# Deep Uncertainty and Transition to a Low-Carbon Economy*

Christian Haas[a]
Henriette Jahns[b]
Karol Kempa[a]
Ulf Moslener[a c]

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**Abstract**

We show that the transition to a low-carbon economy systematically generates situations, where firms and investors face deep uncertainty. Standard modeling-based decision support tools used by these private actors are of limited value in a deep uncertainty context. Thus, deep uncertainty deters decision making and delays investment that is needed to reach the ambitions climate goals. In this paper, we analyze how deep uncertainty negatively affects the transition. We provide an overview of approaches for decision making under deep uncertainty and discuss their applicability for firms and investors. Based on this micro-level analysis, we derive policy recommendations. Two key issues that should be addressed by policy makers are (i) to increase transparency where needed to assist the decision process and (ii) to focus on the credibility of long-term policies signaling high ambition levels. In cases where this might seem impossible, policies may be targeted at enabling the use of decision support instruments, e.g., through creating hedge instruments eventually backed by the government.

**Keywords:** Deep uncertainty · climate change · decision making · energy transition · investment

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a FS - UNEP Collaborating Centre for Climate & Sustainable Energy Finance, Frankfurt School of Finance and Management, Adickesallee 32-34, 60322 Frankfurt am Main, Germany.

b SENTUS, Kamminer Str. 33A, 10589 Berlin, Germany.

c Corresponding author: u.moslener@fs.de.

## 1. Introduction

Climate change is widely recognised as a tremendous (economic) challenge. Limiting global warming to well below 2◦C, and correspondingly reducing carbon emissions to net-zero by mid-century as agreed under the Paris Agreement (UNFCCC, 2015; IPCC, 2018), requires changing the trend of rising emissions throughout the last decades into steeply falling global carbon emissions. This transformation towards net-zero-carbon-emission economies within very few decades will require substantial change in the energy sector. Using and transforming energy is naturally connected to capital intense physical infrastructure and assets such as power plants, planes or cars in combination with electricity grids, airports or fuel stations. The investment volume required to enable this change is massive (e.g., Hall et al., 2017; OECD, The World Bank, UN, 2018) and given the short time frame available to shift the emission trend in the face of lead-times for infrastructure-related assets, this substantial investment is required soon (e.g., Höhne et al., 2020; OECD, 2020; Soergel et al., 2021).

However, sufficient levels of investment in low-carbon development are impeded by market failures such as emission externalities and spill overs from low-carbon innovation (Bennear and Stavins, 2007; Jaffe and Stavins, 1995; Jaffe et al., 2005) and imperfections in financial markets (see, e.g., Haas and Kempa, 2021; Kempa and Moslener, 2017; Kempa et al., 2021; Pahle and Schweizerhof, 2016; Polzin, 2017). Therefore, ambitious policies are required to drive and facilitate the structural change – including the investment (Nordhaus, 2018; Stern, 2018).

Beyond these market imperfections, policy makers and investors alike are facing challenges related to uncertainty in the context of the transformation. This uncertainty is related to the physical climate change itself (e.g., Knutti et al., 2010; Millner, Dietz and Heal, 2013; Stern, 2016), but also related to technological development or innovation (e.g., Creutzig et al., 2017; Jaxa-Rozen and Trutnevyte, 2021; Way et al., 2021). In addition, there is uncertainty about future policies (e.g., Atsu and Adams, 2021; UNEP, 2018; UNEP 2020). Both, policy makers and investors need to find ways to deal with this uncertainty from their different perspectives to move the transition forward.

In this article, we discuss the role of uncertainty in the energy transition and emphasize the perspective of the investor, rather than the policy maker perspective. Further, we focus on the challenge related to one specific type of uncertainty, namely so-called “deep uncertainty”, where literature to date – particular covering the investment perspective in a climate context – is rather sparse. Deep uncertainty is typically separated from the concept of risk, which represents a situation with uncertainty where the different possible outcomes are known, and the actor is able to attach some reasonable probabilities to the different outcomes. In contrast, deep uncertainty typically refers to a situation with no information about the probabilities and where not even the possible outcomes are known (see, e.g., Courtney, 2001; Kwakkel et al., 2010; Makridakis et al., 2009;Walker et al., 2003; Walker et al. 2013).[1]

We argue that, for investment in the context of the energy transition, the share of deep uncertainty in overall uncertainty is particularly relevant: For certainty as well as for investment situations with risk, the private sector, including the investment community, has already developed a comprehensive toolbox to guide decision making. It is based on either technical or market-related knowledge, or statistical concepts such as expected return, volatility, correlation, or diversification. That is not surprising as it is essentially the business-model of any private sector actor or investor to examine a project or an investment opportunity, form his/her own opinion about the risk and return, and then potentially decide to take (and manage) the risk and be rewarded for that.

As deep uncertainty is difficult or impossible to quantify, it creates substantial challenges for making an investment decision. This challenge is amplified by the fact that commercial actors often use financial markets to hedge particular risks in case they do not see a competitive advantage in quantifying and taking them. However, in most cases of deep uncertainty financial markets will

[1] A more precise definition will be provided in Section 2.

turn out to be incomplete as they do not offer those hedging opportunities. This raises the question about potential welfare increasing policies that could help facilitating the energy transformation by lowering the investment barrier created by deep uncertainty.

