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The key role of historic path-dependency and competitor imitation on the electricity sector low-carbon transition

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ABSTRACT

Market players in the energy sector transition are heterogeneous, have bounded rationality and are influenced by their own past failures, as well as imitating the successes of their competitors. However this agent heterogeneity and complex behaviour in investment choices is not taken into account in traditional energy-economy models used to inform energy sector policies. By using BRAIN-Energy, an agent-based model of investment in electricity generation, which enables to study the impact of actors' heterogeneous characteristics on the transition pathways of the UK, German and Italian electricity sectors, this paper shows how historic path-dependency in investment choices displaces low-carbon in favour of high-carbon investments under a weak regulatory framework. By contrast, imitation can help the diffusion of renewable technologies, through a self-reinforcing positive feedback when government subsidies to low-carbon investments are in place.

1. Introduction

Mitigating climate change requires rapid and strong efforts to reduce global greenhouse gas (GHG) emissions. The 2015 Paris Agreement aims to stabilise global average temperature increase to well below 2 °C above pre-industrial levels, and national governments are required to report on their GHG reduction strategies and progress. As the production of electricity is among the main sources of CO_2 emissions around the world [84], a gateway to decarbonising transport and buildings [97] is key to decarbonise the energy sector to successfully achieve climate change mitigation targets. Especially electricity production will have to be carbon-free by 2050, and low carbon substantially before this [1,86]. Moreover, the transition of the energy sector to be sustainable in the long term will need to address the so called "energy policy trilemma" of reducing CO_2 emissions, while providing a secure and affordable supply of energy [2].

Facilitating the energy transition requires policies which successfully encourage low-carbon investments. Such policies should take into account the heterogeneity of agents involved in the energy transition [3,83], their bounded-rationality, different motivations, risk-propensities and characteristics [4], learning and adaptation, and interactions [5]. Kraan et al. [6] argue that the not perfectly rational behaviours of actors and investors involved in the energy sector transition is a critical element influencing the success of the energy sector low-carbon transition. In particular, policies aimed at mitigating climate change and stimulating low-carbon investments should recognise that the energy system, which can be defined as a complex adaptive system [7], is characterised by inertia and is slow to change from its current state [8,92]. This happens because agents' investment choices and resulting changes in technology are subject to non-linear increasing returns and positive feedbacks, which make change path-dependent and at risk of "lock-in" [7,8,92]. Gazheli et al. [9] argue that insights about bounded-rationality, social interactions, learning and path-dependency can make energy and environmental policies more effective at tackling barriers and at responding to opportunities to realise a sustainable low-carbon transition.

Kuzemko et al. [10] stress that a wider range of actors should be considered in energy governance structures, especially since the growth of renewable and storage technologies which have allowed new actors to emerge which often have different agency structures and objectives as opposed to some incumbent energy companies [11]. However, energy-economy models, which are key tools to aid decision-making on climate and energy problems, aggregate actors and simplify their behaviour [12], and tend to mainly focus on the transition's techno-economic aspects, neglecting attention to its complex dynamics [7] and to its non-linearity [13]. Gazheli et al. [9] find that features such as historic path-dependency, imitation of competitors, and learning have not received enough attention and have been insufficiently

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incorporated in the design of sustainability policies. The risk of not accounting for these complex characteristics in energy-economy models used for policy-making is to not properly incentivise low-carbon investments, potentially leading to the lock-in of existing high-carbon technologies [14,15] and preventing the achievement of the climate change mitigation targets.

By using the agent-based model BRAIN-Energy (Bounded Rationality Agents Investment), whose strength is its sophisticated representation of agent behaviour and agent heterogeneity, this paper aims to understand what the key impacts of agents' historic investment choices and imitation of competitor's successful strategies are on the future transition pathways of the electricity sector. Specifically, this paper aims to answer the following questions:

- To what extent do historic path-dependency and competitor imitation in investment choices affect the electricity sector's low-carbon transition in terms of:
  - o Overall achievement of climate change mitigation targets?
  - o Decarbonisation costs?
  - o Security of supply metrics?
  - o Market shares of different types of actors?

The case studies are the UK, German and Italian electricity sectors. These three countries have been chosen (see section 3.2), because their national electricity sectors are characterised by different types and numbers of market players [16,96]. Examples of market players modelled in BRAIN-Energy include electricity generators such as incumbent and municipal utilities, institutional investors and households.

The structure of this article is as follows: section 2 reviews and explains the concepts of historic path-dependency and imitation, and why these are critical for the energy sector transition. This section also highlights the main limitations of current modelling approaches. Section 3 focuses on the methodology in BRAIN-Energy and on explaining how historic path-dependency and imitation influence the investment choices of the market players. Section 4 details a focused set of comparative scenarios, and section 5 describes and discusses the main findings.

2. Literature review

2.1. Historic path-dependency and competitor imitation

The concept of path-dependency has gained increasing importance in the fields of economics, social sciences and technology diffusion to show that "history matters" as the evolution of a system is the result of self-reinforcing mechanisms which are caused by former events, and that evolutionary processes are bounded by history [17,18]. As emphasised by Schumpeterian and evolutionary economics, in the real world technological change and economic growth are path-dependent processes [19–23]. Path-dependency is caused by contingent and past events, and is sustained through self-reinforcing mechanisms which lead to positive feedback loops [24]. Self-reinforcing mechanisms are processes which reproduce a given pattern of events [25], and can be caused by economies of scale, expectation effects, investment and learning effects [22,24–26]. Such self-reinforcing mechanisms and positive feedback loops make technological development an S-shaped process [19, 22], in which the adoption of a new technology or innovation is likely to be followed by the adoption of a similar technology [19]. In fact, these mechanisms can lead to stability and lock-in [24] in evolutionary processes and changes of a system, making it difficult to change or reverse a certain path of technological development. Dosi [27] called this "technological paradigms" where technological progress advances in an incremental way along "technological trajectories".

Infrastructure investments in the energy sector have a long life-time [3,28], and the risk is to remain locked-in to undesired technologies in the long-term [3]. Therefore, path-dependency is a key aspect to take into account when studying strategic investment decisions in the power sector. Capturing path-dependency in energy models is key for policy-makers to understand how complex societal transitions, such as the low-carbon transition of the electricity sector, can unfold in a sustainable way avoiding the lock-in of conventional generation technologies [14,15]. As explained in section 3.3.2 BRAIN-Energy specifically captures historic path-dependency as re-assessment of past investments, which influences market players' new investments and leads to habits (rather than a broader technology adoption phenomenon). This representation of historic path-dependency links to Gazheli et al. [9]; who talk about habits and routines, which can derive from actors' bounded-rationality and can lead to path-dependency and lock-in, as main behavioural features which can create barriers to sustainability transitions to a low-carbon economy. Moreover, Bale et al. [7] argue that among the main characteristics of complex systems, such as the energy system, we find learning and path-dependency due to non-linear increasing returns, which lock-in many aspects of current energy systems based on past decisions.

Imitation has been found to be a key behavioural feature of agents, and it can either delay or encourage sustainability transitions [9]. As such, it is critical to take it into account in energy models when studying sustainability transitions. Moreover, imitation is an important driver of selection dynamics in evolutionary economics [20–22]. Also, 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 [29–31]. For the above mentioned reasons, imitation has been introduced as one important element of the agents' investment strategies in BRAIN-Energy (section 3.3.3).

