_{0.01} = 3.45$ is the normal distribution. Other $k_p$ values can be calculated.
[3] $-1 \le s \le 1$ with $s = 0$ for the normal distribution.
[4] $0 < p < 0.5$.

symmetry and kurtosis may not exist or may be unreliable in the presence of fat tails (Davidson, 2012). Note that expectile-based dispersion, symmetry and kurtosis can be estimated in a similar fashion: $d_\omega(t) = e_{1-\omega}(t) - e_\omega(t)$. Note that $t$ can be replaced with an explanatory variable such as natural gas demand. By way of an example, Fig. 5 shows a 2-D density estimation of the relationship between natural gas production and natural gas demand based upon the 'Collective View' scenario discussed below.

The narratives of the 'Collective View' and 'Golden Age' Scenarios are summarised by discussing the simulated results in terms of the estimated quantiles, expectiles and quantile-based measures of dispersion and kurtosis. Measures of kurtosis are particularly important for assessing the resilience of long-term strategies because kurtosis quantifies the tail probability of observing (positive or negative) significant production jumps. It is important to note that quantile-based measures of dispersion is one way of quantifying the variation around the central projection of natural gas production. Collectively, quantiles, expectiles as well as quantile-based measures of dispersion and kurtosis enable us to explore the uncertainty within each scenario narrative.

### 3.1. Collective View Scenario

Fig. 6 shows time-varying smoothed quantiles of natural gas production. The median, $q_{0.5}$, is represented by the black line. The median production simply states that given the 'Collective View' there is 50% probability that the actual production of natural gas will be above the 'black line' and there is 50% probability that the actual production of natural gas will be below the median production represented by the 'black line'. An interesting observation here is that the growth of production of natural gas declines from 2015 onward. It is also important to explicitly state that we do not observe a peak of natural gas production given the time horizon of the Collective View Scenario. The upper quantile, $q_{0.99}$, states that there is only 1% probability that the actual natural gas production will be above the upper quantile production. Therefore, the upper quantile production might be considered as a stochastic production frontier. Similarly, the lower quantile, $q_{0.01}$, states that there is only 1% probability that the actual natural gas production will be below the lower quantile production. Therefore, the lower quantile production might be interpreted as the floor of natural gas production. Time-varying quantiles provide a comprehensive description of the distribution of the natural gas production and the way it changes over time. The choice of quantiles depends on what aspects of the distribution are to be highlighted.

Fig. 7 shows time-varying smoothed expectiles of natural gas production. The time-varying expected (mean) production of natural gas, $e_{0.5}$, is represented by the black line. We do not observe a peak of the expected natural gas production given the time horizon of the Collective View Scenario. The upper expectile, $e_{0.99}$, can be interpreted as the asymmetrically weighted expected ceiling of natural gas production. Similarly, the lower expectile, $e_{0.01}$, might be interpreted as the asymmetrically weighted expected floor of natural gas production. Clearly, there is a variability around the asymmetrically weighted expected ceiling and floor. In this instance, both expectiles and quantiles show a similar picture of the profile of natural gas production. However, the 'level' of production is different. The quantiles can be used if a strategy is to be tested against certain probabilities (e.g., a variant of the Value-at-Risk) while expectiles can be used if a strategy is to be tested against variants of expectations (e.g., a variant of expected shortfall). These two measures are very different when the shape of the distribution of natural gas production changes over time (see also De Rossi and Harvey, 2007).

Fig. 8A shows two measures of dispersion using Eq. (6). What we observe is that the dispersion increases rapidly until about 2015. The dispersion with $p = 0.25$ stabilises from about 2015 onwards. The dispersion with $p = 0.01$ is more erratic. What we observe is that the dispersion falls between 2015 and 2025 and then increases again. The different dynamics of the time-varying dispersion give an indication of the 'tail dispersion' and changing kurtosis, which is shown in Fig. 8B. Note that the kurtosis of the distribution of natural gas production is estimated by the ratio of the two dispersions shown in Fig. 8A. Here the shape of the distribution of natural gas changes over time (from a platykurtic distribution to Gaussian/Normal distribution). This reconfirms the observations made above based upon time-varying quantiles and time-varying expectiles.

