The impact of heterogeneous market players with bounded-rationality on the electricity sector low-carbon transition

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Abstract:

The energy sector transition requires large financial investments in low-carbon generation technologies, to be delivered by a variety of actors with heterogeneous characteristics. Real-world actors have bounded-rationality, reflected by their limited foresight and heterogeneous expectations, and as past trends influence their investments. Agent-based models are highly suitable modelling frameworks to study such realistic and complex energy transition dynamics. This paper introduces BRAIN-Energy, a novel agent-based model which explicitly allows to explore the impacts of actors' heterogeneous characteristics, and of their interactions, on the transition pathways of the UK, German and Italian electricity sectors. Results show that actors' heterogeneous characteristics pose barriers to effective decarbonisation efforts, affect the speed of the transition, and impact the transition's security of supply and affordability

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dimensions. Limited foresight and path-dependency lead to investment cycles (both virtuous and vicious). The country comparison highlights how such effects are stronger in markets with more heterogeneous market players.

Keywords: agent-based modelling; bounded-rationality; heterogeneity of actors; investment decisions; energy sector; low-carbon transition

1. Introduction

The electricity sector is the largest producer of greenhouse gas emissions in Europe (Eurostat[2]), and as imposed by national and international climate change reduction objectives it needs to be decarbonised. Decarbonising the electricity sector, and subsequently electrifying transport and heating will allow decarbonisation targets to be met cost-effectively (Anandarajah et al., 2008; Ekins et al., 2011; Williams at al., 2012). Low-carbon assets will have to account for the largest share of electricity production by 2050 and be supported by carbon capture and storage (CCS) technologies.

Meeting these challenging decarbonisation goals requires large financial investments in low-carbon technologies (IEA/IRENA, 2017), to be delivered by an increasing variety of market actors and investors (Hansen et al., 2019) and by new financing niches (Bolton and Foxon, 2014). These market actors are heterogeneous and have diverse investment behaviours (Bergek et al., 2013; Mazzucato and Semieniuk, 2017). They operate with bounded-rationality, and not having

[2] https://ec.europa.eu/eurostat/statistics-explained/index.php/Greenhouse_gas_emission_statistics#Trends_in_greenhouse_gas_emissions

exact knowledge about the future. Hence they rely on past experiences, expectations and habits. Such adaptive and heterogeneous behaviours, and their interactions, add complexity to the energy transition and uncertainty to what shape the future energy system will have, leading to a multitude of possible decarbonisation pathways. Energy systems are, hence, complex adaptive systems which Bale et al. (2015) understand as systems characterised by heterogeneous and interrelated elements (such as agents, objects and dimensions), the evolution of which is an emergent property of the behaviours and interactions of the different elements. For example the energy transition in Germany, called “Energiewende”, dramatically changed the structure of electricity supply in Germany, leading to a growth in decentralised renewable electricity production and to the rise of “third parties” (Brunekreeft et al., 2016). The emerging property of this increasing competition was the impact on the financial viability of incumbent utilities, and the need of new business models for such actors to be able to continue delivering electricity and the necessary low-carbon investments (Brunekreeft et al., 2016).

However, equilibrium and optimisation models have been mostly used to study the energy transition and investments in low-carbon technologies leading to future decarbonisation pathways. These models assume homogeneous and rational economic actors (Bale et al., 2015), and neglect attention to the actors’ bounded-rationality (Iychettira et al., 2017; Wüstenhagen and Menichetti, 2012) and to their diverse strategies and interactions with other market players and policy-makers. Hence, new methods and modelling approaches are needed to provide suitable policy insights and decision-making tools (Ringler et al., 2016) to achieve a sustainable decarbonisation of the electricity sector (Mercure et al., 2016). Modelling of sustainability transitions should pay attention to the heterogeneous behaviours and characteristics of the key stakeholders involved in the low-carbon transition (Gazheli et al., 2015), to understand the barriers that such aspects could pose to reaching a sustainable transition. Moreover, new modelling approaches should take into account the different dimensions involved in the transition, and the emergent properties arising from their complex interactions and feedback between each other (Hansen et al., 2019; Hoekstra et al., 2017; Deissenroth et al., 2017).

This paper introduces BRAIN-Energy (Bounded Rationality Agents Investment model), an agent-based model (ABM) whose strength is its sophisticated representation of agent behaviour. BRAIN-Energy's novelty lies in introducing a greater diversity of market players and behaviours compared to existing energy system ABMs, and in having a stronger focus on how past experience and imitation influence the investment behaviours of such market players. By comparing three countries (UK, Germany and Italy), characterised by different types of market players and ownership structures of renewable energy plants in their electricity sectors (Hall et al., 2016), this paper aims to answer the following research questions:

1) To what extent do the heterogeneous characteristics of the market players impact future investments in the electricity sector and its low-carbon pathways?
2) How does the structure of the electricity sector change to 2050 in terms of market shares of the market players (which players survive and which lose)?

Chapter 2 provides a review of existing agent-based models in the energy sector and highlights the strengths of BRAIN-Energy, and Chapter 3 introduces the model, its main agents, their characteristics and investment procedures. Scenarios are discussed in Chapter 4, and Chapter 5 discusses BRAIN-Energy's results for the three case studies, with conclusions and policy implications in Chapter 6.

2. Literature review

2.1 Challenges of modelling complex energy transitions and heterogeneous actors

The energy transition has mainly been studied through conventional equilibrium and optimisation energy system models. Prior models have focused on either the full range of possible technology pathways, such as MARKAL in the UK (Strachan et al., 2008), TIMES/TIAM (Loulou and Labriet, 2008), MESSAGE, used by IIASA in the GEA (2012), or on providing a detailed spatial and temporal resolution for supply-demand balancing in the electricity sector such as WeSIM (Strbac et al, 2015). Despite their high degree of technological detail and mathematical precision, these models had to compromise on defining and aggregating decision-makers. For this reason Bale et al. (2015) argue that equilibrium models might not be suitable to study real systems made of agents. Hoekstra et al. (2017) criticise equilibrium models for being static and for having rational, utility maximising actors, which leads such models to being disconnected from the reality of the energy system's transition, where agents do not necessarily act in a fully rational way, but rather exhibit bounded-rationality (Li, 2017; Mercure et al., 2016; Trutnevyte, 2016). Moreover, optimisation models fail to capture the interactions between agents, and do not account for the fact that multiple solutions and path-dependency can arise from agents' non-optimal investment decisions (Mercure et al., 2016). The combination of these weaknesses prevents such models from being able to address the breadth of current challenges of the energy transition, and limits their ability in capturing the drivers and barriers to the energy system transition in the long-term (Bale et al., 2015).

Energy systems are, in fact, made of a multitude of actors, with different behaviours and potentially conflicting interests, and which influence each other. Actors interact with each other through networks disciplined by institutions (Bale et al., 2015). The main actors and investors in the electricity sector are electricity producers such as incumbent utilities, and new types of investors, such as households and institutional investors. Interactions between these diverse market players and the institutional dimension (made of national government, electricity regulator agent and their policies) give rise to a variety of emergent techno-economic properties of the electricity sector, and to different possible future transition pathways and feedback loops (Hoekstra et al., 2017). These real-world actors have bounded-rationality. This means that instead of being profit-maximising, agents base their investment choices on routines, habits and past experience, as they have limited information about the future (Simon, 1953, 1955, 1956; Nelson and Winter, 1982). This leads to “satisficing” investment choices, which are adaptive and path-dependent. Li (2017) argues that, because of their influence on energy sector's decarbonisation pathways, actors' heterogeneous and non-optimal behaviours should gain a central role in energy system models.

2.2 *Advantages and disadvantages of using agent-based models for energy analysis*

Agent-based modelling approaches have the potential of dealing with the increasing complexity involved in the transition of the energy system (Hansen et al., 2019; Köhler et al., 2018; Hoekstra et al., 2017; Bale et al., 2015; Pfenninger et al., 2014). Agent-based models (ABMs) are bottom-up dynamic simulation models, and their main strength is the representation of autonomous and heterogeneous agents (Köhler et al., 2018) and their interactions. With ABMs it is, therefore, possible to represent the increasing variety of stakeholders taking part in the energy transition (Hansen et al., 2019), and to represent the complexity in decision making processes that actors face in the real world (Ma and Nakamori, 2009). Also, in ABMs it is possible to represent agents with bounded-rationality, whose strategies are adaptive and path-dependent. Hence, ABMs can model learning, strategizing and interacting agents, which is one of the features that modelling approaches able to deal with complexity should have (Hoekstra et al., 2017; Bale et al., 2015). Moreover, in ABMs the emergent properties of a system can be modelled as a dynamic result of the different micro-economic strategies of the actors and their interactions, rather than being the outcome of equilibrium solutions (Ponta et al., 2018; Köhler et al., 2018). Also according to Hoekstra et al. (2017) ABMs are the best approach to model emergence as opposed to other simulation techniques. A further strength of ABMs lies in being able to capture the dynamic feedback which develop between the different dimensions involved in the energy transition (Hansen et al., 2019; Deissenroth et al., 2017; Bale et al., 2015), which is a limitation of equilibrium models. Understanding such dynamic feedbacks allows to better understand uncertainty involved in the energy transition (Köhler et al., 2018). Moreover, ABMs make it easier to address institutional and governance barriers in energy transitions (Busch et al., 2017), and to understand the side-effects which path-dependency, bounded-rationality, myopic foresight, and heterogeneous strategies have on energy and climate policies (Chappin et al., 2017). In fact, according to Chappin et al. (2017) social elements which pose challenges to the energy transition are best studied through ABMs.

Disadvantages of ABMs include the challenge to adequately represent the operations of the electricity system. A further challenge for ABMs is linked to the difficulty in calibrating and validating them against empirical data (Tesfatsion, 2006; Ringler et al., 2016; Weidlich and Veit, 2008). Moreover, due to their flexibility, ABMs are hard to compare between themselves (Fagiolo et al., 2007b), and the absence of a standard protocol to describe ABMs makes them difficult to compare and replicate (Grimm et al., 2006 and 2010).

2.3 Agent-based models in the energy and electricity sector

As a result of their advantages, ABMs studying the energy transition (Table 1) have flourished, with the majority of such studies being published in 2017, highlighting the growing importance of ABMs for energy policy (Hansen et al., 2019). Weidlich and Veit (2008) and Hansen et al. (2019) provide a review of the most prominent ABM studies covering electricity markets, while Ringler et al. (2016) specifically focus on ABMs studying electricity grids.