The paper is structured as follows. The following Section 2 illustrates the challenges created by deep uncertainty in the context of the energy transition. Section 3 provides an overview of the existing approaches to decision making under deep uncertainty. Section 4 then discusses the applicability of these approaches to investment decisions of firms and investors in the energy transition. Section 5 provides some guidance on how policy makers could help to reduce deep uncertainty faced by firms and investors in the energy transition. Section 6 concludes.

## 2. Deep Uncertainty – Concepts, Levels, and Sources

Concepts and classifications of uncertainty are numerous and have a long history.[2] One of the most recognised classifications can be attributed to Knight (1921) who distinguishes between "risk" as uncertainty that can be quantified and – in principle – controlled and "uncertainty" in a narrow sense as non-quantifiable and uncontrollable uncertainty; the latter is often referred to as "Knightian uncertainty". Building on this distinction, the literature, in particular on decision theory[3], has advanced mainly in two ways. Firstly, progress was made related to the applicability of the two concepts or functional categories.[4] Secondly, more nuanced classifications evolved, enabling the

[2] The interested reader is referred to Agusdinata (2008), Morgan and Henrion (1990), Smithson (1989), and van Asselt (2000) for historical context and use of concepts in different fields.

[3] See Luce and Raiffa (1957) and Morgan and Henrion (1990) for overviews of decision-making under risk and decision-making under uncertainty.

[4] A central discussion relates to the scope of Bayesian decision theory and its role as normative imperative. While it is widely accepted that risk is not only limited to objective probabilities but can also describe situations with subjective probabilities (see Gillies, 2000, for an overview of the different interpretations of probabilities) necessary "real-world" conditions for sensible use of Bayesian decision theory are disputed. See De Finetti (1977) and Savage (1954), particularly Savage's elaboration on decision-making in large worlds, for the classical, opposing positions. Binmore (2008) and Gilboa et al. (2008) provide discussions on the applicability of Bayesian decision theory for real-world problems.

evolution of descriptive and normative theory, including the development of specific methods to cope with situations (perceived as) under uncertainty.[5]

It is worth to note that it is widely accepted that risk is not only limited to objective (frequentist) probabilities (often associated with the throw of a die) but can also describe situations with subjective probabilities (one may think of assigning probabilities to the winner of a horse race).[6] However, an increasingly extensive literature deals with the question whether individuals are always equipped with or can form (meaningful) subjective probabilities and how a lack of those, typically referred to as situations of "ambiguity" (i.e., un- or only partially known probabilities), translates into decision-making.

Part of this larger field of research is a vivid strand that relates to the term deep uncertainty and aims to be particularly elucidating for situations under Knightian uncertainty. Deep uncertainty as concept and category within uncertainty in a broader sense was introduced by Lempert et al. (2003).[7] Following a model-based multiple stakeholder approach, they define deep uncertainty as "a situation in which the experts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe the interactions among a system's variables, (2) the probability distributions to represent uncertainty about key variables and parameters in the models, and/or (3) how to value the desirability of alternative outcomes" (Lempert et al., 2003: 3-4).

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[5] Significant progress was made subsequently to the (thought) experiments of Allais (1953) and Ellsberg (1961). The literature on individual decision-making contains four widely used categories or classes of uncertainty:

(i) Certainty, typically associated with complete knowledge;
(ii) Risk, which refers to probabilistically quantifiable uncertainty;
(iii) Ambiguity, which describes (a) probabilistically quantifiable (e.g., considered as second- or higher-order probability distributions over probabilities, see, e.g., Marschak, 1975) and (b) non- or partially quantifiable uncertainty. The latter is often referred to as situation of *unknown probabilities*;
(iv) (complete) Ignorance, as limiting case of uncertainty when no information is available and/or known. It comprises situations of *unknown probabilities* and *unknown possibilities.*

See Bradley and Drechsler (2014), Camerer and Weber (1992), and Luce and Raiffa (1957) for discussions and further references. The concept of ambiguity with non- or partially known probabilities and ignorance is most closely related to the concept of deep uncertainty.

[6] See Gillies (2012) for an overview of the different interpretations of probabilities.

[7] Ben Haim (2006) uses the term "severe uncertainty" for a similar concept.

Alternative definitions applicable to non-model-based approaches are provided by Hallegatte et al. (2012) and Marchau et al. (2019). The former define deep uncertainty as the presence of one or more of the following three elements: (i) Multiple possible future worlds without known relative probabilities, (ii) multiple divergent but equally valid worldviews, including values used to define criteria of success, and (iii) decisions which adapt over time and cannot be considered independently. Marchau et al. (2019: 2) define deep uncertainty as situations, in which "the experts do not know or the parties to a decision cannot agree upon (i) the external context of the system, (ii) how the system works and its boundaries, and/or (iii) the outcomes of interest from the system and/or their relative importance [...]."

