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Complexity in low-carbon transitions: Uncertainty and policy implications ☆

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ABSTRACT

We explore the uncertain dimension induced by the complexity of energy systems, analyzing whether and under which conditions low-carbon transitions can effectively take place. By accounting for social and environmental considerations, heterogeneous single utility-maximizing agents optimally decide whether to adopt a green technology which reduces carbon emissions, allowing eventually for a green energy transition. We characterize the determinants of the success of such a transition, emphasizing that even if the favorable conditions are met the low-carbon transition may not result in long run environmental improvements due to the path-dependency and metastability phenomena which characterize the complexity arising from agents' interactions. Public policy may solve these issues by increasing the incentive for single individuals to adopt, ensuring thus the achievement of a permanent low-carbon state. By extending the analysis to a spatial network characterized by multiplexity due to the social and environmental interconnections, we show that spatial interactions negatively affect agents' adoption incentive and reduce the effectiveness of public policy by interacting in a complex way with path-dependency and metastability. In particular, spatial interactions may require a larger subsidy to support a permanent low-carbon transition, thus neglecting their effects on agents' behavior and environmental outcomes may compromise our chances to achieve a greener future.

1. Introduction

The need for actions to effectively mitigate the effects of climate change are stronger than ever (IPCC, 2022). Growing scientific evidence regarding the health consequences of air pollution (Landrigan, 2017; Proedrou, 2018) and socio-economic considerations related to energy security and the diffusion of popular pro-environment movements (Guivarch and Monjon, 2017; McCauley and Heffron, 2018) have jointly contributed to increase the demand for a low-carbon future. Responding to this need, the Glasgow Climate Pact recently signed by almost 200 countries at the 26th Conference of the Parties in November 2021 aims at accelerating climate mitigation to establish carbon neutrality by 2050 in order to limit global warming below 1.5 °C (UN, 2022). Whether such objectives will be truly achieved though is an open question, since several factors, including political and financial issues, may prevent a low-carbon transition to effectively take place (Aklin and Urpelainen, 2013; OECD, 2019). Among the possible obstacles, uncertainty and complexity play a key role in determining the eventual success of green transitions, but nevertheless very little is known about the type of problems they might give rise to and the possible strategies to overcome them (Hafner et al., 2020). Extant literature stresses that assessing the likelihood of low-carbon transitions is particularly problematic in the context of uncertainty which complicates forecasting and scenario analysis, since such transitions require and induce important technological and behavioral changes which may take place over long time periods (Cullenward et al., 2011; Hughes et al., 2013). Moreover, these behavioral and technological changes may occur at different societal levels, such that the heterogeneity of economic agents and their interactions through environmental and social networks make energy systems as complex systems, which cannot be fully understood by relying on a mere economic perspective (Cherp et al., 2011; Bale et al., 2015). The goal of this paper consists thus of shedding some light on the problems generated by the uncertainty induced by the complexity of energy systems in the context of green transitions. In particular, we develop a normative approach to identify possible policy tools to address such difficulties and support the effective implementation of a low-carbon transition.

We integrate a traditional economic framework with ingredients from complexity science in order to characterize the feedback effects

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between individual behavior and green transitions. Specifically, we analyze an analytically tractable agent-based model in which utility maximizing agents optimally choose whether to adopt a green technology by accounting for social and environmental considerations. Heterogeneity in agents' characteristics implies that for some it may be convenient to adopt the green technology while for others it may not. The green technology reduces emissions which are an adoption incentive, exactly as imitation motives, thus as some households adopt the importance of social (environmental) considerations strengthens (weakens) inducing other households to adopt (not to adopt) driving the changes in the adoption rate. We show that in such a setting by aggregating households' behavior in order to abstract from uncertainty we can clearly predict the long run outcome which may be associated with unique or multiple equilibria, characterizing the conditions consistent with a transition to a low-carbon economy. Even if such favorable conditions are met though, because of path-dependency the legacy of past adoptions may negatively affect future adoptions precluding thus the possibility of a green transition to take place if the initial adoption rate is not large enough. Moreover, by considering the implications of uncertainty we show that it may be possible that the random system dynamics are characterized by metastability, which implies that a transition to a low-carbon economy may actually represent only a transient phase after which the economy may return to a high-carbon intensity state. This suggests that the complexity in the socio-environmental dynamics induced by the feedback effects between agents' behavior and emissions may preclude us to reliably assess the likelihood that a low-carbon transition may effectively occur. However, specific policies taking the form of a small subsidy may solve these issues by providing agents with an adoption incentive sufficiently strong to more than compensate for the weakening of the environmental considerations associated with a reduction in carbon emissions.