Chappin et al. (2017) and Richstein et al. (2014 and 2015) use the EmLab model, a flexible, modular and open-source ABM (De Vries et al., 2015) to simulate two interconnected electricity markets in typical European countries and to explore the effects of the investment decisions of the market players with bounded-rationality under different policy settings and market structures. Their goal is to understand how different policies influence the development of European electricity markets in the long term, and also the need for flexibility options such as demand response practices and electrical energy storage in an electricity system with a capacity mechanism (Khan et al., 2018). Agents in this model include electricity generators, an aggregated energy consumer agent, the government, an electricity spot market, and a market for trading CO_2 emission permits. Similarly, electricity generators are the main agents in the ABM developed by Kwakkel and Yücel (2014) and Yücel and Van Daalen (2012), which studies the Dutch electricity system using a socio-technical perspective. Electricity generators are the main agents also in the AMIRIS model (Deissenroth et al. 2017), a socio-technical ABM which focuses on the German electricity sector, and in the PowerACE model (Sesnsfuss et al., 2008; Bublitz et al., 2017). This ABM also focuses on the German electricity sector, and studies the impact of the EU ETS and of increasing renewable energies on the structure of the market and on the generators' investment choices. The CASCADE ABM (Rylatt et al., 2013; Allen et al., 2013; Allen and Varga, 2014) also has electricity generators as main agents, but the purpose of the ABM is mainly to study their short term bidding decisions in the UK electricity market, as opposed to long-term investments and their impacts on the low-carbon transition. Kraan et al. (2018, 2019) use an ABM to study the behaviour of heterogeneous investors with different views of the future, and whose investment choices are affected by their past performance, on the long-term evolution of the electricity sector. The heterogeneity of investors is, however, limited to existing and new investors in these studies. ABMs focused on the Italian electricity market are more immature, and the most prominent example is offered by Palmer et al. (2015) who study the evolution of PV investments as a result of communication and imitation between household agents.

Table 1 summarises the key aspects of the ABM studies reviewed above and of BRAIN-Energy. BRAIN-Energy's novelty compared to the above reviewed studies includes a greater focus on depicting diverse market players and their heterogeneous behaviours, and key investment aspects such as bounded-rationality and limited foresight. As discussed in section 3.4, this emerges both from learning from previous periods which leads to path-dependency in investment choices, and from imitation of other players' successful investment strategies. A further novelty in BRAIN-Energy is the inclusion of financial sector actors, which has not been done in energy sector ABMs yet. This paper also adds a country comparison to existing ABM studies, with the aim of highlighting if the heterogeneous investment behaviour of the market player influences the low-carbon transition differently depending on the presence of different types and numbers of market players.

Reference	**Main agents**	**Bounded-rationality**	**Path-dependency**	**Imitation**	**Power sector operations**	**Geographical context**
De Vries et al. (2015); Richstein et al. (2014; 2015); Chappin et al. (2017); Khan et al. (2018)	Electricity generators	Yes	No	No	Detailed + CO_2 trading market + storage	2 connected electricity markets in typical European countries
Kwakkel and Yücel (2014); Yücel and Van Daalen (2012)	Electricity generators (differentiated by size)	Yes	No	No	Endogenous demand changes	Netherlands
Deissenroth et al. (2017)	Electricity generators (differentiated by type of generation technology), direct marketers	Limited	No	No	Hourly resolution	Germany
Sesnsfuss et al. (2008); Bublitz et al. (2017)	Electricity generators (incumbent utilities) and consumers		No	No		Germany
Rylatt et al. (2013); Allen et al. (2013); Allen and Varga, (2014)	Electricity generators, consumer agents	Limited	No	No	Detailed (as focus is on short term bidding decisions)	UK
Kraan et al. (2018, 2019)	Investors in electricity sector (existing and new)	Yes	Yes	No	Yearly resolution + constant electricity demand	Liberalised European market
Palmer et al. (2015)	Households	No	No	Yes	Yearly resolution	Italy
BRAIN-Energy	Electricity generators of different types, institutional investors, aggregated household agents	Yes	Yes	Yes	Yearly resolution	3 countries (UK, Germany and Italy)

Table 1 - ABM studies in electricity sector and key aspects

3. Methodology

3.1 Model overview and design

BRAIN-Energy is an ABM of electricity generation and investment. Its focus is the representation of heterogeneous agent characteristics in investment decisions and multi-agent interaction, and an exploration of the impacts of those aspects on the electricity sector transition. BRAIN-Energy was developed in the open-source software environment Netlogo (Wilensky, 1999), and iterates in yearly time steps from a calibration year of 2012 (to be able to validate the model, by comparing BRAIN-Energy's results with a few years of historical data), through to 2050. The annual resolution of BRAIN-Energy is justified by the fact that the investment decisions of the market players and their interactions – the core of BRAIN-Energy's analysis - are better captured on a yearly basis. Section 3.3 explains how BRAIN-Energy deals with intermittent renewable generation and peak requirements, and load factors for the different generation technologies are provided in the Appendix.

BRAIN-Energy is calibrated for each of the three country case studies – UK, Germany and Italy. These three countries have been chosen as case studies (Figure 1), because they represent a different spectrum of market structures (from more centralised as the UK, to highly decentralised as Germany), a different spectrum of governance arrangements (from more market oriented as the UK, to more civil society oriented as Germany), and finally different types of market players, stakeholders and ownership structures of renewables in the electricity sector (Hall et al., 2016).

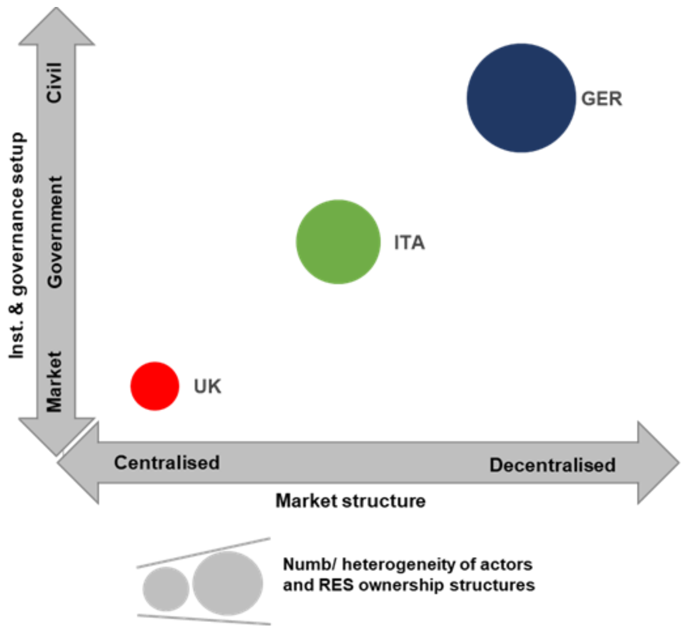

Figure 1 - Case studies in BRAIN-Energy

BRAIN-Energy gives a stylised representation of each country's power sector, in terms of existing generation technologies and available generation technologies in the future, type of market players and prevailing policy environment. For each country the market participants are clearly defined (section 3.2) based on extensive literature search. For the operational decision process (section 3.3), at every time-step these market players first take decisions about electricity production and dispatch from their existing power plants. The revenues and financial positions of the market players are updated based on their electricity sales. Subsequently (section 3.4), market players decide about decommissioning unprofitable power plants, and make investment decisions in new generation assets. An overview of BRAIN-Energy's yearly flow is depicted in Figure 2.

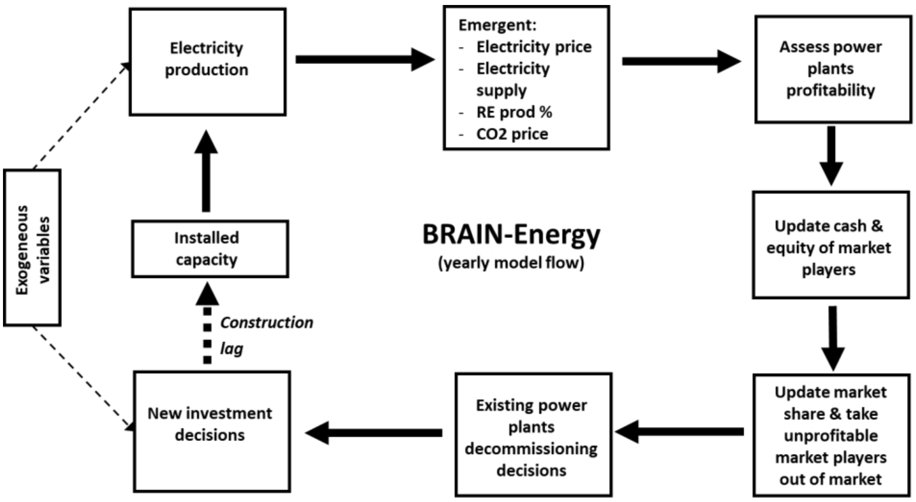

Figure 2 - BRAIN-Energy's yearly flow

Table 2 summarises BRAIN-Energy's main calibration variables for the three country case studies at calibration year, indicating if these are static or dynamic. The dynamic values used in BRAIN-Energy for the capital costs of technologies can be found in the Appendix, which also contains information for future electricity demand projections in the three countries. Further detail on installed capacity, and technical power plant data are provided in the Appendix.