Walker et al. (2013) frame the concept of deep uncertainty within uncertainty in a broader sense and provide a comprehensive classification system.[8] Their classification builds on different degrees of existing and known information about four elements of a decision situation,

i. future states,
ii. (future) system models,
iii. outcomes,
iv. weights that the various stakeholders put on the outcomes,

and their qualitative assessment regarding number and variation within each of these elements. They distinguish between five intermediate levels, limited by two extremes denoted as complete certainty and total ignorance. Level 1 uncertainty represents the situation in which an individual is not completely but sufficiently certain to refrain from considering uncertainty explicitly. Level 2 uncertainty is any uncertainty that can be adequately described in statistical terms and relates to a rather low number and variation within each of the decision elements listed above. Level 3 uncertainty represents a situation in which an individual is able to enumerate multiple alternatives and

[8] Walker et al. (2013) build on Courtney (2001), Walker et al. (2003), Makridakis et al. (2009), and Kwakkel et al. (2010).

rank these alternatives according to their (subjectively perceived) likelihood. Variation in and number of potential future states, system models, and outcomes is considered rather low.

Level 4 uncertainty is characterised by the existence of multiple alternatives, but in contrast to Level 3 uncertainty, individuals lack the ability to rank alternatives or assign any subjective probability. Plausible system models are manifold and the range of outcomes is wide. Level 5 uncertainty represents the deepest level of recognised uncertainty and is characterised by the inability to enumerate alternatives. System models and outcomes are unknown and hence evade an explicit assessment. Level 4 and 5 are defined as situations of "deep uncertainty", where in the earlier, there is no general agreement upon and in the latter no knowledge about the elements enumerated in Lempert et al.'s (2003) definition (models, probability distributions, and desirability of outcomes). Particularly characteristic for levels of deep uncertainty is the wide (Level 4) or unknown (Level 5) range of possible (future) states, system models, outcomes, and the multiplicity of weights put on outcomes by different stakeholders.

It is worth to note that the concept of deep uncertainty was developed in the context of long-term model-based policy decision support. It merges elements of the theoretical and experimental work in the field of rational decision-making with real-world challenges from applied methods, the (perceived or recognised) inadequacy of existing methods. When applied to a firm's or an investor's environment, multiple-perspective and multiple-stakeholder aspects (particularly differences in the desirability of outcomes) may lose importance, in contrast to the policy context. The potential lack of relevant information about future states and outcomes, acts and related models, and their respective probabilities, however, is no less critical.

For our analysis of the energy transition, we will use the approach introduced by Walker et al. (2013) as it provides a comprehensive classification system including different levels. The approach also relates to models behind decisions which makes it particularly suitable for our discussion in the context of investment decision making – which is traditionally supported by modelling.

In the context of firms' or investors' decision making, identification of potential sources of uncertainty can be structured at macro, meso, and micro or firm level. Obviously, the different levels should not be considered strictly separate, but rather interconnected. Macro-level sources can be derived from the STEEP framework that is regularly used for business analysis and valuation (e.g., Fisher et al. 2020). The framework comprises six, potentially interlinked (e.g., Sammut-Bonnici and Galea, 2014), categories considered relevant in an investment context: society, technology, environment, economy, and politics (regulation). The number of categories, the specificity of domain-related knowledge, and the interdependences between categories, typically leading to analyses of sub-systems, e.g., the socio-economic or socio-technological system, give rise to potential high intricacy, complexity, and information requirements in a decision-making context – imposing significant challenges for integrated model development and potential deep levels of uncertainty when analysis of the integrated system is relevant.

At a meso or industry level, sources of uncertainty can be related to changes in suppliers and customers (value chain), competitors and new entrants (and their strategies), and potential substitute products (e.g., Porter, 1979). At a firm level, analysis of sources for uncertainty usually refers to structures and processes, (e.g., financial and human) resources of an organisation and the capability to acquire and maintain them. A highly dynamic industrial environment as potential source of uncertainty might result in moderate (so-called Level 2 and Level 3) as well as deep levels (Level 4 and Level 5) of uncertainty for individual actors (firms and investors), where the depth is moderated by firm/investor and industry characteristics and the historical context.

A (technical) source of deep (levels of) uncertainty, emphasising its characterising features of wide range of outcomes and system models is related to the concept of path-dependency and self-reinforcing mechanisms. It is well known that some of the sub-systems enumerated above possess these characteristics (e.g., Cowan, 1990; David, 1985; Kenney and von Burg, 2001). Small changes in the starting conditions or early decisions can have large effects on the ultimate outcomes and the direction of development (e.g., Mahoney, 2000; Pierson, 2000; Thelen, 1999). Path-dependency and self-reinforcing mechanisms can lead to so-called lock-in of certain paths and settings, technological and institutional arrangements due to accumulation of experience around established structures, self-fulfilling expectations about the persistence of these arrangements, and increasing benefits of moving in the established direction (Patashnik, 2008; Unruh, 2000). It is worth to note that these feedback effects can also be (transitionally) destabilising, leading to reversals of development and disruption, e.g., if self-reinforcing developments in one part of a system result in a latent accumulation of impacts in another part and ultimately destabilising the established (equilibrium) path of the integrated system (e.g., Jacobs and Weaver, 2015; Jordan and Matt, 2014).