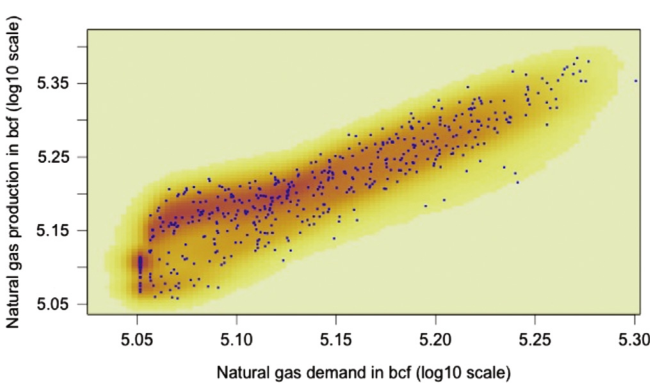


**Fig. 5.** 2-D density of natural gas production and demand.

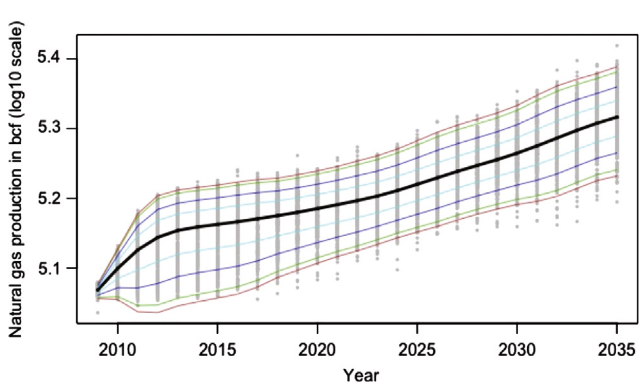


**Fig. 6.** Quantiles of natural gas production.

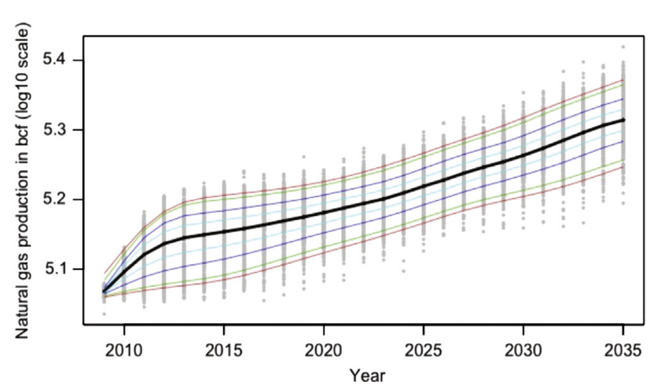


**Fig. 7.** Expectiles of natural gas production.

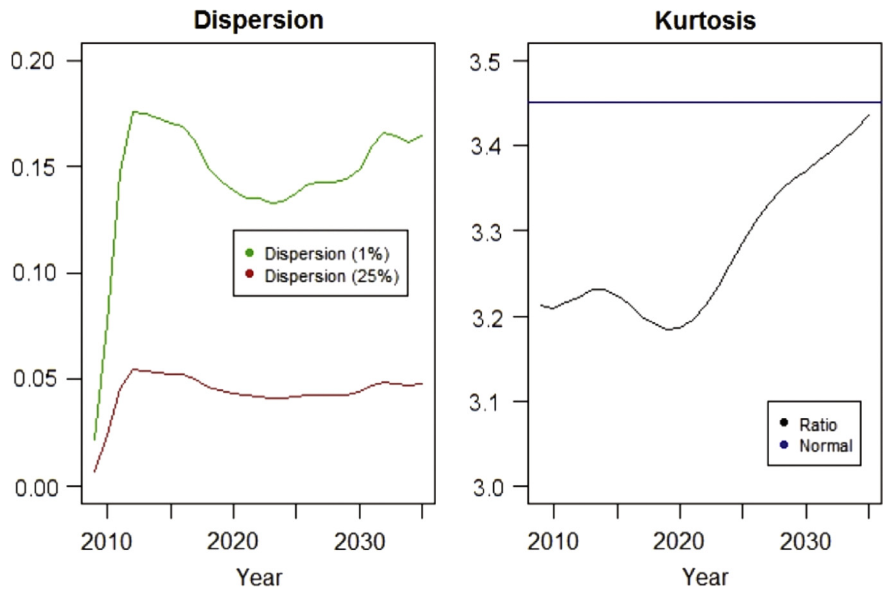


**Fig. 8.** (A) Quantile-based measures of dispersion and (B) quantile-based measures of kurtosis.

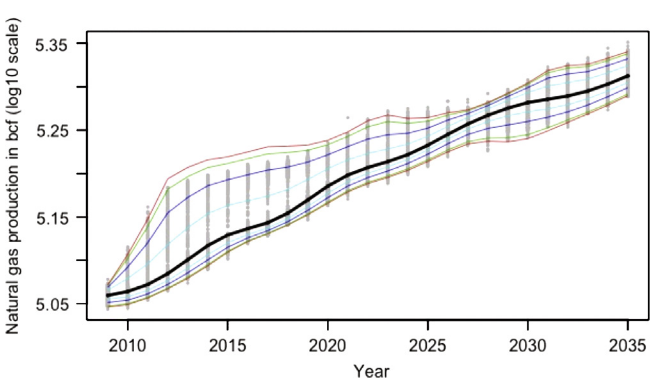


**Fig. 9.** Quantiles of natural gas production.

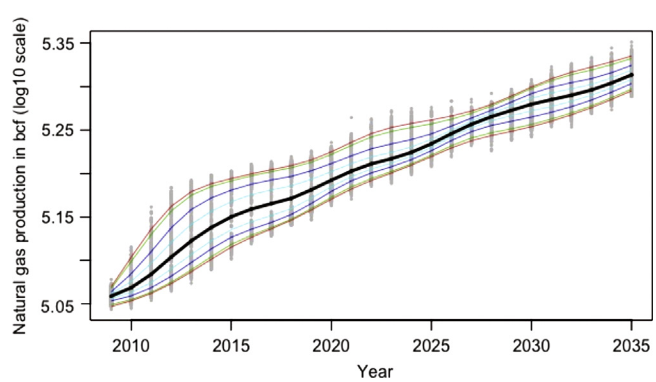


**Fig. 10.** Expectiles of natural gas production.

### 3.2. Golden Age Scenario

Fig. 9 shows time-varying smoothed quantiles of natural gas production. The median, $q_{0.5}$, is represented by the black line. An interesting observation here is the non-linear growth of production of natural gas production. It is important to explicitly state that we do not observe a peak of natural gas given the time horizon of the Golden Age Scenario. The upper quantile $q_{0.99}$ smooths out after 2030. This is because the Golden Age scenario assumes a favourable upstream investment environment. An important observation is that the variation around the central projection (the median natural gas production) reduces from 2020 onwards. It seems that the favourable upstream investment environment causes a high-degree of production uncertainty in the early years (until about 2018).

Fig. 10 shows time-varying smoothed expectiles of natural gas production. The expected (mean) natural gas production is represented by the black line. We do not observe a peak of the expected natural gas production given the time horizon of the Golden Age Scenario. The upper expectile, $e_{0.99}$, is interpreted as the asymmetrically weighted expected ceiling of natural gas production for the Golden Age Scenario. Similarly, the lower expectile, $e_{0.01}$, is interpreted as the asymmetrically weighted expected floor of natural gas production of the Golden Age Scenario. It is interesting to observe the reduction in the variability between the different asymmetrically weighted expectation of natural gas production from 2015 onwards.