2.2. Shortcomings of current modelling approaches and advantages of agent-based models

To date, the treatment of path-dependency is missing in many energy-economic models such as equilibrium models, which fail to account for path-dependency and the multiple equilibria and pathways this phenomena gives rise to Ref. [19]. The risks associated with that are to underestimate opportunities and dangers inherent in the energy transition and related to climate change, as these feature feedback loops, tipping points and exponential and non-linear developments [32]. Moreover, equilibrium and optimisation models which dominate energy policy analysis to date due to their techno-economic completeness and accuracy, assume aggregated, homogeneous and rational profit-maximising decision-makers [7]. However, this doesn't represent the complexity and reality of the energy sector's transition where agents do not necessarily act in a fully rational way, but have bounded-rationality [19,33–35]. Hoekstra et al. [32] argue that new modelling approaches to the energy system transition and climate change should require a detailed representation of actors, which need to be heterogeneous and strategizing, and whose behaviour is characterised by learning and interactions which each other.

Dobusch et al. [36] proposed a framework to analyse path-dependence as a theoretical concept in empirical research, and what aspects of path-dependence should be tested. Evolutionary economics studies, both qualitative [3] and quantitative [23,37–40] have been used to study path-dependency in technological change required for climate change mitigation.

Agent-based models (ABMs) are great tools to capture the complexities arising from path-dependency and the side effects that path-dependency could have on policy making [28,41]. Hoekstra et al. [32] find ABMs to be the best tools to model emergence and learning among heterogeneous actors, making them particularly suited to studying path-dependency. Moreover, ABMs have been recognised as a suitable modelling technique to model complex adaptive systems [42] and the complexity of electricity markets [41,43]. Barazza and Strachan [44] provide a review of ABMs focused on the electricity sector highlighting their key characteristics and limitations, while Barazza and Strachan [45] review existing ABMs with a specific focus on their treatment of policy and co-evolutionary dynamics between market players' investments in the energy sector and the policy dimension. ABMs have also been used to study behavioural choices of households in residential heating technologies [46,47]. ABMs with a macro-economic focus, such as the EURACE model [48], have been used to study other sustainability issues in the energy sector transition, such as how banking and regulatory policies can encourage green investments [49], and to compare the short-term fiscal costs needed to finance the low-carbon transition, with the long-term environmental benefits [78].

The focus of this paper, however, is the treatment of path-dependency and imitation in ABMs, which is one of the main limitations of existing energy sector ABM studies, which BRAIN-Energy aims to address. [82] find that in current ABM studies analysing the electricity sector's low-carbon transition there are few links to path-dependency and technological change as evolutionary economics concepts. Currently only two ABM studies address path-dependency in investment decisions. In the ABM developed by Kraan et al. [6,50] path-dependency takes the form of an investor's future investments being influenced by the performance of his past investments. The second study is the study by De Vries et al. [51] which introduces a risk aversion function linked to historical profits in investment decisions in the EMLab model.

3. Methodology and model

3.1. BRAIN-energy: model overview and novelty

BRAIN-Energy (Bounded Rationality Agents Investment) is an ABM of electricity generation and investment [44,45,52,53]. The main strength and novelty of BRAIN-Energy are its detailed representation of market players' heterogeneous characteristics in investment decisions and the representation of historic path-dependency and imitation in market players' investments. The goal of BRAIN-Energy is to explore how market players' heterogeneous characteristics (section 3.2), historic path-dependency (section 3.3.2), imitation (section 3.3.3) and interaction between market players affect the long-run evolution and transition of the electricity sectors in the three countries under analysis, to help informing policies which can steer the electricity sector transition in a sustainable direction.

BRAIN-Energy was developed in the open-source software environment Netlogo [54]. The model iterates in yearly time steps from 2012, BRAIN-Energy's calibration year, to 2050. The focus of the model is the electricity sector - the UK, Germany and Italy are the case studies - with each country having different heterogeneous market players (section 3.2), different policy/regulatory frameworks (section 4) and different installed technologies. An annual resolution has been chosen, as investments and interactions between players are better analysed on a yearly basis. Given this annual resolution, BRAIN-Energy uses peak constraints and declining capacity contributions to deal with the intermittency of renewables and their ability to meet peak requirements. Details can be found in BRAIN-Energy's online model documentation at: https://www.ucl.ac.uk/energy-models/models/brain-energy. Fig. 1 shows BRAIN-Energy yearly flow, highlighting the feedback between dimensions where historic path-dependency and imitation operate.

At the beginning of each year, market players (section 3.1.2) decide on production and dispatch of electricity from their existing generation assets and bid their production into the market. After electricity has been dispatched (section 3.1.2), the market players' revenues, financial positions and market shares are updated. After these operational steps, market players decide about decommissioning unprofitable generation assets and evaluate future investment options (section 3.3.1). If new investments are committed by the market players, these become operational after a construction lag. The resulting technology mix, and electricity production mix, is hence an emergent property of the market players' investment decisions and interactions in BRAIN-Energy.

3.1.1. Data and calibration

BRAIN-Energy is calibrated to 2012 for all three country case studies. Table 1 details the main exogenous variables in BRAIN-Energy, providing information on the sources used for both historical and projected future data. Further details on calibration data (together with the full values from 2012 to 2050 for all exogenous variables) can be found on the online model documentation[1]

3.1.2. Operations of the power sector

In BRAIN-Energy electricity produced by the assets of the market players is dispatched[2]on a merit order basis, meaning that the market players' bids with the lowest short run marginal cost are accepted first, up to the level when electricity demand is satisfied. The yearly electricity price (p_t) is the short run margin[3]al cost of the most expensive bid accepted into the market, which is required to meet electricity demand in that year. The production mix by technology which results from the merit order determines the amount of CO2 emissions which are produced in that year and the carbon intensity of electricity generation. Yearly electricity demand (Table 1), an exogenous variable in BRAIN-Energy, was divided into a yearly day average demand and yearly night average demand[4] in each of the three countries to account for variations in the load profile.[5]To ensure an adequate treatment of intermittent renewable electricity generation sources given the yearly resolution of BRAIN-Energy, a yearly peak demand was defined to make sure that the model is able to satisfy peak electricity requirements.[6] Yearly peak demand is defined 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.

Moreover, the installed capacity of renewable assets was de-rated by their load-factor to capture the effects of the intermittency of these plants on total generation capacity, running time of thermal plants and electricity price. Also, the marginal contribution of each additional renewable generation asset in meeting peak demand is declining the more renewables are installed in the system, leading new renewable assets to only contribute 5% of their capacity to peak generation, during periods when 80% and over of electricity is produced from renewable sources [51].

3.2. Market players

The core strength of BRAIN-Energy is the representation of heterogeneous market players, which are all active decision-making agents. Market players differ with respect to: 1) their type, and 2) their behavioural characteristics.

The different types of market players in BRAIN-Energy are explained in detail in the online model documentation[7] and in [44]; and are also summarised in Table 2. These have been set-up based on an extensive review of existing literature of private sector actors involved in the energy sector transition. In BRAIN-Energy there are 6 types of market players: incumbent utilities, municipal utilities, independent power producers, new-entrants, institutional investors and households. There are only 3 types of market players in the UK model (Table 2), to reflect the fact that incumbent utilities own the majority of the conventional generation assets in the UK electricity market [16], and that ownership of renewable generation assets by community and non-corporate actors

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

[2] https://data.open-power-system-data.org.