# 3. Deep Uncertainty in the Transition to a Low-Carbon Economy and its Impact of Firms and Investors

In the context of global efforts to reduce net carbon emissions to zero within this century, so far 59 countries (covering more than half of the global green-house-gas emissions) including the EU, the US and China have communicated net-zero emission targets, more than 150 of the parties to the Paris agreement have submitted national action plans (UNFCCC, 2021; van Soest et al., 2021). Most countries envisage a timeframe of 2050 (UNFCCC, 2021). With energy-related carbon emissions dominating the statistics, this requires a transition to a low-carbon economy. An essential part is the energy transition, i.e., a substantial and lasting change in the way energy is transformed or used.

## 3.1. Deep Uncertainty in the Transition towards a Low-Carbon Economy

Pearson (2018) looks at historic energy transitions. He finds a variety of definitions of energy transitions from narrow perspectives focusing on the shift in major primary energy carriers to broader concepts considering energy use patterns and policy and societal features. He points to complexity as a common element across energy transitions in general, as "[t]hey have often also influenced and been influenced by industrial revolutions or 'long waves' of economic development […]" and emphasizes that energy transitions have often been "entangled with other, broader socio-economic, demographic, technological and environmental changes and processes".

It is therefore plausible that the energy transition towards a low-carbon economy, which needs to unfold in different but significantly interdependent sectors in parallel (e.g. transportation, industry, power generation, buildings, etc.) will also carry strong elements of complexity – one potential driver of (deep) model uncertainty. Consequently, the sub-system level, or so-called spheres of transformation as part of the overall transition [macro-meso levels], cannot be analysed independent of each other since consistency across the sub-systems is required. Similarly, it is argued that energy transitions tend to be path-dependent (see, e.g., Foquet, 2016), another potential source of (epistemic) model uncertainty.

Although such a system environment can plausibly generate situations of so-called Level 2 or Level 3 uncertainty (which can either be described in statistical terms or ranked according to subjective probabilities), complexity and path-dependency may also lead to situations in which multiple alternatives (governed by different models) exist where there is no probability raking or not even proper information about the alternative models themselves (so-called Level 4 or Level 5 deep uncertainty). In other words, situations in which common statistical approaches (such as expected profits) are not applicable to support decision making.

Some scholarly work has already looked at the energy transition with a particular focus on uncertainty. Based on our previous considerations about system complexity and path dependency as potential drivers of situations with deep uncertainty, we will take a broader look at this work and identify areas where deep uncertainty occurs. Most of the work that touches deep uncertainty in the context of the transition towards a low carbon economy relates to the macro-perspective and correspondingly the perspective of a policy maker. Thereafter we will – after providing a brief overview on the macro level – turn to the investor's view on such situations.

Heal and Millner (2014) provide an overview on the (interacting) climate impact and socioeconomic sources of deep uncertainty in the context of climate policy. Socioeconomic sources of deep uncertainty can be further broken down into technology uncertainty, policy uncertainty and uncertainty as regards broader societal transformations (see also Bornemann et al. (2019) and Sharmina et al. (2019) for a more detailed discussion of attributes of coupled natural and human systems under deep uncertainty). Heal and Millner (2014) further conclude that major empirical uncertainties are fundamentally unknown. These include, e.g., uncertainties concerning future technologies for abatement, the global economy's long-run growth path, or the capacities of societies to adapt to climate change. The authors argue that the frequently applied expected utility framework for decision making under uncertainty might not be suitable in the context of the climate problem and discuss potential alternative approaches in the context of climate policy choice based on the literature on decision making under uncertainty originating from Gilboa and Schmeidler (1989).[9]

### 3.2. Introducing the Firm / Investor (Micro) Perspective

While we observe that most of the work to date has taken a macro-perspective or at least has been focussing on informing policy choice, there is considerably less literature on the micro-perspective, and on the role of the firm-level actors, including financial investors. This micro-perspective, however, is highly relevant for a complete understanding of challenges in the context of the energy transition. For example: as the vast majority of carbon emissions is generated by firm-level corporate actors (e.g., power producers or heavy industry) or through using products of corporate actors (e.g., car industry), it is those actors who will need to make investment decisions that are in line with a path towards carbon neutrality (e.g., IEA, 2021; Lamp et al., 2021). These firms are

[9] Further overviews of the role of uncertainty in the context of climate change on a macro level are provided by Pindyck (2007) and Aldy and Viscusi (2014).

potentially active in R&D and innovation and invest in physical capital. For the investment itself, the firms typically rely on external funding sources (Howell, 2017; Kempa et al., 2021; Nanda et al., 2015; Noailly and Smeets, 2021). These would be investors in public or private equity or debt providers through providing loans or buying bonds.

