The co-evolution of climate policy and investments in electricity markets: Simulating agent dynamics in UK, German and Italian electricity sectors

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Abstract:

Achieving electricity sector transitions consistent with stringent climate change mitigation under the Paris Agreement requires a careful understanding both of the coordinating role of national governments and of its interactions with the heterogeneous market players who will make the low-carbon investments in the electricity sector. However, traditional energy models and scenarios generally assume exogenous policy targets and fail to capture this co-evolution between policy-makers and heterogeneous private and public investors. This paper uses BRAIN-Energy, a novel agent-based model of investment in electricity generation to simulate and contrast government and investor dynamics in the transition pathways of the UK, German and Italian electricity sectors. Key findings show that a successful transition – which achieves the energy policy "trilemma" (low carbon, secure, affordable) – requires the co-evolution of the policy dimension (strong and frequently updatable CO_2 price, renewable subsidies and capacity market) with the strategies of the heterogeneous market players. If this dynamic balance is maintained then incentives are politically feasible and suppliers learn and evolve (in what we term a virtuous cycle). If either the incentives are too weak to drive learning or too expensive so the policy regime collapses, then the transition fails on one of its key dimensions (in what we term a vicious cycle). Getting this balance right is harder in risky markets that also have players with more pronounced bounded rationality and path dependence in how they make investments.

Keywords: agent-based modelling; co-evolution; heterogeneity of actors; governance; electricity; investment decisions

1. Introduction

National commitments in the Paris Climate Agreement enhance prior efforts for countries to decarbonise their energy systems to mitigate global climate change. The UK pledged in the 2008 Climate Change Act to reduce greenhouse gas emissions (GHGs) by 80% by 2050 compared to the 1990's level. It also legislated five-yearly carbon budgets, to be set by the Committee for Climate Change (CCC), to reach this target in a cost-effective way [1,2]. These decarbonisation targets have led

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to a substantial development of low-carbon energy sources in the UK, with the electricity sector leading this transition. Policy instruments continue to be required to incentivise further investments in renewables [3], and to regulate the integration of the growing share of renewables in the energy sector. Regulatory change is key to initially stimulate investments into renewable technologies [4], but the subsequent growth of such technologies is strongly aligned with the strategic response of utility companies. If utilities manage to align their capabilities with the regulatory framework virtuous co-evolutionary cycles between firm strategies and policies are initiated which help the diffusion of renewable energy technologies. Hence, to be effective and successful in managing the energy policy trilemma (low-carbon, secure and affordable energy supply), governments should acknowledge the linkages which arise between the policy instruments, the market players' investment decisions and their outcomes [5]. Approaches which rely on complex system thinking, such as agent-based models (ABMs), are able to capture these interactions which take place between the institutional dimension and heterogeneous actors [6]. Hence ABMs can study the co-evolution between policy instruments and investor strategies and how this can lead to a sustainable energy transition [7]. Failing to account for such dynamics could badly miscalculate investment flows in low-carbon technologies, leading to unintended consequences such as the lock-in of existing high-carbon technologies [8]. This is in contrast with traditional energy (optimisation) models, which tend to simplify the representation of institutional and industry/societal actors in the energy sector, not capturing the interplay between them [9].

This paper uses the agent-based model (ABM) BRAIN-Energy to study how the endogenous policy choices of the institutional agents (the government and the regulator agent) interplay and co-evolve with the investment choices of the market players. BRAIN-Energy focuses on the electricity sector as this sector is at the forefront of the energy transition's policy architecture and new technology investment. The goal is to understand under which conditions do the interplay of policies and market players' choices create a virtuous cycle between market players' investments and the regulatory framework to spur decarbonisation efforts, and when this creates a vicious cycle with barriers to a sustainable transition. Understanding how positive feedback cycles between low-carbon technologies and policies are created, and which policy designs can be effective at targeting key groups of "low-carbon" actors is very important to successfully achieve the long-term decarbonisation targets, and more research is needed in that direction [10]. Also of critical interest are the costs and security of supply of the energy transition. By focusing on the electricity sectors of the UK, Germany and Italy, this paper aims to understand what lessons can be learned from countries with different market structures, types of actors and governance set-up [11]. The country case studies are reviewed in section 3.1.

The rest of the article is structured as follows: chapter 2 reviews different approaches to studying actors in the energy sector transition, their limitations and advantages with regards to studying the interplay of institutional actors and market players, and chapter 3 highlights BRAIN-Energy's novelty and strengths and its key features and enhancement for this article. Chapter 4 introduces the scenarios, before discussing results in chapter 5, and leading to the conclusions and policy recommendations in chapter 6.

2. Modelling of key actors in energy transitions

2.1 Actors and institutional agents in energy models

Quantitative energy models are key tools to study the energy transition, and are crucial for policy-making and industrial decision-making. At the global level, integrated assessment models (IAMs) have been extensively used to assess the feasibility of reaching climate change targets, and have been the underpinning of the Intergovernmental Panel on Climate Change [12]. Other types of energy models, such as partial equilibrium optimisation models [13,14], are used to asses national energy and climate change policies and to produce future decarbonisation scenarios of the energy sector at a national level. These models minimise total-energy system costs based on an end-point policy constraint or carbon reduction target. While such models are highly mathematically and technologically detailed, and focus on the technological configuration which future energy systems should have, they assume aggregated, perfectly rational and utility-maximising decision makers. They lack attention to the role, actions and motivations of the actors involved in shaping the future of the energy sector, to the role of governance arrangements and institutions, and to the co-evolutionary processes between the technological, institutional and behavioural dimensions [15].

The majority of existing energy system models assume rational and homogeneous decisions makers [16], which doesn't represent reality [17], and over-simplifies the path-dependent interactions between market and institutional agents. The heterogeneity of the actors and their behaviours remains therefore largely overlooked in energy models. Moreover, equilibrium and optimisation models are not suited to incorporate the growing complexity and uncertainty between different dimensions in the energy transition [6].

The complexity of the energy sector's low-carbon transition is given by the interplay, the co-evolution and the potential self-reinforcement of the technological dimension, the social dimension, and the institutional dimension. Therefore this links technologies and infrastructure (which define the way energy is produced, transported and consumed), with different agents and stakeholders involved in the energy transition, and with policies and regulatory instruments. Co-evolution is an important concept in evolutionary economics [18,19], and takes place whenever one dimension's evolution influences the direction and scale of other dimensions. Co-evolutionary dynamics between the technological and the institutional dimensions have been used to understand the process of lock-in to high carbon technologies, which hinders the uptake of new and alternative technologies [8,20,21]. However, [9] find that only a few energy models account for co-evolutionary dynamics between policies, behaviour of actors and technologies [22], claiming that such dynamics are key and that energy models should not only look at technologies to be useful for effective climate-change mitigation efforts [23].

[16] and [24] argue that when studying sustainability transitions new modelling approaches are needed, which analyse policy interventions in the energy sector and their impacts on agents' investments, business models and social practices. This should be done by taking into account feedback loops between dimensions (or system elements), reinforcing mechanisms resulting from interactions between agents and the institutional dimensions, and co-evolution, which may lead to multiple solutions and transition pathways [24]. These new modelling approaches should also introduce agents which explicitly take decisions for sound climate policy-making [25].

2.2 Agent-based modelling of energy transitions

Agent-based modelling is a computational social science [26,27]. Agent-based models (ABMs) are bottom-up simulation models which involve multiple and heterogeneous agents, which have decisions rules, and which can interact in different temporal and spatial scales [28-30]. In ABMs the decisions and interactions of agents give rise to emergent macro phenomena.

Given their ability to account for heterogeneity, non-linearity, emergence and co-evolution, ABMs are very suitable to model the complexity of electricity markets and their low-carbon transition [31]. For the above mentioned reasons, [31] find that the use of ABMs for energy policy and for studying the low-carbon transition in the energy sector has rapidly grown over the past decade. Moreover, ABMs are considered to be one of the most effective modelling approaches to study the effects of changing policy instruments on market players investment decisions [5], and to determine the side effects of energy and climate policies in an energy sector characterised by a multitude of diverse actors, with bounded-rationality (that in decision-making, rationality is finite with good-enough choices being acceptable) and heterogeneous strategies [31,32].

Despite these distinctive advantages, the majority of the most prominent ABMs studying the low-carbon transition of the electricity sector, and the impacts of energy and climate change policies on investment decisions in the power sector, still treat policy changes as exogenous. Similarly to optimisation approaches, co-evolutionary dynamics between the market players and institutional agents remain often overlooked.

[32] use an ABM called EmLab to evaluate the impacts of different energy and climate policies on investments in the power sector, which [33] extend to explore the need for flexibility options and electricity storage in an electricity system with a capacity mechanism, while [34-36] use the same model to assess the effects of capacity mechanisms and strategic reserve. The EmLab model is also used to quantify the effects of renewable energy support schemes on social welfare [37]. In all these studies policy changes are treated as exogenous and are pre-determined as scenarios at the beginning of the simulations. Co-evolutionary dynamics between the policy dimension and the investment choices of the market players are not captured.

The AMIRIS ABM model [5] aims to explore the impacts of different policy instruments on the performance of renewable energy operators. However in this model the regulatory framework agent, which is responsible for all energy policy to integrate renewables into the electricity market, is classified as an agent “without scope for decision making”.

Similarly, in the ABM developed by [38,39], which aims to study the investment behaviours of heterogeneous investors with heterogeneous expectations of the future, policy instruments are exogenous and different CO_2 price scenarios are defined at the beginning of the simulations.

