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**Document Version** Final published version

Publication date: 2024

License Unspecified

### Citation for published version (APA):

Gade Christiansen, A., Llorca, M., Jamasb, T., & Zhao, T. (2024). *Energy Network Innovation in the EU: A Tripartite Evolutionary Game Approach*. Department of Economics. Copenhagen Business School. CSEI Working Paper No. 2024-09Working Paper. Department of Marketing. Copenhagen Business School No. 11-2024

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Download date: 04. Jul. 2025









**CSEI Working Paper 2024-09** 



## Energy Network Innovation in the EU: A Tripartite Evolutionary Game Approach





## **Department of Economics**

**Copenhagen Business School** 

### Working paper 11-2024

### **Energy Network Innovation in the EU:** A Tripartite Evolutionary Game Approach

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### Energy Network Innovation in the EU: A Tripartite Evolutionary Game Approach

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24 June 2024

### Abstract

This paper investigates how energy networks in the European Union can be encouraged to increase innovation to reach the decarbonisation goals. We design and analyse a tripartite evolutionary game model with the European Commission, national energy regulators, and energy network companies being the groups of players in the game. We find that the only evolutionary stable state of the game is where the three groups of players choose cooperation strategies. For the Commission and the national regulatory authorities, inducing innovation involves adopting new policy and regulatory mechanisms, respectively. For the energy networks, it involves investing in innovation with decarbonisation goals. We assume that the initial probability of the Commission choosing its cooperation strategy is relatively high and the initial probabilities of the regulators and the energy networks choosing cooperation strategies is relatively low. Numerical simulations suggest that the convergence rate to the evolutionary stable state can be increased if the Commission increases the probability of energy networks receiving external funding and penalty imposed on regulators to adapt their incentive mechanisms to induce innovation. The Commission clearly plays a key role in reaching the stable state.

**Keywords:** Energy networks; innovation; regulation; green transition; tripartite evolutionary game.

JEL classification: C7, L5, L9, O3, Q4, Q5.

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Acknowledgements: Financial support from the Copenhagen School of Energy Infrastructure (CSEI) is acknowledged. The activities of CSEI are funded in cooperation between the Copenhagen Business School and energy sector partners.

### 1. Introduction

In December 2019, the European Green Deal was presented by the European Commission (European Commission, n.d.-a). Through this initiative, the European Union (EU), set the ambitious goal to become the first climate-neutral continent by 2050. This goal was written into law by July 2021 when the European Climate Law entered into force (European Commission, n.d.-d). According to figures from the Commission, more than 75% of greenhouse gas emissions in the EU are from the production and use of energy (European Commission, n.d.-c). To reach the goals of the European Green Deal, decarbonising the energy sector is an essential step. A fundamental part of this, is the promotion of a well-planned and integrated EU energy infrastructure (European Commission, 2021), which is the main objective of the Trans-European Networks for Energy (TEN-E) Regulation (European Commission, n.d.-h).

An integral part of this EU's energy networks development, is the selection of critical cross-border infrastructure projects, known as Projects of Common Interest (PCIs), which are identified from the Ten-Year Network Development Plan (TYNDP). These plans are biennially prepared by the European Network for Transmission System Operators (ENTSOs), who are responsible for managing the energy networks across the Member States, identify investment gaps and coordinate the planning of network investments (European Commission, n.d.-g).

Nevertheless, despite the Commission's efforts to coordinate energy infrastructure development with the objective of pursuing energy market integration and decarbonising the economy, there remains some effort ahead. It is acknowledged in the literature that innovation is key to achieving the green transition (Jamasb et al., 2023; Poudineh et al., 2020; Rong et al., 2022). Innovation can be defined as "*the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations*" (OECD/Eurostat, 2005, para. 146). In order to arrive at the implementation of innovations, innovation activities such as Research and Development (R&D) need to be conducted (OECD/Eurostat, 2005).

The energy sector has been one of the least R&D intensive, and R&D spending in the sector decreased further after the liberalisation of the sector in the 1990s (Jamasb and Pollitt, 2008). Especially the network segments lack innovation incentives due to the natural monopoly characteristics of the energy networks (Poudineh et al., 2020). This paper investigates how energy networks in the EU can be encouraged to increase innovation towards decarbonisation goals. The term *innovation* here refers to innovation activities such as R&D that are conducted with the purpose of implementing innovations as described above. While this question has been discussed in the literature (Jamasb et al., 2023), here we use a novel approach by using a game theory framework. We build a tripartite evolutionary game with the Commission, the National Regulatory Authorities (NRAs) and the energy networks interest organisations being the three groups of players. Using this approach, we can analyse the strategic interactions of the various stakeholders and whether it is possible to reach a stable state where energy networks invest in innovation with decarbonisation goals.

The remainder of the paper is as follows. Section 2 reviews the literature. Section 3 gives an outline of the internal energy market in the EU. Section 4 describes the methodology and how the game is set up. In section 5, the equilibrium points of the game are derived, a stability analysis is conducted, and numerical simulations are performed. In section 6, policy implications of the results are discussed. Section 7 concludes and presents limitations of the methodology, and direction for future research.

### 2. Literature Review

In this paper, the question of how energy networks in the EU can be promoted to increase innovation with decarbonisation goals lies at the interface of three research areas: economic regulation of (natural) monopolies, inducing innovation in regulated monopolies, and employing evolutionary game theory in environmental regulation.

Dupuit (1952) and Hotelling (1938) suggest that optimal regulation of natural monopolies involves setting prices at marginal cost while paying the firm a subsidy corresponding to their fixed costs in order to induce them to produce. However, a major issue when regulating monopolies is to encourage the monopolist to correctly report its costs. Baron and Myerson (1982) derive an optimal regulatory policy which maximises social welfare and incentivises the monopolist to correctly report its costs. Baron and Besanko (1984) extend the model by adding the element of the regulator being able to, at some cost and after production, audit the costs incurred by the firm and impose a penalty if they find that the firm has misreported its costs ex ante.

Laffont and Tirole (1986) assume that the regulator can observe the cost of the firm ex post, but they do not assume auditing to be costly. Furthermore, in their model the ex post cost level is not uncertain. Lim and Yurukoglu (2018) study a problem of moral hazard, as also presented by Baron and Myerson (1982) and Laffont and Tirole (1986), as well as the time inconsistency problem of policymakers not being able to credibly commit to future policies and the interaction of these two forces with the political environment in the context of regulating the US electricity distribution utilities. Lim and Yurukoglu (2018) specify and estimate a dynamic game theoretic model of the interaction between the regulator and the monopolist which captures both of these issues. Fiocco and Guo (2020) study the effect of regulatory risk, which corresponds to what Lim and Yurukoglu (2018) called time inconsistency, on vertical integration and upstream investment by a regulated firm, though their conclusions differ from those of Lim and Yurukoglu (2018).

A corner of the literature on regulating monopolies deals with designing regulatory mechanisms that induce innovation in regulated firms. One of the reasons this is relevant to energy networks is that a significant decline in energy R&D spending followed the liberalisation of the sector. Jamasb and Pollitt (2008) review the industrial organisation literature on R&D and innovation to examine the effect of the liberalisation of the electricity sector on R&D activities. Cantner and Kuhn (1999) analyse how process innovations of a natural monopoly can be regulated in an asymmetric information case. Poudou and Thomas (2010) find that the results found by Cantner and Kuhn (1999) are only applicable where R&D investments and efficiency are complements, meaning R&D is more advantageous to efficient agents. They extend this work to the case where R&D investments and efficiency are substitutes, meaning R&D is more advantageous to inefficient agents. Lewis and Yildirim (2002) extend the model by Baron and Myerson (1982) and study how a monopolist with unknown costs can be induced to develop and adopt cost-saving technologies. Contrary to the other studies presented here, they study innovation through learning-by-doing and not through R&D investments, but they find that some of the ideas could be applied to the case of R&D.