Both, firms' investment in physical capital as well as the behaviour of financial investors is also subject to and influenced by uncertainty[10], and sometimes deep uncertainty, despite not being explicitly identified as such. Specific sources of uncertainty that affect the corresponding decision makers are diverse, as described in Section 2. Considering societal and environmental dimensions as a larger frame, sources of uncertainty are often considered in three groups: (i) Uncertainty about technology development (for example car manufactures need to form their expectation about the future roles of hydrogen-fuelled vehicles versus battery-electric vehicles); (ii) Uncertainty about policy (instrument timing, commitment, paths), and (iii) Uncertainty about behaviour of competitors within the same industry and in other industries. However, when considering the aspects of deep uncertainty, we have already established that the socio-technological or socio-political subsystems within a transformation cannot be considered independent of each other.

Referring to the definition of Lempert et al. (2003) above, characterising deep uncertainty as a situation in which parties do not know the system model, probability distributions of the corresponding model parameters or relative importance of alternative consequences, numerous situations of deep uncertainty can be identified. Based on an expert survey in the UK, Li and Pye (2018) confirm the complex interlinkages between technology, society and politics, and also show that both, socio-political as well as technological uncertainties are considered major in the UK energy transition context. Bardt and Schäfer (2017) show for the German context that decision makers in the energy industry are postponing investments because of policy uncertainty, particularly when (future) course-setting policy decisions are expected (see also Julio and Yook, 2016). They also

[10] For an analysis of how a stochastic policy process may lead to unexpected capital write-offs (stranded assets) see, e.g., Bretschger and Soretz (2018).

provide evidence that this effect is systematically stronger for the industry as compared to the services sector and substantially more pronounced for large firms, making it even more relevant for the low-carbon transformation as large firms tend to be more involved in the infrastructure investments needed for the energy transition.

Mazur et al. (2015) point out that the transition to new technologies in the automotive industry can and most likely will change value chains in a fundamental way, indicating high complexity and interdependencies at meso and firm levels. In that context, Mosquet et al. (2020) emphasise the often fragmentated regulatory environment as potential source of uncertainty and hurdle for private infrastructure investments (for similar arguments, see also Rothenberg and Ettlie, 2011). Frigant (2011) argues that existing competitive advantages of specific industries (might) shape policy-making thereby add another dimension to policy uncertainty (see also Hooftman et al., 2018, for a historical example for the automobile industry).

In a study on European offshore wind farm investments, Sun (2021) identified numerous situations of deep uncertainty and associated delayed investment. The study indicates that deep uncertainties are not only concentrated in the initial phase of the investment, but sources of deep uncertainty are shifting over the years from the technical to the political sphere. Moreover, they show that deep uncertainty materialises in unexpected developments and that uncertainties from the different spheres are very strongly interrelated and often mutually reinforcing.

More detailed insights into the perspective of long-term infrastructure investment decisions and how they traditionally work through the prediction[11] of one or multiple future states that leads to acting on investment decisions today are provided by Hallegatte et al. (2016). Deep uncertainty in the context of climate change, however, leads to a vanishing confidence in these kinds of predictions. Sharmina et al. (2019) argue in a more general and interdisciplinary way that climate change

[11] This is often referred to as the "predict-then-act" paradigm, see also Lempert et al. (2003). An overview on a broader set of climate-related financial risk assessments can be found in Bingler et al. (2020).

causes an additional layer of deep uncertainty because of the required paradigm shift and by pointing out that uncertainty is a natural factor in any long-term investment decision.

Because of this prevalence of deep uncertainty across the key areas where investment is required for the energy transition, standard stochastic tools supporting investment decisions are of limited use in this context and alternative approaches are needed.

## 4. Approaches for Decision Making under Deep Uncertainty

Investment decisions by real economy actors can be structured in various ways. One is, to distinguish investment in physical capital stock on the one hand and R&D investments on the other. There is broader consensus that the former tends to be negatively affected by uncertainty in general while for the latter evidence is more ambiguous (e.g., Bloom et al., 2007; Czarnitzki and Toole, 2011, 2013; Ghosal and Loungani, 2000; Gulen and Ion, 2015; Kalamova et al., 2012). In this section, we analyse approaches for (investment) decision making under deep uncertainty. We first discuss probabilistic concepts and then move to partially- or non-probabilistic approaches.

### 4.1. Probabilistic Concepts

Among the probabilistic concepts the most prominent ones are the cost benefit approach (CBA) and the maximum net present value (NPV) method. Both approaches need agreement on a set of assumptions describing the different possible outcomes. The decision alternatives are compared and ranked based on those outcomes. In both approaches, the analysis is traditionally completed up to the level of a prediction before the decision.

The decision process may be illustrated as follows:

i. Identify competing projects;
ii. Identify sources of uncertainty and future possible states of the world;

iii. Evaluate the costs and benefits for each project;
iv. Calculate the present value of costs and benefits;
v. Calculate the net present value of different competing projects.

In an adaption of this approach to situations comprising deep uncertainty, additional and significant efforts are spent to evaluate the robustness of the result (see, e.g., Lempert, 2014).