3. Methodology: BRAIN-Energy

3.1 Novelty, key features, and case study application

BRAIN-Energy employs a different approach from the ABM studies reviewed in section 2.2. Policy changes in BRAIN-Energy are endogenous, and institutional agents (the government and the regulator) adjust policies (the level of the CO_2 price, or capacity auctions) depending on the emergent techno-economic properties which arise at each time-step from the investment choices of the market players and from their interactions. Hence, the novelty of BRAIN-Energy lies in the fact that the investments of the market players co-evolve with the institutional dimension and governance structure, as well as in having a strong focus on depicting actors with heterogeneous characteristics and bounded-rationality.

BRAIN-Energy is an ABM of electricity operations and investments [40,41][2]. The model's focus is on the electricity supply sector – both for model tractability, and as this sector is at the forefront of the energy transition's policy architecture and new technology investment. The model is characterised by a set of different types of market players with bounded-rationality and heterogeneous characteristics (explained in section 3.2.1) and institutional agents, such as the government and the regulator agents (section 3.2.2). The goal of BRAIN-Energy is to study the evolution of the electricity sector until 2050 as a result of the interacting investment decisions of the heterogeneous market players, and of the co-evolution of the policy choices of the institutional agents with the market players' investments. BRAIN-Energy, hence, aims to explore future decarbonisation scenarios of the electricity sector under a realistic representation of both actors and governance frameworks.

BRAIN-Energy is calibrated to the UK electricity sector. Selected scenarios have also been run for the German and Italian electricity sectors (section 4.1). Germany and Italy have been chosen as case studies to compare to the UK (Figure 1), because – similarly to the UK – they have ambitious decarbonisation targets, but their national electricity systems have key differences:

1) they include different types of market players and investors in the national electricity sector [11,42,43];
2) they have a different institutional structure;
3) they have a different and more decentralised market structure [11].

Figure 1 is an illustrative diagram that shows this diversity, characterising the three countries by the types of market players and the level of centralisation. The increasing size of the circles in Figure 1 shows the number and heterogeneity of the market players. Therefore in the UK the ownership of renewable assets is mainly is the hands of incumbent utilities [44] and the resulting governance structure is more market oriented. In contrast, in Germany the ownership of renewable generation assets is extremely fragmented and diverse, and non-corporate and non-state models dominate [11] leading to a market where a "civil" society logic prevails. Italy illustrates a middle-ground in the centralisation of the electricity market, but with a greater investment role by the national government.

[2] Conference paper to be found at: https://www.iaee.org/proceedings/article/15046 (Barazza, 2018) and online model documentation to be found at: https://www.ucl.ac.uk/energy-models/models/brain-energy (Barazza, 2019)

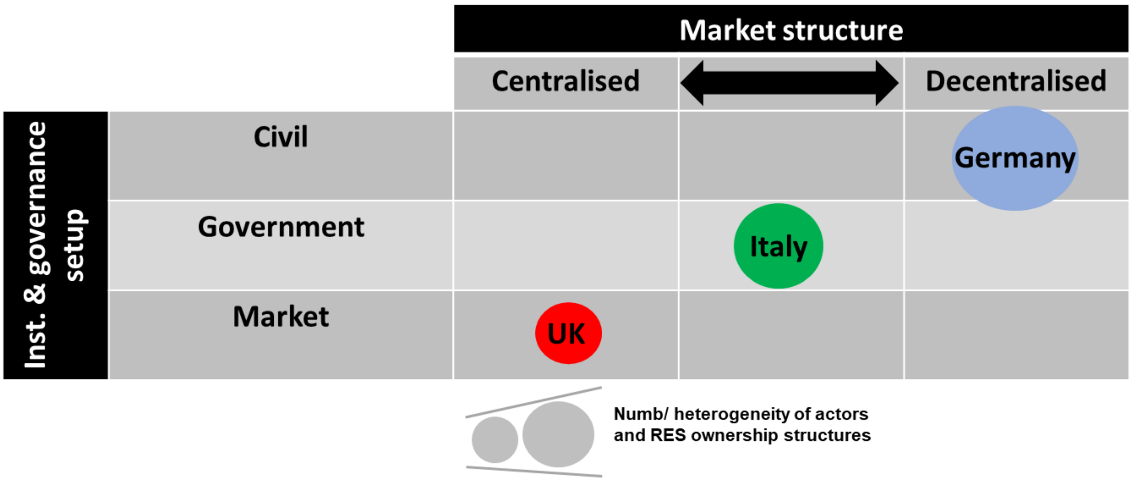

Figure 1 – Illustrative diagram of country case studies in BRAIN-Energy

2012 is the calibration year (for data availability, and to be able to compare BRAIN-Energy's results with a few years of historical data). The main exogeneous variables include: electricity demand, fossil fuel prices, operational and maintenance costs of power plants, capital costs of generation technologies, and the "no-increase" CO_2 price (the CO_2 price used in BRAIN-Energy is explained in detail in section 3.2.2). Table 1 summarises the sources used for both historical and projected future data for these variables. Further details on the data used for calibrating BRAIN-Energy in its three country versions can be found on the online model documentation[3] [41] and in the Appendix.

Exogenous variables	Initialisation	Source
Electricity demand	**UK:** 309 TWh **GER:** 593 TWh **IT:** 328 TWh	**UK:** *Historical*- National Grid half-hourly data *Future*- [45], "Two Degree" scenario **GER:** *Historical*- Open Power System Data Platform[4], AG Energiebilanz[5] *Future*- [46] **IT:** *Historical*- GME[6] *Future*- [47,48]
Fuel costs	Gas: UK: 20.3 GBP/MWh GER and IT: 29 EUR/MWh Coal (GER): 37 EUR/MWh	**UK:** *Historical*- [49] *Future*- [49], "Reference" scenario **GER and IT:** *Historical*- BmWi Energiedaten database[7] *Future*- [46]
Capital costs of technologies (EUR/kW)	Gas: 400 Coal: 1,800 Nuclear: 6,000	[50]

[3] https://www.ucl.ac.uk/energy-models/models/brain-energy
[4] https://data.open-power-system-data.org
[5] https://ag-energiebilanzen.de/7-0-Bilanzen-1990-2016.htmlx
[6] http://www.mercatoelettrico.org/it/Download/DatiStorici.aspx
[7] https://www.bmwi.de/SiteGlobals/BMWI/Forms/Listen/Energiedaten/energiedaten_Formular.html?&addSearchPathId=304670

	Onshore wind: 1,300 Offshore wind: 3,000 PV: 1,560 Biomass: 2,500	
Operational & Maintenance (O&M) costs		**UK:** [51] **GER and IT:** [50]
CO_2 price ("no-increase" trajectory)	**UK:** 6.39 GBP/t **GER and IT:** 7.36 EUR/t	**UK:** *Historical* – [49] *Future* – [49], "Reference" scenario **GER and IT**: *Historical*- EEX Exchange *Future*- [46]

Table 1 – Exogenous variables in BRAIN-Energy

BRAIN-Energy is built in the open-source software environment Netlogo [52], and has a yearly resolution to best be able to study investment decisions and their co-evolution with the policy environment.

Every year the market players (section 3.2.1) take operational decisions about producing and dispatching electricity from their power plants (section 3.3), and subsequently their revenues, financial positions and market shares are updated. Subsequently, the government agent checks the progress in meeting the interim decarbonisation targets and eventually adjusts the CO_2 price if progress lags behind the set targets (section 3.2.2). The regulator agent can enforce capacity auctions if they believe security of supply to be at risk (section 3.2.2). The fact that the government and the regulator agent are active decision-makers is an enhancement in the version of BRAIN-Energy used in this paper, and their activity and the feedback loops created by their actions are depicted in green in Figure 2. As a last step, market players decide about decommissioning unprofitable plants and take investment decisions about new power plants (section 3.4). Figure 2 shows BRAIN-Energy's annual flow, where the black arrows are the model's operational flow.

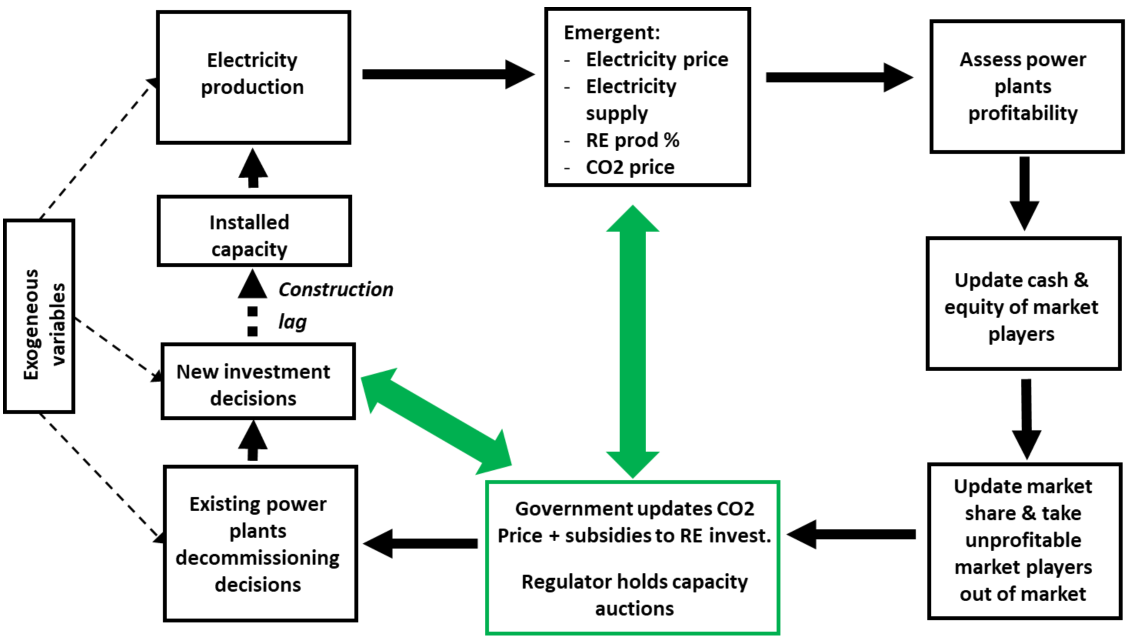

Figure 2 - BRAIN-Energy's operational flow and feedback mechanisms

3.2 Agents and their characteristics

3.2.1 Market players

In BRAIN-Energy there are 6 different types of market players – the colourful pawns in Figure 3, and as detailed in Table 2 – all of which are active decision makers. These are: incumbent utilities, municipal utilities, independent power producers (IPPs), new-entrants, institutional investors and households. The online documentation[8] [41] contains an explanation of the different types of market players in BRAIN-Energy.