[3] https://ag-energiebilanzen.de/7-0-Bilanzen-1990-2016.htmlx.

[4] http://www.mercatoelettrico.org/it/Download/DatiStorici.aspx.

[5] https://www.bmwi.de/SiteGlobals/BMWI/Forms/Listen/Energiedaten/energiedaten_Formular.html?&addSearchPathId=304670.

[6] Refer to online model documentation for further detail: https://www.ucl.ac.uk/energy-models/models/brain-energy.

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

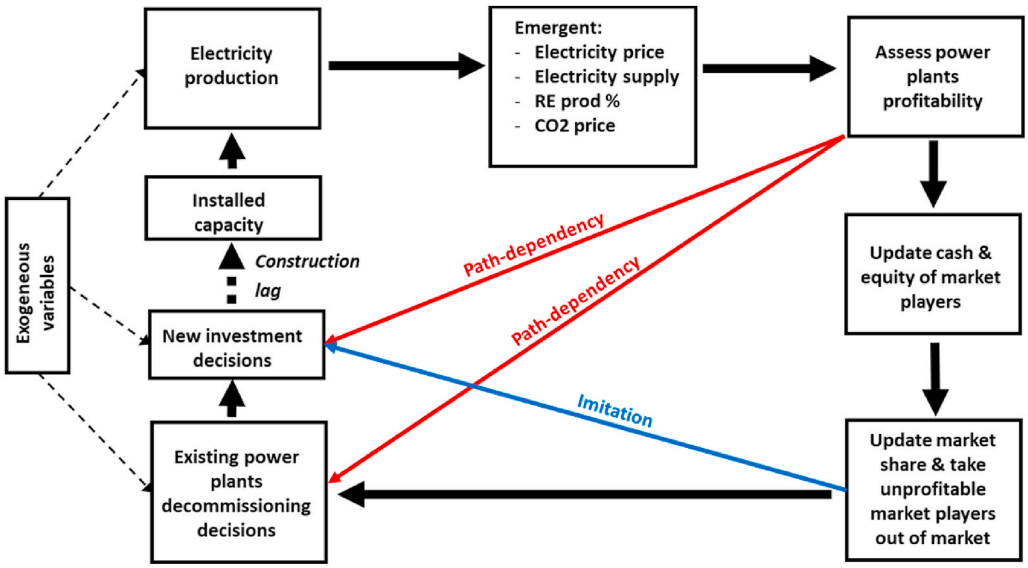

Fig. 1. BRAIN-Energy's yearly model flow.

Table 1
Main calibration variables in BRAIN-Energy.

Exogenous variables	Initialisation	Source
Electricity demand	**UK:** 309 TWh **GER:** 593 TWh **IT:** 328 TWh	**UK:** *Historical*- National Grid half-hourly data *Future*- National Grid FES 2016, "Two Degree" scenario [94] **GER:** *Historical*- Open Power System Data Platform, AG Energiebilanz *Future*- Prognos [55] **IT:** *Historical*- GME *Future*- Terna [56,57]
Fuel costs	Gas: UK: 20.3 GBP/MWh GER and IT: 29 EUR/MWh Coal (GER): 37 EUR/MWh	**UK:** *Historical*- BEIS [58] *Future*- BEIS [58]; "Reference" scenario **GER and IT:** *Historical*- BmWi Energiedaten database *Future*- Prognos [55]
Capital costs of technologies (EUR/kW)	Gas: 400 Coal: 1800 Nuclear: 6000 Onshore wind: 1300 Offshore wind: 3000 PV: 1560 Biomass: 2500	DIW [59]
Operational & Maintenance (O&M) costs		**UK:** BEIS [60] **GER and IT:** DIW [59]
CO_2 price	**UK:** 6.39 GBP/mt **GER and IT:** 7.36 EUR/mt	**UK:** *Historical* – BEIS [58] *Future* – BEIS [58]; "Reference" scenario **GER and IT**: *Historical*- EEX Exchange *Future*- [55]

still remains small in the UK [16]. Energy companies owned by local authorities are beginning to enter the UK electricity sector, but at present those still remain limited in number and market share. For this reason, municipal utilities and household agents have not been introduced in the UK version of BRAIN-Energy [44]. In contrast, the German and Italian model exhibit a greater variety of market players [16,56,62,69,96] (Table 2). It is worth noting that market actors across electricity markets are likely to evolve over time in terms of types and numbers, and hence future work on BRAIN-Energy will entail updating the investors mix to reflect new developments in the market.

In BRAIN-Energy, it is assumed that households are aggregated market players, with one household aggregating 1000 households.[8] Households in BRAIN-Energy can invest in small scale PV to cover self-consumption and eventually sell any surplus (Table 2). Table 2 also details the number of players for each market type simulated in BRAIN-Energy in each country at the calibration year. Within each type of market player in BRAIN-Energy, the modelled players differ by their initial technology portfolio (within the range of technologies mentioned in Table 2), money endowment, cost of capital and foresight (the values for the cost of capital and the foresight for each player are within the boundaries provided in Table 2). Therefore, there are market players in BRAIN-Energy which only invest in renewable technologies (new-entrants in Table 2), and others (incumbent utilities) which can invest in both conventional and renewable generation technologies. As regards to the foresight, this is the number of years in the future over which market players evaluate possible future investment options [44].

Table 2 also summarises the main characteristics and behaviours of each type of market player, which are: 1) aim, 2) technology preference, 3) cost of capital, 4) foresight, and 5) number of years before market players switch off unprofitable assets. A full description of the market players' main characteristics can be found in [44]; which also provides the literature sources on which the players' characteristics are based on.

All market players in BRAIN-Energy have bounded-rationality. Bounded-rationality is caused by the market players' limited foresight of the future, which affects their investment decisions, and by the fact that the players' investment decisions are based on their own heterogeneous expectations of electricity demand, fuel and technology costs.

Market players exhibit bounded-rationality also because they do not take maximising investment decisions, but rather satisficing choices, based on the past [20,71–73], and on learning from own previous successful (or unsuccessful) investments (see historic path-dependency in section 3.3.2). Moreover, emerging knowledge about the other players' strategies also affects the investment decisions of the market players (see imitation in section 3.3.3) contributing to their bounded-rationality.

[8] the average household investment in PV in Germany and Italy is 10 kW [69,70] and the minimum investment size in PV in BRAIN-Energy is 10 MW.