Cost-benefit analysis as described by, i.a., Boardman et al. (2017) is equivalent to analysing a subgame (after nature's act) of a larger game (player(s) ignore that a larger game exists or assume certainty w.r.t. nature's act). There are variants of cost-benefit analyses that include subjective probabilities for the central future scenario/state (Gilboa, 2009), while others work with equal probabilities for possible future scenarios (de Jalon et al., 2013). Reliability weighted approaches use transformed probabilities where average probabilities are calculated using individual weights for each probability corresponding to its degree of reliability. Furthermore, best- and worst-case scenarios are typically considered in a cost-benefit analysis framework.

### 4.2. Partially and Non-Probabilistic Concepts

There are several partially or even non-probabilistic approaches discussed in the context of deep uncertainty. They vary strongly with respect to the starting point, involved modelling effort, flexibility over time, etc. Therefore, they represent different fits to decision situations characterized by e.g., available information or parties to be involved in (or affected by) decision making, which can then guide the choice of the proper decision-making approach. Within these types of concepts, we will focus on the approaches of robust decision making, real option analysis, hedging and diversification, info-gap decision theory and dynamic adaptive planning.

In the framework of *robust decision making*, the goal is to reduce vulnerability across a variety of plausible futures. Reduced vulnerability might be reached at the cost of primary (financial) performance, often described as strict optimality (Lempert and Collins, 2007). Different futures are typically derived from many simulations, but no probabilities are assigned (although, some future outcomes might occur more often). Strategies are evaluated in each of the different future scenarios. This approach might allow to identify dominated strategies. Challenges of this framework are that robust decision making is considered as very data and resource intensive (Hallegatte et al., 2012) and might involve subjectivity (choosing among options that cannot be ranked by objective measures like Pareto criteria). Lempert et al. (2003) suggest identifying the lowest level of trade-off between optimizing returns (in each scenario) and robustness. Robust decision making involves evaluation of a set of strategies in different scenarios instead of identifying the optimal strategy for each scenario (policy first approach instead of science first approach). The IPCC suggests applying such an approach in a situation with deep uncertainty (Jones et al. 2014). Here, the decision process may be illustrated as follows:

i. Derive and explore scenarios;
ii. Stress-test strategies over plausible paths into the future;
iii. Identify robust strategies.

This approach has been discussed more frequently in the policy making context, rather than investment related. From the perspective of a firm or a financing investor, it may become an issue that this approach is considered very data and resource intensive. Costs of exploring a non-standard-alternative (e.g., a switch to a new technology) will be attributed to this new alternative (e.g., the new technology), thereby making it less profitable and less attractive. Further, the robustness of the individual strategies of the firm or investor may strongly be influenced by the policy maker.

Therefore, the policy-maker's perspective on the investor's perspective may inform on two important aspects: One aspect could be to identify ways to support robust decision making through reducing the costs of the resource intense analytical robust-decision-making process. Another aspect could be to consider the investor's robustness perspective in policy design, thinking about which policy approach will generate higher degrees of robustness (or reduce the costs of identifying robust strategies). Moreover, policy makers should consider the different evaluation criteria of investors in the context of deep uncertainty. Marginal changes in policies that have an effect on investors in situations of risk may fail to alter investors' behavior in situations of deep uncertainty (e.g., if the envelope of possible future systems is not affected by a policy measure).[12]

*Real option analysis* (Arrow and Fisher, 1974; Henry, 1974; Cox et al. 2002; Dixit and Pindyck, 1994; Merton, 1973) aims at analyzing and quantifying the value of flexibility and adjustability. Investment (as an alternative) is associated with two options: A call option that allows to invest later or partially invest later. A put option that allows to disinvest or resell the initial investment later. General discussion can be found at Abel et al. (1996) and Dixit and Pindyck (1994), overview of both theoretical and empirical literature is provided in Butzen and Fuss (2002).

The potential of a reduction of uncertainty (i.e., learning, using new information becoming available) may increase the value of acting later. The central trade-off in real option analysis is between benefits from an earlier investment and benefits from a delayed and (due to more information / decreased uncertainty) potentially better suited investment. Real option analysis is typically used for large irreversible investments with long lifetimes with a high chance of over- or underinvesting combined with opportunity costs of waiting, i.e., if there is a need for action in the present. It has a timeliness and a flexibility implication: first, real option analysis evaluates the benefits of postponing part or all of an (irreversible) investment, and second, it can assess technical options created or destroyed through the project (Wang and De Neufville, 2005). A flexible strategy (partly postponing the investment or choosing a strategy that allows technical flexibility) typically is initially more expensive than a supposedly optimal solution but provides some level of reassurance if the future does not unfold as expected (Ranger et al., 2010). Real options analysis is frequently applied for investment projects in a business context (Copeland and Tufano, 2004), often also in a context of environmentally friendly technology implementation (Schachter and Mancarella, 2016).

[12] See, e.g., Luce and Raiffa (1957) for an overview of evaluation criteria under uncertainty.