Based on a review of the existing literature, the UK model has 3 types of market players: incumbent utilities, IPPs and new-entrants. The German and Italian scenarios exhibit a greater variety of market players: incumbent utilities, IPPs, new-entrants, municipal utilities (only in the German model), institutional investors, and households [11,42,47,53,54,].

Households are aggregated market players in BRAIN-Energy. One household aggregates 1,000 households[9].

Table 2 summarises the main characteristics and behaviours of each type of market player, and the number of market players of each type which have been modelled in the UK, German and Italian versions of BRAIN-Energy at the calibration year. The bounded-rationality of the market players in BRAIN-Energy is reflected in the fact that their investment decisions are affected by their limited foresight of the future, and are based on their own heterogeneous expectations of electricity demand, fuel and technology costs. Furthermore, bounded-rationality is also reflected in the fact that emerging knowledge about the other players strategies affects the investments of the market players (see imitation in section 3.4), and also learning from own previous successful (or unsuccessful) investment (see path-dependency in section 3.4).

[8] https://www.ucl.ac.uk/energy-models/models/brain-energy

[9] the average household investment in PV in Germany and Italy is 10 kW (CPI, 2012; GSE, 2016) and the minimum investment size in PV in BRAIN-Energy is 10 MW

Type	Number at 2012	Aim	Technology preference	Cost of capital	Foresight	Number of years before switching off unprofitable assets
Incumbent utility • UK • Germany • Italy	 4 3 2	Production of electricity to meet demand and provision of stable dividends to shareholders [54-56]. Vertically integrated.	Can invest in all technologies	5%-7% [54,57,58]	15-20 years	7
Independent power producer • UK • Germany • Italy	 2 2 2	Profit maximisation and increased market share [54,59]. Not vertically integrated.	Gas and nuclear. Renewables: onshore- and offshore wind [54]	8%-10% in Germany and UK, 8-12% in Italy [60]	10-15 years [59]	5
New-entrant • UK • Germany • Italy	 None None None	Their main expertise is not electricity generation, but they want to maximise profits attracted by subsidies	Only renewable generation technologies	12%	10 years	5
Municipal utility • Germany	 2	Investment choices are driven by financial return expectations, but also by wider environmental considerations [11,54]	Gas and renewable generation technologies (PV, onshore wind and biomass). Larger municipalities also invest in offshore wind [54]	4% [11], as they can borrow from local banks	25 years, as supply of energy to their region is their main business	7-10
Institutional investors • Germany • Italy	 2 2	Seek stable, predictable and long-term returns and cash-flows to match their long term liabilities [54,59,61]	Onshore wind and PV. More experienced institutional investors can also invest in offshore wind. Preference for large projects [54,55,59,62]	5%-10% in Germany and UK 5-12% in Italy, [59,60]	20-25 years, as this matches their long-term liabilities [54,55,63]	5-10
Households • Germany • Italy	 8 6	Invest for self-production and eventually sell surplus [53,64]	Small scale PV [42,43,54,64]	3%-6% [58]	5 to 15 years (pay-back period)	

Table 2 - Market players in BRAIN-Energy and their characteristics/behaviours

3.2.2 Institutional agents

Institutional agents in BRAIN-Energy are the government and the regulator agent. Representing governments as active players, who like the other players in BRAIN-Energy have bounded-rationality, can improve how energy models can be useful to understand barriers and opportunities of sustainability transitions [65]. Governments have bounded-rationality because they are not always able to produce policy outcomes which are best from a social welfare point of view [65], and because policy makers are not more rational than private companies when making decisions [66]. Hence, BRAIN-Energy represents institutional agents as active players with the aim of understanding how barriers to effective climate change mitigation efforts, such as inertia and lock-in can arise in interaction with other market players and how these can best be addressed to give rise to a sustainable low-carbon transition.

In BRAIN-Energy, the government agent is motivated to achieve the 2050 climate change mitigation targets set by law (in each of the three country case studies). The agency power of the government agent is defined by the fact that it can intervene in the electricity market by enforcing subsidies to renewable energy investments and by applying a price on CO_2 emissions to reach the 2050 decarbonisation objectives.

In practice, the interaction between the government and the market players in BRAIN-Energy works as follows: each year the government agent checks the carbon intensity of electricity generation (in the UK model), or the share of electricity produced through renewables (in the German and Italian models), compares the progress against the interim carbon budgets (Table 3), and decides whether to increase or not the CO_2 price. Hence, government intervention in BRAIN-Energy is triggered by the outcomes of the investment decisions (and decommissioning decisions) of the market players, which determine the share of electricity produced through renewable technologies and the carbon intensity of electricity generation. This is how co-evolution between the policy-making dimension and the investments of the market players unfolds in BRAIN-Energy (Figure 3).

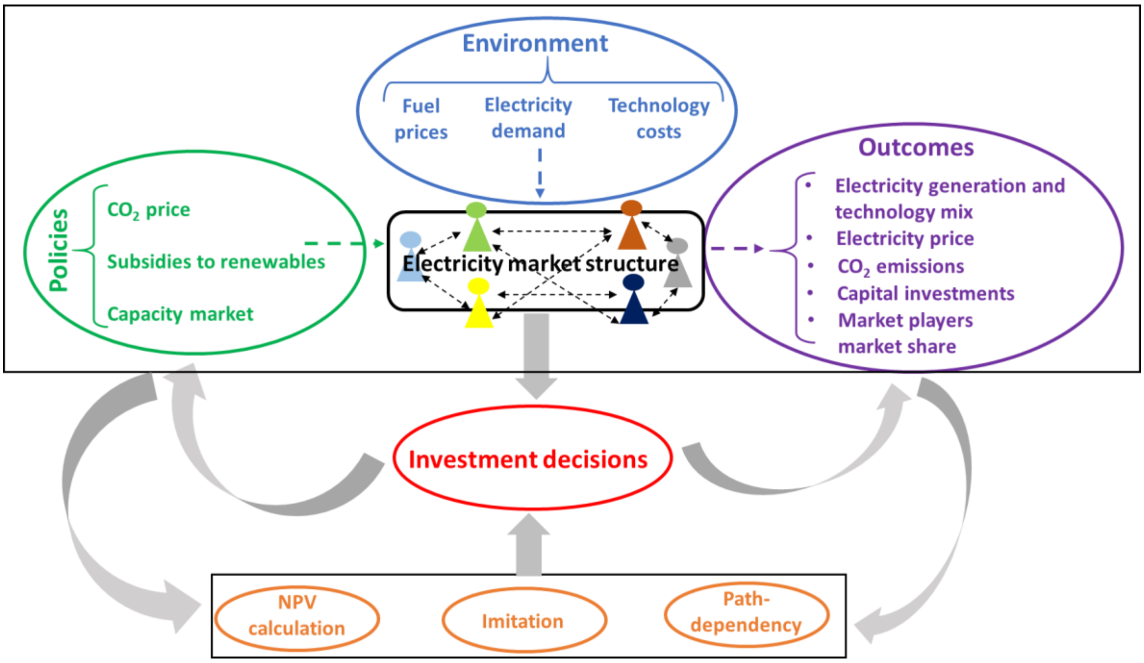

Figure 3 – Co-evolution of electricity market structure, policies and investments in BRAIN-Energy

The level by which the government agent can increase the CO_2 price over the "no-increase" price when progress doesn't meet the interim carbon budgets is scenario-dependent and can be as high as 200%. This is called "strong" CO_2 price trajectory in BRAIN-Energy, which brings the CO_2 price to GBP 302/t at 2050 in the UK model, in line with the CO_2 marginal abatement cost used in optimisation models in the UK [67,68], simulation models [69], and the UK Government's high CO_2 price trajectory [70]. In the German and Italian models, the CO_2 price would go up to EUR 228/t at 2050 under the "strong" trajectory, a value consistent with the one used by optimisation models focusing on the European energy sector [71,72].

The government increase in the CO_2 price is in percentage terms, as this allows an exponential growth profile if required for progress towards the 2050 long-term objective. If in interim periods the electricity sector achieves the desired level of carbon intensity of electricity generation, or the desired share of electricity produced through renewables is reached, the government decreases the CO_2 price again to the "no-increase" trajectory. The calibration of the "no-increase" trajectory in each of the three country case studies can be found in Table 1.