While the abovementioned papers study innovation with cost-efficiency as the purpose, Poudineh et al. (2020) study how to incentivise innovation with decarbonisation as the objective. They study regulatory models of electricity network utilities and find that when there is a difference in the risk profile of cost-efficiency and innovation, different incentive schemes should be used to account for the additional level of risk associated with innovation. Since the regulator cannot observe the firm's effort level, there is an issue of moral hazard, and the remuneration of the firm must be linked to performance instead of effort. Ribeiro and Jamasb (2024) compare the effect of cost pass-through versus weighted

average cost of capital incentive of innovation activities in the form of innovation projects and patents in the UK and Italy. Rong et al. (2022) describe how markets without environmental regulation lack incentives to develop and adopt so-called green or environmental technologies and how this is primarily due to incentive incompatibility and information asymmetry. Taking these two factors into account, they analyse how a social welfare-minded regulator, regulating a profit-maximising firm, should design a policy to motivate the development and adoption of green technologies.

Game theory is a suitable framework to analyse actors' mutual interest conflicts and interactive nexus, and is applied to study interplay between various actors in the process of decision-making (Zhao et al., 2016). However, stakeholders in real life are interlinked in the evolution process of games where they decide strategies dynamically. Therefore, the evolutionary game theory, a dynamic game, can provide a dynamic insight into the evolution of strategy of the actors, which is suitable for exploring the authentic interaction of the game (An et al., 2021). Another feature of the evolutionary game theory is that it relaxes the hypothesis of complete rationality within the traditional game theory and presents the evolution of strategy and investigate which strategy will eventually be chosen by the actor. Evolutionary game theory views the game course as a dynamic process to be consistent with real life, which has been proved to be an effective method to gain dynamic insights into the interplay between stakeholders (Tang et al., 2021).

Evolutionary game theory has been used for environmental policymaking. Faber and Frenken (2009) conduct a review of the literature that employs evolutionary modelling in environmental studies. Encarnação et al. (2018) use evolutionary game theory to investigate the strategic interactions of governments, firms and consumers in relation to the adoption of electric vehicles. Tang et al. (2021) study the interactions of local governments in China and users of distributed photovoltaic systems. Unlike the majority of the research using evolutionary game theory to study environmental regulation, they combine the evolutionary game model with empirical analysis to study the quantitative relationship between the variables of the model, which is an advantage of empirical analysis, and strategy evolution while taking individual rationality into account. Chong and Sun (2020), Jiang et al. (2019) and Sheng et al. (2020) set up a tripartite evolutionary game like Encarnação et al. (2018), but with the central government, local governments and polluting enterprises in China being the stakeholders and environmental regulation in China as the area of interest. They provide a thorough review of applications of evolutionary game theory in environmental regulation. Yang et al. (2021) set up an evolutionary game to study possible conflicts of interests between local governments, university groups and industry groups in a green innovation ecosystem.

The review above shows that some research has been conducted on topics related to regulating monopolies, inducing innovation in regulated monopolies, and applying evolutionary game theory to environmental regulation. However, to the best of our knowledge, no study has used evolutionary game theory to investigate how to encourage innovation in regulated energy networks. We extend this field of research by studying a key issue of the green energy transition in the EU.

### 3. Policy Background

The liberalisation of the European energy sector began in the 1990s. Prior to that, the energy networks were mainly vertically integrated state-owned monopolies that included generation, transmission, distribution, and retail supply segments. Through a set of energy packages containing a number of Directives and Regulations issued by the Commission, the internal energy markets in the EU were liberalised and integrated (Nouicer et al., 2021). The objective of competitive and integrated energy markets was

to ensure an affordable and reliable supply of energy for consumers (European Commission, n.d.-b). As part of the liberalisation, the four formerly vertically integrated segments were unbundled (Jamasb and Pollitt, 2005) to separate the segments that could be opened for competition from the natural monopoly activities. Thus, the generation and retail supply segments were made open for competition, while Member States were required to create an independent NRA to regulate the monopoly transmission and distribution networks (Nouicer et al., 2021; Jamasb and Pollitt, 2005).

With the Third Energy Package in 2009, the European Union Agency for the Cooperation of Energy Regulators (ACER), and the European Network for Transmission System Operators for Gas (ENTSOG), were estab-Ished (European Commission, n.d.-g). One role of ACER is to ensure cooperation between the national regulators. By doing so, ACER supports the integration of the national energy markets in the EU, monitors the smooth functioning and transparency of the internal market, including retail prices and consumer rights, and advises the institutions of the EU on trans-European issues related to energy infrastructure (ACER, n.d.-b). As part of this, ACER decides on cross-border issues if the regulators have a disagreement (European Commission, n.d.-g). ACER also monitors the work of the ENTSOs and ensures that their EU-wide Ten-Year Network Development Plan (TYNDP), described below, are aligned with the priorities set by the Commission. ACER is independent of the Commission, national governments, and energy companies.

The members of ENTSOs are the energy networks through which they work together. This is necessary in to ensure the optimal management of the networks across the borders of the Member States. One of the responsibilities of the ENTSOs is to identify investment gaps and coordinate the planning of network investments. As part of this, they are responsible for publishing the abovementioned TYNPDs for electricity and gas, which are non-binding Union-wide plans that build on national development plans prepared by the energy networks (ACER, n.d.-d, n.d.-c; European Commission, n.d.-g). The TYNDPs also provide the basis for selecting the so-called PCIs, that were introduced with the TEN-E Regulation since the PCIs are chosen from the most recent TYNDP. The idea behind the PCIs will be outlined below together with the TEN-E Regulation.

The focus of the TEN-E Regulation is to link the energy infrastructure of the Member States (European Commission, n.d.-h). Among other things, this involves the identification of eleven priority corridors and three priority thematic areas. Within these, the Commission supports the collaboration in developing better connected energy networks. The aforementioned Projects of Common Interest (PCIs) are energy infrastructure projects linked to the priority corridors or thematic areas (European Commission, n.d.-f). The investment costs of PCIs are split through Cross-Border Cost Allocation (CBCA), which ACER decides on in case the involved regulators are not able to reach an agreement, as mentioned above (ACER, n.d.-a). In addition to that, PCIs are eligible to receive funding from the Connecting Europe Facility (CEF) (European Commission, n.d.-e), which is a financial instrument of the EU to support trans-European networks and infrastructures in transport, energy, and telecommunications.

In July 2021, the European Climate Law entered into force (European Commission, n.d.-d). With this, the target of net zero greenhouse gas emissions by 2050 of the European Green Deal was made legally binding. This involves that EU institutions and Member States are required to take the necessary measures at both EU and national levels to meet this target. Decarbonising the energy system is crucial for reaching the goal of climate neutrality by 2050 (European Commission, n.d.-c). The part of the European Green Deal that concerns a clean energy transition focuses on three key principles. One of these is to develop a fully integrated, interconnected and digitalised energy market (European Commission, n.d.-c). This relates to the TEN-E Regulation as described above. In the wake of the adoption of the European Green Deal, a revision of the TEN-E Regulation with the purpose of making it compatible with

the European Green Deal was made (European Commission, n.d.-h). Amongst other matters, this includes promoting energy system integration and continuously linking the energy infrastructure within the EU. The significance of the TEN-E Regulation for achieving the decarbonisation goals of the European Green Deal will be elaborated later.