The real options approach has clear strengths from an investment decision maker perspective in that it explicitly assigns a value to information that will be learnt over time, to fully evaluate the real options. However, the information available in situations with deep uncertainty will often be insufficient: the concept relies on baselines as reference values and expected values, which can easily be meaningless if little is known about the underlying model alternatives (see, e.g., Kwakkel, 2020). In fact, if - from an investor's perspective - the conclusion is that in cases of deep uncertainty the value of learning (in other words the value of waiting) is even larger, then this is an even stronger channel through which deep uncertainty slows down energy transition related investment (see, e.g., Miao and Wang, 2011; Cartea and Jaimungal, 2017, for a discussion of the timing of option exercise under uncertainty). From an economic perspective on the energy transition, this is particularly problematic if there is time pressure, in other words, the welfare losses caused by delay are felt by the whole society, not necessarily by the investor delaying the decision. The role for the government to reduce those welfare losses could be to provide a mechanism to either help to evaluate the different options or to essentially reduce the value of waiting to the investor.

Another approach would be so-called *hedging or diversification*. As suggested by the name, it has its roots in classical portfolio theory (Markowitz, 1952). The idea is to choose strategies such that returns are maximized for a given risk or risk is minimized for a given return. Thereby, this approach identifies efficient strategies (using returns, risks, and covariances of different strategies). Applications employing Modern Portfolio Theory in the context of adaptation to climate change can be found in Ando and Mallory (2012) and Crow and Parker (2008). Challenges in the application of this result in an energy transition context appear to be the need for a – even if imprecisely measured – probability distribution as a starting point. In a second step, the important effect of diversification is then strongly determined by correlation, which may or may not be well identified, depending on the specific decision situation.

While a government can try to reduce unpredictability of its own decisions, it will be difficult to support technology-related predictions. An example, where the government can limit the negative effect of technological uncertainty, are the so-called Carbon Contracts for Difference (see Chiappinelli and Neuhoff, 2020). These contracts are discussed to be offered to steel producers to ensure a high value of carbon emissions avoided – irrespective of the (uncertain) market price of CO2.

The so-called *Info-Gap Decision Theory* (Ben-Haim, 2017) considers the difference between known knowledge on the one hand and the knowledge that is necessary for a responsible decision on the other hand. The difference is called info-gap. This approach does not use probability distributions. However, the underlying uncertainty model does introduce some metrics to distinguish outcomes that are more similar versus less similar. Therefore, the approach is not robust to outcomes which are completely unexpected. The application starts with a so-called uncertainty model that measures uncertainty by a distance between the parameters about which there is uncertainty. Based on this uncertainty model a so-called robustness model is established in context with the decision at hand, which seeks to quantify how large the uncertainty can be, while there remains a certain level of confidence that the (desired) outcome will be reached. The goal of the final decision-making model is then to identify which among the decision alternatives – given the desired outcome – can resist the highest level of uncertainty.

Because of the intense and often rather abstract modeling requirements, which need to be translated into system and decision-specific models, this approach has often been applied in smaller well-defined contexts, such as engineering or biology. An application to the value-at-risk (VaR) in financial decision-making focuses on non-probabilistic Knightian info-gaps in the size and shape of the lower tail of the probability density function and suggests a "robustness premium as a supplement to the incremental VaR for comparing portfolios" (Ben Haim, 2005). Application in the context of the energy transition may appear suitable in only a very limited number of well-defined subsystems, or aggregated to the portfolio-level, where standard-measures such as the VaR may be improved.

The approach of *Dynamic Adaptive Planning* (Walker et al., 2019) starts by specifying objectives as well as constraints. The planning/decision making that follows is not static but does explicitly include sub-decision in connection with timeframes and contingent action based on information that becomes available in-between. The key pf this approach is the identification of vulnerabilities of the plan, i.e., deviations from the planning assumptions that may cause the plan to fail. Based on these vulnerabilities, a monitoring is put in place to signal if one or more critical vulnerabilities have reached a critical level. This would then trigger ideally pre-determined action to help the plan stay on track. Should the monitoring indicate that objectives get out of reach, the whole process is started all over again: the plan will be reassessed, and objectives redefined. The framework of Dynamic Adaptive Planning has been applied to some cases of uncertainty in policy makers' decision making, e.g., the area of flood risk management in a climate change context (Rahman et al., 2008) or the implementation of urban transport infrastructure (Marchau et al., 2008).

This approach is highly flexible as it – at least in principle – even allows to deal with Level 5 uncertainty and "unknown unknowns". It also appears to be implementable to a wide range of cases, ranging from situation where no detailed modelling is possible for epistemic, resource or other reasons all the way to including highly advanced (and perhaps constantly evolving) modelling skills. Thus, the approach is open to be at least in part applied jointly with suitable components of other decision-making frameworks. In this sense, it is rather an over-arching framework for planning. However, it may be challenging to evaluate its performance versus other decision rules given that it may not only include parts of them but even the option to change objectives as part of the plan.

The high degree of flexibility makes the approach of Dynamic Adaptive Planning also appear suitable to investors, including real-economy actors with distinguished objectives changing over time. The policy maker can support the application of a dynamic adaptive planning broadly by easing planning and monitoring. Where the monitoring of the investor includes the actions of the policy maker itself, long-term credible signals will be particularly helpful. In a broader perspective, the policy maker may also play a role as the overall regulatory framework – which may entail rigidities, e.g., on the labour market – is an important driver of firms' flexibility.