Carbon budgets in the three countries are summarised in Table 3. In the UK model carbon budgets (frequency and level) are set according to the five-yearly carbon budgets set out by the Committee on Climate Change [1]. In the German model carbon budgets are based on the share of electricity produced from renewables as set out in the renewable electricity targets in the 2017 Renewable Energy Sources Act (EEG 2017), and are set for 2025, 2035 and 2050. Also, a 2020 carbon budget has been added in the German version of BRAIN-Energy, in accordance with EU targets, to have at least 20% of electricity produced through renewables by 2020. Italian law only sets out a target of 55% share of electricity production from renewables at 2030 in the Strategia Energetica Nazionale 2017 [73] and the 2050 long-term goal of producing at least 80% of total electricity through renewables at 2050. However, to make the Italian version of BRAIN-Energy comparable with the UK and German ones, carbon targets in BRAIN-Energy have been set also at 2020 (based on EU's 20-20-20 targets) and at 2040, calibrated based on the most prominent Italian modelling scenarios as summarised in RSE Colloquia [74].

	UK	**Germany**	**Italy**
Year	**Carbon intensity of power generation**	**Share of electricity produced through renewables**	
2020	250 gCO_2/kWh	20%	20%
2025	200 gCO_2/kWh	45%	
2030	100 gCO_2/kWh		55%
2035	50 gCO_2/kWh	60%	
2040	25 gCO_2/kWh		70%
2045	15 gCO_2/kWh		
2050	Near-zero	>=80%	>=80%

Table 3 - Carbon budgets in UK, German and Italian versions of BRAIN-Energy

Moreover, the government subsidises investments in renewable technologies: this is done through Contracts for Difference (CfDs) in the UK, and through feed-in-tariffs (FITs) in Germany and Italy. On- and offshore wind plants, biomass plants and PV technologies are covered by the CfDs, which guarantee these technologies' returns for 15 years. FITs in Germany cover all renewable generation technologies, while in Italy they exclude PV[10]. The levels of the FIT payments can be found in the Appendix. CfD auctions take place every three years in BRAIN-Energy, to match the historical frequency [75]. Winners of the auctions are paid the difference between an auction's strike price and the prevailing market price for 15 years, hence providing stability and predictability to investors' revenues for 15 years. The mathematical formulations behind the CfDs are provided in the online model documentation[11] [41].

The regulator's objective in BRAIN-Energy is to manage the security of supply aspect of the low-carbon transition, and to minimise demand-supply gaps. It does this by enforcing a capacity market with capacity auctions for conventional generation technologies (and nuclear in the UK). The capacity market only works in the UK version of BRAIN-Energy (as foreseen by the Electricity Market Reform), and in the Italian model where a capacity market has been active since 2018. No capacity market is modelled in the German model, as German law doesn't foresee such a mechanism.

In practice, the regulator in BRAIN-Energy has bounded-rationality, and based on its expectations it forecasts every year the maximum potential electricity production at $t + 4$ (max_{t+4}) by estimating the maximum potential electricity production of all active power plants with plant life of at least or greater than $t + 4$. If max_{t+4} is lower than peak demand at year $t + 4$, then the regulator agent holds a capacity auction at year t. The capacity to be auctioned(CA_t) is:

$$CA_t = PeakDemand_{t+4} - max_{t+4}$$

Alternatively, the regulator agent can enforce a capacity auction if the de-rated capacity margin (defined as the amount of excess electricity generation over annual peak demand, adjusted by the specific availability of each type of plant according to its technology) hits 5% in the UK model. This level has been defined according to Ofgem's and National Grid historical values [76], and the same has been applied in the Italian model for comparison reasons.

However, the regulator agent has bounded-rationality and it cannot foresee whether between t and $t + 4$ some power plants will be closed due to unprofitability, which leads to possible supply gaps (periods during which peak electricity demand, explained in section 3.3, is not met). Hence, similar to the government agent setting the CO_2 price, the decisions of the regulator agent co-evolve with those of the market players (see Figure 3).

3.3 BRAIN-Energy's operations

In BRAIN-Energy electricity demand is exogeneous and calibrated based on half-hourly national data (Table 1). Additional information can be found in the Appendix and in the online model documentation [41]. To match BRAIN-Energy's yearly resolution, and to account for variations in the load profile, the half-hourly data was divided into a yearly day average demand and yearly night average demand in each of the three countries. Also a yearly peak demand was defined to make sure BRAIN-Energy is able to deal with peak electricity requirements. The yearly peak demand is defined as

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[10] PV investments were subsidised by the Fifth Conto Energia (https://www.gse.it/servizi-per-te/fotovoltaico/conto-energia). This set an aggregated cap on public spending for PV incentives of EUR 6.7 billion, which was exceeded in July 2013, after which the Fifth Conto Energia came to an end

[11] https://www.ucl.ac.uk/energy-models/models/brain-energy

yearly average day demand multiplied by the peak factor, calibrated on historical observations of the absolute yearly peak electricity demand in the UK, Germany and Italy (see Appendix).

For intermittent renewable electricity generation assets their installed capacity has been de-rated by their load-factor (see Appendix) to capture the effects on total generation capacity, running time of thermal plants and electricity price. Renewable assets also have a declining "contribution to peak" in BRAIN-Energy. This leads to a declining marginal contribution of each additional renewable generation asset in meeting peak demand the more renewables are installed in the system, which leads renewables to only contribute 5% of their capacity to peak generation, when over 80% of electricity is produced from renewable sources [77].

In BRAIN-Energy electricity bids from the market players from their different type of plants are dispatched on a merit-order basis to satisfy yearly average day and night electricity demand. The short run marginal cost of the most expensive bid accepted into the market, which is required to meet electricity demand in that year, sets the yearly electricity price (p_t). The yearly electricity production mix which results from the merit order gives rise to the yearly CO_2 emissions generated by the power sector, and to the carbon intensity of electricity generation.

Additional information on BRAIN-Energy's power sector operations can be found in the model's online documentation[12] [41].

3.4 Investments in BRAIN-Energy

Market players in BRAIN-Energy decommission unprofitable plants after a certain number of years that these have been loss-making (see Table 2) and decide about investing in new production assets. Their investment decisions (Figure 3) are based on an NPV calculation, which is the result of their heterogeneous expectations about future cash-flows *n* years ahead. *n* differs by type of market player (Table 2) and reflects their limited foresight. Future cash-flows are based on heterogeneous expectations about electricity demand, merit order expectations, fuel and capital costs of technologies. Also, market players use different discount rates *r* in their NPV calculations, which equal their cost of capital (Table 2).

Moreover, investment choices in BRAIN-Energy are path-dependent. The long life-time of electricity generation assets [78] makes it essential to take path-dependency into account when studying investments in the power sector [32]. Path-dependency is currently modelled in BRAIN-Energy as "historic" path-dependency. This means that the performance of past investments influences future investment decisions taken by the market players, which makes investments adaptive and path-dependent (Figure 3). In practice historic path-dependency works in BRAIN-Energy as: 1) learning from own successful past behaviour and investments, which lead to increasing revenues for a market player. This learning-by-doing process results in a growing market share of market players which make successful investments, and to an increased ability to invest in new projects in the future; 2) learning from own unsuccessful past investments.

Market players' investment choices are also influenced by imitation in scenarios with heterogeneous market players (Figure 3). This means that market players have emergent evidence about the evolution of the market shares of the other players, and they choose to imitate the market

[12] https://www.ucl.ac.uk/energy-models/models/brain-energy.

player whose market share grew the most the previous year. Imitation can either delay or encourage sustainability transitions [65], and for this reason it has been introduced in BRAIN-Energy.

Extensive details and equations about economic criteria in investment decisions, and about the functioning of path-dependency and imitation can be found in BRAIN-Energy's online model documentation [41] and in [40].

4. Scenarios

4.1 Core scenarios

Four core scenarios (Figure 4) have been created to illustrate the interplay between the institutional agents and the market agents in the UK electricity market. The aim of the scenarios is to capture how investments co-evolve with the policy-making and governance structure, and what effects this has on the long-term decarbonisation scenarios. To investigate the impacts that different types of market players, and different electricity market structures have on future decarbonisation pathways, the results of UK2 and UK4 scenario have been compared to similar scenarios for Germany (GER2 and GER4) and Italy (IT2 and IT4). The country comparison has only been introduced for scenarios 2 and 4, because in these scenarios market players are heterogeneous, and it is hence interesting to compare countries with different types of market players.

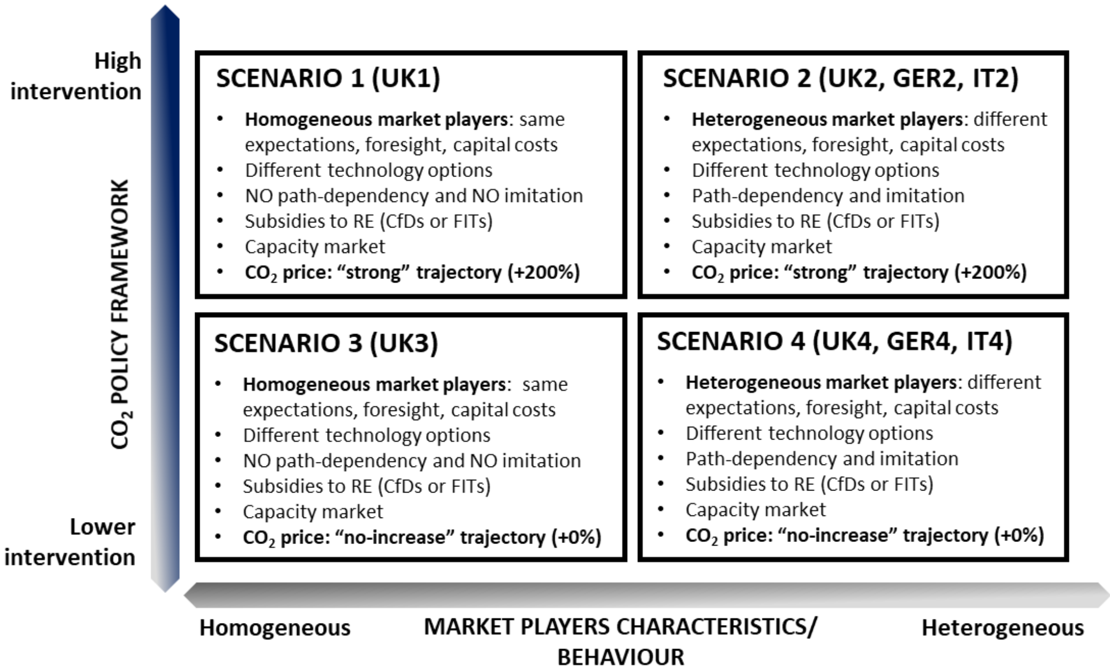

Figure 4 – Scenario matrix

Scenarios are arranged along two axes (Figure 4): the stringency of the policy framework and the characteristics of the market players, to explore the coevolution of these drivers in BRAIN-Energy. Exogeneous variables are the same in all four core scenarios (Table 1 summarises their calibration). Overall parameters used in the scenarios are summarised in Table 4.