Exogenous variables	Initialisation	Nature	Source
Electricity demand	**UK:** 309 TWh **GER:** 593 TWh **IT:** 328 TWh	Dynamic	**UK:** *Historical*- National Grid half-hourly data *Future*- National Grid FES (2016), "Two Degree" scenario **GER:** *Historical*- Open Power System Data Platform[3], AG Energiebilanz[4] *Future*- Prognos (2014) **IT:** *Historical*- GME[5] *Future*- Terna (2016, 2018)
Fuel costs	Gas: UK: 20.3 GBP/MWh GER and IT: 29 EUR/MWh Coal (GER): 37 EUR/MWh	Dynamic	**UK:** *Historical*- BEIS (2016) *Future*- BEIS (2016), "Reference" scenario **GER and IT:** *Historical*- BmWi Energiedaten database[6] *Future*- Prognos (2014)
Capital costs of technologies (EUR/kW)	Gas: 400 Coal: 1,800 Nuclear: 6,000 Onshore wind: 1,300 Offshore wind: 3,000 PV: 1,560 Biomass: 2,500	Dynamic	DIW (2013)
Operational & Maintenance (O&M) costs		Static	**UK:** BEIS (2016a) **GER and IT:** DIW (2013)
CO_2 price	**UK:** 6.39 GBP/mt **GER and IT:** 7.36 EUR/mt	Dynamic	**UK:** *Historical* – BEIS (2016) *Future* – BEIS (2016), "Reference" scenario **GER and IT**: *Historical*- EEX Exchange *Future*- Prognos (2014)

Table 2- Main calibration variables in BRAIN-Energy

3.2 Market players

3.2.1 Type of market players

6 different types of market players are modelled in BRAIN-Energy, with Table 3 showing which players invest in each country's market, and Table 4 describing their characteristics. 3 types of market players can be found in the UK model: incumbent utilities, independent power producers (IPPs) and new-entrants. The variety of market players is greater in the German (CPI, 2012, 2016) and Italian models, where 6 types of market players have been modelled: incumbent

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

utilities, IPPs, new-entrants, municipal utilities (only in the German model), institutional investors, and households. A household market player in BRAIN-Energy is an aggregation of 1,000 households, to reflect the fact that 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.

This set-up reflects the fact that the main market players in the UK electricity supply sector are incumbent utilities, which own the majority of conventional generation assets (Hall et al., 2016), and 47% of renewable assets (BEIS, 2014). The ownership of renewable generation assets by non-corporate or community actors in the UK is negligible at 0.3% (BEIS, 2014), and hence no households nor institutional investors have been modelled in BRAIN-Energy's UK version. Although energy companies owned by local authorities are starting to enter the UK electricity market[7], with the goal of tackling fuel poverty, these are currently very limited in number and market share. Hence UK municipal utilities have not yet been introduced in the current version of BRAIN-Energy. In contrast, in the German electricity sector the ownership of renewable generation assets is fragmented, and non-corporate, municipal and non-state models dominate (Hall et al., 2016). Private individuals (households and cooperative of households) own 46% of total renewable installed capacity, and 43% is owned by institutional investors (Trend:research, 2013). Households are very important investors also in the Italian market, especially on solar PV, and so are institutional investors (Terna, 2016).

[7] Energy companies owned by local authorities include Robin Hood Energy, Bristol Energy, Liverpool Energy Community Company and Angelic Energy

Type of market player	UK	Germany	Italy
Incumbent utilities	4	3	3
IPPs	2	2	2
New-entrants	None at 2012 – up to 6 through to 2050	None at 2012 – up to 6 through to 2050	None at 2012 – up to 6 through to 2050
Municipalities	N/a	2	N/a
Institutional investors	N/a	2	2
Households	N/a	8	6

Table 3 – Number of market players in UK, Germany and Italy at calibration year

3.2.2 Heterogeneity of market players

The market players in BRAIN-Energy are heterogeneous based on the type of organisation and their characteristics. This consists of five elements (specific characteristics in Table 4):

1. Aim: different types of market players have different strategies and aims which define their behaviour and actions through time (Table 4). The aim of the different types of market players in BRAIN-Energy is based on a literature review and on real-world characteristics.
2. Technological preferences: market players only operate or invest into determined types of technologies (Table 4). This is because different electricity generation technologies bear different types of risks, which can best be managed by different types of owners which have different capabilities, sizes, risk propensities, etc. (CPI, 2017a, 2017b; Mazzucato and Semieniuk, 2017). The different types of technologies which market players own, operate and invest in have an impact on the revenues which market players are able to generate at each time step in BRAIN-Energy, and hence on their future investments and the evolution of their market shares.

3. Foresight: different types of market players evaluate future investment options over a different number of years in the future. The length of the foresight of the market players depends on their investment behaviours, risk propensity and return expectations and wider behavioural assumptions modelled in BRAIN-Energy and summarised in Table 4.
4. Number of years before unprofitable assets are closed down: incumbent and municipal utilities are willing to absorb losses for longer years, as electricity generation is their main business, in contrast to IPPs and new entrants who have a more speculative behaviour (CPI, 2016; Global Capital Finance, 2014). The number of years during which market players are willing to absorb losses for before closing unprofitable plants is calibrated in BRAIN-Energy based on the market players' wider strategies in the literature (Global Capital Finance, 2014; BNEF, 2012; CPI, 2012, 2016, 2017b) and is summarised in Table 4.
5. Cost of capital: the different costs of capital for market players have been calibrated based on values found in the literature (H.M. Treasury, 2011; Hermelink and De Jager, 2015; Global Capital Finance, 2014; Steinbach and Staniaszek, 2015) and on the financial statements of the major European utilities (Uniper, 2017; E.ON, 2017; Enel, 2017; Scottish Power, 2018; RWE, 2016). These reflect the risk profile of each type of actor also taking into account the risk profile of the country in which they operate (Diacore, 2015), and represent a company's weighted average cost of capital (WACC).

This heterogeneity of the market players in BRAIN-Energy also illustrates bounded rationality, as investment decisions are affected by the market players' limited foresight of the future, and are hence based on their own heterogeneous expectations of electricity demand, fuel and technology costs. As discussed later in sections 3.4.2 and 3.4.3, the market players' characterisation further captures both path dependence and imitation, as investment decisions are influenced by the success of each market player’s own portfolio, as well as by emerging knowledge of the outcomes of the other players’ investments.

Market players	Characteristics and strategies
Incumbent utilities Main players in the electricity sector, whose main business is electricity generation. Some are vertically integrated companies, which also own the supply business.	• *Aim*: production of electricity to meet demand and provision of stable dividends to shareholders (Blyth et al., 2015; Caldecott and McDaniels, 2014; CPI, 2016). Once out of the market, no new incumbents are created in BRAIN-Energy • *Technology preferences*: invest across all technologies (within the pool of their accepted technologies) • *Foresight*: 15-20 years. Incumbents are willing and able to absorb losses from unprofitable plants longer than other generators • *Number of years losses are allowed for before plants are switched off*: 7-10 years • *Capital costs*: 5%-7% (Hermelink and De Jager, 2015; Steinbach and Staniaszek, 2015; CPI, 2016)
Independent power producers (IPPs) Project developers, which develop, own, operate new generation assets, and eventually then sell these on. IPPs are not vertically integrated.	• *Aim*: profit maximisation and increased market share (CPI, 2016; Global Capital Finance, 2014). Opportunistic investment style. • *Technology preferences*: gas and nuclear. Renewables: onshore- and offshore wind (CPI, 2016) • *Foresight*: 10-15 years. IPPs switch off unprofitable plants sooner than incumbents or municipalities (Global Capital Finance, 2014). • *Number of years losses are allowed for before plants are switched off*: 5 years • *Capital costs:* 8%-10% in Germany and UK, 8-12% in Italy (Diacore, 2015). IPPs seek higher returns from investments than incumbents, and are willing to undertake riskier projects (Global Capital Finance, 2014)
New-entrants New-type of electricity generators (e.g. IT companies entering the electricity market). Their main business is not electricity generation. Not existent at the beginning of the simulations in BRAIN-Energy.	• Aim: their main expertise is not electricity generation, but they want to maximise profits attracted by subsidies • *Technology preferences*: only renewable generation technologies • *Foresight*: 10 years, as supply of energy is not their main business, they are just being speculative • *Number of years losses are allowed for before plants are switched off*: 5 years • *Capital costs*: 12%, as they seek high return
Municipal utilities Directly or indirectly owned by a municipality or city, and operate only in their regions, to which they are strategically committed.	• Aim: investment choices are driven by financial return expectations, but also by wider environmental considerations (CPI, 2016; Hall et al., 2016) • *Technology preferences*: gas and renewable generation technologies (PV, onshore wind and biomass). Larger municipalities also invest in offshore wind (CPI, 2016) • *Foresight*: 25 years, as supply of energy to their region is their main business • *Number of years losses are allowed for before plants are switched off*: 7-10 years • *Capital costs*: 4% (Hall et al., 2016), as they can borrow from local banks
Institutional investors Institutional investors (such as pension funds and insurance companies) are financial institutions that manage funds on behalf of others.	• *Aim*: seek stable, predictable and long-term returns and cash-flows to match their long term liabilities • *Technology preferences*: Onshore wind and PV. More experienced institutional investors can also invest in offshore wind. Pension funds seek to invest EUR 100-250 million at once, while insurance companies look to invest EUR 20-100 million at once (Global Capital Finance, 2014; Blyth et al., 2015; CPI, 2016, 2017b) • *Foresight*: 20-25 years, as this matches their long-term liabilities (Blyth et al., 2015; CPI, 2016; Mazzucato and Semieniuk, 2017) • *Number of years losses are allowed for before plants are switched off*: 5-10 years • *Capital costs*: 5%-10% in Germany and UK and 5-12% in Italy, to reflect the riskier environment (Global Capital Finance, 2014; Diacore, 2015)
Households Aggregated to 1,000 households	• *Aim: t*hey invest in small scale renewable energy facilities, to cover self-consumption, and might sell surplus locally. • *Technology preferences*: households only invest in small scale PV (Palmer et al., 2015; GSE, 2016b; Trend:research, 2013; CPI, 2016). • *Foresight:* investment decisions based on pay-back period of assets, which can vary from 5 to 15 years depending on single actors • *Capital costs*: reflect market cost of capital and are between 3%-6% (Steinbach and Staniaszek, 2015)

Table 4 – Characteristics of market players

3.3 Power sector operations

Each year market players in BRAIN-Energy bid potential electricity production from each of their power plants p into the market (we assume market players sell all electricity they produce through the wholesale market, and don't take into account the fact that they might be vertically integrated or have power purchase agreements). Each market player's bidding strategy at time t (b_t) is a function of the short run marginal cost per MWh of electricity produced by power plant p ($SRMC_{p,t}$), and of the potential available production capacity of power plant p at year t ($ep_{p,t}$):

$$b_t = f(SRMC_{p,t}, ep_{p,t})$$

Electricity demand is exogenous in BRAIN-Energy and has been calibrated on half-hourly national data (Table 2). Additional information can be found in the Appendix. To account for variations in the load profile, electricity demand has been divided into a yearly day average demand, yearly night average demand and a yearly peak demand. Yearly peak demand is calculated as 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). All bids from the market players are then collected, and electricity is dispatched on a merit-order basis to satisfy yearly average day and night electricity demand. The electricity price at year t (p_t) is equal to the short run marginal cost of the last and most expensive bid accepted into the market, which is required to meet electricity demand in that year. Based on the electricity production mix resulting from the merit order, total emissions in the power sector and carbon intensity of electricity generation are calculated.