Complexity may affect green transitions not only through uncertainty but also through the spatial channel, which represents the fact that modern economies are interconnected via social and environmental mechanisms. In order to account for this feature we extend our benchmark setup to a network representing a spatial economy characterized by multiple local economies interconnected by multiplex ties. In such a spatial network agents located in different venues decide whether to adopt the green technology considering also what happens in others. Due to the transboundary nature of pollution emissions generated in one location affect other locations as well, thus what really matters for adoption decisions is the overall emissions level within the network. Moreover, due to the fast and wide spread of information in modern economies also imitation motives may be driven not by local but by global adoption rates within the network. These two different layers of interconnections between local economies give rise to a multiplex network, which may modify our conclusions regarding the likelihood that a low-carbon transition takes place and that a subsidy effectively promotes such a transition. By abstracting from uncertainty we show that spatial interconnections tend to reduce green technology adoptions increasing thus emissions, and to increase the initial adoption level required for a green transition to occur. Moreover, uncertainty further complicates the picture, since the metastable properties of the random system dynamics earlier discussed still apply and in this case a small subsidy may be no longer enough, thus a substantially larger subsidy may be required to prevent a green transition to represent only a short-living phenomenon. This suggests that determining the intensity of environmental policy without properly quantifying spatial interactions may be misleading, precluding the possibility to ensure that a permanent low-carbon transition effectively takes place.

Our work relates thus to two different branches of the literature. We contribute to the extensive and growing economics literature on low-carbon transitions by analyzing the role of agents' behavioral change, focusing in particular on how individual decisions depend and affect emissions reduction objectives (Zhang et al., 2020; Bhattarai et al., 2021). Several works discuss the importance of behavioral aspects for understanding the green transitions along with the fact that social barriers can represent important obstacles to their actual implementation (Li and Strachan, 2017; Mercure et al., 2019), stressing the need for a multidisciplinary approach in order to address these issues from a broader policy perspective (Blazquez et al., 2020; Hafner et al., 2020). We contribute also to the growing literature applying complexity science in the social sciences domain, focusing on the role played by uncertainty and multiplex ties in the context of green energy transitions (Arthur, 1999; Farmer and Foley, 2009). Several works address the importance of revitalizing social sciences and economics in particular by borrowing some complexity tools (Foxon, 2013; Foxon et al., 2013), while others highlight that the stochastic features of random dynamical systems and the spatial implications of interconnections within networks may generate important consequences for long run outcomes (Marsiglio and Tolotti, 2018; Bisin and Moro, 2022). To the best of our knowledge, ours is the first paper integrating economics and complexity science principles in an analytically tractable framework of green technology adoption to clearly outline the mechanisms driving individual agents' behavior and identify policies capable to favor an effective low-carbon transition by successfully interacting with such mechanisms.