Scenarios 1 and 2 differ from Scenarios 3 and 4 by the level of government intervention in the electricity sector for CO_2 mitigation goals. In all four core scenarios the government subsidises investments in renewable generation assets (as thus is also linked to industrial strategy policy), and the regulator agent always manages security of supply through capacity auctions (except in GER2 scenario). In Scenarios 1 and 2 the government agent uses a "strong" CO_2 price trajectory, meaning that whenever carbon budgets are not met it increases the CO_2 price by 200% over the "no-increase" trajectory (the calibration of which was explained in Table 1). In Scenarios 3 and 4, in contrast, the government agent doesn't adjust the CO_2 price when carbon budgets (Table 3) are not met, and keeps the CO_2 price on the "no-increase" trajectory. Hence, scenarios 3 and 4 are characterised by a lower level of co-evolution of policies and investments.

To explore the impacts of different policy conditions and degrees of government intervention on the electricity sector's evolution we examine the transition under two assumptions: homogeneous and heterogeneous market players. In Scenario 1 and Scenario 3 market players are homogeneous. Except for having different technology options, they have the same capital cost, foresight, expectations about future technology costs and they all close unprofitable plants down after the same amount of loss-making years. Also, in these scenarios investments of the market players are not affected by the past and are not path-dependent, and market players do not imitate others. There is no (historic) path-dependency (and no imitation either) in the scenarios with homogeneous market players (1 and 3) for two main reasons. First, scenarios with homogeneous market players aim to represent an "indicative" and "stylised" world where all market players behave the same, and where investment decisions are taken according to strict economic rationality criteria as it is in cost optimisation models [16]. Therefore, in these "stylised" scenarios no learning opportunities based on past investments are taken into account in investment decisions. Second, the success of new investments is the same in scenarios with homogeneous market players, as they all have the same expectations of future costs (fuel and technology) and electricity demand. Therefore, there is no variation in how all market players learn (and this would just cause, for example, all gas plants to shut down at a certain point in time, leading to severe supply gaps).

In contrast, in Scenarios 2 and 4 market players are heterogeneous: this is defined as having different technology options based on their company strategy and expertise, and different expectations on capital cost, future technology costs and demand, and on the time taken before closing loss-making plants. Investment choices are path-dependent, and market players imitate others. Table 4 provides details about the homogeneous and heterogeneous characteristics of the market players, with further details in the online documentation [41].

	Scenario 1	Scenario 2			Scenario 3	Scenario 4		
	UK1	**UK2**	**GER2**	**IT2**	**UK3**	**UK4**	**GER4**	**IT4**
Exogenous variables	Table 1	Table 1			Table 1	Table 1		
CO_2 price	"strong" CO_2 price	strong" CO_2 price			"no-increase" CO_2 price	"no-increase" CO_2 price		
Subsidies to renewables	CfDs (UK), FITs (Germany and Italy)							
Capacity market	Active (UK and Italy), not active (Germany)							
Market players behaviours	HOMOGENEOUS	HETEROGENEOUS			HOMOGENEOUS	HETEROGENEOUS		
• Path-dependency	N/a	Yes			N/a	Yes		
• Imitation	N/a	Yes			N/a	Yes		
• Capital costs	6%	Table 2			6%	Table 2		
• Foresight	10 years	Table 2			10 years	Table 2		
• Fuel costs expectations	Table 1	+/-20% compared to level in Table 1			Table 1	+/-20% compared to level in Table 1		
• Electricity demand expectations	Table 1	+/-15% compared to level in Table 1			Table 1	+/-15% compared to level in Table 1		
• Technology costs expectations	Table 1	+/-25% compared to level in Table 1			Table 1	+/-25% compared to level in Table 1		

Table 4- Characterisation of scenarios by agent heterogeneity and policy framework

4.2 Sensitivity scenarios

We created two sensitivity scenarios to explore the impacts of less frequent (ten-yearly as opposed to five-yearly) carbon budgets in the UK scenarios. These sensitivity scenarios explore a looser coupling and co-evolution of the policy framework on the investments of the market players and the outcomes on the electricity sector's transition. The resulting sensitivity scenarios are UK1-10y and UK2-10y (there are no sensitivity scenarios for UK3 and UK4, because the government agent is not increasing the CO_2 price in these scenarios).

5. Results and discussion

In this chapter we show the impacts of the co-evolution between the institutional agents' policy-making and the market agents' investment decisions on reaching climate change mitigation targets and on the cost and security of the low-carbon transition.

5.1 Impact of agents co-evolution on decarbonisation efforts in the UK

To assess how the scenarios meet the climate change targets in the UK we explore: a) the share of electricity produced through renewables at 2050, b) its evolution from 2012 to 2050, c) the CO_2 price, d) the technology mix at 2030 and 2050.

Results on renewable deployment show that the level of the CO_2 price which the government agent uses is key to produce environmentally successful pathways (Figure 5). In fact, only scenarios where the government agent increases the CO_2 price by 200% over the "no-increase" trajectory (UK1 and UK2 scenarios) successfully manage to produce at least 80% of electricity from renewables at 2050 (Figure 5). However heterogeneous agents make the level of the CO_2 price less effective at meeting the 2050 decarbonisation objective (Figure 5).

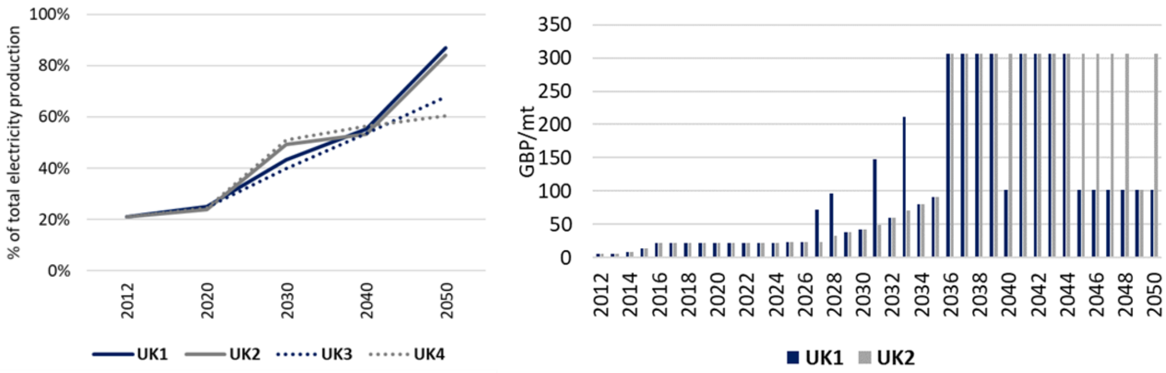

Figure 5 – Evolution of share of electricity produced through renewables and CO_2 price in UK scenarios

Figure 5 also shows CO_2 prices in BRAIN-Energy in the UK. CO_2 prices rise up to 302 GBP/t in UK1 scenario between 2036 and 2044 to successfully achieve an 80% share of electricity produced through renewables at 2050. In UK2 scenario with heterogeneous market players the CO_2 price remains at the level of 302 GBP/t from 2036 to 2050 to achieve the decarbonisation objectives. Therefore, results show how a stronger CO_2 price is required to address the barriers which market players with heterogeneous characteristics and path-dependent investment choices pose to effective climate change mitigation efforts.

Results from the sensitivity scenarios around the frequency of the carbon budgets in the UK model also show that it is key for the government agent to frequently update the CO_2 price, hence to have frequent five-yearly carbon budgets. Even if the government uses a "strong" CO_2 price trajectory, if moving from five- to ten-yearly carbon budgets (Figure 6), UK1-10y only achieves a 65% share of electricity produced through renewables at 2050 (compared to 87% in UK1), and in UK2-10y only 60% of electricity is produced through renewables at 2050 (compared to 84% in UK2). This happens because total investments in renewables between 2012 and 2050 decline by 30% between UK1 and UK1-10y scenario and by 38% between UK2 and UK2-10y scenario (Figure 6). Hence, the frequency of the carbon budgets alone is a key driver of the scenarios environmental performance, and having frequent carbon budgets is even more important when market players are heterogeneous.

Results show therefore that it is a necessary condition to have a closely co-evolving and responsive government agent, who uses a strong and frequently updatable CO_2 price to give rise to a virtuous cycle to meet the low-carbon transition, especially with heterogeneous market players.