Fig. 11A shows two measures of dispersion using Eq. (6). The dispersion with $p=0.25$ stabilises after about 2013. The dispersion with $p=0.01$ is more erratic. What we observe is that the dispersion decreases rapidly from 2013 until about 2028. The different dynamics of the time-varying dispersion give an indication of the 'tail dispersion' and changing kurtosis, which is shown in Fig. 11B. Note how the meso-kurtosis of the Normal/Gaussian distribution is crossed by the estimated kurtosis of the distribution of natural gas production of the Golden Age Scenario. Effectively, time-varying kurtosis of natural gas production changes from platykurtic to leptokurtic and then to platykurtic over time. Thus, it is very important to test the resilience of any long-term gas strategy from about 2010 to about 2030.

It is unlikely that the reality will be either the 'Collective View' Scenario or the 'Golden Age' Scenario. It is likely that the reality might be a mixture of the two exploratory scenarios presented here. It is important to note that although the ACEGES framework can account for political factors that can constrain production by means of subjectively specified stochastic processes, the scenarios presented here assume that production will continue to increase unconstrained by factors such as deliberate withholding, military conflicts and social unrest.

## 4. Conclusions

We recognise that to predict the exact future evolution of the natural gas market is impossible. However, we consider that it is realistic to provide continuous scenarios based upon the information available at time $t$. The information used in designing scenarios

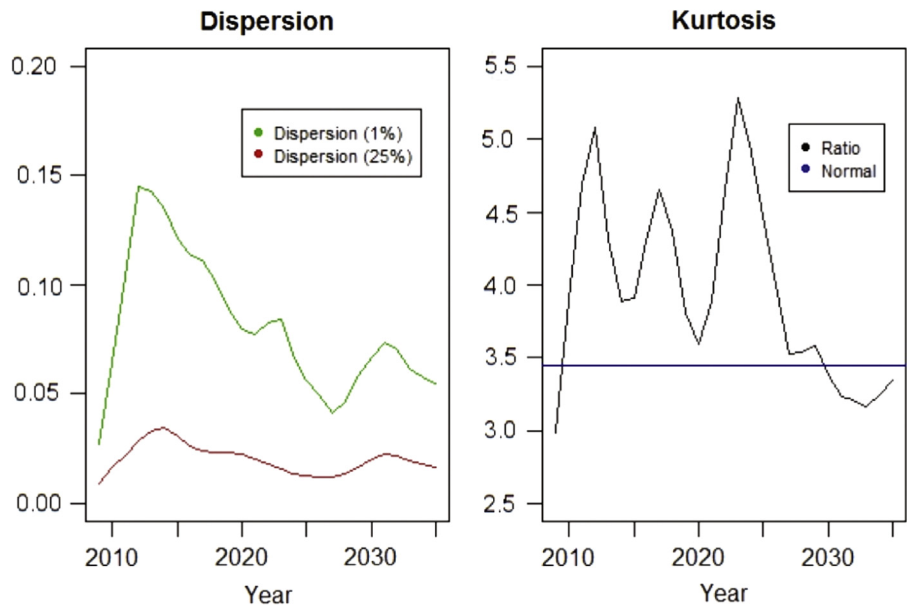


**Fig. 11.** (A) Quantile-based measures of dispersion and (B) quantile-based measures of kurtosis.

should be based upon history and current forces in the pipeline. Scenarios should not be based on wishful thinking but alternative opinions should be explored by means of controlled computational experiments.

It is demonstrated that the ACEGES model offers a new and novel way for the exploration of plausible futures of the dynamics of the natural gas market. We have also employed time-varying quantiles and time-varying expectiles as a way of analysing and visualising various aspects of the time-varying distribution of natural gas production given the two scenario narratives presented here.

The ACEGES model can simulate a very large number of scenarios by adjusting any of the most important and uncertain driving forces of the scenarios. We presented two different continuous scenarios of natural gas production, namely the 'Collective View' and 'Golden Age' Scenarios. We have discussed the plausible impact of favourable upstream investment environments observing, for example, the different quantile-based measure of dispersion and kurtosis.

Our longer-run goal for the ACEGES model is to consolidate a computational laboratory that rings true to industry participants and policy makers and that can be used as a research and training tool for long-term planning and investment processes.

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