## 5. Reducing Deep Uncertainty for Firms and Investors – the Role of Policy

The different approaches available to deal with uncertainty have their individual strengths and challenges. In general, individual firms and investors can be expected to be best suited to choose their own approach and associated effort to properly deal with situations of deep uncertainty as it is in their own interest. However, the main downside of a slow transition will be borne by the whole society and the downside on early but (ex-post) wrong decisions will be felt by the investing firms. Both effects tend to delay private sector investment.

Therefore, the policy maker can play a key role in assisting firms to deal with these situations and therefore reducing the negative externality of investment delay. One obvious and important difference between using the approaches for policy design versus investor decision making is the following: In the case of investment decisions, the policy maker is, on the one hand, a potential source of uncertainty itself. Any reduction of this (policy) uncertainty is likely helpful for decision making of firms and investors. On the other hand, there may be reasons why policies are not formulated early and long-term. Apart from democratic elections or other changes in the government, there is also the issue of technology-neutrality. It is widely argued that policy, in particular support policies, should not be distorting by choosing – instead of the demand / market – the technology that will prevail (see, e.g., David, 1985 and Liebowitz and Margolis, 1995 for historical examples of (inefficient) technological lock-ins; Kverndokk et al., 2004 for arguments in the context of low-carbon technology development).

Many of the approaches for decision making under deep uncertainty involve modelling, often (e.g., in the case of Robust Decision Making) modelling may represent a substantial part of the total costs associated with the decision process. So general support of those modelling efforts could be useful, particularly in a so-called pre-competitive phase. This refers to a phase in which the institutions tend to exchange and cooperate, because this is in their common interest. If the activities are too close to proprietary methods or other areas which are used by market participants to distinguish themselves from each other, then the actors are less willing to cooperate but rather compete and government support in this context needs to be very balanced (and is likely less efficient and less accepted).

Another approach pursued by the policy maker could be to target the robustness of decisions more directly. For example, if firms and investors feel forced to decide between alternatives, this may be anticipated by the policy maker and she might take measures to ensure that the lack of knowledge about the future is not delaying needed investments. The literature on vaccine development during a pandemic may serve as an example as it is efficient to start developing many different vaccines, in spite of the knowledge that most will fail in the end (see, e.g., Cleve, 2021).

For those firms and investors applying real option theory, some general support in the modelling sphere can be helpful and seems possible in a technology neutral fashion. Again, for the policy maker it could be relevant to anticipate the situation and support timely investment by aiming at reducing the value of waiting to the investor. A specific policy may serve as an example: Carbon contracts for difference, as described above, are foreseen to allow steel producers to invest in carbon free steel plants. Those carbon contracts then effectively guarantee a high carbon price for those who are offered the contract in case they are able to produce steel without CO2 emissions. In this case, the government offers a contract to potential investors that essentially converts a situation of uncertainty (about future price) into certainty, thereby reducing the complexity of the decision substantially.

## 6. Conclusion

This paper shows that situations involving deep uncertainty do indeed appear systematically frequent in the context of the energy transition. The fundamental reasons for this are the interlinkages of, e.g., socio-economic and technical subsystems, which are each path dependent. Further, we show that indeed this increased presence of deep uncertainty systematically delays investment associated with the transition towards a low-carbon economy.

We provide an overview on the diverse approaches that are used in decision making under deep uncertainty. So far, they have mostly been used for policy design and require different levels of modelling support, different amounts of information on future expectations or probabilities, and show different strengths and challenges.

Defining an appropriate role for the policy maker to reduce the negative externality originating from the systematic investment delay appears to be difficult and case specific. From an overall economic perspective, one may argue that diversification is an important element in dealing with all types of uncertainty. However, for such large-scale path dependencies as they appear with capital intense energy-related infrastructure, it appears more efficient to have diversification at the economy-level rather than at the firm-level. This, however, creates the challenge how to reduce the fear of individual firms and investors to "bet on the wrong horse". Here, it might be helpful if the policy maker creates hedging instruments and essentially takes the risk related to the deep uncertainty as a state but offers a less uncertain hedge to the firm. An example may be the carbon contracts for difference, which are discussed to be offered to steel producers to ensure a high value of carbon emissions avoided – irrespective of the (uncertain) market price of CO2.

There are two issues which are generally important to support investor decision making – particularly in a high-uncertainty environment. These are transparency and policy credibility. Transparency helps market actors to form expectations about the future, this can include the technological as well as the political perspective. This could mean government supported information campaigns making information available that is expected to shape the technological path of the energy transition. The second – more relevant – aspect would be that policy should seek to minimize deep uncertainty originating from the policy sphere itself. Here, long-term credibility of policy decisions is key. Often, this credibility is difficult to achieve by simple policies alone since policymakers do not dispose of many instruments to commit to their plans (The carbon contracts for difference above are one example in a limited sphere.) This introduces an element of uncertainty that is not existing from the perspective of the policy design, making it systematically more difficult for investors to deal with uncertainty.

After all, there is urgent need for a fast energy transition to avoid severe net welfare losses for society. If individual economic actors are expected to drive fast change, then they need the society and its policy makers to take some of the burden of ambiguity and risk of failure off their shoulders.

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