### 4. Methodology

### 4.1 Game Players and Their Strategies

### 4.1.1 The European Commission

A key player in the tripartite evolutionary game is the European Commission. The Commission strives to reach decarbonisation goals as specified in the European Green Deal. As stated earlier, developing an integrated energy market is part of the solution to decarbonising the energy system. There is broad consensus in the literature on the importance of increasing innovation in the energy sector, especially in energy networks (Jamasb et al., 2023). The Commission and its co-legislators (the European Council and the European Parliament) have adopted the TEN-E Regulation. This regulation was revised in June 2022 with one of the objectives being to promote the development of innovative technologies to decarbonise the trans-European energy networks (Schittekatte et al., 2021). As part of this, they recommended a revision of the PCI list to update it with the decarbonisation goals of the European Green Deal. Furthermore, they suggested interpreting cross-border relevance in a broader way, since some infrastructure projects that enabled integration of the energy sector could be seen to compete with or complement traditional cross-border infrastructure, although they did not geographically have a cross-border footprint.

Energy infrastructure projects typically involve high private costs early in the innovation process, whereas social and environmental costs and benefits are accrued over a longer time horizon (Schittekatte et al., 2021). Therefore, a social discount rate and a sufficiently long-time horizon should be used when conducting cost-benefit analyses as part of the TYNDP. In this way, future social and environmental costs and benefits will be valued higher. They also proposed integration of the TYNDPs for gas and electricity by the two ENTSOs. Moreover, they posed that the only award criterion linked directly to CEF-E funding to energy projects, should be affordability, i.e. when the net welfare benefits of a project are positive, but the energy consumers cannot afford it.

Haffner et al. (2019) investigate whether a change in the EU regulation would make sense for increasing innovation in energy networks. They find that the EU can require the firms to consider innovative solutions and perform social cost-benefit analyses for large projects that are not part of the TYNDPs. However, at first, they suggest merely working out a recommendation for both points, i.e., there would be no direct consequence for the regulators or networks if the recommendations are not followed. We do not consider this in the game since translating this into payoffs is not straightforward, although subtle persuasion and nudging can have some effect. The Commission can choose a cooperative strategy, which implies it will seek new legislation to induce innovation, or it can choose a non-cooperative strategy which means it will not change the current legislation. Further, we assume that if the Commission chooses its cooperation strategy as described before, it incorporates into the legislation that regulators must change their practice to induce innovation. If the regulators do not do so, the Commission could start some form of legal action against them. In previous cases, the Commission has initiated infringement procedures against member states for failing to ensure the independence of NRAs (Haffner et al., 2019). Therefore, assuming that the Commission can impose this form of penalty (i.e., infringement procedure) on the NRAs through their respective member states is a reasonable assumption.

#### 4.1.2 Regulators

The next players are the national energy regulators of the Member States, organised under ACER with regards to the EU level regulation matters. As mentioned, one of the roles of the regulators is to oversee and regulate the natural monopoly energy networks. The regulators try to reduce the asymmetry of information with the regulated companies, i.e. the energy networks, and to protect consumers by avoiding that the regulated companies set too high prices (Directive (EU) 2019/944, 2019). At present, the majority of financial remuneration methodologies used by regulators fall into one of the categories of cost-based regulation, incentive-based regulation, a combination of these two or state budgetary control over state-owned bodies (Haffner et al., 2019). Cost-based regulation guarantees the firm their cost of production plus a pre-defined rate of return on the asset base under rate of return regulation or their cost of production plus a pre-defined profit margin in the case of cost-plus regulation (Haffner et al., 2019; Jamasb et al., 2023). Thus, cost-based regulation does not provide incentives for innovation and might lead the firm to misreport its costs. On the other hand, incentive-based regulation provides the firm with incentives for improving their performance by allowing it to retain a share of the extra profits from over-fulfilling the regulator's goal to improve the cost-efficiency of the networks.

The literature has addressed different aspects of the regulation of innovation in monopolies. While much of the literature focuses on innovation with cost-efficiency at aim, Poudineh et al. (2020) suggest incentive schemes that address the moral hazard issue of not being able to observe the firm's effort level for inducing innovation with decarbonisation as the goal. They suggest using an input-based mechanism for regulating the earlier and risky innovation stages and an output-based mechanism for the later innovation stages that might have the same risk profile as the normal activities of the firm. By using an output-based mechanism, the networks can be remunerated based on their performance rather than their effort which takes the moral hazard issue into account.

Jamasb et al. (2023) state the need for moving away from regulatory mechanisms focused on shortterm cost-efficiency and instead incorporate mechanisms that focus on long-term goals and consider the higher risk profile of innovations in energy networks. In connection with this, they suggest using an input-based regulatory mechanism for incentivising innovation where costs are incurred today while benefits emerge in the long term and are uncertain. Furthermore, they propose combining the inputbased mechanism with an output-based mechanism that allows the firm to benefit from an improvement of outcomes. This corresponds to suggestions made by Poudineh et al. (2020).

Lewis and Yildirim (2002) suggest that sharing the surplus from innovation might benefit both parties. Haffner et al. (2019) find regulatory uncertainty to be a potential barrier to invest. This is supported by Lim and Yurukoglu (2018) who find a potential solution to be to set the rate-of-return policy so that more weight is placed on the profits of the firm than on consumer surplus. Hence, this also suggests that sharing the surplus from innovation with the networks might mitigate the negative effect of regulatory uncertainty on investments in innovation.

As with the Commission, the regulators can choose either a cooperative or a non-cooperative strategy. The cooperative strategy involves changing to a combination of input-based and output-based regulatory mechanisms to incentivise investment in innovation with decarbonisation as the goal. On the basis of the research findings discussed above, this combination of mechanisms is thought to overcome more of the reasons presented by Jamasb and Pollitt (2008) for the decline in R&D spending in the energy sector following the liberalisation such as increased uncertainty and pressure for short-term profitability. Alternatively, they can choose the non-cooperative strategy of continuing to use a regulatory mechanism which is cost-based or focuses on improving cost-efficiency.

### 4.1.3 Energy Network Firms

The third and last group of players are the energy network firms. There has been a significant decline in R&D spending in the energy sector following the liberalisation of the sector in the 1990s. A legal obligation of the energy networks is to operate, maintain and develop the networks (Haffner et al., 2019). Also, it is the responsibility of the energy networks to work with other firms on cross-border and integrated market issues. Since a key principle of the European Green Deal is to develop a fully integrated, interconnected and digitalised energy sector, the network firms play an important role in the decarbonisation of the sector.

The energy networks work together through the ENTSOs who amongst other matters are tasked with identifying the investment gaps and coordinating the planning of network investments. Although both the Commission and the regulators are important players to promote innovation in energy sector, the networks constitute the most important stakeholders, and the main objective of the evolutionary game analysis is to investigate how they can be encouraged to invest in innovation. Following this, the cooperative strategy of the network firms is to invest in innovation whereas their non-cooperative strategy is to not invest. Figure 1 summarises the strategies of the three groups of players.



Figure 1: Strategies of the game Source: Authors' own work

### 4.2 Evolutionary Game Theory

A strength of evolutionary game theory is in the assumption that the players are not fully rational and that they can learn during the game. Hence, in this sense, the model is more realistic than many other economic models. Evolutionary game theory falls under the category of non-cooperative game theory (Weibull, 1995). But, where traditional game theory builds on the strong assumption of all players being fully rational, evolutionary game theory works with the somewhat less strong assumption of bounded rationality of players (Chong and Sun, 2020). Thus, a strength of evolutionary game theory is that players are assumed to be boundedly rational, which contrasts with the full rationality assumption of traditional game theory approach. Additionally, evolutionary game theory assumes that the game is repeated and that one randomly drawn player from each population, playing some pure strategy h, plays the game each period (Weibull, 1995). Hence, another important assumption of evolutionary game theory is that players are assumed to be able to learn over time and adjust their strategies accordingly (Yang et al., 2021).