Our framework contains most of the elements identified as crucial aspects of the complex nature of energy systems and green transitions, such as agents' heterogeneity, equilibrium multiplicity, path-dependency, out-of-equilibrium dynamics, social networks and uncertainty (Hughes et al., 2013; Hafner et al., 2020). Its analytical tractability allows us to derive closed-form solutions which help us in identifying the working mechanisms of the behavioral changes conductive of green transitions. In particular, by analyzing separately the role of uncertainty and network multiplexity we pinpoint the problems that neglecting such important socio-environmental characteristics of energy systems may generate for the reliability of our predictions and policy analysis. Probably, the paper most closely related to our is Zeppini's (2015), which analyzes a discrete choice model in which agents' adoption decisions driven by social interactions determine the success of a green transition, and the occurrence of such a transition is the result of a coordination problem with multiple equilibria. Our work differs from theirs along several dimensions: (i) social factors are not the only driver of adoption decisions, but also environmental considerations matter; (ii) we do not restrict our analysis only to a deterministic approximation of the system dynamics, but we specifically explore how uncertainty affects social and environmental outcomes; and (iii) we introduce spatial interactions by allowing individual adoption decisions to affect and be affected by social and environmental factors arising within a spatial network. Despite some similarity in the theoretical setting the scope and breath of our work are wider, and our analysis allows us to derive interesting conclusions regarding the implications of uncertainty and complexity completely missing in Zeppini's (2015).

The paper proceeds as follows. Section 2 introduces our benchmark agent-based model of green technology adoption stressing the implications of uncertainty for forecasting and policy analysis. Section 3 extends our baseline framework to analyze how results may change in a network characterized by multiplexity, and in particular what this implies for policymaking. Section 4 presents concluding remarks and directions for future research. Technicalities are presented in Appendix.

2. The benchmark

We analyze a technology adoption framework in which a green technology, consisting of a durable perishable good, is available on the market to reduce carbon emissions (Bass, 1969; Zeng et al., 2020). Heterogeneous agents, consisting of households-firms as households entirely own the firm in which they are employed, differ in their individual valuation of the technology and they decide whether to adopt the green technology accounting for social and environmental considerations, represented by the overall adoption level within the society and emissions respectively (Chi, 2022; Flores and Jansson, 2022).

Therefore, each agent's decision to effectively adopt affects the choice of others since on the one hand it increases the adoption level and on the other hand it decreases emissions. There exist thus feedback effects between individual behavior and environmental outcomes driven by interactions at the social level.

Specifically, there exists a large number, N, of heterogeneous agents, indexed by $i = 1, \dots, N$. The emissions generated by each agent through their consumption and production activities, associated with the use of a freely available brown technology, is equal to $e > 0$. The green technology reduces emissions by a factor $0 < \psi < 1$, such that the emissions generated by agents adopting the green technology is ψe. Because of wear and tear, the green technology may break down with a constant probability $0 < \delta < 1$. Each agent needs to decide whether to purchase the green technology in an attempt to maximize their utility. The utility function of agent i, who at time t has not purchased the green technology yet, is associated with the choice $\omega_{i,t} \in \{0,1\}$ such that $\omega_{i,t} = 1$ ($\omega_{i,t} = 0$) denotes that the agent adopts (does not adopt) the technology. Their utility depends on three elements: an economic component which is agent-specific, a social component and an environmental component which are both common to all agents. The economic component is driven by the net benefit from adoption and is given by $\epsilon_i = b - \varepsilon_i$, which is the difference between a deterministic term common to all agents, $b \in \mathcal{R}$, and a random agent-specific term drawn from a cumulative uniform distribution (with support on the unit interval [0,1]) determining the effective valuation that each agent i attaches to the technology, ε_i. The social component quantifies the importance for the single agent to conform to others' decisions and is given by $s_t^N = c x_t^N$, where $c > 0$ measures the degree of conformism and $x_t^N = \frac{1}{N}\sum_j \omega_{j,t}$ represents the adoption rate (i.e., the share of agents adopting the green technology). The environmental component represents the fact that adoption decisions depend on the environmental quality proxied by the per-capita emissions level $e_t^N = \frac{E_t^N}{N}$ where E_t^N denotes aggregate emissions. Following the random utility literature, we specify agents' utility function as follows (Brock and Durlauf, 2001, 2002):

$$u_{i,t}(\omega_{i,t}) = \omega_{i,t}\left(b - \varepsilon_i + c x_t^N + e_t^N\right). \tag{1}$$