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

Type	Number of players at 2012	Aim	Technology preference	Cost of capital	Foresight	Number of years before switching off unprofitable assets
Incumbent utility		Production of electricity to meet demand and provision of stable dividends to shareholders [61]; Caldecott and McDaniels, 2014; [62]. Vertically integrated.	Can invest in all technologies	5%–7% [62–64]	15–20 years	7
•UK	4					
•Germany	3					
•Italy	2					
Independent power producer		Profit maximisation and increased market share [62,65]. Not vertically integrated.	Gas and nuclear. Renewables: onshore-and offshore wind [62]	8%–10% in Germany and UK, 8–12% in Italy [66]	10–15 years [65]	5
•UK	2					
•Germany	2					
•Italy	2					
New-entrant		Their main expertise is not electricity generation, but they want to maximise profits attracted by subsidies	Only renewable generation technologies	12%	10 years	5
•UK	None					
•Germany	None					
•Italy	None					
Municipal utility		Investment choices are driven by financial return expectations, but also by wider environmental considerations [16,62]	Gas and renewable generation technologies (PV, onshore wind and biomass). Larger municipalities also invest in offshore wind [62]	4% [16], as they can borrow from local banks	25 years, as supply of energy to their region is their main business	7–10
•Germany	2					
Institutional investors		Seek stable, predictable and long-term returns and cash-flows to match their long term liabilities [62,65,67]	Onshore wind and PV. More experienced institutional investors can also invest in offshore wind. Preference for large projects [61, 62,65,87)	5%–10% in Germany and UK 5–12% in Italy [65,66],	20–25 years, as this matches their long-term liabilities [4,61, 62]	5–10
•Germany	2					
•Italy	2					
Households		Invest for self-production and eventually sell surplus [68,69]	Small scale PV [62,68,70,96]	3%–6% [64]	5–15 years (pay-back period)	
•Germany	8					
•Italy	6					

3.3. Investments

3.3.1. Economic criteria

Each year market players in BRAIN-Energy decide about decommissioning unprofitable power plants. These are switched off by their owners after a certain (market player's specific) number of loss-making years (Table 2). Market players also decide about investing in new production assets. Investment decisions are based on an NPV calculation, and each player estimates future cash-flows for each investment option within their range of preferred technologies (Table 2). Cash-flows depend on the players' heterogeneous expectations about electricity demand, fuel and capital costs of technologies. Also each market player calculates cash-flows and NPV up to n years ahead. n differs by type of market player (Table 2) and reflects the market players' limited foresight. Market players use heterogeneous discount rates r in their NPV calculations, which equal their cost of capital (Table 2). Market players need to be able to pay at least 20% of the investment cost from their own pool of cash, and can raise debt for the remaining 80% at a market player's specific cost of capital r.

In BRAIN-Energy, it is assumed that households have a different economic calculation of possible investment options, and this is based on the technologies' expected pay-back period. The pay-back period is defined as the year at which the NPV of a new investment passes from being negative to positive [68]. The length of the pay-back period has to be equal or greater to a household's accepted pay-back period (Table 2) for an agent to decide to invest in it.

A detailed explanation of the investment process with all the formulae can be found in BRAIN-Energy's online model documentation.[9] Fig. 2 depicts the investment process of market players in BRAIN-Energy, highlighting both the economic evaluation, and how historic path-dependency and imitation affect investments, which are explained respectively in section 3.3.2 and section 3.3.3.

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

3.3.2. Historic path-dependency

In BRAIN-Energy investments are adaptive and path-dependent (see section 2.1), in the sense that the performance of past investments influences future investment decisions taken by the market players.

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. And 2) learning from own unsuccessful past investments. The profitability of all new power plants starts being assessed by their owners after five years that these started operations, and after that profitability is assessed every year. If at any given year t plant's (e) cumulative profits ($PF_{e,t}$) over the previous five years, defined as:

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

are lower than the 5-yearly share of the new plant's total capital cost ($\frac{CAPEX_e}{l_e} \times n$) then the new investment is flagged as unprofitable. l_e is the lifetime of plant, $prod_{e,t}$ is the electricity production of plant e at year t, p_t is the electricity price at year t, and $totCost_{e,t}$ comprise variable and fixed production costs and yearly capital costs. When a plant is unprofitable for more years in a row than the numbers of years a market player is willing to absorb losses for (Table 2), then it is shut down by its owners even before the end of its operating life. This market player will then refrain from investing in the same technology, up to the point when this technology becomes profitable again. This means that this technology's NPV will have to be greater than zero, and its ROI will have to be equal or greater than the capital cost r of the market player (Table 2) plus a threshold α which differs by type of market player. α, which can have a value between $1 \leq \alpha \leq 2$, has been calibrated for each type of market player based on the wider behaviours of the market players explained in Table 2 α = 1 for more aggressive market players, such as new-entrants and independent power producers. For institutional investors and incumbent utilities α = 1.5, while for municipal utilities α = 2, because

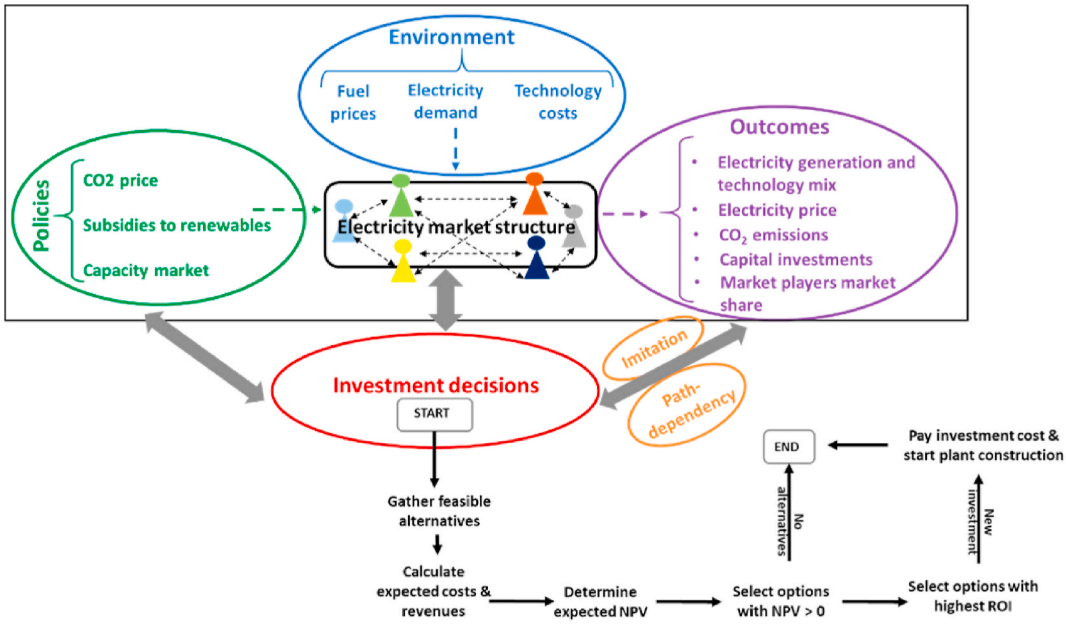

Fig. 2. Investment process in BRAIN-Energy.

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 [62]. However, as they are also driven by political considerations in their investment decisions [62] they are more cautious when learning from unsuccessful past experiences, hence the higher value of α for them. Household agents start to assess the profitability of their investments at the time a new PV plant should have completed its expected pay-back period. If the actual pay-back period is longer than the expected one, then an investor increases its expected pay-back period for future investments to match the actual pay-back time.

3.3.3. *Imitation*

The imitation mechanism in BRAIN-Energy is the one which allows market players to learn from each other's successful investments. Market players in BRAIN-Energy have bounded-rationality, and given their myopic foresight the only information which they have available about other players is emergent evidence about the evolution of their market shares. Therefore, market player a choses to imitate market player x, which is the one whose market share (MS_x) is growing the most compared to the previous year in relation to other market players. However, given the market players' bounded rationality, they don't have perfect information about which exact power plant or new investments led the market share of a player to grow. Therefore 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 household sector actors) and which is an allowed technology given its technology preferences reported in Table 2. All market players types can imitate each other, except for households which can only imitate other household agents.