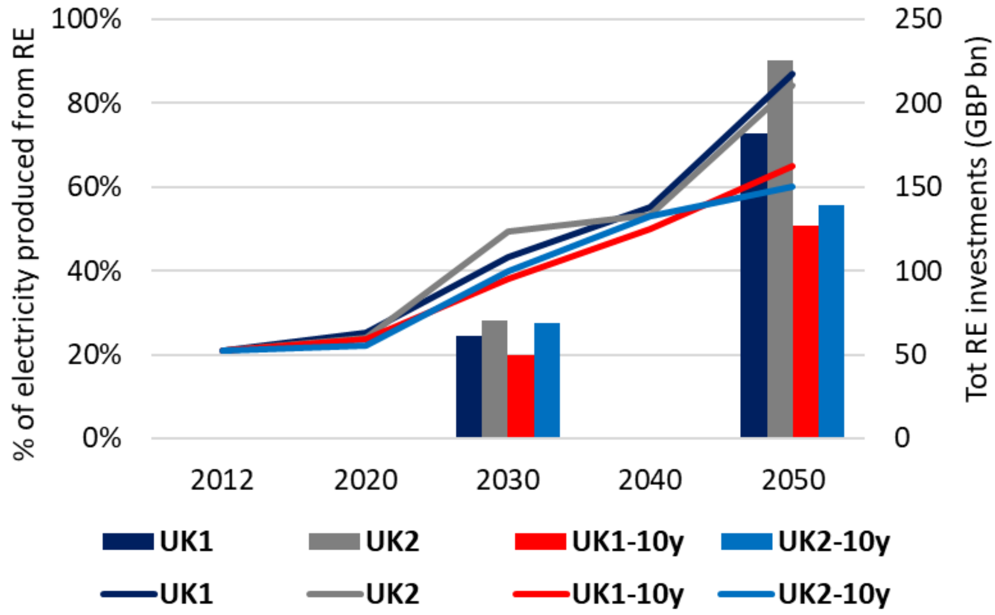

Figure 6 - Share of electricity produced through renewables and total investments in renewable in UK core scenarios and scenarios with 10-yearly carbon budgets

As regards to the technology mix (Figure 7), gas installed capacity in the UK is higher in scenarios with a "no-increase" CO_2 price (UK3 and UK4), and especially in UK4 (154 GW) where market players are heterogeneous. In this scenario gas generation reaches 68 TWh in 2050, as opposed to only 11 TWh in UK1 scenario. This happens because the lower CO_2 prices in UK4 scenario make running gas plants less expensive, and as market players' investment choices are path-dependent, market players tend to repeat investments in gas assets and invest less in other technologies. Offshore wind benefits both from market players having heterogeneous characteristics, and from higher CO_2 prices. This happens because market players have heterogeneous expectations about the evolution of technology costs in the future, hence some market players expect offshore wind prices to be lower in the future, and offshore wind plants to be more profitable especially under a "strong" CO_2 price trajectory. Under these circumstances, imitation in UK2 scenario then helps the diffusion process (Figure 7). In fact, UK2 scenario has the highest amount of offshore wind installed capacity at 2050 among UK scenarios (30 GW) which produce 119 TWh of electricity. Hence, heterogeneity (on its own) mainly impacts technology choices and hence CO_2 emissions, because the different expectations about future levels of technology and fuel costs lead market players to favour certain technologies over others. Path-dependency (on its own), under low CO_2 prices, leads to more gas investments.

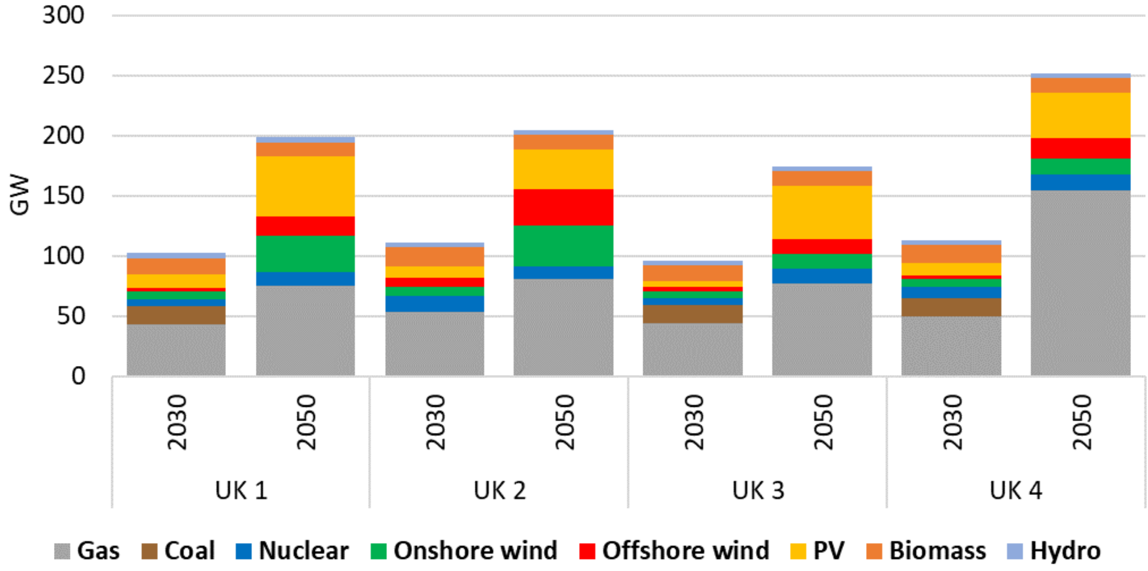

Figure 7 - Installed technology mix in UK scenarios at 2030 and 2050

5.2 Impact of agents co-evolution on the transition's costs and security of supply

The interplay of the strategies of the institutional agents with homogeneous or heterogeneous market players leads to different capital costs of the electricity sector's low-carbon transition and different timing of investments (Figure 8). UK2 scenario – with a "strong" CO_2 price and heterogeneous market players which take path-dependent investment choices – is the most capital intensive of all UK scenarios, with aggregate investment levels between 2012 and 2050 of GBP 348 billion. In this scenario 31% of total investments in renewable technologies are made by 2030, but the stronger government CO_2 price intervention helps to keep investment levels in renewable technologies up after 2030. In fact, 84% of total investments in offshore wind generation plants are made between 2030 and 2050 in UK2 scenario. In contrast, in UK4 scenario, which also has heterogeneous market players which take path-dependent investment choices, the fact that the government is less responsive doesn't help maintaining investment levels in renewable technologies up after 2030 (Figure 8), leading to only 60% of electricity being produced through renewable sources at 2050 (as opposed to 84% in UK2). Therefore, sustaining a closely evolving government post-2030 helps maintain investments levels in renewable technologies (in a virtuous co-evolutionary cycle) and hence to successful transitions. Furthermore, UK2 and UK4 scenarios are more capital intensive than UK1 and UK3, because path-dependency leads market players to shut down unprofitable assets before the end of their operating life. This creates supply gaps and opportunities for investments by other market players. Hence path-dependency creates "investment cycles", which lead to higher total capital investments. However, with a weak and non-responsive government such "investment cycles" may lead to unnecessary investments and to "failed" transition which do not achieve the 2050 decarbonisation objectives as in UK4 scenario. Therefore, a responsive government is also key to break the vicious cycles that path-dependency could create.

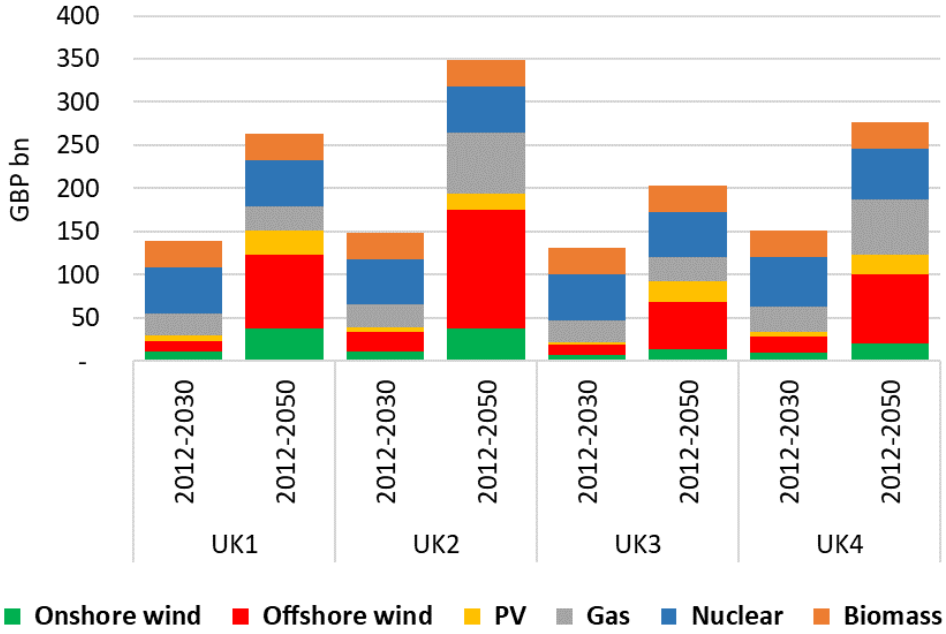

Figure 8 - Aggregated capital investments in UK scenarios

UK2 scenario with stronger government intervention and heterogeneous market players also has the most expensive electricity prices (Figure 9). This is because the electricity price is the short run marginal cost of the most expensive technology producing in a given year (section 3.3), which reflects the higher CO_2 price in UK2 scenario. Moreover, the fact that UK2 scenario has peak supply gaps (Figure 9) leads to higher electricity prices, as increasing the electricity price is one of the levers the regulator agent can use to incentivise more capacity investments. Peak supply gaps in UK2 scenario happen because market players' investments are path-dependent and market players actively manage their power plants, which they are able to shut down if unprofitable. The regulator agent can't always foresee such early closures due to its bounded-rationality. For this reason and even if a capacity market is active there are peak demand supply gaps in UK2 scenario. In contrast, there are no supply gaps in UK3 and UK4 scenarios, which also exhibit electricity prices constantly below GBP 100/MWh (Figure 9). These scenarios make a cheaper and secure electricity system from a supply point of view, however they represent a failed "transition" as they don't meet 2050 decarbonisation objectives (Figure 5). Therefore, results show that security of supply issues illustrate an additional co-evolution between institutional and market agents, and that a higher CO_2 price should be supported by a capacity market, which is the main instrument to mitigate supply gaps.