Each agent needs thus to compare the null utility from non-adoption (if $\omega_{i,t} = 0$ then $u_{i,t}(0) = 0$) with the utility from adoption (if $\omega_{i,t} = 1$ then $u_{i,t}(1) = b - \varepsilon_i + c x_t^N + e_t^N$), suggesting that only some agents will effectively adopt it (i.e, adoption takes place if $\varepsilon_i < b + c x_t^N + e_t^N$). This characterizes a probabilistic choice model in which the probability of adoption is given by: $\mathbb{P}(u_{i,t}(1) > u_{i,t}(0) | \omega_{i,t} = 0, x_t^N, e_t^N) = \mathbb{P}(\varepsilon_i < b + x_t^N + e_t^N) = \eta(b + x_t^N + e_t^N)$, where $\eta(\cdot)$ is the cumulative uniform distribution function, namely:

$$\eta(z) = \begin{cases} 0 & \text{if} \quad z \le 0 \\ z & \text{if} \quad 0 < z \le 1 \\ 1 & \text{if} \quad z > 1 \end{cases} \tag{2}$$

We can observe that whether the above choice problem translates into an adoption decision positively depends on economic, ϵ_i, social, s_t^N, and environmental factors, e_t^N.[1] In order to better understand the determinants of agents' adoption decisions in (1) we can think of the green technology as a photovoltaic power plant or a hybrid motor vehicle which reduces the agent's ecological footprints. In these contexts the role of economic factors in driving individual behavior is undeniable (Wang et al., 2017; O'Shaughnessy, 2022), but also social and environmental considerations have been extensively documented to affect adoption decisions (Pettifor et al., 2017; Su and Moaniba, 2017). The adoption of a clean technology entails some economic cost (i.e., the purchasing and installation price, reduced production efficiency) and generates some economic benefit (i.e., energy saving, personal satisfaction), determining the net benefit of adoption b which may be positive, negative or null, and which may change from agent to agent due to individual characteristics, captured by the random term ε_i. However, the perceived incentive to adopt depends also on social influence and environmental quality. Others' adoption behavior spreads information about the quality and reliability of the technology, favoring imitation effects and increasing the desirability to conform to extant social norms through a social channel (Bollinger and Gillingham, 2012; Curtale et al., 2021). Moreover, the importance of individual actions changes with environmental degradation, which by increasing environmental awareness determines the urgency of behavioral changes, thus higher emission levels promote adoption through an environmental channel (Zhang et al., 2011; Cui et al., 2021). In reality, abstracting for a while from the heterogeneous individual valuations of the technology, it may be reasonable to believe that the cost of adoption exceeds its benefits such that $b < 0$: economic factors deter adoption while social and environmental issues promote it, such that the tension between these different drivers ultimately determines the adoption outcome.

Since green technology adoptions reduce emissions, the choice of each single agent affects at the aggregate level the evolution of carbon emissions which are given by: $E_t^N = e\left(N - \sum_i \omega_{i,t}\right) + \psi e \sum_i \omega_{i,t}$ (Perino and Requate, 2012; Marsiglio and Tolotti, 2020). Aggregate emissions are the sum of the emissions generated by non-adopters who keep relying on a brown technology (the first term) and adopters who instead rely on the green technology (the second term). It follows that per-capita emissions are equal to:

$$e_t^N = e - e(1-\psi)x_t^N, \tag{3}$$

that is the emissions associated to the prolonged use of the brown technology decreased by the effects associated with the adoption of the green technology. For a low-carbon transition to be possible a large share of agents needs to choose to adopt the green technology in order for emissions to fall over time and stabilize eventually at a lower level.

Agents' optimization problem in (1) characterizes a dynamic probabilistic choice model in which the likelihood of adoption for the single agent changes over time. In fact, individual agent's utility varies over time due to social and environmental considerations, given by x_t^N and e_t^N respectively, and depends on their specific valuation of the green technology, captured by the idiosyncratic term ϵ_i. Posing the problem in a continuous-time setting, Eq. (1) characterizes the probability that an agent decides to switch from the "non-adoption" state to the "adoption" state. However, the eventual breakdown of the green technology may lead an adopter to return to the "non-adoption" state and thus to face again the adoption decision.[2] Summarizing, at any moment in time t the transition probability that agent i will decide to adopt and the transition probability that an installed green technology breaks down are respectively given by:

$$\mathbb{P}(\omega_{i,t+\Delta t} = 1 | \, \omega_{i,t} = 0, x_t^N, e_t^N) = \eta\left(b + c x_t^N + e_t^N\right) \tag{4}$$

$$\mathbb{P}(\omega_{i,t+\Delta t} = 0 | \, \omega_{i,t} = 1, x_t^N, e_t^N) = \delta, \tag{5}$$

where $\eta(\cdot)$ is the cumulative uniform distribution given in (2).