To account for the intermittency of renewable generation assets, and for their effect on capacity, on load factors of thermal plants and on the electricity price formation, their installed capacity has been de-rated by their load-factor (see Appendix). To account for intermittency of renewable source, renewable assets 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. Renewable plants only contribute 5% of their capacity to peak generation, when over 80% of electricity is produced from renewable sources (De Vries et al., 2015).

To incentivise investments into renewable energy technologies and achieve at least an 80% share of electricity produced through renewables at 2050 in all three countries as dictated by national regulations[8], a CO_2 price operates in BRAIN-Energy, as well as policies such as Contracts for Difference (CfDs) in the UK and feed-in-tariffs (FITs) in Germany and Italy. Moreover, a capacity market is active in the UK and Italian models to manage security of supply. The CfD mechanism and the capacity market are modelled in BRAIN-Energy as auctions, while FITs have static values through time (see Appendix). The CO_2 price changes through the years, and its values can be found in the Appendix. Detailed explanation about the functioning of the CfD mechanism, FITs and the capacity market can be found in BRAIN-Energy’s online documentation. For additional information on the power sector operation see BRAIN-Energy’s model documentation on: https://www.ucl.ac.uk/energy-models/models/brain-energy

3.4 Investments

3.4.1 Economic criteria in investments

[8] For the UK: 2008 Climate Change Act
For Germany (Renewable Energy Sources Act 2017) (in German Erneubares Energien Gesetz- EEG: http://www.gesetze-im-internet.de/eeg_2014/EEG_2017.pdf
For Italy (Strategia Energetica Nazionale (Ministero dello Sviluppo Economico, 2017)): https://www.mise.gov.it/images/stories/documenti/Testo-integrale-SEN-2017.pdf

In BRAIN-Energy market players evaluate investment opportunities based on an NPV calculation. If an investment option has an NPV higher than zero, market players select the options with the highest expected return on investment (ROI) which is equal or above their cost of capital. Market players have different technology options, and their NPV calculations are based on *n* years ahead. *n* is different by market player, to represent their heterogeneous limited foresight. Also, market players use different discount rates *r* in their NPV calculations, which reflect their different cost of capital. Finally, market players use heterogeneous expectations about future electricity demand, fuel and technology costs in their NPV calculations. Before investing, market players make sure to be able to pay at least 20% of the investment cost from their own cash, and to be able to raise the remaining amount as debt. Debt is raised at a market player's specific cost of capital *r* as in Table 4 (the same value is used as the discount rate in the NPV calculation), and market players are assumed to pay back the loans in fixed annual instalments during the lifetime and depreciation time of the power plant for which construction the loan has been taken. Figure 3 shows the investment process of the market players in BRAIN-Energy and the different dimensions influencing them.

Further details about the investment process and mathematical formulations can be found on BRAIN-Energy's online documentation on https://www.ucl.ac.uk/energy-models/models/brain-energy.

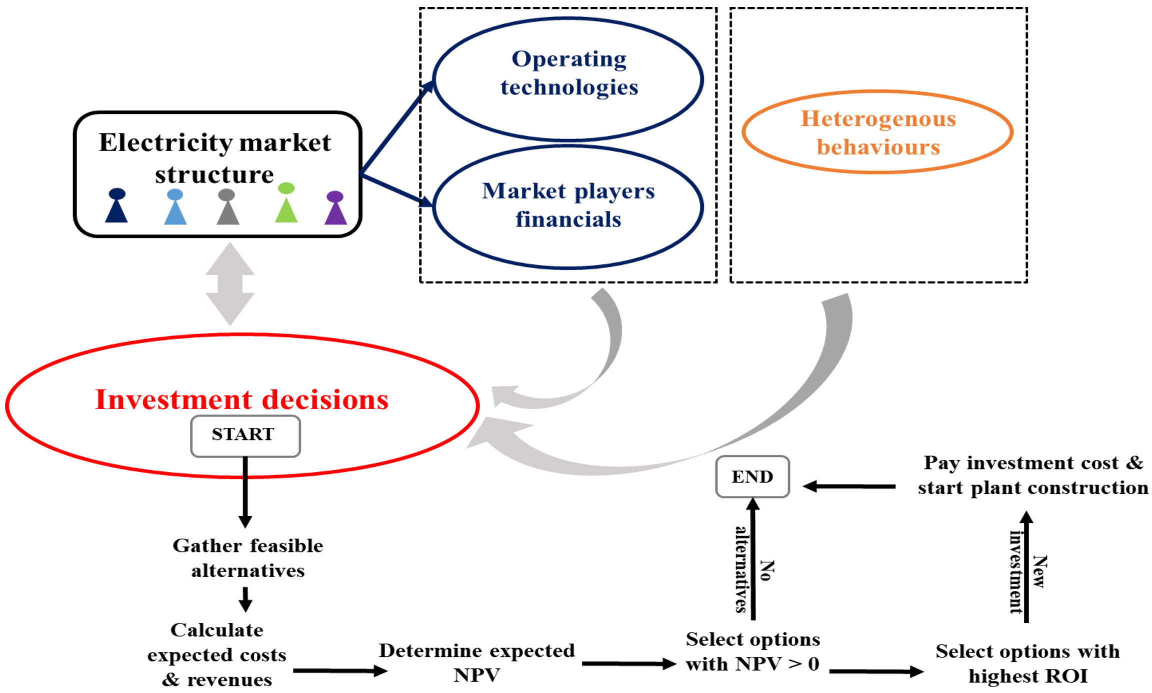

Figure 3 – Investment process

3.4.2 Influence of past performance and path-dependency

The performance of past investments influences future investments of the market players, making these adaptive and path-dependent. Path-dependency arises when there are feedback and reinforcing mechanisms stemming from increasing returns and economies of scale, knowledge accumulation, and learning-by-doing (Safarzynska and Van den Bergh, 2010). Given the long life-time of electricity generation assets (Chappin et al., 2017), it is key to take path-dependency into account when studying investments in the power sector.

In BRAIN-Energy market players learn from own successful past investments, and this is reflected in a market player's growing profit and improving financial situation. Hence, learning-by-doing and accumulation of knowledge in BRAIN-Energy lead to growing market shares and ability to commit new investments. Market players in BRAIN-Energy also learn from their own unsuccessful past investments. After five years that a new plant started operations, market players assess its profitability every year. If at any given year a plant's cumulative profits over the previous five years defined as:

$$\sum_{y=t}^{n} PF_{p,t} = (prod_{p,t} \times \, p_t) - \, totCost_{p,t}$$

are lower than the 5-yearly share of the new plant's total capital cost ($\frac{CAPEX_p}{l_p} \times n$) then the new investment is flagged as unprofitable. l_p is the lifetime of plant p, $prod_{p,t}$ is the electricity production of plant p at year t, p_t is the electricity price at year t, and $totCost_{p,t}$ comprise variable and fixed production costs and yearly capital costs. If the number of years during which the new plant is unprofitable in a row is greater than the number of years a market player is willing to absorb losses for (Table 4), then it is shut down. A market player will not invest in the same technology until such technology becomes profitable again. At this point, if the technology's NPV calculation is greater than zero, and if the ROI is equal or greater than the capital cost of the market player plus a threshold α which differs by type of market player, the market player will invest again in this technology. These thresholds have been calibrated based on the behaviours of the market players explained in Table 3. Threshold α can be between $1 \leq \alpha \leq 2$. For more aggressive market players, such as new-entrants and independent power producers, α = 1. For institutional investors and incumbent utilities α = 1.5, while for municipal utilities α = 2, because such players take longer than others to switch off unprofitable plants, given that they are not only motivated by return considerations in their investment decisions (CPI, 2016). However, as they are also driven by political considerations in their investment decisions (CPI, 2016) they are more cautious when learning from unsuccessful past experiences, hence the higher value of α for them.

3.4.3 Imitation in investments

In BRAIN-Energy investment choices are also influenced by the successful investments of other market players. Imitation has been introduced in BRAIN-Energy because it is a key aspect of sustainability transitions, which imitation can either delay or encourage (Gazheli et al., 2015). Imitation, brought about by peer effects and social interactions has been recognised as a key driver of technology adoption, especially solar PV, by several studies (Janssen and Jager, 2002; Bollinger and Gillingham, 2012; Graziano and Gillingham, 2015).

In BRAIN-Energy households can only imitate other households. All other agents can imitate each other, excluding households. As market players in BRAIN-Energy have bounded-rationality the only information which they have available about other players is the evolution of their market shares. If a market player's *x* market share MS_x is growing compared to the previous year, hence if $MS_{x,t+1} > MS_{x,t}$, market player *a* chooses to imitate the market player *x* whose market share grew the most at year *t+1*. However, as market player *a* has bounded-rationality and doesn't have perfect information about which exact power plant or new investments led the market share of player *x* to grow, market player *a* decides to imitate the generation technology of player *x* with the highest expected ROI based on its own myopic expectations (or the shortest pay-back period for households) and which is an allowed technology given their technology preferences.

4. Scenarios

To illustrate the functioning of BRAIN-Energy and to capture key agent-focused elements of the evolution of the UK, German and Italian electricity sectors, four core scenarios (Figure 4) have been developed in each of the three country case studies. The aim of these scenarios is to study how market players with heterogeneous characteristics as it is in the real world (and whose investments are path-dependent) impact the long-term decarbonisation scenarios of the UK, German and Italian electricity sectors and their emergent techno-economic properties, as opposed to an "idealised" world with homogeneous market players. By testing different regulatory frameworks, we aim to understand if different policy conditions are needed with homogeneous versus "real-world" heterogeneous market players (whose investments are path-dependent) to achieve a successful transition.