4. Scenarios

Two core scenarios for each country, with two sensitivity scenarios each for each country, have been created to investigate the key impacts of historic path-dependency and imitation on the UK, German and Italian electricity sector's low-carbon transition until 2050 (Fig. 3). Outputs focus on emergent techno-economic properties, electricity generation mix, CO_2 emissions, security of supply and costs. This analysis aims to understand if historic path-dependency and imitation pose barriers, or help accelerate the electricity system's transition.

Table 3 summarises the main parameters (and their associated values) used in the simulations of the core scenarios: whether historic path-dependency and imitation are active behaviours or not, characteristics of the market players, regulatory framework parameters (subsidies, capacity market and CO2 price) and exogenous variables.

In both core scenarios 1 and 2 market players have heterogeneous characteristics: they have different technology preferences, foresights, capital costs, expectations about future technology and fuel costs and electricity demand, and they close unprofitable plants down after a different number of years (see Table 2). Furthermore, in core scenarios 1 and 2 the investment choices of the market players are path-dependent (section 3.3.2), and are affected by imitation (section 3.3.3). Table 3 details the calibration of the different characteristics of the market players across the core scenarios.

The core scenarios differ by the level of government intervention and policy conditions. Core scenario 1 (UK1, GER1, IT1) is characterised by a strong policy framework, in which there are subsidies to renewable energy investments (which take the form of Contracts for Difference (CfDs) in the UK and of feed-in-tariffs (FITs) in Germany and Italy), and a capacity market. The capacity market was introduced in the UK version of BRAIN-Energy, because this instrument is one of the four pillars of the Electricity Market Reform [88], introduced in the UK in 2013. The capacity market is also active in the Italian model from 2020 (as the capacity market in Italy at present is not functioning yet, but has been approved by law and should start being operative by 2020). As German law doesn't foresee a capacity market there is no such mechanism in the German version of BRAIN-Energy. The CO2 price in scenario 1 reaches GBP 302/mt at 2050 in the UK model, in line with the CO2 marginal abatement cost used in optimisation models in the UK [74,75], simulation models [33], and the UK Government's high CO2 price trajectory [91]. In the German and Italian models, the CO2 price reaches EUR 228/Mt at 2050, in line with the value used by optimisation models focusing on the European energy sector [76,77].

In contrast, core scenario 2 is characterised by a weaker regulatory framework. There are no subsidies to renewables and no capacity market. The CO2 price is weaker in scenario 2, and reaches GBP 100/mt in 2050 in the UK [58], and EUR 76/mt in 2050 in Germany and Italy [55].

The sensitivity scenarios aim to study the key impacts of only historic path-dependency (UK1-PD/GER1-PD/IT1-PD), and only imitation (UK1-Imit/GER1-Imit/IT1-Imit) under a strong regulatory framework,

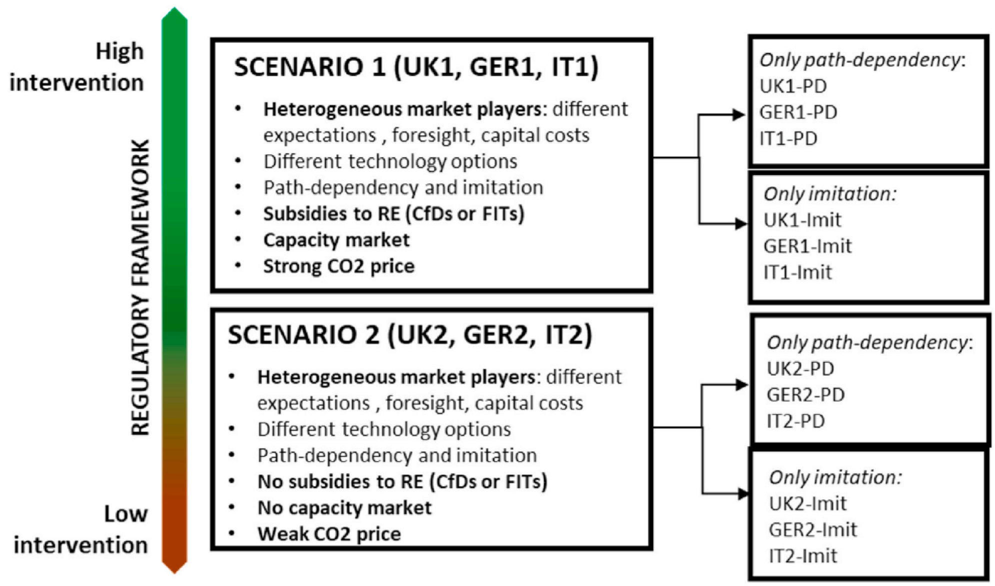

Fig. 3. Overview of core and sensitivity scenarios.

Table 3
Core scenarios: characterisation by market player behaviour and characteristics, strength of the policy framework and exogenous variables.

	Scenario 1			Scenario 2		
	UK1	GER1	IT1	UK2	GER2	IT2
Historic path-dependency	Yes	Yes	Yes	Yes	Yes	Yes
Imitation	Yes	Yes	Yes	Yes	Yes	Yes
Technology	Table 2	Table 2	Table 2	Table 2	Table 2	Table 2
Capital costs	Table 2	Table 2	Table 2	Table 2	Table 2	Table 2
Foresight	Table 2	Table 2	Table 2	Table 2	Table 2	Table 2
Fuel costs expectations	±20% compared to level in Table 1			±20% compared to level in Table 1		
Electricity demand expectations	±15% compared to level in Table 1			±15% compared to level in Table 1		
Technology costs expectations	±25% compared to level in Table 1			±25% compared to level in Table 1		
Renewable energy subsidies	CfDs	FITs	FITs	N/a	N/a	N/a
Capacity market	Yes	No	Yes	N/a	N/a	N/a
CO_2 price	Strong	Strong	Strong	Weak	Weak	Weak
Exogenous variables	Table 1	Table 1	Table 1	Table 1	Table 1	Table 1

Table 4
Characterisation of sensitivity scenarios.

	Sensitivity scenario 1		Sensitivity scenario 2	
	UK1-PD GER1-PD IT1-PD	UK1-Imit GER2-Imit IT2-Imit	UK2-PD GER2-PD IT2-PD	UK2-Imit GER2-Imit IT2-Imit
Historic path-dependency	Yes	N/a	Yes	**N/a**
Imitation	N/a	Yes	N/a	**Yes**

and of only historic path-dependency (UK2-PD/GER2-PD/IT2-PD), and only imitation (UK2-Imit/GER2-Imit/IT2-Imit) alone under a weak regulatory framework (Fig. 3). Table 4 details the set-up of the sensitivity scenarios with respect to historic path-dependency and imitation, while the other simulation parameters for the sensitivity scenarios remain the same as the corresponding core scenarios and can be looked up in Table 3.

5. Results and discussion

To analyse how historic path-dependency and imitation in market players' investment decisions impact the electricity sector in UK, Germany and Italy this paper focuses on five outcome parameters. For each country these are:

- To track progress towards decarbonisation targets: (1) share of electricity produced through renewables at 2030 and 2050, and (2) capital investments in different low-carbon and gas technologies (section 5.1)
- To track costs: (3) electricity price (section 5.2)
- To check security of supply: (4) supply gaps in peak electricity demand (section 5.2)
- The evolution of the market shares (5) of the different types of market players through year 2050 (section 5.3)

5.1. Impacts on decarbonisation targets

Results show how historic path-dependency and imitation in investment decisions have a strong impact on the scenarios' environmental performance, either improving or deteriorating it, especially in scenarios with a weaker regulatory framework (UK2-PD, UK2-Imit, GER2-PD, GER2-Imit, IT2-PD, IT2-Imit) (Fig. 4). This is a key insight produced by BRAIN-Energy, which highlights how critical market players' strategies are in shaping the electricity sector's decarbonisation, and how a strong government intervention (in the form of a high CO_2 price, subsidies to renewable investments and a capacity market) is needed to achieve the desired targets.