[1] Note that the probability of non-adoption is given by $\mathbb{P}(u_{i,t}(1) \le u_{i,t}(0)|\omega_{i,t} = 0, x_t^N, e_t^N) = \mathbb{P}(\varepsilon_i \ge b + x_t^N + e_t^N) = 1 - \eta(b + x_t^N + e_t^N)$, and thus it depends on economic, social and environmental factors exactly in the opposite way in which the probability of adoption does.

[2] We could also interpret our model as the representation of subsequent waves of green technologies in which the interaction between the technology breakdown and the obsolescence brought on by the introduction of a newer vintage determines the dynamics of adoptions. If a newer vintage makes the previous obsolete, at a random time t_1 an agent needs to decide whether to purchase the prevailing technology (i.e., the newest vintage) at that time. If they choose to adopt it, after a (random) period, say ω, such a technology may break down and the agent may return to the non-adoption state. Therefore, starting from time $t_2 = t_1 + \omega$, the same agent may face the choice to purchase a new technology (i.e., the prevailing one at time t_2). If new green technology vintages are simply associated with cheaper purchasing prices (thus to a higher b), all our conclusions will apply also in the context of multiple technologies.

Unfortunately, analyzing explicitly the above random dynamics when the agents' population is finite is not possible thus before proceeding into numerical analysis, it may be convenient to present a deterministic approximation which characterizes the above dynamics when the agents' population is infinitely large (Blume and Durlauf, 2003; Marsiglio and Tolotti, 2018). Indeed, when $N \to \infty$ the sequence of stochastic processes $\{x_t^N\}_{t\geq 0}$ and $\{e_t^N\}_{t\geq 0}$ converge to x_t and e_t respectively; therefore, the probability that a "representative" agent adopts at time t can be now written as $\eta\left(b + cx_t + e_t\right)$. The change in the adoption rate is given by the difference between the share of agents switching from the non-adoption to the adoption state (given by the product between the adoption probability and the proportion of non-adopters) and the share of agents switching back from the adoption to the non-adoption state (given by the product between the breakdown probability and the proportion of adopters). This leads to the following law of motion for x_t (and the related value for e_t):

$$\dot{x}_t = (1 - x_t)\eta(b + cx_t + e_t) - \delta x_t \tag{6}$$

$$e_t = e - e(1 - \psi)x_t. \tag{7}$$

The above expressions describe the evolution of the share of agents adopting the green technology and emissions, which in turn affect the green adoption dynamics. Indeed, by plugging (7) into (6) the green adoption rate can be rewritten as follows:

$$\dot{x}_t = (1 - x_t)\eta(h + Jx_t) - \delta x_t, \tag{8}$$

where $h \equiv b + e$ and $J \equiv c - e(1 - \psi)$ represent the effective benefit from adoption and the effective degree of conformism, respectively. Note that different from the net benefit and degree of conformism, b and c respectively, their effective counterparts are adjusted to account for the effects of emissions, which partly drive the perceived benefit of adoption (through the e term) and partly the perceived desire to conform to others' behavior (through the term $e(1 - \psi)$). In particular, emissions increase the effective benefit (through their effects on health and environmental conditions, higher emission levels provide agents with a stronger incentive to adopt) but decrease the effective degree of conformism (as more agents adopt the green technology emissions fall, providing thus a weaker incentive for the single agent to adopt). Therefore, it is not obvious a priori whether higher emissions translate into higher or lower adoption rates, as this ultimately depends on their relative impact on h and J.