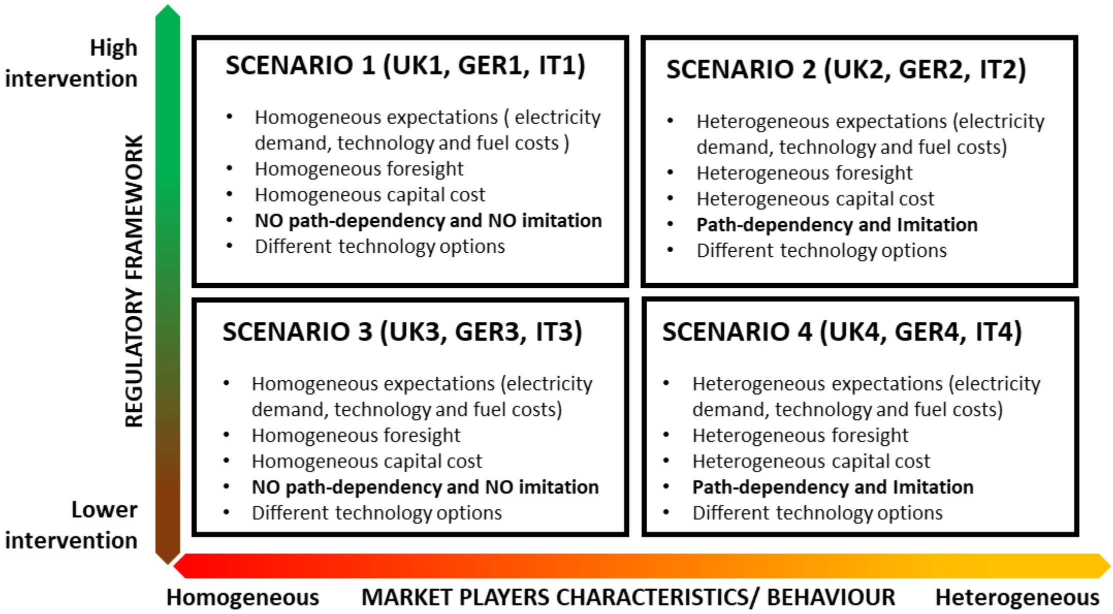

Figure 4 – Overview of scenarios

Exogenous variables are the same in all four core scenarios, and are calibrated as explained in Table 2, while Table 5 summarises the overall parameters used in the scenarios.

The four core scenarios differ according to two main variables: 1) characteristics of the market players, and 2) regulatory framework.

Characteristics of the market players refer to market players being homogeneous or heterogeneous, and to them taking or not path-dependent investment choices, and imitating or not other players. Introducing diverse market players and their heterogeneous behaviours is a key novelty of BRAIN-Energy (section 2.3). This has been done because depicting heterogeneous agents, as opposed to a single decision-maker as in conventional equilibrium and optimisation models, is key to study a complex phenomenon such as the electricity sector's low-carbon transition (section 2.2). In Scenario 1 (UK1, GER1, IT1) and Scenario 3 market players have the same capital costs, foresight, expectations about future technology costs, expectations about variance in expected demand and they all close unprofitable plants down after the same amount of loss-making years. In contrast in Scenario 2 (UK2, GER2, IT2) and Scenario 4 (UK4, GER4, IT4) market players have heterogeneous technology preferences, capital costs, foresights, expectations about future technology and fuel costs and electricity demand, and they close unprofitable plants down after a different number of years. Table 5 gives the detailed differences in homogeneous versus heterogeneous characteristic between Scenario 1 and 3, and Scenarios 2 and 4 respectively. Furthermore, investment choices in Scenario 2 and Scenario 4 are path-dependent and affected by imitation, as explained in sub-chapters 3.4.2 and 3.4.3. Market players' investment choices are not path-dependent (and not affected by imitation) in Scenarios 1 and 3, because these scenarios represent a "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 (Mercure et al., 2016). Therefore, in these "stylised" scenarios market players' investments are not affected by learning opportunities based on past investments. Moreover, as all market players have the same expectations of future costs (fuel and technology) and electricity demand, the success of new investments is the same in scenarios with homogeneous market players. Therefore, all market players would have the same learning opportunities, and introducing path-dependency in these scenarios would just cause, for example, all gas plants to shut down at a certain point in time, leading to supply gaps.

The regulatory framework refers to the scale of the government intervention in the electricity market and is treated as an exogenous variable in the four core scenarios. Examining the impact of heterogeneity under different policy conditions allows understanding of the scale of intervention needed to achieve a successful transition with heterogeneous market players. Scenario 1 and Scenario 2 are characterised by a strong regulatory framework, with a CO_2 price, subsidies to renewables, which take the form of Contracts for Difference (CfD) in the UK and of feed-in-tariffs in Germany and Italy (FITs), and a capacity market. The capacity market is applicable in the UK model as it is one of the four pillars of the Electricity Market Reform (Grubb and Newbery, 2016), introduced in the UK in 2013, and in the Italian model starting from 2020 (as the capacity market in Italy at present is not functioning yet, but has been approved by law). In contrast, German law doesn't foresee a capacity market, hence there is no such mechanism in the German model. Section 3.3 provided detail about the functioning of CfDs, FITs, capacity market, the strength of the decarbonisation goals and the CO_2 price in the three countries with further detail given in the online model documentation and in the Appendix. In Scenario 3 and Scenario 4 the regulatory framework is much weaker, and only characterised by the presence of a CO_2 price. The regulatory framework is an exogenous variable in this paper in order to focus only on the impacts caused by the actions of homogeneous or heterogeneous market players.

	Scenario 1			Scenario 2			Scenario 3			Scenario 4		
	UK1	**GER1**	**IT1**	**UK2**	**GER2**	**IT2**	**UK3**	**GER3**	**IT3**	**UK4**	**GER4**	**IT4**
Exogenous variables	Table 2			Table 2			Table 2			Table 2		
Regulatory framework												
• Subsidies	CfDs	FITs	FITs	CfDs	FITs	FITs	N/a			N/a		
• Capacity market	Yes	No	Yes	Yes	No	Yes	N/a			N/a		
Market players behaviours												
• Path-dependency	N/a			Yes			N/a			Yes		
• Imitation	N/a			Yes			N/a			Yes		
• Capital costs	3.5% (social discount rate (H.M. Treasury, 2011)			Table 4			3.5% (social discount rate (H.M. Treasury, 2011)			Table 4		
• Foresight	10 years			Table 4			10 years			Table 4		
• Expectations												
• Fuel costs	Table 2			+/-20% compared to level in Table 2			Table 2			+/-20% compared to level in Table 2		
• Electricity demand	Table 2			+/-15% compared to level in Table 2			Table 2			+/-15% compared to level in Table 2		
• Technology costs	Table 2			+/-25% compared to level in Table 2			Table 2			+/-25% compared to level in Table 2		

Table 5 - Characterisation of scenarios by agent heterogeneity and strength of the policy framework

5. Results and discussion

Five outcome parameters have been chosen to highlight how market players with heterogeneous characteristics shape the decarbonisation of the electricity sector and the achievement of the energy policy trilemma. These are discussed in section 5.1:

- To monitor affordability: (1) total capital investments, and (2) electricity price
- To monitor progress towards decarbonisation goals: (3) share of electricity produced through renewables, and (4) evolution of the installed capacity mix
- To monitor security of supply: (5) supply gaps (both peak and average)

Section 5.2 further discusses how the market shares of the market players evolve through the years from 2012 to 2050, highlighting which market players improve their market shares and which in contrast lose importance through the years.

5.1 *Impacts of heterogeneous characteristics of the market players on the electricity sector transition*

5.1.1 Impacts on affordability

In Scenarios 2 and 4 market players, with heterogeneous characteristics, impact aggregated investment levels in high carbon and renewable technologies. Aggregated capital investments between 2012 and 2050 are on average 15% higher in UK2 and UK4 scenarios compared to UK1 and UK3 scenarios (Figure 5). As capital investments in renewable technologies remain substantially unchanged in the UK model, the difference in aggregated investment levels is given by higher gas investment. These are on average 54% higher in scenarios UK1 and UK2, because of the capacity market, compared to UK3 and UK4, and reach GBP 70 bn in UK2 scenario.

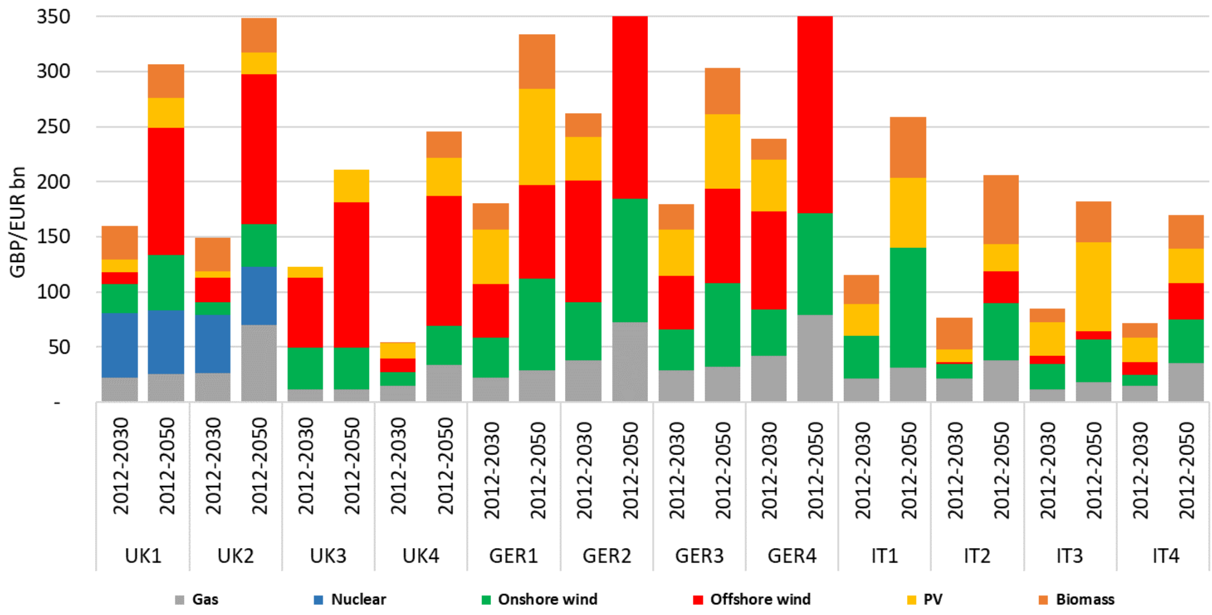

Figure 5 – Cumulative capital investments in UK, Germany and Italy

Heterogeneity also leads to on average 55% higher aggregated investments between 2012 and 2050 in German GER2 and GER4 compared to GER1 and GER3 scenarios (Figure 5), highlighting the strong impact that heterogeneity of behaviours has on the electricity sector transition of a decentralised market as Germany. Such higher investment amounts in GER2 and GER4 scenarios where market players have heterogeneous behaviours are mainly driven by the fact that municipal utilities are not only motivated by risk-return considerations in their investment decisions.