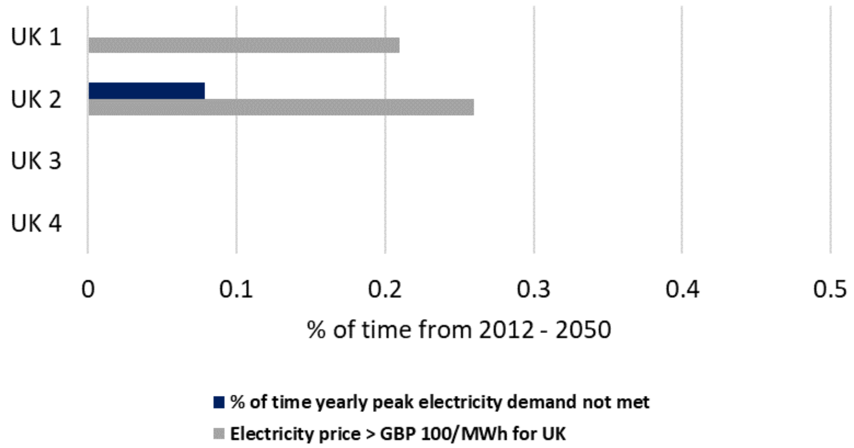

Figure 9 - Supply gaps and electricity price in UK scenarios

5.3 Country comparison

Both GER4 and IT4 scenarios lag significantly behind GER2 and IT2 scenarios in reaching the 2050 decarbonisation targets (Figure 10). In Italy both scenarios are not environmentally successful, and in IT4 scenarios only 39% of total electricity is produced through renewables at 2050 (Figure 10). This happens because in the Italian scenarios market players have a higher cost of capital to reflect the riskier investment environment in Italy [60] as highlighted in Table 2. This prevents scenarios from reaching decarbonisation targets even when the government uses a “strong” CO_2 price trajectory (Figure 10). Hence, results from the country comparison show how also in the German and Italian scenarios the level of the government intervention, measured as strength of CO_2 price in BRAIN-Energy’s scenarios, is key to give rise to virtuous co-evolutionary cycles with heterogeneous and path-dependent market players leading to a higher electricity production through renewables. This is even more pronounced when market players face higher costs of capital.

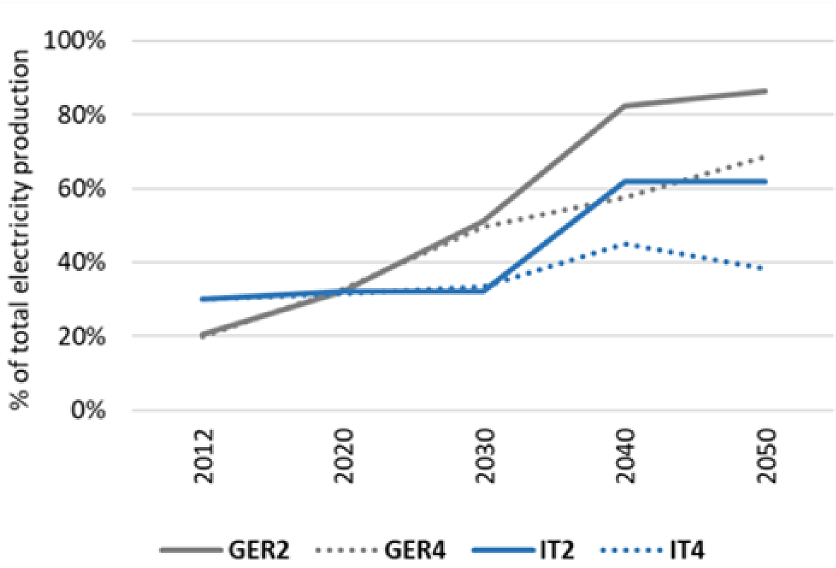

Figure 10 - **Evolution of share of electricity produced through renewables in German and Italian scenarios**

Moreover, the Italian scenarios gas reaches the highest installed capacity at 2050 (78 GW) (Figure 11) and production (255 TWh) in IT4 scenario under the same logic as for the UK scenarios as explained in section 5.1. In both GER2 and GER4 scenarios offshore wind is the main generation technology at 2050 (181 TWh in GER2, and 148 TWh in GER4 scenario) and reaches respectively 50 GW and 40 GW of installed capacity in the two scenarios (Figure 11) at 2050. However, as only 37% of total offshore wind investments are made by 2030 in GER4 scenario (compared to 46% in GER2 scenario) (Figure 11), GER4 is slower to decarbonise compared to GER2 scenario and misses out on the 2050 decarbonisation targets (Figure 10). Hence, German scenarios also show how a stronger government intervention is key with heterogeneous and path-dependent market players to encourage early investments in renewables to meet decarbonisation targets in a timely fashion.

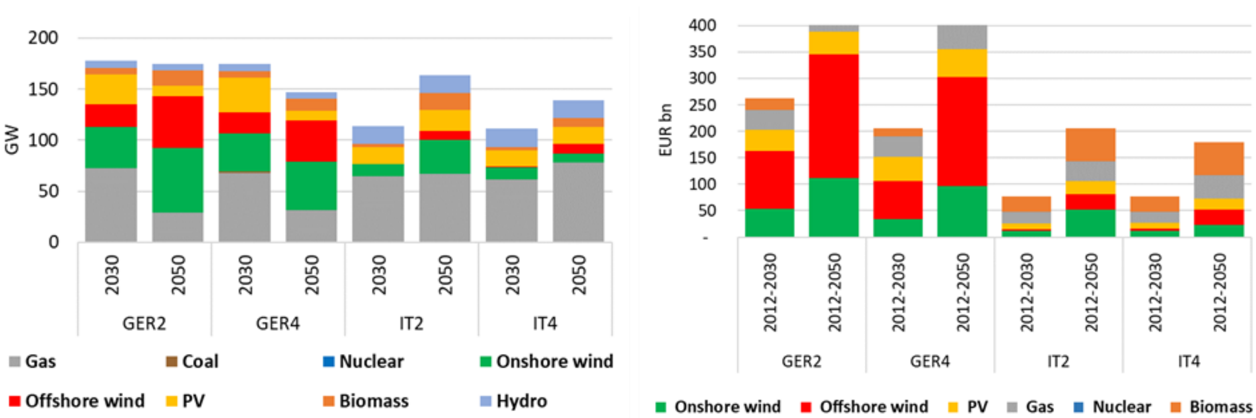

Figure 11 - Installed technology mix and aggregated capital investments in German and Italian scenarios

Similarly to the UK scenarios, GER2 and IT2 scenarios are more expensive in terms of electricity price than GER4 and IT4 scenarios (Figure 12), as this reflects the stronger CO_2 price in GER2 and IT2 scenarios. However, (and similarly for the UK), with heterogeneous market players whose investments are path-dependent a strong CO_2 price alone is not sufficient to either guarantee a secure supply of electricity (as in GER2 scenario) (Figure 12) without a capacity market, or to meet decarbonisation objectives in IT2 scenario where market players face higher costs of capital. This leads to "failed" transition either under a security or environmental point of view.

Hence, the findings from the country comparison strengthen the insights on how virtuous cycles between market players' investments and institutional agents may be created to reach an environmentally successful and secure transition.

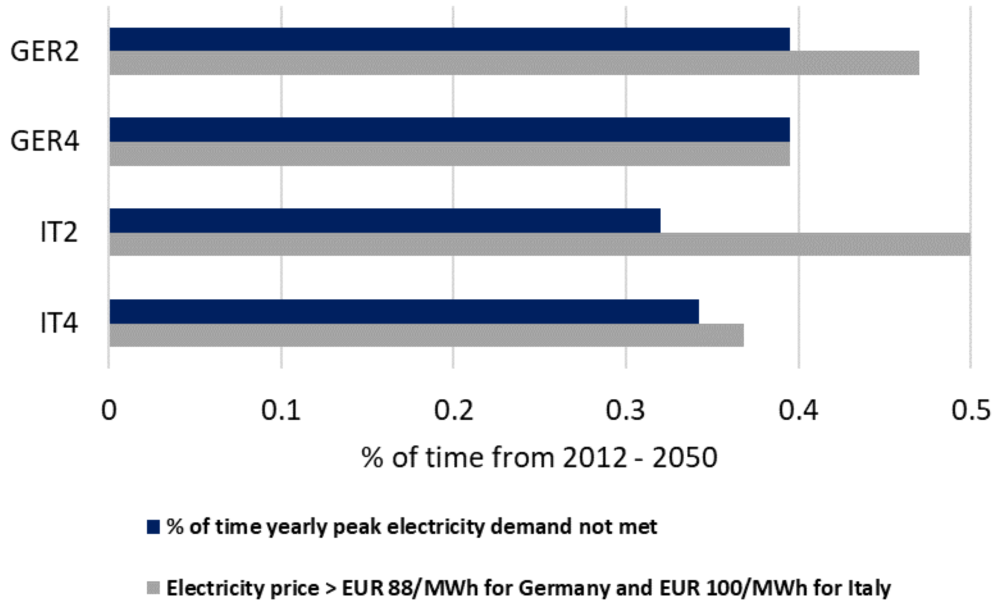

Figure 12 - Supply gaps and electricity price in German and Italian scenarios

6. Conclusions

This paper introduced a novel energy modelling feature via an agent-based model (BRAIN-Energy) with institutional agents endogenously adjusting policies as a result of the emergent properties of the market players' investment decisions. Hence, BRAIN-Energy aims to analyse the impacts of a co-evolving governance structure with the investment choices of the market players on the long-run transition of the UK, German and Italian electricity sectors.