The differential equation (8) can be analyzed explicitly in order to determine the implications on green technology adoption. Next proposition characterizes the possible long run outcomes of the adoption rate, which in turn determine the long run emissions level through (7).

Proposition 1. *Define $x_\delta = \frac{1}{1+\delta} \in (0,1)$ and $x_{+,-} = \frac{J-h-\delta \pm \sqrt{[J-h-\delta]^2+4Jh}}{2J}$, along with the thresholds $\widehat{h}_1 = 2\sqrt{J\delta} - J - \delta < 0$ and $\widehat{h}_2 = 1 - \frac{J}{1+\delta} > \widehat{h}_1$. Then, three cases may occur.*

(i). If $h \leq \widehat{h}_1$, then there exists a unique locally stable equilibrium $\overline{x} = 0$.
(ii). If $\widehat{h}_1 < h < 0$, then there exist three equilibria $\overline{x}_L = 0$, $\overline{x}_M = x_-$ and $\overline{x}_H = \min\{x_+, x_\delta\}$, with the extremes $\overline{x}_L$ and $\overline{x}_H$ being locally stable while the middle $\overline{x}_M$ locally unstable, and in particular $\overline{x}_H = x_+$ if $h < \widehat{h}_2$ while $\overline{x}_H = x_\delta$ if $h \geq \widehat{h}_2$.
(iii). If $h > 0$, then there exists a unique locally stable equilibrium $\overline{x} = \min\{x_+, x_\delta\}$, and in particular $\overline{x} = x_+$ if $h < \widehat{h}_2$ while $\overline{x} = x_\delta$ if $h \geq \widehat{h}_2$.

Proposition 1 states that the green technology adoption equilibrium can be characterized by either uniqueness or multiplicity. The equilibrium is unique whenever the effective benefit from adoption is particularly small (i.e., $h \leq \widehat{h}_1$) or particularly large (i.e., $h > 0$), while there exist multiple equilibria when the effective benefit from adoption takes intermediate values (i.e., $\widehat{h}_1 < h < 0$). Quite intuitively if the effective benefit from adoption is small then in the long run none will ever adopt the green technology (i.e., $\overline{x} = 0$) such that emissions will not decrease and a low-carbon transition cannot take place, while if the effective benefit is large then a substantial share of adoptions will occur such that emissions will decrease and a low-carbon transition effectively occurs. In this latter scenario long run adoptions turn out to be larger and thus emissions to be smaller (i.e., $\overline{x} = x_\delta$) whenever the effective benefit is larger than a certain threshold value (i.e., $h \geq \widehat{h}_2$), otherwise (i.e., $h < \widehat{h}_2$) adoptions will be smaller and emissions larger (i.e., $\overline{x} = x_+$). For some intermediate values of the effective benefit instead the possible outcomes are more complicated, since with multiplicity there exists an intermediate equilibrium value (i.e., $\overline{x}_M = x_-$) which separates the basins of attraction of the low equilibrium associated with zero adoptions and no green transition (i.e., $\overline{x}_L = 0$) and the high equilibrium associated with substantial adoptions and an effective green transition (i.e., $\overline{x}_H = \min\{x_+, x_\delta\}$). Similar to what discussed earlier, in the latter scenario long run adoptions turn out to be larger and thus emissions to be smaller (i.e., $\overline{x}_H = x_\delta$) whenever the effective benefit is larger than a certain threshold value (i.e., $h \geq \widehat{h}_2$), otherwise (i.e., $h < \widehat{h}_2$) adoptions will be smaller and emissions larger (i.e., $\overline{x}_H = x_+$).