In contrast to the UK and German models, total investments decline by in average 13% in IT2 and IT4 scenarios compared to IT1 and IT3 scenarios (Figure 5), with cumulative investments in renewables being in average 22% lower. Aggregated investments decline with heterogeneous market players in the Italian model, because this version of BRAIN-Energy is characterised by a riskier investment environment where market players have higher costs of capital and return expectations compared to the other two countries (Diacore, 2015).

An emergent property of BRAIN-Energy across the three country case studies is how heterogeneity and path-dependency leads to investment cycles (Figure 6), which mainly happen around gas technologies. Such investment cycles are a key element of market players' heterogeneity, and mainly result from their short and myopic foresight, which can lead market players to make uneconomic investments, or to over- or under-invest. Investment cycles are intensified by market players' path-dependency in investment choices, and can lead to unnecessary investments being committed, hence to higher capital costs of the low-carbon transition, and to supply-gaps, as uneconomic investments are successively closed down by market players. Investment cycles, therefore, affect both the cost dimension and the security of supply dimension of the transition.

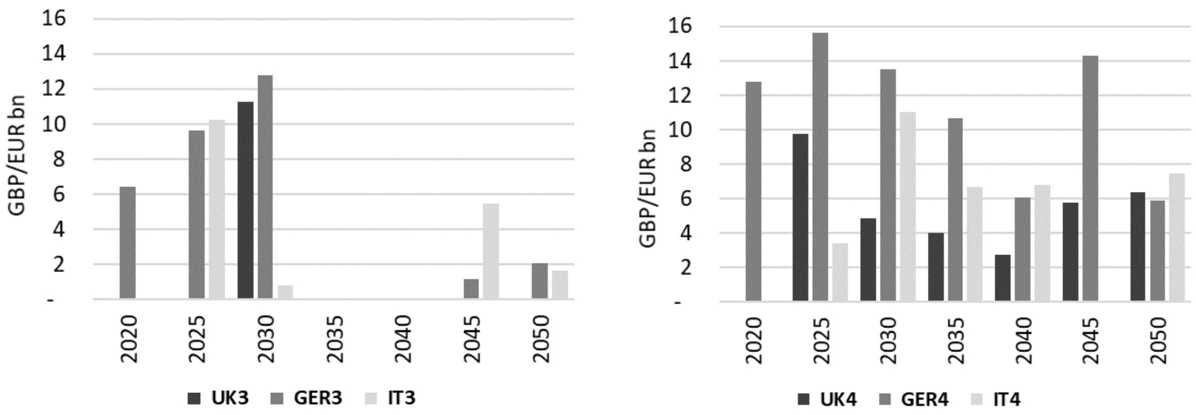

Figure 6 - Investment cycles in gas technologies in scenarios with heterogeneous market players

5.1.2 Impacts on progress towards decarbonisation goals

Heterogeneity impacts the timing of the investments (Figure 5 and 7). The impact is stronger with lower government intervention in UK4 scenario versus UK3, where the absence of the capacity market leads to no nuclear investments to 2030, and the absence of CfDs to significantly lower investments in renewables to 2030. In UK3 58% of total investments are delivered by 2030, while only 22% in UK4 (Figure 7). At 2030, this leads to 28% of electricity being produced through renewable sources in UK3, while only 22% is produced though renewables in UK4 (Figure 8).

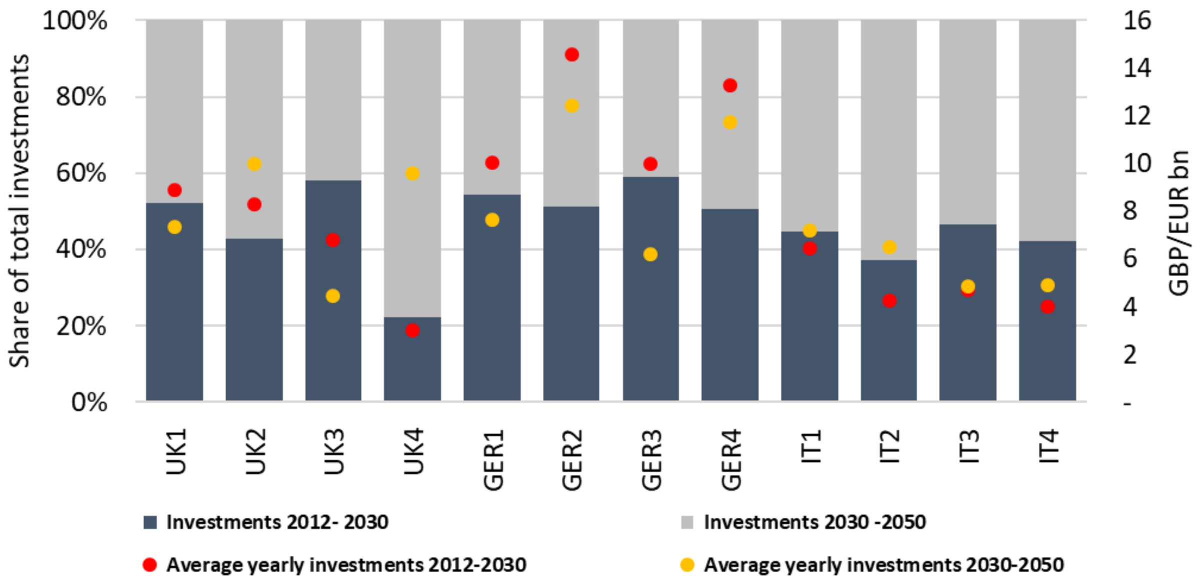

Figure 7 - Timing of investments and average yearly investments in GBP/EUR

In GER3 59% of total investments are delivered by 2030, leading to a share of renewables in electricity production of 52%, while only 50% of total investment are committed by 2030 in GER4 scenario (Figure 7). In the Italian model IT2 and IT4 scenarios also lag behind IT1 and IT3 scenarios in terms of investments committed by 2030 (Figure 7), and subsequently the share of electricity generated through renewables at 2030 (Figure 8) is significantly lower in IT3 and IT4 scenarios. Therefore, heterogeneous characteristics impact the speed of the electricity sector's low-carbon transition to 2030.

Riskier investment environments also impact the successful achievement of the decarbonisation targets at 2050 as highlighted by the Italian case study. At 2050, neither IT2 nor IT4 reach at least an 80% share of electricity generated through renewables (Figure 8). In the UK scenarios with heterogeneous market players feature a surge in investments after 2030 (Figure 7). In UK4 scenario aggregated renewable investments made after 2030 increase by up to 252% compared to investments made by 2030 to meet the 2050 decarbonisation targets, and reach an 80% share of electricity produced through renewables (Figure 8). GER2 and GER4 scenarios with heterogeneous market players receive substantially higher offshore wind investments after 2030 (Figure 9) compared to before 2030, which leads these two scenarios to decarbonise faster after 2030 compared to GER1 and GER3 scenarios. Therefore, both in the UK and German models heterogeneity leads to a back-loading as opposed to front-loading of investments.

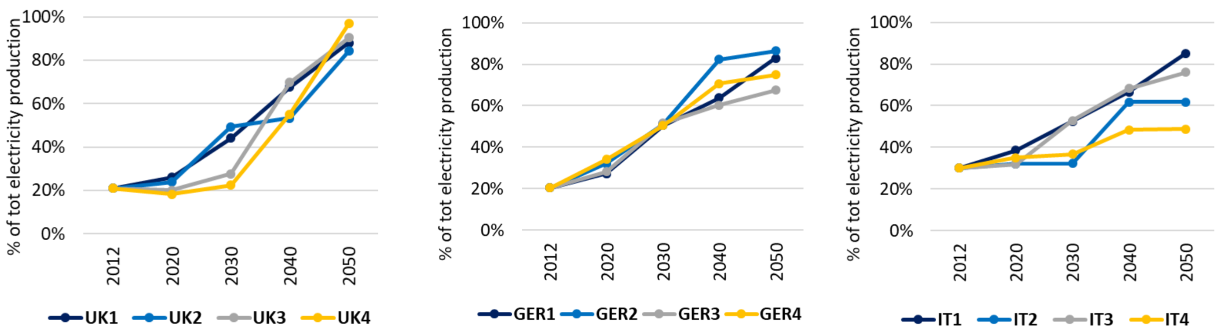

Figure 8 - Share of electricity produced through renewables

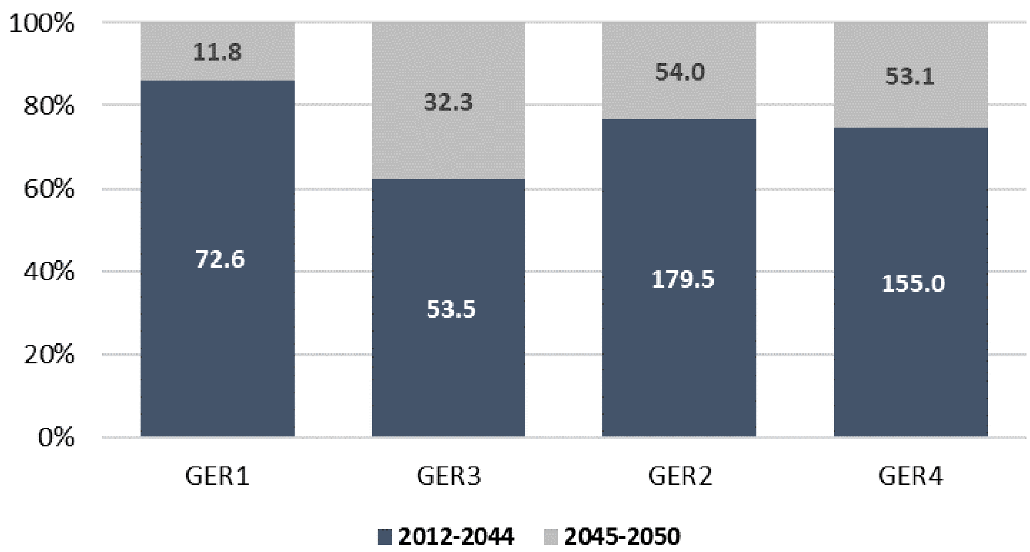

Figure 9 - Timing and level (EUR) of offshore wind investments in Germany

The scenarios' technology mix also varies according to market players having homogeneous or heterogeneous characteristics (Figure 10), and affects the evolution of the share of electricity produced through renewables. While PV benefits from market players being homogeneous in the German and Italian models, the more expensive offshore wind reaches a higher installed capacity at 2050 in Germany and Italy when market players have heterogeneous characteristics. This is linked to the market players' heterogeneous expectations about the evolution of technology costs in the future, which lead some market players to expect offshore wind prices to be lower in the future and hence to a higher expected profitability for offshore wind plants. In scenario with heterogeneous expectations, imitation then helps the offshore wind diffusion process. Heterogeneity also leads to a successful reduction of the installed capacity of conventional technologies in Germany, while it leads to a growing installed capacity of gas in Italy. This is linked to the market players' heterogeneous capital costs, and especially to the fact that capital costs are higher in Italy to reflect the riskier investment environment. These higher capital costs in scenarios IT2 and IT4, compared to the other two countries, incentivise gas investments and deter low-carbon investments.