Evolutionary game theory develops as a means to predict the expected distribution of individual behaviours in a system (Smith and Price, 1973). The theory's predictions of equilibrium correspond to solutions of the game formed through payoff comparisons of different strategies. The actors would repeat a game by pairing randomly in the group and finally find evolutionary stable states (Shan and Yang, 2019). This analytical process is analogous to the behavioural mode in practical decision-making. The core of the evolutionary game model is to investigate the strategic adjustment mechanism. A fundamental result is that, at a stable state, no actor can increase its payoff by unilaterally changing strategy (Cressman and Apaloo, 2018).

When the rationality of the actors is involved, the replicator dynamics can be used to simulate their dynamic evolution trajectories (Taylor and Jonker, 1978). The replicator dynamics is the foremost game dynamics studied in connection with evolutionary game theory (Ross and Yi, 2014). The replicator dynamics equation is from the biological perspective to predict the evolutionary outcome of behaviour. Following standard replicator dynamics, the growth rate of the strategy h can be expressed as the excess expected payoffs of choosing this strategy over the average payoffs in the population. Hence, the change in the proportion of the population playing this strategy, or the change in the probability that a randomly drawn player from the population plays this strategy, over time can be expressed by the replicator dynamics equation (Weibull, 1995):

$$F(x_h) = \frac{dx_h}{dt} = x_h[u_h(x) - u(x)]$$
(1)

where  $x_h$  is the proportion of the population playing strategy h, or the probability that a randomly drawn player from the population plays strategy h, while  $[u_h(x) - u(x)]$  is the excess expected payoffs of choosing this strategy over the average payoffs in the population. This implies that if the payoffs from a strategy h exceed the average payoffs in the population, then the proportion  $x_h$  of the population playing this strategy will grow over time.

If the replicator dynamics equation,  $F(x_h)$ , reaches a stable state in iteration, then strategy h is an evolutionary stable strategy, and the state is an Evolutionary Stable State (ESS) (Shan and Yang, 2019). A necessary and sufficient condition for determining whether a derived equilibrium point is asymptotically stable is that all eigenvalues of the Jacobian matrix for the equilibrium point must be negative (Shan and Yang, 2019). Asymptotic stability in this sense means that sufficiently small shocks to the equilibrium results in a movement back to the ESS (Weibull, 1995). For instance, the Jacobian matrix for a tripartite game can be set up as follows, following Friedman (1998):

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix}$$
(2)

Then, the eigenvalues of the matrix are the solutions  $\lambda_1$ ,  $\lambda_2$  and  $\lambda_3$  to the equation  $|J - \lambda I| = 0$ , where I is the identity matrix (Friedman, 1998). If one or more of the eigenvalues are not negative, then the examined point is not an ESS but a source or a saddle point, meaning that it is not stable (Chong and Sun, 2020).

### 4.3 Payoffs

As mentioned, the cooperative strategy of the Commission is to initiate legislative proposals, which among other things involves revising the TEN-E regulation to make investment in innovation with decarbonisation objectives more favourable. The alternative strategy that the Commission can choose is

to not propose changes in the current legislation. The regulators will receive a negative payoff p, corresponding to the penalty imposed by the Commission, if they choose their non-cooperative strategy while the Commission chooses its cooperative strategy. Imposing a penalty on the regulators is assumed to involve a cost  $c_2$  for the Commission.

The payoffs of the networks are affected by the strategy chosen by the Commission if they choose their cooperative strategy of investing in innovation. If the Commission proposes new legislation, it will become more favourable to invest in innovative projects. We assume the networks in this case, if they choose to invest in innovation, will receive an expected amount  $\alpha_1 \times F$  in external funding, such as CEF-E funding. If the Commission does not propose new legislation, the networks will only receive an expected amount  $\alpha_2 \times F$  with  $\alpha_1 > \alpha_2$ , corresponding to the amount of funding today. F is the average external funding for a project, while  $\alpha_1$  and  $\alpha_2$  can be thought of as the percentage of the average external funding that the networks receive or the probability of getting the average external funding. We assume that spillovers from other networks, through cross-border cost allocation, average out and is thus not considered here. If the networks choose to invest in innovation, this will result in positive environmental benefits  $E_1$  for the Commission. On the other hand, there will be an environmental cost  $E_2$  for the Commission if the networks do not choose to invest in innovation.

Since the Commission directs the TEN-E regulation and the TYNDPs and hence has a stake in funding, the external funding the networks receive in case they choose to invest in innovation is assumed to be deduced from the Commission's payoffs. Furthermore, the strategy which is chosen by the Commission also has a direct effect on its own payoffs. If it chooses its cooperative strategy, there is a cost  $c_1$  associated with all the work involved in the process of changing regulation. There is also a negative payoff for the Commission associated with choosing its non-cooperative strategy of not changing the regulation.

As a consequence of the European Climate Law, the Commission is bound to take necessary measures to meet the legally binding target of net zero greenhouse gas emissions by 2050 (European Commission, n.d.-d). If it does not change legislation with the aim of inducing innovation with decarbonisation objectives, this is thought to contradict the European Climate Law, and this is assumed to result in a penalty of size q on the Commission. Who is responsible for imposing this penalty, and choosing the size of it and if it is exogenously determined, in this model can be a matter of debate and will be discussed later.

The effect of the strategy chosen by the regulators on the payoffs of the energy networks is clear. As seen earlier, the cooperative strategy that can be chosen by the regulators involves changing to a combination of an input-based and output-based mechanism which is supposed to incentivise investment in innovation. For the sake of calculating payoffs, we assume that the input-based part of the mechanism involves that the expenses associated with the innovation, i.e., the investment costs I, are directly transferred to consumers, represented by the regulators. At the same time, we assume that a given innovation leads to a cost reduction s of which a share  $\beta$  goes to the energy networks as a result of the output-based mechanism. The remaining share,  $1 - \beta$ , goes to the regulators who represent the consumer interest. If the regulators choose the non-cooperative strategy of not changing their regulatory mechanism to one which induces innovation, then it is assumed that the entire cost reduction s in the case that networks invest goes to the regulators. In this case, the networks themselves will bear the cost I associated with investing in innovation. The regulators get a cost  $c_3$  from changing their regulatory practice.

We set up the following assumptions for the game (Zhao et al., 2022):

- 1. The Commission can either choose its cooperation strategy with probability  $x, 0 \le x \le 1$ , or choose its non-cooperation strategy with probability 1 x.
- 2. The regulators can either choose their cooperation strategy with probability y,  $0 \le y \le 1$ , or choose their non-cooperation strategy with probability 1 y.
- 3. The networks can either choose their cooperation strategy with probability  $z, 0 \le z \le 1$ , or choose their non-cooperation strategy with probability 1 z.
- 4. All players are boundedly rational.
- 5. All players can learn over time and adjust their strategies accordingly.

A description of the different parameters is summarised in table 1. Then, we can set up eight payoff functions for each of the three groups of players. In table 2, the payoffs of the three groups of players in each state of the world are summarised. The payoff functions corresponding to the eight possible outcomes of the game are specified in table 3.