In the UK model, historic path-dependency in investment choices leads UK2-PD scenario with a weak regulatory framework to significantly fall short of the 2050 decarbonisation targets: in this scenario only 36% of total electricity is produced through renewable sources at

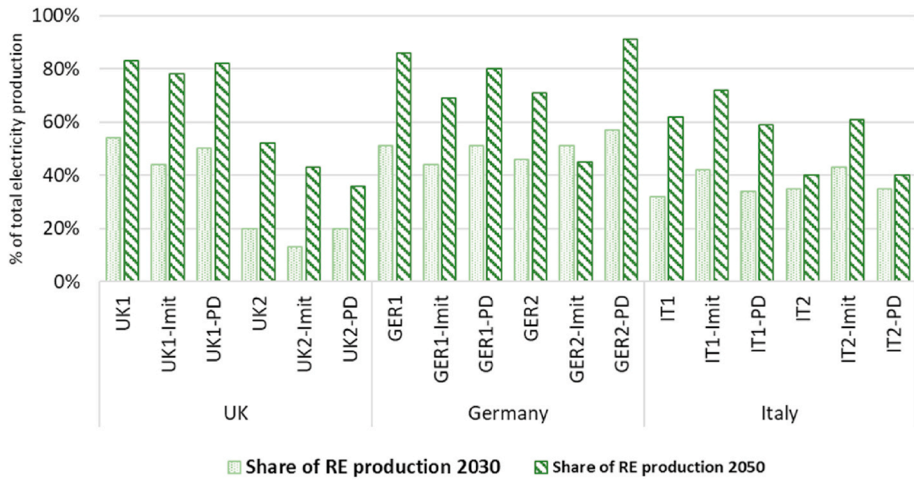

Fig. 4. Share of electricity produced through renewables in core and sensitivity scenarios in 2030 and 2050 in UK, Germany and Italy.

2050 (and only 20% at 2030), compared to 82% in UK1-PD scenario where the regulatory framework is strong, and to 52% in UK2 scenario (where the regulatory framework is weak and where market players' investment are affected by both path-dependency and imitation). This happens because path-dependency in UK2-PD causes renewable investments to decline by 33% compared to UK2 scenario (Fig. 5), decreasing from GBP 94 billion to GBP 63 billion, and by 71% compared to UK1-PD. The low CO2 price and the absence of CfDs in UK2-PD scenario leads market players who have undertaken investments in renewables to find them unprofitable after reassessing them, eventually closing plants down and not repeating investments in such generation technologies because of the path-dependent nature of their investments. Only investments in the most established technologies such as onshore wind and PV are still made in UK2-PD scenario, while the most affected technology is offshore wind, which without CfDs and with a low CO2 price doesn't receive any investments at all (Fig. 5).

Historic path-dependency in investment decisions leads to a similar trend in the Italian version of BRAIN-Energy, where offshore wind investment decline by 100% both under a strong (UK1-PD) and a weak (UK2-PD) regulatory frameworks. However, in the Italian model given that PV investments increase by 67% in IT1-PD compared to IT1, and by 88% in IT2-PD compared to IT2, the share of electricity produced by renewables in IT1-PD and IT2-PD is not affected at 2050 compared to IT1 and IT2 scenarios. In contrast, in the German model path-dependency doesn't reduce investments in renewable technologies neither under a strong nor a weak regulatory framework (Fig. 5), and actually increases total renewable investments by 20% in GER2-PD scenario compared to GER2 scenario. For this reason GER2-PD scenario is quicker to decarbonise at 2030 and reaches an 89% share of electricity produced through renewables at 2050, compared to 71% in GER2 scenario. This is because municipal utilities are active in the German version of BRAIN-Energy, and these market players invest in renewables even if returns are lower than expected, given the importance of wider environmental considerations on their investment choices (Table 2).

Imitation has the strongest impact on aggregated PV investments, especially under a strong regulatory framework with a strong CO2 price and subsidies to renewable investments. As PV is a stronger technology in Germany and Italy, compared to the UK, impact of imitation on PV investments are markedly higher (Fig. 6). In Italy total PV investment increase by 166% between IT1-Imit and IT1 and by 140% between IT2-Imit and IT2, leading to a faster decarbonisation at 2030 and to a higher share of electricity produced through renewables at 2050 in IT1-Imit and IT2-Imit compared to IT1 and IT2. In Germany imitation leads to a massive 258% increase in PV investments from GER1 to GER1-Imit (Fig. 6). However, this leads to a reduction in both onshore wind and

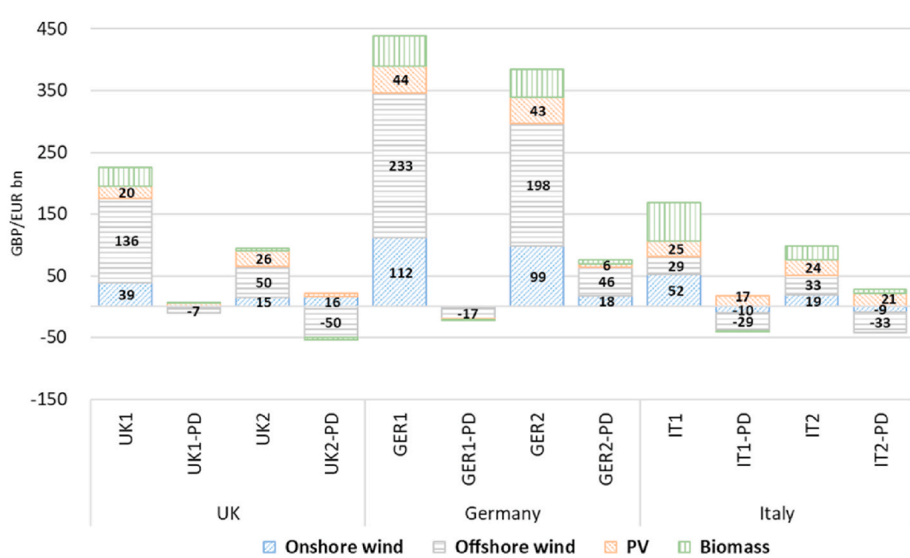

Fig. 5. Difference in capital investments in renewable technologies between core and sensitivity scenarios with path-dependency only in UK, Germany and Italy.

