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An expert elicitation of climate, energy and economic uncertainties ☆

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HIGHLIGHTS

- We conduct an expert elicitation of 25 UK energy experts from academia, industry and government.
- We obtained expert beliefs for six national and international drivers of energy demand.
- A linear pool of expert beliefs on oil price in 2030 is insensitive to correlation between the experts.
- Experts agree on dependence structure of energy uncertainties, but individual assessments of future values exhibit variation.

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ABSTRACT

Critical energy policy decisions rely on expert assessments of key future uncertainties. But existing modelling techniques that help form these expert assessments often ignore the existence of uncertainty. Consequently, techniques to measure these uncertainties are of increasing importance. We use one technique, expert elicitation, to assess six key uncertain parameters with 25 UK energy experts across academia, government and industry. We obtain qualitative descriptions of the uncertain parameters and a novel data set of probability distributions describing individual expert beliefs. We conduct a sensitivity analysis on weights for a linear opinion pool and show that aggregated median beliefs in 2030 are: for oil price $120/barrel (90% CI: 51, 272); for greenhouse gas price $34/t$CO_2$e (90% CI: 5, 256) and for levelised cost of low-carbon electricity 17.1 US cents/kWh (90% CI: 8.3, 31.0). The quantitative results could inform model validation, help benchmark policy makers' beliefs or provide probabilistic inputs to models.

1. Introduction

Investment and policy decisions made now have a substantial effect upon the composition of the future energy system due to the long lifetimes of energy plant and infrastructure and the consequent effects of path dependency and technology lock-in. Conversely, the current beliefs of decision makers regarding the value of key future parameters effect the decisions they make today. For example, Strachan et al. (2008) and Usher and Strachan (2012) have shown that energy transition pathways are sensitive to a range of uncertainties. Clearly, while it would be useful to have perfect knowledge regarding the future so that one could make perfect decisions, an approach which takes into account the range of possible future values is more realistic. Such decision theoretic approaches that allow a full range of possible futures to inform current decisions readily exist, such as stochastic programming (Keppo and Zwaan, 2011), real-options (Siddiqui et al., 2007) and uncertainty analysis (Morgan et al., 1992). However, while empirical data sources exist for the values of some key uncertainties, such as forward markets for oil (which could reflect traders' collective beliefs about the future oil price), for other important uncertainties there exist no sources of data. Furthermore, just as caution is required when extrapolating findings from a sample to a population, statistical data about the past is not necessarily indicative of the future. So, even when empirical data does exist, it may not be suitable for decision support. In such cases, a formal expert elicitation can provide quantified subjective beliefs for parameters with no alternative data sources.

To provide evidence for decision makers in the energy field, computer models are commonly used to support and codify expert knowledge of the integrated energy and climate change system (Rotmans and van Asselt, 2001b). In the process of constructing models, researchers make judgements about the structure of these models, the selection of parameters and the values of inputs. Commonly, the inputs to one model are derived from outputs of other models. For example, Integrated Assessment Models use formulae that emulate the relationships between energy technologies, the macro-economy and GHG emissions (Rotmans and van

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Asselt, 2001a). Researchers can incorporate estimates of uncertainties for these model inputs only if such data exists, or if they have the specific expertise to make sound scientific judgements as to the range and likelihood that represent these uncertainties. Consequently, the knowledge obtained from the outputs of models is inherently conditional on the assumptions made by the modeller (Stirling, 2010).

We propose that expert elicitation is an improvement upon the current situation. Firstly, an expert elicitation is a formal process that can produce high quality, traceable, transparent and explicitly subjective data on parameters for which there is no empirical alternative. Secondly, data from an expert elicitation can displace existing informal approaches to gathering data for uncertain parameters in models.

We claim that the formal approach provided through expert elicitation can enhance the policy making process through improved transparency and through the provision of more representative data.[1] We offer caution here, because there is potential for misuse and because there are some troubling aspects of the elicitation approach that undermine the benefits unless handled correctly. One important aspect is that expert elicitation does not provide an objective data set *de jure*, but the subjective beliefs of individual or a group of experts. Thus decisions based on this data are explicitly linked to the subjective beliefs held within the data. The integrity of the subsequent decisions rely both on the accuracy of the expert's beliefs and that of the process by which those beliefs were quantified. However, the former is the inherent nature of relying upon subjective judgements to make decisions, be they explicit or implicit and encoded within a model. Expert elicitation is rightly concerned with minimising the error in the latter through accounting for the influence of bias and heuristics upon an expert's judgement.