Symbol	Description	Value range		
<i>E</i> <sub>1</sub>	Environmental benefits for the Commission when networks invest in in-	$\geq 0$		
	novation with decarbonisation goals			
$E_2$	Environmental costs for the Commission when networks do not invest	$\geq 0$		
	in innovation with decarbonisation goals			
F	Average external funding for innovative projects	$\geq 0$		
α1	Probability of receiving average external funding when the Commission	$1 \ge \alpha_1 > \alpha_2$		
	changes legislation	$\geq 0$		
α2	Probability of receiving average external funding when the Commission			
	does not change regulation			
<i>c</i> <sub>1</sub>	Cost of changing legislation for the Commission	$\geq 0$		
<i>C</i> <sub>2</sub>	Cost of penalising regulators for the Commission	$\geq 0$		
<i>C</i> <sub>3</sub>	Cost of changing regulatory practice for regulators	$\geq 0$		
Ι	Cost of investing in innovation with decarbonisation goals	$\geq 0$		
S	Cost reductions from innovation with decarbonisation goals	$\geq 0$		
β	Percentage of cost reductions given to energy networks if regulators	$1 \ge \beta \ge 0$		
	change their regulatory practice			
p	Penalty on regulators if they do not change their regulatory practice and	$\geq 0$		
	the Commission changes its legislation			
q	Penalty on the Commission if it does not propose change to legislation	$\geq 0$		
Table 1: List of parameters in the game				

Strategies	Payoffs
(Commission, Regulators, Energy Networks)	(Commission, Regulators, Energy Networks)
(C, C, C)	$(\pi_{EC-1}, \pi_{R-1}, \pi_{EN-1})$
(C, C, N)	$(\pi_{EC-2},\pi_{R-2},\pi_{EN-2})$
(C, N, C)	$(\pi_{EC-3}, \pi_{R-3}, \pi_{EN-3})$
(N, C, C)	$(\pi_{EC-4},\pi_{R-4},\pi_{EN-4})$
(C, N, N)	$(\pi_{EC-5}, \pi_{R-5}, \pi_{EN-5})$
(N, C, N)	$(\pi_{EC-6}, \pi_{R-6}, \pi_{EN-6})$
(N, N, C)	$(\pi_{EC-7}, \pi_{R-7}, \pi_{EN-7})$
(N, N, N)	$(\pi_{EC-8}, \pi_{R-8}, \pi_{EN-8})$

Table 2: Payoff matrix. C and N stands for cooperation and non-cooperation, respectively



	Commission ( $\pi_{EC}$ )	Regulators ( $\pi_R$ )	Energy Networks ( $\pi_{En}$ )
π <sub>1</sub>	$E_1 - \alpha_1 F - c_1$	$(1-\beta)s - I - c_3$	$\alpha_1 F + \beta s + I - I$
$\pi_2$	$-E_{2}-c_{1}$	$-c_3$	0
$\pi_3$	$E_1 - \alpha_1 F - c_1 - c_2$	s-p	$\alpha_1 F - I$
$\pi_4$	$E_1 - \alpha_2 F - q$	$(1-\beta)s-l-c_3$	$\alpha_2 F + \beta s + I - I$
$\pi_5$	$-E_2 - c_1 - c_2$	-p	0
$\pi_6$	$-E_2-q$	$-c_3$	0
$\pi_7$	$E_1 - \alpha_2 F - q$	S	$\alpha_2 F - I$
$\pi_8$	$-E_{2}-q$	0	0

Table 3: Pavo	ffs for the Commiss	on, NRAs, and	firms in the	different outcor	nes of the game
Tuble 5. Tuyo		on, nu o, une		unici chi outcoi	ies of the guine

### 5. Results and Analysis

### 5.1. Replicator Dynamics Equations

This section presents the outcomes of the game introduced in section 4. First, we derive the replicator dynamics equations for each group of players. The equilibrium points of the game are reported in section 5.2, and the stability of the equilibrium point involving cooperation from the networks is examined. Finally, in section 5.3, we conduct numerical simulations of the game for the ESS.

To derive the possible ESS, we set up and solve a system of replicator dynamics equations as described earlier. This first involves deriving the expected payoffs from cooperation and non-cooperation, respectively, for all three groups of players after which the replicator dynamics equations can be derived.

The expected payoffs of the Commission from cooperation are:

$$\pi_{\text{EC-C}} = y[z(\pi_{EC-1}) + (1-z)(\pi_{EC-2})] + (1-y)[z(\pi_{EC-3}) + (1-z)(\pi_{EC-5})] = z(E_1 + E_2 - \alpha_1 F) - E_2 - c_1 - (1-y)c_2$$

The expected payoffs of the Commission from non-cooperation are:

$$\pi_{\text{EC-N}} = y[z(\pi_{EC-4}) + (1-z)(\pi_{EC-6})] + (1-y)[z(\pi_{EC-7}) + (1-z)(\pi_{EC-8})] = z(E_1 + E_2 - \alpha_2 F) - E_2 - q$$

Then, the average expected payoffs of the Commission is:

$$\overline{\pi}_{EC} = x(\pi_{EC-C}) + (1-x)(\pi_{EC-N})$$
  
=  $z(E_1 + E_2) - E_2 - x(c_1 + (1-y)c_2) - (1-x)q - zF(x\alpha_1 + (1-x)\alpha_2)$   
(5)

The expected payoffs of the regulators from cooperation are:

$$\pi_{R-C} = x[z(\pi_{R-1}) + (1-z)(\pi_{R-2})] + (1-x)[z(\pi_{R-4}) + (1-z)(\pi_{R-6})] = z((1-\beta)s - I) - c_3$$

(6)

(3)

(4)

While the expected payoffs of the regulators from non-cooperation are:

$$\pi_{R-N} = x[z(\pi_{R-3}) + (1-z)(\pi_{R-5})] + (1-z)[z(\pi_{R-7}) + (1-z)(\pi_{R-8})] = zs - xp$$

Thus, the average expected payoffs of the regulators is:

$$\overline{\pi}_{R} = y(\pi_{R-C}) + (1-y)(\pi_{R-N}) = zs - y[z(\beta s + I) + c_{3}] - (1-y)xp$$

(8)

(10)

(7)

Finally, the expected payoffs of the energy networks from cooperation are:

$$\pi_{\text{EN-C}} = x[y(\pi_{EN-1}) + (1-y)(\pi_{EN-3})] + (1-x)[y(\pi_{EN-4}) + (1-y)(\pi_{EN-7})] = y(\beta s + I) - I + (x\alpha_1 + (1-x)\alpha_2)F$$
(9)

While the expected payoffs of the energy networks from non-cooperation are:

$$\pi_{\text{EN-N}} = x[y(\pi_{EN-2}) + (1-y)(\pi_{EN-5})] + (1-x)[y(\pi_{EN-6}) + (1-y)(\pi_{EN-8})] = 0$$

Making the average expected payoffs of the energy networks to be:

$$\overline{\pi}_{EN} = z(\pi_{EN-C}) + (1-z)(\pi_{EN-N})$$
  
= z[y(\beta s + I) - I + (x\alpha\_1 + (1-x)\alpha\_2)F]  
(11)

Then, the replicator dynamics equations can be set up composed of a system of ordinary differential equations. In this system, the growth rates of x, y and z equal the excess expected payoffs of choosing this strategy over the average payoffs in the population. Therefore, in this paper, F(x), F(y) or F(z) represent the growth rate of the probability choosing the strategy of cooperation within each actor.