In order to better understand the implications of Proposition 1 it may be convenient to reason on what high or low values of the effective benefit may actually represent. Indeed, the value of the effective benefit depends on the net benefit from adoption b and the emissions generated by the brown technology e. The case (i) requires that h is negative and large in absolute value, that is the net benefit needs to be negative and more than compensate the positive level of emissions: whenever agents' cost to purchase and install the green technology is high and the brown emissions are not large enough to overturn the sign of the effective benefit, clearly adopting makes no sense leaving no room for a green transition. The case (iii) requires that h is positive, that is the net benefit needs to be positive or negative but small in absolute value: whenever agents' benefit from adoption exceeds its cost or whenever agents' cost is small compared with the brown emissions, it is convenient to adopt the green technology ensuring an effective green transition. The case (ii) lies between the two previous situations, requiring that h is negative and small in absolute value: whenever agents' adoption cost is small, such a cost (providing an incentive not to adopt) and emissions (providing instead an incentive to adopt) interact in a complex way implying that the green technology adoption may or may not be convenient according to the initial adoption rate. If initial adoptions are small (i.e., $x_0 < \overline{x}_M$) then adoption will not be optimal and a green transition will not occur, while if they are large (i.e., $x_0 > \overline{x}_M$) adoption becomes a more sensible choice and a green transition will occur. This discussion allows us to identify the conditions under which a green transition may occur as follows.

Proposition 2. *A low-carbon transition may take place whenever $h > \widehat{h}_1$.*

According to Proposition 2, for a green transition to eventually take place it is enough that the effective benefit from adoption is not too small, and in particular the effective benefit may be negative but not too large in absolute value. According to the magnitude of this parameter though, two very different situations may occur. If this is positive (i.e., $h > 0$) the green transition will certainly occur, independently of the initial level of adoptions, while if it is negative (i.e., $0 > h > \widehat{h}_1$) the green transition will take place only if the initial adoption level is sufficiently large (i.e., $x_0 > \overline{x}_M$). This last result suggests that low-carbon transitions may be characterized by path-dependency, thus even if the conditions consistent for a green transition are in place it is not obvious that it will effectively occur since the legacy from past adoption decisions may affect future adoptions driving thus long run environmental outcomes. Between the two previous scenarios, the former identifies a trivial situation in which the adoption incentive due to environmental considerations is sufficiently strong to dominate the disincentive induced by economic issues, ensuring an effective transition to a low-carbon state. The latter instead identifies a

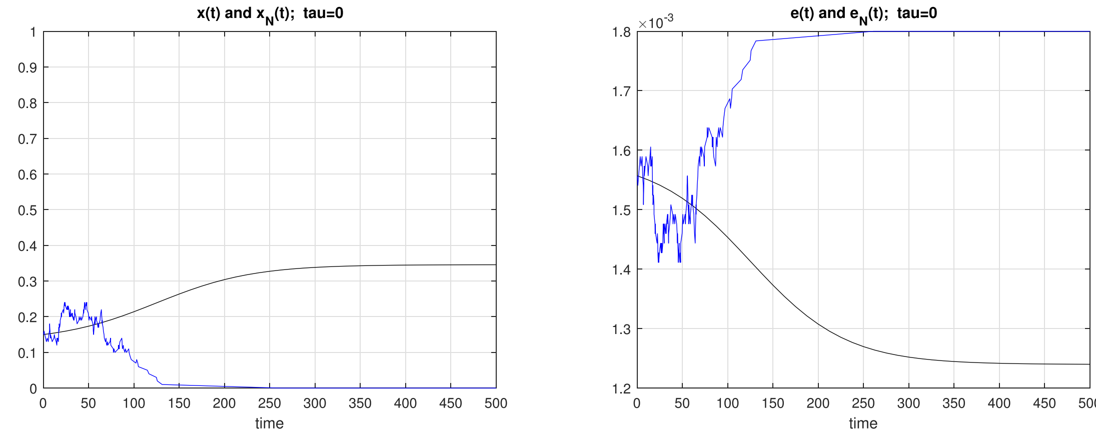

Fig. 1. Dynamics of the adoption rate (left) and emissions (right) in the deterministic (black) and stochastic (blue) settings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

more realistic situation in which economic and environmental motives compete in driving adoption decisions and thus emissions. It seems convenient thus in the following to focus only on this scenario in which a low-carbon transition may take place but it does not necessarily have to occur (i.e., $0 > h > \hat{h}_1$), in order to characterize the issues which may affect the likelihood of green transitions.