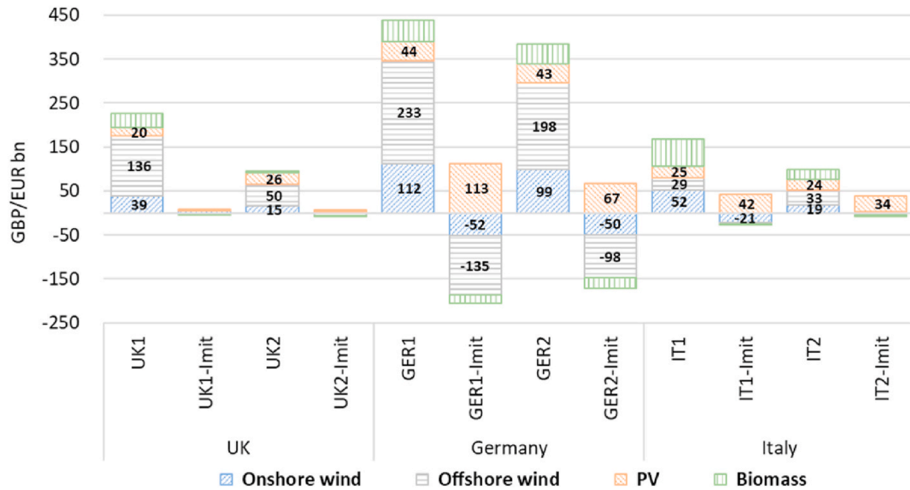

Fig. 6. Difference in capital investments in renewable technologies between core and sensitivity scenarios with imitation only in UK, Germany and Italy.

offshore wind investments creating barriers to a successful achievement of the 2050 decarbonisation objectives. Fig. 4 shows how GER1-Imit and GER2-Imit achieve a lower share of electricity produced through renewables at 2050 compared to GER1 and GER2.

Gas investments in the UK model are affected differently by historic path-dependency and imitation depending on the prevailing regulatory framework (Figs. 7 and 8). Results show how without subsidies to renewables and with a weaker CO2 price as in UK2-PD scenario path-dependency leads total gas investments to increase by 32% reaching GBP 33.5 billion compared to UK2 scenario, and to increase by 70% compared to UK1-PD scenario where CfDs, a strong CO2 price and a capacity market are in place. In UK2-PD gas investments account for 25% of total investments by 2050, compared to 19% in UK2. Therefore, path-dependency under a weak regulatory framework displaces investments in renewable technologies in favour of high-carbon technologies. In contrast, in UK1-PD scenario total gas investment decline by 72% compared to UK1, signalling that when a capacity market is in place the majority of gas investments is driven by imitation. Fig. 8 shows how total gas investments increase by 20% in UK1-Imit compared to UK1 scenario. In Germany path-dependency (Fig. 7) doesn't lead to increasing gas investments in GER2-PD compared to GER2 as in the UK model (but actually to a 28% reduction in total gas investment between GER2-PD and GER2), because of the investment behaviour of the municipal utilities explained earlier, which do not stay locked-in to gas investments under a weaker regulatory framework. In Italy, results show that gas investments are mainly driven by path-dependency, as they don't substantially change in sensitivity scenarios with only path-dependent behaviour (Fig. 7) especially when a capacity market is in place as in IT1-PD. In contrast, total gas investments decline sharper when only imitation in investment decisions is considered (Fig. 8), especially in IT2-Imit as there is no capacity market in this scenario.

Therefore, it emerges from the analysis of the results in UK, Germany and Italy that the impacts of historic path-dependency and imitation on the achievement of the 2050 decarbonisation targets are linked to the strength and type of regulatory framework, the market players' characteristics and technological choices, and the country set-up. In contrasting our findings using an energy focused ABM with those of a macro-economic ABM [78], both analyses show the importance of strong regulation (high CO2 price and subsidies (CfDs or FITs). In the energy ABM this can overcome the history-driven and imitation-driven decision by energy layers, whilst in the macro-economic ABM this can ensure adequate capital flows when comparing investment opportunities across the full economy.

5.2. Impacts on costs and security

Historic path-dependency mainly affects overall investment amounts in different electricity generation technologies, but doesn't have a significant impact on electricity prices, nor on the security of supply of the electricity sector.

In contrast, imitation has an impact on capital investments (section 5.1), and also on electricity prices and on the transition's security of

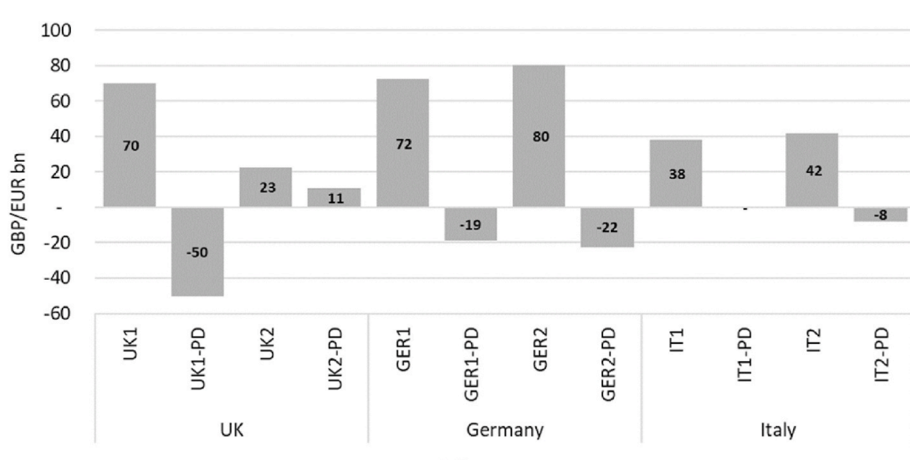

Fig. 7. -Difference in capital investments in gas generation technologies between core and sensitivity scenarios with path-dependency only in UK, Germany and Italy.

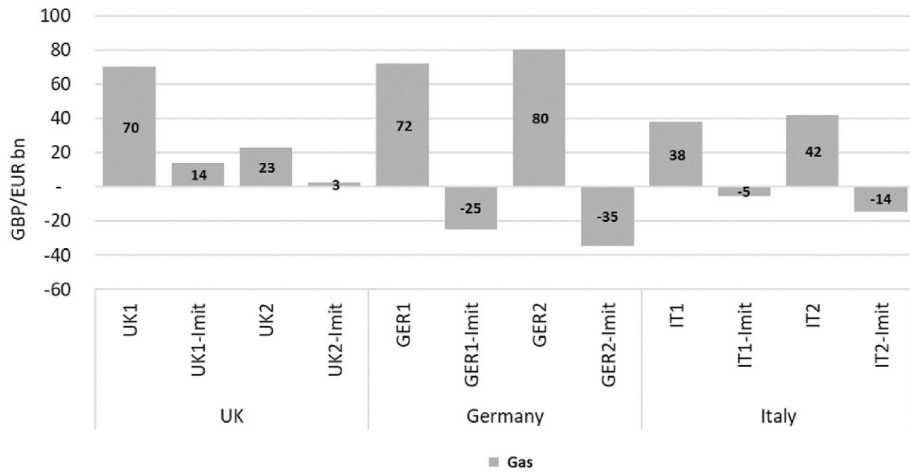

Fig. 8. Difference in capital investments in gas generation technologies between core and sensitivity scenarios with imitation only in UK, Germany and Italy.