The replicator dynamics equation for the cooperation strategy of the Commission is:

$$F(x) = \frac{dx}{dt} = x(\pi_{EC-C} - \overline{\pi}_{EC})$$
  
= x(1-x)[zF(\alpha\_2 - \alpha\_1) - c\_1 - (1-y)c\_2 + q] (12)

While the replicator dynamics equation for the cooperation strategy of the regulator is:

$$F(y) = \frac{dy}{dt} = y(\pi_{R-C} - \overline{\pi}_R) = y(1-y)[xp - z(\beta s + I) - c_3]$$
(13)

And the replicator dynamics equation for the cooperation strategy of the energy networks is:

$$F(z) = \frac{dz}{dt} = z(\pi_{EN-C} - \overline{\pi}_{EN})$$
  
=  $z(1-z)[y(\beta s + I) - I + (x\alpha_1 + (1-x)\alpha_2)F]$  (14)

### 5.2. Equilibrium and Stability Analysis

Therefore, to derive the equilibrium points of the evolutionary game, we insert equations 12, 13 and 14 into one equation and obtain the dynamical system shown in equation (15).

$$\begin{cases} F(x) = x(1-x)[zF(\alpha_2 - \alpha_1) - c_1 - (1-y)c_2 + q] \\ F(y) = y(1-y)[xp - z(\beta s + I) - c_3] \\ F(z) = z(1-z)[y(\beta s + I) - I + (x\alpha_1 + (1-x)\alpha_2)F] \end{cases}$$
(15)

When the replicator dynamics equation reaches a stable state in iteration, the given strategy is an ESS. Hence, in order to derive the possible ESSs of the game, we first solve the following dynamic differential system when the dynamical system equals 0:

$$\begin{cases} F(x) = 0\\ F(y) = 0\\ F(z) = 0 \end{cases}$$

(16)

By solving for x, y and z, we arrive at Proposition 1:

**Proposition 1** *The dynamic differential system in equation 16 has eight equilibrium points,* E(x, y, z)*, in pure strategies:*  $E_1(0,0,0)$ ,  $E_2(1,0,0)$ ,  $E_3(0,1,0)$ ,  $E_4(0,0,1)$ ,  $E_5(1,1,0)$ ,  $E_6(1,0,1)$ ,  $E_7(0,1,1)$  *and*  $E_8(1,1,1)$ .

**Proof 1** When x = 0 or x = 1, y = 0 or y = 1 and z = 0 or z = 1, then F(x) = 0, F(y) = 0 and F(z) = 0. Hence,  $E_1 - E_8$  are equilibrium points of the dynamic differential system in equation 16. Since the players can play no other pure strategies, these are the only equilibrium points in pure strategies of the dynamic differential system.

After deriving the equilibrium points from solving this system of replicator equations, we conduct a stability analysis using the Jacobian matrix as described in section 4.2 to establish whether each equilibrium point can be an ESS. As mentioned in the introduction to this section, the stability of all equilibrium points that involve cooperation from the energy networks will be examined. This concerns  $E_4(0,0,1)$ ,  $E_6(1,0,1)$ ,  $E_7(0,1,1)$  and  $E_8(1,1,1)$ . This is done by setting up the Jacobian matrix as follows:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix}$$

(17)

Then, each of the four equilibrium points of interest is, one at a time, inserted into the matrix to determine the stability of each point.

### $E_4(0, 0, 1)$

By substituting  $E_4(0,0,1)$  into the Jacobian matrix, it reduces to:

$$J = \begin{bmatrix} F(\alpha_2 - \alpha_1) - c_1 - c_2 + q & 0 & 0\\ 0 & -\beta s - I - c_3 & 0\\ 0 & 0 & I - \alpha_2 F \end{bmatrix}$$
(18)

Then, following the procedure described in section 3.1 of deriving the eigenvalues of the Jacobian matrix, the following must hold:

$$\begin{cases} F(\alpha_{2} - \alpha_{1}) - c_{1} - c_{2} + q < 0 \\ -\beta s - I - c_{3} < 0 \\ I - \alpha_{2}F < 0 \end{cases}$$
(19)

For the last condition to hold, the expected external funding the energy networks would receive for an investment in innovation, if the Commission did not change its legislation, should exceed the investment paid (net of cost efficiency gains from the innovation) by the energy networks. This is not realistic, meaning the equilibrium point is not stable.

### $E_6(1, 0, 1)$

After substituting  $E_6(1,0,1)$  into the Jacobian matrix, it reduces to:

$$J = \begin{bmatrix} -F(\alpha_2 - \alpha_1) + c_1 + c_2 - q & 0 & 0\\ 0 & p - \beta s - I - c_3 & 0\\ 0 & 0 & I - \alpha_1 F \end{bmatrix}$$

(20)
------

Then, the following must hold:

$$\begin{cases} -F(\alpha_2 - \alpha_1) + c_1 + c_2 - q < 0\\ p - \beta s - I - c_3 < 0\\ I - \alpha_1 F < 0 \end{cases}$$

(21)

Even if the Commission does pass its new legislation, it does not seem realistic that the expected external funding the energy networks would receive for an investment in innovation should exceed the investment paid by the energy networks which must be the case for the last condition to hold. Thus, this is not a stable equilibrium either.

### $E_7(0, 1, 1)$

By substituting  $E_7(0,1,1)$  into the Jacobian matrix, it reduces to:

$$J = \begin{bmatrix} F(\alpha_2 - \alpha_1) - c_1 + q & 0 & 0 \\ 0 & \beta s + I + c_3 & 0 \\ 0 & 0 & -\beta s - \alpha_2 F \end{bmatrix}$$

Then, the following must hold:

$$\begin{cases} F(\alpha_{2} - \alpha_{1}) - c_{1} + q < 0\\ \beta s + I + c_{3} < 0\\ -\beta s - \alpha_{2} F < 0 \end{cases}$$
(23)

(22)

Since all parameters are greater than or equal to zero, the middle condition can never hold. Thus, the equilibrium is unstable.

#### $E_8(1, 1, 1)$

When substituting  $E_8(1,1,1)$  into the Jacobian matrix, it reduces to:

$$J = \begin{bmatrix} -F(\alpha_2 - \alpha_1) + c_1 - q & 0 & 0\\ 0 & -p + \beta s + I + c_3 & 0\\ 0 & 0 & -\beta s - \alpha_2 F \end{bmatrix}$$
(24)

Then, the following must hold:

$$\begin{cases} -F(\alpha_{2} - \alpha_{1}) + c_{1} - q < 0\\ -p + \beta s + l + c_{3} < 0\\ -\beta s - \alpha_{1}F < 0 \end{cases}$$
(25)

Since all parameters are greater than or equal to zero, cf. table 1, the last condition always holds. Then, it can be inferred from equation 25 that equilibrium point  $E_8(1,1,1)$  is stable if the following two conditions are met:

$$\begin{cases} F(\alpha_1 - \alpha_2) + c_1 < q\\ \beta s + I + c_3 < p \end{cases}$$
(26)

The first condition implies that the penalty imposed on the Commission in case it does not choose its cooperation strategy must be greater than the expected additional financing it will pay to the firms if they choose to invest, and the Commission proposes changes in legislation plus the cost associated with changing the regulations. The second condition means that the sum of the penalty imposed on regulators if they choose their non-cooperative strategy while the Commission chooses cooperation must exceed the fraction of the cost reduction given to the firms and the investment costs passed to consumers, represented by the regulators, in case the firms choose to invest in innovation and regulators change their practice to one that induces innovation plus the cost of changing the regulatory practice. If this case, the equilibrium point is stable, the entire game system will stabilise at  $E_8(1,1,1)$ .

Thus, several numerical simulations will be conducted to investigate the effect of the four chosen parameters on the convergence to this equilibrium as described later.

### 5.3. Numerical Simulations

### 5.3.1. Parameter Assignment

To make the analysis visualisation, validate the equilibrium result of the game and conduct sensitivity analyses, we use the numerical simulation to examine the dynamic trajectory of each player from the initial state to the stable strategy. Specifically, we carry out the numerical simulations based on Eq. (15). The impacts of initial willingness of actors and changes of key parameters on the game system are analysed. To observe the behavioural dynamic evolution of the three stakeholders, we conduct the simulations with the numerical inputs and to simulate the dynamic evolution trajectory from the initial state to the equilibrium state.

Following the literature on evolutionary game theory (e.g., Chong and Sun, 2020; Zhao et al., 2022; Sheng et al., 2020), we conduct several numerical simulations to investigate the impact of a number of chosen parameters on the convergence to a stable state. There is great uncertainty with several of the parameters, for instance, costs of changing regulations, cost reductions from innovation, and how large a percentage of innovative projects in energy networks in the EU can receive additional funding. Due to this, numerical simulations on the ESS  $E_8(1,1,1)$  will be conducted for four different scenarios, following the procedure by Chong and Sun (2020).