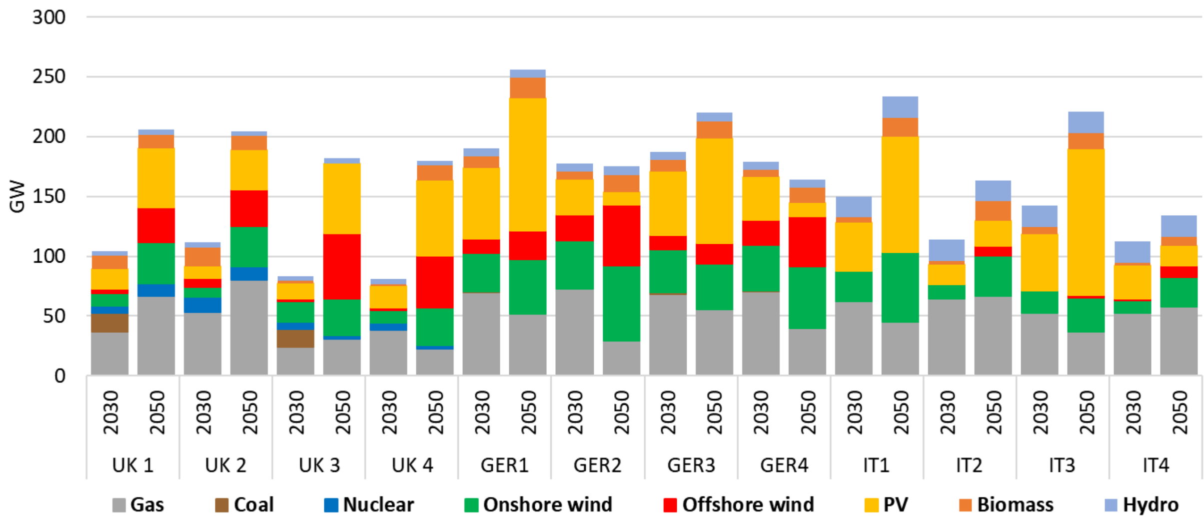

Figure 10 - Installed capacity at 2030 and 2050 in UK, Germany and Italy

5.1.3 Impacts on security of supply

The security of supply dimension of the transition is measured by supply gaps which arise whenever the amount of electricity produced by the existing assets at any time-step is not sufficient to either cover yearly average or yearly peak demand (Figure 11). Results from the UK, German and Italian case studies showed how scenarios with heterogeneous market players are less secure in terms of electricity supply. Heterogeneity can lead to up to 26% more time during which yearly peak electricity demand is not met, and to up to 8% more time during which average yearly electricity demand is not met (Figure 11). The impact is particularly strong in Germany and Italy where no capacity mechanism is in place. The more frequent supply gaps lead to higher electricity prices in scenarios with heterogeneous market players (Figure 11). This is an emergent property of BRAIN-Energy across the three country case studies, and an instrument to attract more investments to close the supply-gaps.

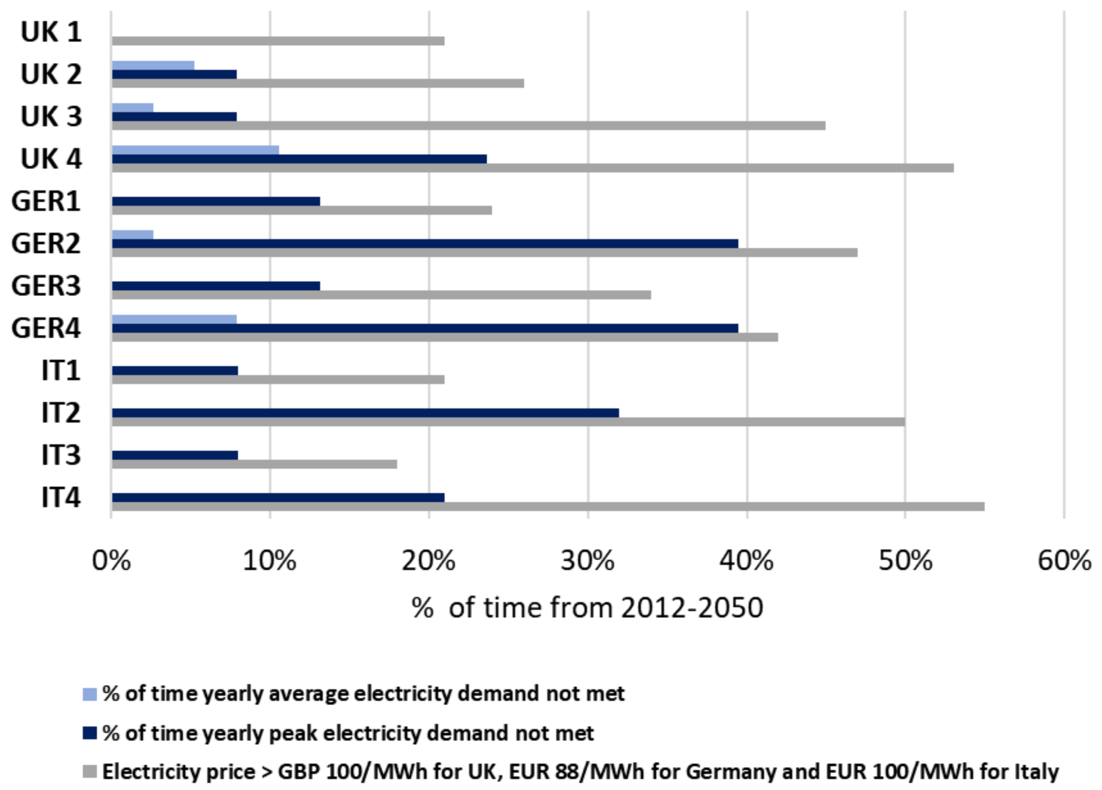

Figure 11 - Supply gaps and electricity price

5.2 Evolution of market players' market shares

The evolution of incumbent utilities' market shares and the diversification of the electricity sector in terms of market players is an important metric from a political point of view. Results showed that the evolution of the aggregated market share of the different types of market players and what type of market players are strongest at 2050 depends on the interplay of the heterogeneous characteristics of the market players (including their heterogeneous technology preferences) with the prevailing country structure in the electricity market in terms of type of market players and regulatory framework.

Figure 12 shows how the aggregated market share of incumbent utilities is affected by the heterogeneity of the market players' characteristics. In the UK and German models incumbent utilities lose 60% of their aggregated market share in a weaker regulatory framework (scenarios

UK4 and GER4). This is explained by the fact that newer market players can pursue more successful strategies, unless a capacity market helps incumbents maintain a high market share as in UK2 scenarios.

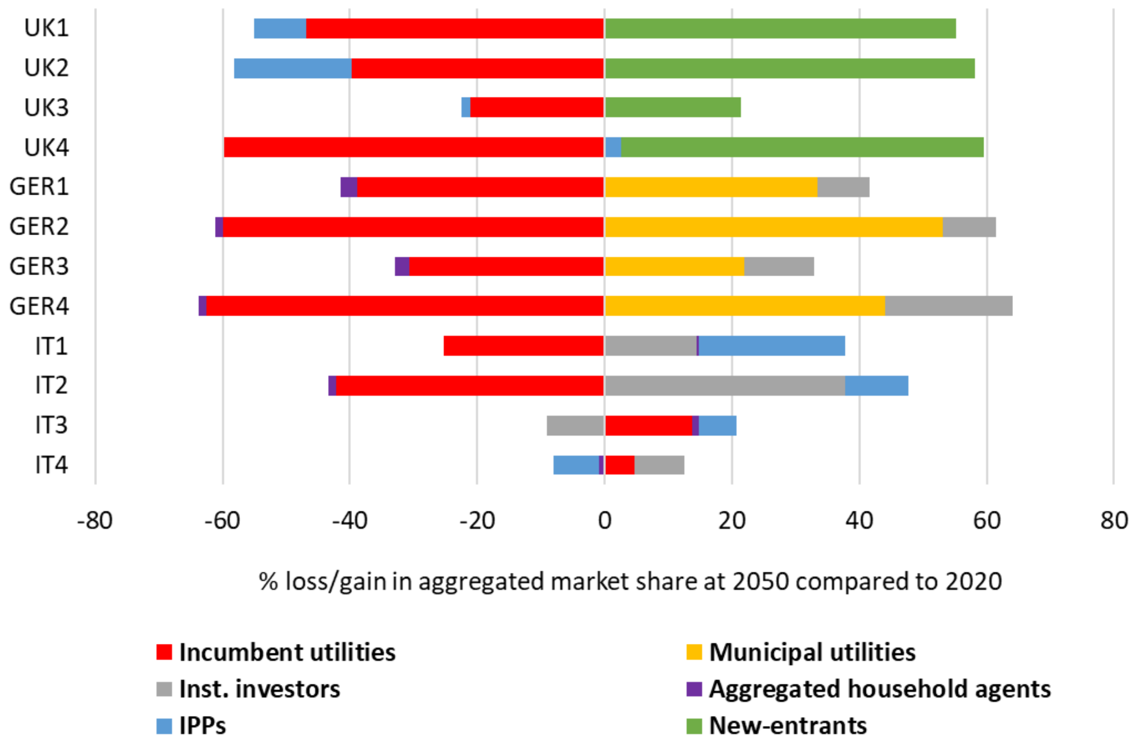

Figure 12 – Evolution of market players' aggregated market shares

The German model shows how municipal utilities are the main market players at 2050 when market players have heterogeneous characteristics (Figure 12), and how given their "relaxed" risk-return considerations in investment decisions they contribute to successfully meeting the 2050 decarbonisation targets especially when FITs are in place as in GER2 scenario. The growth of institutional investors' market shares is also greater in scenarios where market players have heterogeneous characteristics both in the German and Italian case studies.