This work captures a snapshot of the beliefs of 25 UK energy experts in late 2011 about the value of six key uncertain parameters in 2030. We collected data on both the range of plausible values and the associated likelihoods for each parameter, through a formal one-to-one interview process. This study shows how expert elicitation can be used to produce data for use in energy-economic modelling. These results show the subjective beliefs of UK energy experts for parameters of national and international importance. The resulting probability distributions are of interest to a wide range of international and national stakeholders including those in academia, decision makers in the public and private sectors, governments and investors. The included data set can be used both to verify and validate existing scenario studies, to benchmark policy maker's beliefs or to inform model inputs.

1.1. Literature review

Bayesian probability theory stipulates that subjective beliefs about a well defined parameter can be described using a probability distribution (De Finetti, 1974). Expert elicitation is the process by which expert beliefs are encoded (Garthwaite et al., 2005) using methods that mitigate the detrimental effects of heuristics and biases (Kahneman et al., 1982).

O'Hagan (2006) provides a review of a number of heuristics and biases, first explored by Kahneman et al. (1982). Heuristics are tools or shortcuts used by individuals to replace reasoned decision making. Bias is a systemic distortion introduced into data through an unaccounted factor. Key biases and heuristics include anchoring and adjusting—respondents to not adjust their judgement sufficiently from an anchor value; availability bias—ideas that come more easily to mind are deemed more probable than those difficult to recall; representativeness—respondents are incoherent in their probability assessment (probabilities do not sum to one).

Elicitation methodologies received considerable attention between the 60s and 80s, predominantly at the junction of statistics and psychology. As such, there are a wide selection of methodologies from which to choose. Potential candidates include the fixed and variable interval methods for direct elicitation of continuous parameters. Alternatively, the elicitation can focus on statistical summaries of parameters, such as mean and variance. However, individuals are often poor estimators of statistical summaries, and the elicitation of intervals gives better results (see Garthwaite et al., 2005, for a detailed discussion).

Expert elicitation has been used in energy and climate policy to derive quantitative probabilistic judgements on key climate variables and their impact on climate sensitivity from sixteen USA-based climate experts (Morgan and Keith, 1995). There have been a range of subsequent elicitation studies on climate change impacts and adaptation uncertainties (Zickfeld et al., 2007; Granger Morgan et al., 2001; Hagerman et al., 2010). In terms of mitigation and energy pathway uncertainties, there have been fewer formal elicitation studies. Indeed these have largely been limited to assessments of individual key technologies (Baker et al., 2010; Baker and Keisler, 2011; Bosetti et al., 2012; Zubaryeva et al., 2012) and single policy measures (Baker et al., 2009), exploring the relationship between research and development funding and technological learning. Also, elicitation has been used to obtain data on uncertain input parameters, for which there is no other data source, such as the permeability of rock beneath proposed nuclear waste repositories (Bonano et al., 1990; O'Hagan, 1998). When data is unlikely to be readily forthcoming, for example through analysis of forward market prices, a formal elicitation process forms one of the only ways in which the subjective beliefs of experts can be captured.

1.2. Layout

We first discuss the selection of parameters and experts and how we conducted one-to-one interviews with 25 energy experts from academia, government and industry to elicit uncertainties for six parameters that influence decision making in the energy sector. We then present results for five of the six parameters, and show the implications of two different approaches to pooling beliefs using expert beliefs for oil price in 2030 as a case study. We conclude with implications for policy makers and energy modellers, and suggestions for further work.

2. Methods

2.1. Selection of uncertain parameters

The selection of the six uncertain parameters (see Table 1) explored in this paper followed experience of modelling uncertainty in the energy system (Usher and Strachan, 2010, 2012) and interaction with policy makers. We selected a range of international and national drivers of energy demand including those parameters to which the structure of the future energy system is most sensitive. The parameters chosen are important drivers of energy demand, energy system structure, or energy system cost. Population is a strong scaling factor of energy demand, as is the change in GDP or relative affluence (Rosa and Dietz, 2012). Behavioural aspects of energy, such as the temperature to which individual homes are heated are important when multiplied over a population (Beugin and Jaccard, 2011). Prices of GHG and oil result in very different technology pathways in energy system modelling studies (Usher and Strachan, 2012). Consequently, expectations of

[1] i.e. representative of the actual beliefs of experts.