The parameters  $E_1$ ,  $E_2$ , F,  $\alpha_2$ ,  $c_1$ ,  $c_2$ ,  $c_3$ , I and s are assumed to be given. The parameters  $\alpha_1$ ,  $\beta$ , p and q are adjustable, since these are assumed to be the result of the regulations implemented by the Commission and the regulatory practice chosen by the regulators in case these two players choose their cooperation strategies, although it can be discussed who has the power to adjust the parameter q and if it is in fact exogenously determined in the model. Thus, parameters  $\alpha_1$ ,  $\beta$ , p and q will be referred to as policy parameters. Then, the four scenarios are set up such that the parameters assumed to be given are chosen with different ratios between them while sensitivity analyses are conducted for the remaining four parameters to investigate the impact of a change in them on the convergence to the ESS. All parameters are chosen such that the conditions derived in equation 26 are met.

This is evident from figure 2 which shows the evolutionary process of the three groups of players towards the ESS. The figure shows that the players converge to the stable equilibrium point  $E_8(1,1,1)$  in all four scenarios.



Figure 2: Evolutionary process of the three groups of players towards the ESS  $E_8(1,1,1)$  in each of the four scenarios

From the replicator dynamics in equations 12, 13 and 14, it is evident that the environmental benefits,  $E_1$ , and environmental costs,  $E_2$ , which the Commission will achieve in case the networks do or do not, respectively, invest in innovation do not affect the convergence towards the ESS. Therefore, these parameters will not be given a value. The values in each of the four scenarios of the seven remaining parameters that are taken as given are seen from table 4. The four policy parameters are given the same value in the four scenarios, namely  $\alpha_1 = 0.8$ ,  $\beta = 0.5$ , p = 4 and q = 4. The sensitivity analyses are conducted for the four parameters in all four scenarios by decreasing and increasing, respectively, these values by 25%. Furthermore, each of the sensitivity analyses are conducted for the initial probabilities  $x_0 = y_0 = z_0 = 0.2$  and  $x_0 = y_0 = z_0 = 0.8$ . In addition, sensitivity analyses are conducted for the initial probabilities x, y and z to investigate the impact of relatively low and relatively high, respectively, initial probabilities on convergence towards the stable state.

Parameter	Scenario 1 value	Scenario 2 value	Scenario 3 value	Scenario 4 value
F	1	0.75	1	1
α2	0.5	0.4	0.5	0.5
<i>C</i> <sub>1</sub>	0.5	0.5	0.5	0.7
<i>C</i> <sub>2</sub>	0.5	0.5	0.5	0.7
<i>C</i> <sub>3</sub>	0.5	0.5	0.5	0.7
Ι	1	1	1	1
S	2	2	1	2

Table 4: Parameter values in the four different scenarios

### 5.3.2. Sensitivity Analyses

### 5.3.2.1 Sensitivity Analyses of Policy Parameters

First, we briefly explain the meanings of parameters used in this section. We set  $x_0$ ,  $y_0$  and  $z_0$  as the initial probabilities of the Commission, regulators and energy networks choose cooperation strategy respectively, while x, y and z are the dynamic probabilities of the Commission, regulators and energy networks choose cooperation strategy respectively as described before. Further, from table 1,  $\alpha_1$  denotes the probability of receiving average external funding when the Commission foster changes in regulation,  $\beta$  means the percentage of cost reductions given to firms if regulators change their regulatory practice, p stands for the penalty imposed on regulators if they do not change their practice and the Commission changes its legislation, and q is the penalty imposed on the Commission if it does not change its legislation.

Figure 3 shows the impact of a change in  $\alpha_1$  on the convergence rate of x, y and z to the equilibrium in the four different scenarios. From the figure, the value of  $\alpha_1$  has little to no impact on the convergence of x and y to the ESS. On the other hand,  $\alpha_1$  has an impact on the convergence of z to the ESS for a low initial probability  $z_0$ . A higher value of  $\alpha_1$  seems to result in a quicker convergence towards the stable state. For a higher initial value  $z_0$ , it seems there is still some positive effect on the convergence rate of a higher value of  $\alpha_1$ , but this effect seems to be insignificant.

Figure 4 suggests that a change of value in  $\alpha_1$  and  $\beta$  has almost the same effect on the convergence towards the stable state, qualitatively speaking. Again, for a low initial probability  $z_0$ , a higher value of  $\beta$  seems to result in a quicker convergence towards the ESS while changing  $\beta$  seems to have little to no effect on the convergence rate of x. However, one distinction is that a higher  $\beta$  value seems to result in a slightly slower convergence rate for y in all scenarios except scenario 3. As for the case of  $\alpha_1$ , there seems to be a small, but insignificant, positive effect of  $\beta$  on the convergence rate of z for high initial probabilities  $z_0$ .



Figure 3: Sensitivity analysis of  $\alpha_1$ . (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4



Figure 4: Sensitivity analysis of  $\beta$ . (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4

The picture is different in figure 5 which shows the impact of a change in p on the convergence rate of x, y and z to the ESS. A lower p value leads to a much slower convergence of y to the stable state compared to higher values of p, both for high and low initial probabilities  $y_0$ . For low initial probabilities  $z_0$ , a lower p value seems to lead to a slower convergence rate. However, also for this policy parameter, the impact on the convergence rate of x for both high and low initial probabilities  $x_0$  plus on the convergence rate of z for high initial probabilities  $z_0$  seems small to non-existent. The last policy parameter, q, is interesting as it seems to be the only of the four variables that affect the convergence rate of both x, y and z, even in the same direction. A higher value of q seems to imply a quicker convergence towards the ESS, particularly for x, but also for low initial probabilities  $y_0$  and  $z_0$ .(figure 6). However,

for high initial probabilities, the effect on the convergence rate of x from a change in q is somewhat smaller while the effect on the convergence rate of y and z seems insignificant.



Figure 5: Sensitivity analysis of p. (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4



Figure 6: Sensitivity analysis of q. (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4

### 5.3.2.2 Sensitivity Analyses of Initial Probabilities

After analysing the effect of changing the policy parameters on the convergence rates of x, y and z, we turn to the sensitivity analyses of the impact of a change in the initial parameters  $x_0$ ,  $y_0$  and  $z_0$  on the convergence to the equilibrium  $E_8(1,1,1)$ . The reason for this is to be able to deduce if it makes more sense to initially focus on some of the three groups' convergence to the ESS rather than the others' (Zhao et al., 2022).

Figure 7 shows the impact of a change in the initial probability  $x_0$  on the convergence rate of y and z to the equilibrium in the four different scenarios. The impact does not seem to be immense, but a

higher initial probability  $x_0$  does seem to result in a quicker convergence rate for y and z. Especially in scenario 4, this seems to be the case while there seems to be little to no impact in scenario 3. The impact of a change in the initial probability  $y_0$ , seen from figure 8, seems to be small to non-existent for the convergence rate of x to the ESS. On the other hand, it is clear from figure 8 that a higher initial probability  $y_0$  results in a quicker convergence of z to the stable state. The convergence rate of x does not seem to be affected by the initial probability of z either, seen from figure 9, but there appears to be a negative effect on the convergence rate of y of a higher initial probability  $z_0$ . However, the negative effect does not seem to be distinct.