Figure 12 also shows how in a more risky country environment (where capital costs and return expectations are higher), such as Italy, incumbent utilities survive better and even grow their aggregated market share under a weak regulatory framework. In such cases a stronger government intervention is needed to help diversify the electricity market by allowing and incentivising entry of third-parties, which could help in delivering the necessary low-carbon investments, and could help breaking the lock-in of conventional generation technologies by incumbent utilities which otherwise could prevent the achievement of the 2050 decarbonisation goals as in IT3 and IT4 scenarios.

6. Conclusions and policy implications

This paper introduced an new agent-based electricity model (BRAIN-Energy) whose key innovations are the introduction of a greater diversity of types of market players and of their characteristics even within the same type of organisation, the introduction of financial sector actors, and a strong focus on the market players' path-dependent investment strategies and imitation of other players' successful strategies.

Results from the three case studies in BRAIN-Energy showed that introducing market players with heterogeneous characteristics allows to better represent the risks that such real-world agents put on decarbonisation progress, no matter if government policy is strong or weak. In the Italian model, scenarios with heterogeneous market players don't achieve the 2050 decarbonisation objectives, neither under strong nor weak government policy. Moreover, heterogeneity slows the transition down to 2030, requiring a surge in investments between 2030 and 2050. Heterogeneity not only affects the decarbonisation dimension of the energy policy trilemma, but also the cost dimension. In fact, scenarios with heterogeneous market players have different cost requirements, which are higher in the case of UK and Germany. Higher capital requirements are often brought about by investment cycles caused by myopic foresight and strengthened by path-dependency. While path-dependency in investment choices intensifies investment cycles, results showed how imitation can help the diffusion of offshore wind projects. Heterogeneity also impacts the transition's security of supply. Inertia in market players' responses, due to path-dependent investment choices or different future expectations about costs and prices, throw up (severe) supply gaps.

The German case study also showed how in a country where there is a greater variety in the number of market players and their heterogeneous characteristics, heterogeneity has an even stronger influence on overall investment levels and supply-gaps.

The analysis of the evolution of the market players' market shares illustrated how heterogeneity of market players' strategies can lead to more radical changes in which types of organisations supply electricity and especially to a growth of non-incumbent players, such as municipalities and institutional investors. Incumbents remain harder to shift in riskier and more expensive investment environments, and when a capacity market is in place. However, the lower diversification in terms of market players could compromise the achievement of the 2050 decarbonisation goals, showing the importance of reaching a diversified investors base and of encouraging financing niches (Bolton and Foxon, 2014; Blyth et al., 2015) for a successful energy transition.

BRAIN-Energy also tried to address weaknesses of ABMs as regards to modelling power system operations by introducing a declining "contribution to peak" for each new renewable power plant to account for the intermittency of renewable source as explained in section 3.3. To further strengthen the operational side of BRAIN-Energy, future developments will include a demand response module (via an aggregator agent) to improve the ability of electricity systems to meet peak and average demands. Future developments will also include the addition of local agents (such as local energy companies) in the UK version of BRAIN-Energy to acknowledge the growth of these actors and the growing diversification of the UK market.

This paper showed how critical it is to depict diverse market players with heterogeneous characteristics in energy models because of the impacts on key aspects of future decarbonisation pathways, such as achievement of the 2050 decarbonisation targets, robustness of supply and cost effectiveness. Assuming perfectly rational and utility-maximising market players in energy system models, and neglecting attention to their adaptive behaviours, characterised by aspects such as path-dependency and imitation, could lead to poor and ineffective policy design for energy transitions. Hence, findings presented in this paper strengthen the importance of improving realistic decision making processes in energy system models, by using tools such as ABMs. These models are able to deal with the complexities which diverse market players with heterogeneous characteristics and their interactions introduce in the energy transition. This would help to inform effective policies, able to successfully stimulate low-carbon investments towards the level required to ensure a climate-effective capital allocation, helping governments to address crucial international policy issues and priorities such as reducing GHG emissions and mitigating climate change, while making the energy system robust and affordable.

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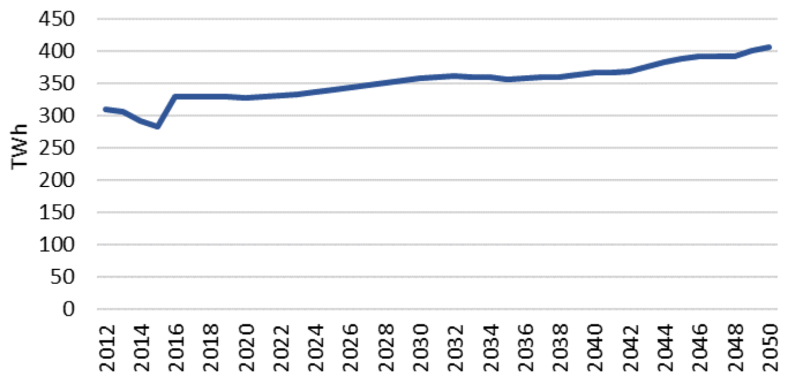
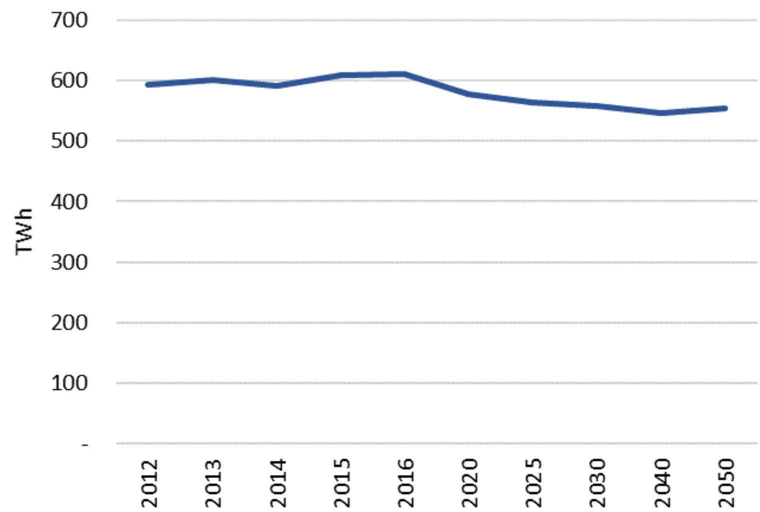
Appendix

Electricity demand:

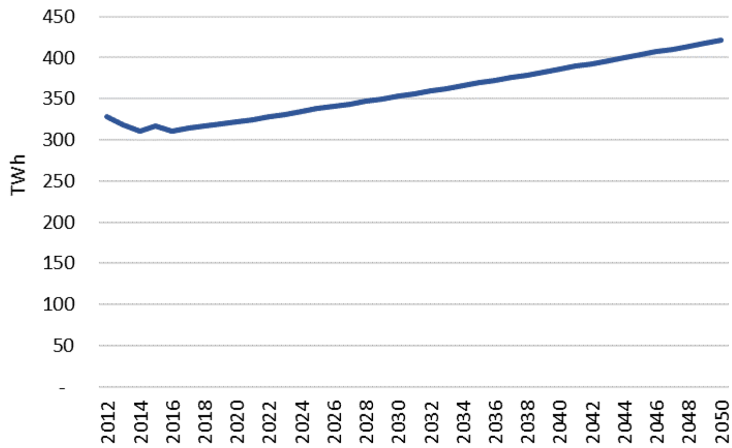
UK



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: BEIS (2016b)

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[9]

[9] 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: Terna (2012)

Capital costs of technologies in 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

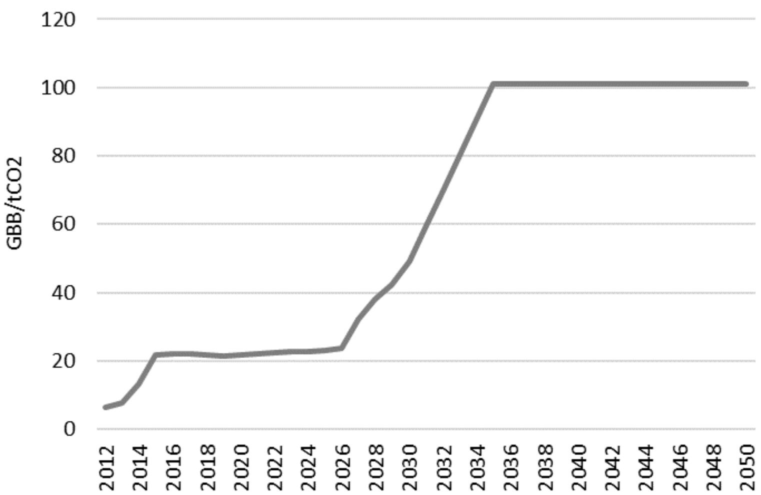
Source: DIW (2013)

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	

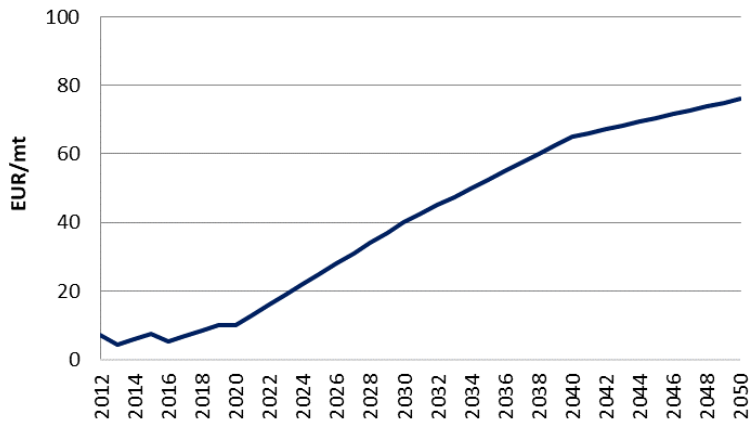
Source: DIW (2013), BEIS (2016a), RSE Colloquia (2017)

CO_2 price in the UK model



Source: BEIS (2016)

CO_2 price in the German and Italian model



Source: EEX Exchange and Prognos (214)

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)