	Security of supply	Cost		Security of supply	Cost		Security of supply	Cost
	Numb of years yearly peak demand not met	Electricity price (number of years price > GBP 100/MWh)		Numb of years yearly peak demand not met	Electricity price (number of years price > EUR 88/MWh)		Numb of years yearly peak demand not met	Electricity price (number of years price > EUR 100/MWh)
UK1	3	10	**GER1**	15	18	**IT1**	12	19
UK1-Imit	None	14	**GER1-Imit**	2	10	**IT1-Imit**	8	13
UK2	7	0	**GER2**	15	17	**IT2**	10	14
UK2-Imit	7	0	**GER2-Imit**	7	8	**IT2-Imit**	8	8

Fig. 9. Security of supply and electricity cost in UK, Germany and Italy core and sensitivity scenarios with only imitation.

supply in the three countries (Fig. 9). As regards to security, results from countries where a capacity market exists (UK and Italy) show that imitation works best at reducing peak supply gaps when a capacity market is active (UK1-Imit and IT1-Imit), as opposed to scenarios with a weaker regulatory framework. As regards to costs, imitation is effective at decreasing electricity prices[10]. As there are less frequent peak supply gaps in scenarios where market players only imitate others, as explained above, electricity prices are lower. This happens especially in Germany, where given the absence of a capacity market, raising electricity prices is the regulator agent's only option to incentivise new investments and manage supply gaps.

5.3. *Market shares of the heterogeneous players*

Historic path-dependency in market players' investment decisions and imitation of other players' successful strategies both have a significant impact on the evolution of the aggregated market shares of the different types of market players between 2012 and 2050 (Fig. 10).

It can be observed that incumbent utilities benefit from historic path-dependency in investment choices in all three countries. This is also linked to their technological preferences (Table 2). In fact, in sensitivity scenarios where market players' investments are only path-dependent, incumbent utilities manage to maintain, or even grow, their aggregated market share at 2050 compared to the core scenarios. This happens especially under a weak regulatory framework in UK2-PD, GER2-PD and IT2-PD, and happens because incumbent utilities favour gas investments, which (as explained in section 5.1) increase due to market players' path-dependent choices when CO_2 prices are lower and no subsidies to renewables or capacity market are present. The riskier regulatory framework in Italy, represented in BRAIN-Energy by the fact that market players have higher costs of capital in Italy [66], particularly benefits incumbent utilities which manage to grow their aggregated market share from 2012 to 2050, especially under a weak regulatory framework and when market players investments are path-dependent. In Germany, the path-dependent nature of the market players' investment mainly benefits municipal utilities, because of their investment behaviour (explained in section 5.1), whose aggregated market share at 2050 reaches 78% in both GER1-PD and GER2-PD. Hence, the path-dependent nature of market players' investments discourages the entry of new market players into the electricity market, and benefits incumbents and municipalities especially under a weak regulatory framework and in more risky market.

Competitors' imitation reduces the aggregated market share of incumbent utilities at 2050 especially under a strong regulatory framework in the UK (UK1-Imit compared to UK1), as subsidies to renewable investments attract different players into the market and this mechanism is reinforced by imitation. In Germany imitation greatly benefits the entry of institutional investors into the electricity market. Hence, imitation helps diversifying the type of actors in the electricity market at 2050.

6. Conclusions and policy implications

This paper used BRAIN-Energy, a novel agent-based model, to specifically explore the impacts of historic path-dependency and imitation in market players' investment choices on the electricity sector transition of the UK, Germany and Italy until 2050. It thus helps to address a gap in the current literature, as the treatment of path-dependency and imitation is one of the main limitations of existing energy and electricity sector modelling studies.

Results showed that historic path-dependency tends to limit the

[10] The threshold of GBP 100/MWh for UK, EUR 88/MWh for Germany and EUR 100/MWh for Italy in Fig. 9 is the average yearly electricity price for industrial consumers from 2005 to 2016 in the three countries, based on.

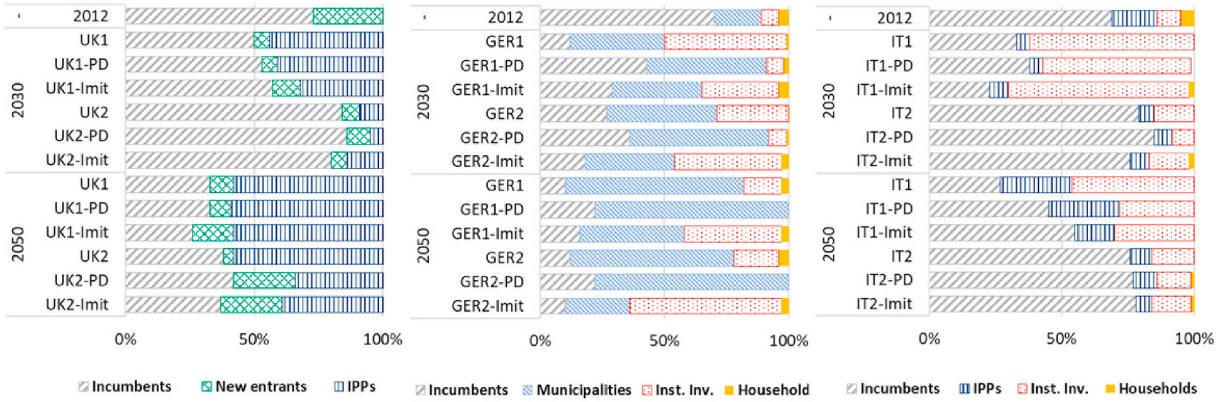

Fig. 10. Aggregated market shares of market players (by type) at calibration year, 2030 and 2050 in UK, Germany and Italy.

success of decarbonisation efforts in the electricity sector, especially when no subsidies for renewable investments are in place and under lower CO_2 prices, by leading to more gas and less renewable investments. Historic path-dependency also tends to reinforce the position of incumbent utilities increasing their aggregated market share through the years, especially in riskier country environments and under weaker regulatory frameworks, limiting the entrance of new type of players and investors into the electricity market. In contrast, imitation works in the opposite direction, by increasing investments in PV technologies through the creation of self-reinforcing feedback loops. This tends to happen particularly when subsidies to renewable investments are in place and under a higher CO_2 price, and in more decentralised markets. Moreover, imitation helps incentivising the entry of new investors, which is key to successfully decarbonise the electricity sector to achieve climate change mitigation targets [3],[61]. Finally, imitation leads to higher gas investment when a capacity market is in place, helping to reduce peak supply-gaps and making the low-carbon transition more politically feasible.

Results, hence, confirmed that the low-carbon transition of the energy sector is constrained by path-dependency of institutions and business choices [16], which in BRAIN-Energy are represented by the regulatory framework and the market players' characteristics, among which are technological choices. Results also confirmed that technological change is path-dependent as emphasised by evolutionary economics approaches [23,79], and that historic path-dependency poses a risk of lock-in to high carbon technologies under weak policy conditions. Policy-makers should, hence, be active in the electricity market through high CO_2 pricing, subsidies to renewable investments and capacity markets to break the barriers posed by historic path-dependency to a successful achievement of the climate change mitigation targets and to encourage the entry of new actors into the electricity market, who benefit from learning from each other and could speed up the diffusion process of renewable technologies. Moreover, the relevance of these results proves that the analysis of path-dependency and competitors' imitation should be integrated into energy system models used for energy and climate change policy-making. ABMs, such as BRAIN-Energy, proved to be suitable modelling approaches to provide insights into complex, non-linear dynamics of the energy transition, and to analyse and capture the barriers and opportunities posed by historic path-dependency and imitation. In fact, ABMs can be key tools to understand which policy designs can be effective at targeting key groups of "low-carbon" actors [80], which could help creating positive feedback between low-carbon technologies and policies needed to limit global temperature increase to below 2°C and on which more research is needed [80].

Credit author statement

Elsa Barazza, Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. Neil Strachan, Writing – review & editing, Supervision

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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