The findings of this co-evolution between the policy-making dimension and the investments of the market players show that a strong CO_2 price signal is key to successfully achieve climate change mitigation targets, especially when market players are heterogeneous and their investment choices are path-dependent. The CO_2 price should not only be strong, but also frequently updatable via a tight coupling with policy to recognise the different investment strategies and responses of heterogeneous market players.

Different policies of the institutional agents also lead to different costs of the transition (in terms of capital investments and electricity prices) depending on the strategies and investments of the market players and the country set-up. Higher capital requirements are needed with heterogeneous market players to successfully decarbonise the UK electricity sector. These higher investment needs in low-carbon technologies are only achieved when the government agent actively manages the CO_2 price. Conversely, using a “no-increase” CO_2 price trajectory – especially with heterogeneous market players – may lead to a cheaper electricity system, but these transitions are not environmentally successful.

If the institutional agents manage to get incentives and prices high enough so firms make profitable investments and then they (and their competitors) learn from these to further invest in a sufficient portfolio of low carbon technologies, but not too high so the transition is prohibitively expensive, virtuous co-evolutionary cycles are created which facilitate a successful low-carbon transition. As in reality market players are heterogeneous, have bounded-rationality, and take path-dependent investment choices, if governments do not pursue a strong and responsive policy-mix (comprising a frequently updated increasing CO_2 price, subsidies to renewables (CfDs or FITs) and a capacity market) this creates a vicious cycle which derails the low-carbon transition.

Future development of the BRAIN-Energy model will build on these insights, test the robustness of the virtuous or vicious cycles, and explore further uncertainties. Specific model developments will first include heat and transport, with the likelihood for much larger and much more uncertain electricity demands, and hence a more challenging iteration between agent decisions and government response. Second, the model will include a demand response (via an aggregator agent) to improve the viability of electricity systems that meet peak and average demands, and also generating consistent costs of successful vs. unsuccessful transitions. Third, the model will include local agents to better capture structural changes in where new technology are sited and impact of the distribution aspects of the electricity system. Fourth, the model will investigate a broader portfolio of policy instruments and how CO_2 pricing plus technology support policies are sequenced and interact. And fifth, path-dependency in BRAIN-Energy could be modelled as a positive learning curve reflecting feedback and reinforcing mechanisms stemming from increasing returns and economies of scale, knowledge accumulation, and learning-by-doing in economic systems [79].

In conclusion, this paper demonstrated (via the BRAIN-Energy agent based model) that it is of critical importance to take into consideration the interplay of both the political and the market players' dimensions of the low-carbon transition of the electricity sector. These findings confirm that the low-carbon transition of the electricity sector is a socio-technical process [80], which results from the “coevolution of economic, business decisions, technological, cultural and institutional developments” [81]. Developing and using models which are able to represent such complex dynamics and co-evolutions is vital to understand critical barriers to a successful and sustainable transition in the energy sector, which could otherwise be overlooked by energy models which mainly focus on technological and cost-minimisation aspects of the energy transition.

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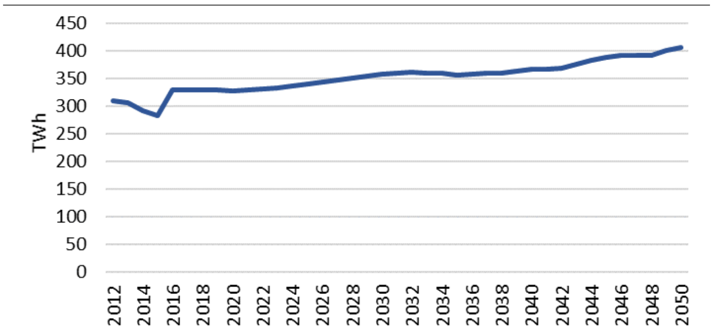
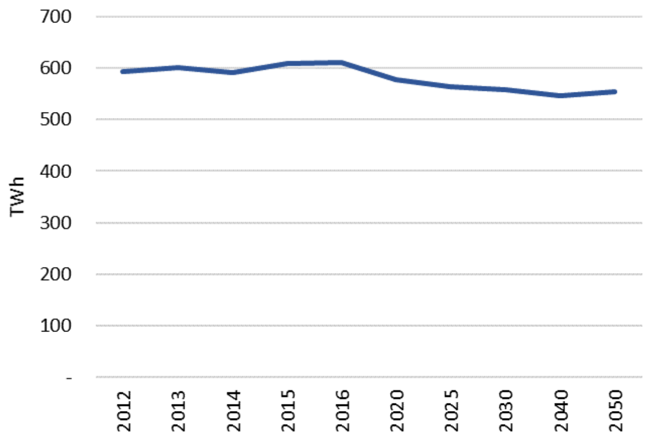
Appendix

Electricity demand:

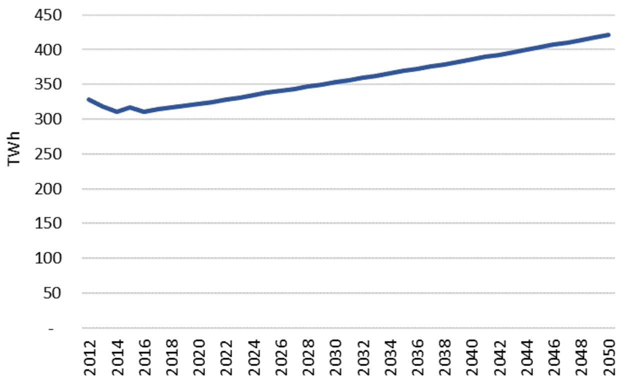
UK



Germany



Italy



Sources: see sources in Table 2

Peak factor:

	% of yearly average day demand
UK	125%
Germany	130%
Italy	150%

Source: see sources in Table 2 (same sources as for electricity demand)

Installed capacity at 2012 in UK:

Technology	GW
Gas CCGT	35
Coal	30
Nuclear	9
Onshore wind	6
Offshore wind	3
PV	2
Hydro	4
Biomass	3
Peaking plants (e.g. oil)	2

Source: [44]

Installed capacity at 2012 in Germany:

Technology	GW
Gas CCGT	29.5
Lignite	22
Hard coal	25
Nuclear	12
Onshore wind	31
Offshore wind	0.6
PV	33.5
Hydro	14.5
Biomass	6
Peaking plants (e.g. oil)	4

Source: Bundesnetzagentur Kraftwerkliste, 2018[13]

[13] https://www.bundesnetzagentur.de/.../Kraftwerksliste/Kraftwerksliste_2018_1.xlsx?__

Installed capacity at 2012 in Italy:

Technology	GW
Gas CCGT	63.8
Coal	8.5
Onshore wind	8.1
PV	16.6
Hydro	22.2
Biomass	3.8
Peaking plants (e.g. oil)	9

Source: [47]

Capital costs of technologies (in EUR/kW):

	EUR/kW								
Technology	**2012**	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
Gas CCGT	400	400	400	400	400	400	400	400	400
Coal	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800	1,800
Nuclear	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000	6,000
Onshore wind	1,300	1,269	1,240	1,210	1,182	1,154	1,127	1,101	1,075
Offshore wind	3,000	2,868	2,742	2,621	2,506	2,396	2,290	2,189	2,093
PV	1,560	950	750	675	600	555	472	448	425
Biomass	2,500	2,424	2,350	2,278	2,209	2,141	2,076	2,013	1,951
Peaking plants (e.g. oil)	400	400	400	400	400	400	400	400	400

Source: [50]

Technical power plant data:

Technology	Average load factor UK and GER	Average load factor Italy	Lifetime	Emission intensity (gCO2/kWh)
Gas CCGT	93%	93%	25 years	365
Coal	90%	90%	30 years	907
Nuclear	90%	N/a	60 years	
Onshore wind	32%	30%	24 years	
Offshore wind	43%	42%	23 years	
PV	11%	16%	25 years	
Hydro	40%	40%	35 years	
Biomass	84%	84%	25 years	
Peaking plants (e.g. oil)	22%	22%	25 years	

Source: [50,51,74]

FIT values in Germany

Technology	EUR/MWh
Onshore wind	65.2
Offshore wind	96.5
PV	108.1
Biomass	95.2

Source: EEG 2017 (https://www.gesetze-im-internet.de/eeg_2014/BJNR106610014.html)

FIT values in Italy

Technology	EUR/MWh
Onshore wind	127
Offshore wind	165
Biomass	122

Source: Legislative Decree 6 July 2012
(https://www.mise.gov.it/images/stories/normativa/DM_6_luglio_2012_sf.pdf)