Figure 7: Sensitivity analysis of x. (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4



Figure 8: Sensitivity analysis of y. (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4



Figure 9: Sensitivity analysis of z. (a), (b) and (c) show the sensitivity analyses in scenario 1, (d), I and (f) show the sensitivity analyses in scenario 2, (g), (h) and (i) show the sensitivity analyses in scenario 3, and (j), (k) and (l) show the sensitivity analyses in scenario 4

### 6. Policy Discussion

This paper investigates the interaction of the key actors and pathways to innovation in European energy networks. We find that the only potentially stable equilibrium which involves that networks firms invest in innovation is equilibrium  $E_8(1,1,1)$ . This equilibrium point implies that the European Commission can initiate changes in legislation to induce innovation in networks and this change directs the regulators to adapt incentive mechanisms that induce innovation. Otherwise, the regulators will be penalised, just as the Commission will be penalised for not changing regulation. Furthermore, the ESS involves that regulators adapt their practice to, for instance, output-based mechanisms. Lastly, this equilibrium involves that network firms invest in innovation and for this equilibrium to be stable, two conditions must be met, as discussed earlier. These conditions imply that the penalties imposed on the Commission and regulators for not cooperating must exceed their additional costs of cooperating compared to choosing non-cooperative strategy, given that the other two groups of players cooperate.

The Commission has revised the TEN-E Regulation to make it compatible with the goals of the European Green Deal. Given this, it is reasonable to assume that the initial probability  $x_0$  lies at the high end. At the same time, considering the need for innovation in the energy sector, it is reasonable to assume that the initial proportion of networks investing in innovation is on the low end, corresponding to a low initial probability  $z_0$ . Likewise, since many regulators use cost-based regulatory mechanisms or incentive-based mechanisms for incentivising cost-efficiency, it is reasonable to assume that the initial probability  $y_0$  is low. Since the initial probabilities matter for the convergence rate to the ESS for the other populations and for the impact of changes in the policy variables on the convergence rate to the ESS this is a matter to consider. The assumed high initial probability  $x_0$  alone is presumed to increase the convergence rates of the networks and regulators to the stable state  $E_8(1,1,1)$  as mentioned, compared to if  $x_0$  had been lower. However, since it seems to be a smaller effect, it is useful to consider which policy parameters can be adjusted to increase the convergence to the stable state.

The only policy parameters where a higher value is equivalent to an increase in the convergence rate towards the ESS for all three populations is q, i.e., the penalty imposed on the Commission in case it

does not change its legislation. However, the question as to who is responsible for adjusting this parameter is yet to be answered. The assumption that the Commission will receive a penalty if it does not choose its cooperation strategy holds based on the European Climate Law specifying that the Commission should take necessary measures to meet the legally binding target of net zero greenhouse gas emissions by 2050. It might not be reasonable to assume that the EU will increase a penalty imposed on one of its own institutions. However, third parties may be able to make legal arguments that the European Climate Law is binding and must be observed. The powers to adjust the parameter q, for instance through intervention by the co-legislators, European Council and European Parliament, is also conceivable but lies beyond the scope of this paper.

Moreover, if we maintain the assumption that the initial probability of the Commission is high, it might not be of much importance to adjust a parameter that also increases convergence towards the equilibrium point for the Commission. Instead, it is better to look at the parameters which the Commission can influence or is responsible for choosing. For low initial probabilities  $y_0$  and  $z_0$ , a higher p increases the convergence rate of both y and z to a high degree compared to the other policy values. Furthermore, an increase in  $\alpha_1$  increases convergence for the networks towards the ESS when it is assumed that the initial probability  $z_0$  is low. Since a change in both parameters appear to have no impact on the convergence rate of the Commission, it seems to be a reasonable way of increasing convergence to the ESS.

The cooperation of the Commission is of great importance when to reach the stable equilibrium. This is in line with the findings by Yang et al. (2021) and Guo et al. (2021) amongst others who find that the greater the subsidies and penalties from the government are, the more likely collaboration is. Furthermore, it supports the findings by Encarnação et al. (2018) that if at first the cooperation of the public sector, in this game the Commission, is ensured, then incentive mechanisms can be implemented to assure the cooperation of the remaining groups of players.

### 7. Conclusions and Outlook

Innovation is key to achieving the green transition, and the energy sector, and especially energy networks need more innovation. This study conceptualises and models the regulatory and policy context within which innovation efforts in regulated energy networks in the EU is formed and can be motivated using a tripartite evolutionary game theory.

The three groups of players in the game are the European Commission, the national regulatory authorities, and the energy system operators representing the political, regulatory, and commercial interests of their members respectively. The players each choose to play a cooperation strategy or a non-cooperation strategy. The cooperation strategy of the Commission is to induce innovation through proposing changes in legislation. This, for instance, involves the actualisation of the TEN-E Regulation to make it more compatible with the decarbonisation goals of the European Green Deal. Furthermore, non-cooperation from the Commission is assumed to contradict the European Climate Law and result in some form of a penalty imposed on the Commission.

The cooperation strategy of the regulators is to implement input-based and output-based incentive regulation mechanisms. This is thought to, through the input-based mechanism, encourage investments in innovation by first, accounting for the increased risk profile of the investments, and second, through output-based regulation, by incentivising improved outcome by benefit-sharing with the networks. The latter mechanism deals with the moral hazard issue of the regulators not being able to observe the efficiency of the networks. The non-cooperation strategy of the regulators is to maintain a

cost-based mechanism, which does not provide incentives for innovation and might lead to networks misreporting their costs, or an incentive-based mechanism that incentivises cost-efficiency. We assume that the Commission can penalise the regulators for not cooperating, given that the Commission cooperates.

In accordance with the objective of the game, the cooperation strategy of the networks is to invest in innovation. Their non-cooperation strategy is to not invest. To derive the equilibrium points of the game, the replicator dynamics equations are calculated and solved. The only point found to be an ESS is the equilibrium point  $E_8(1,1,1)$ , indicating cooperation of the three groups of players. However, for this point to be stable, some conditions must be met. These conditions imply that 'penalties' on the Commission and the regulators, respectively, in case they do not choose to cooperate must be greater than the expected decrease in payoffs they will have from choosing cooperation over non-cooperation, given that the strategies of the other groups of players are fixed.

Sensitivity analyses are conducted for the parameters that are assumed to be determined by policies, given that the Commission and the regulators choose cooperation strategies. However, one parameter, namely the size of the penalty imposed on the Commission in case it does not cooperate, can be exogenous. In addition, we conduct a sensitivity analysis for the initial probabilities of cooperation from the three players. We found that a high initial probability of cooperation from the Commission increases the convergence rate for the regulators and firms to the stable state, given that their initial probabilities are low. The Commission can increase the probability of external funding for the networks, to increase the convergence rate of them to the stable state, and increase the penalty on regulators for not cooperating, which seems to increase the convergence rate of both the regulators and the firms. Our findings support the importance of the involvement of higher authorities able to subsidise and penalise the remaining players of the game. These could be in the form of the European Council or the European Parliament as co-legislators.

Comparable studies using evolutionary game theory for moving towards the green transition, the Commission's role in reaching a stable state where energy networks invest in innovation is indispensable. Since the Commission implements the European Green Deal and takes measures for reaching the decarbonisation goals of this as required by the European Climate Law. A different approach to examining the issue of nudging and incentivising the network firms to increase investment in innovation could be to model the game with the Commission as the social planner who aims to maximise social welfare, while also taking environmental benefits into account.

Regulatory practices towards energy networks differ across Member States. Hence, how the payoffs of regulators and energy networks are determined from state to state and will differ in practice. Furthermore, many of the suggestions in the literature for especially which initiatives the Commission can use to increase innovation in energy networks are difficult to translate into payoffs, for which reason it is difficult to examine their impact in a game theoretic model. External funding in the payoff functions could be defined as a percentage of investment costs. Furthermore, if affordability should be the only award criterion for CEF-E funding, the payoff functions should consider that external funding is only used when consumers cannot afford to pay for the investments. However, how to do this in practice is complicated.

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