In such a case, because of the existence of three equilibria and in particular one unstable equilibrium separating the basins of attraction of the two stable equilibria, the occurrence of a low-carbon transition is clearly not certain and its likelihood depends on the relative size of the basin of attraction of the high equilibrium $\overline{x}_H$. The following proposition quantifies this probability.

Proposition 3. *Assume that* $0 > h > \hat{h}_1$ *and suppose that* $x_0 \sim G$, *where* G *is a suitable cumulative distribution function with support on* $[0, 1]$. *Then the probability that a low-carbon transition takes place is given by* $p = 1 - G(\overline{x}_M)$.

Proposition 3 explicitly quantifies the implications of path-dependency for green transitions determining the likelihood that it may effectively occur. Since by definition G is increasing, such a probability inversely depends on $\overline{x}_M$ which represents the tipping point above which the adoption rate converges to $\overline{x}_H$. It is useful thus to understand how economic, social and environmental factors affect such a tipping point. It is possible to show that the tipping point $\overline{x}_M$ increases with the breakdown probability δ, while it decreases with the net benefit from adoption b, the degree of conformism c, the brown emissions e and the environmental efficiency of the green technology ψ. These parameters determine exactly opposite effects on $\overline{x}_H$, such that whenever $\overline{x}_M$ increases $\overline{x}_H$ decreases. This means that an increase in the tipping point (due for example to an increase in δ or to a decrease in b, c, e or ψ) generates a double negative effect on green transitions: it decreases the probability of a low-carbon transition p, and even if a green transition occurs this will be less effective as in the long run it will be associated with lower adoptions $\overline{x}_H$ and thus higher emissions.

Apart from the complications associated with path-dependency, the likelihood of green transitions may be largely affected by another issue which we have completely neglected thus far, namely uncertainty. Indeed, in our analysis we have simply focused on a deterministic approximation of the true stochastic dynamics, obtained in a context of an infinitely-large number of agents. However, such a deterministic approximation may not be well representative of the behavior of the stochastic system since the random dynamics in a finite-agents context may be characterized by metastability (Marsiglio and Tolotti, 2018; Kollmann et al., 2021). Metastability may occur in the presence of two coexisting locally stable (deterministic) equilibria (such as in our $0 > h > \hat{h}_1$ case), and it implies that, even if the random trajectory starts from the basin of attraction of a particular equilibrium such that we could expect it to converge to such an equilibrium, in finite times it may show out-of-equilibrium dynamics leaving this basin of attraction to enter into another one converging thus to some other equilibrium. Unfortunately though very little can be said from an analytical perspective, and thus in order to clarify the implications of metastability we necessarily need to present some numerical simulations.

Fig. 1 compares the time evolution of adoption (left panel) and emissions (right panel) in the deterministic (black curve) and stochastic (blue curve) settings. The parameters are set according to Proposition 3 such that they are consistent with the possibility of a low-carbon transition, and in particular we set $b = -0.02$, $c = 0.09$, $e = 0.02$, $\psi = 0.1$, $\delta = 0.05$ and $x_0 = 0.015$, implying that $\overline{x}_L = 0$, $\overline{x}_M = 0.13$ and $\overline{x}_H = 0.35$, such that the case (ii) of Proposition 1 applies. Despite our following discussion will be based on the numerical simulations associated with our previous parametrization, it is possible to show that our conclusions are robust and the results we will present are well representative of the possible outcomes arising in the $0 > h > \hat{h}_1$ case. Since $x_0 > \overline{x}_M$ we expect that the stochastic trajectory in Fig. 1 fluctuates around the deterministic trajectory converging to $\overline{x}_H$, such that adoptions gradually increase and emissions gradually decrease, however what we observe is completely different. Till time 50 the stochastic trajectory fluctuates around its mean (i.e, the deterministic dynamic), in line with a green transition; after time 50 we detect an out-of-equilibrium dynamics as the stochastic trajectory abandons its deterministic trend and radically decreases converging to $\overline{x}_L$ and reaching zero at time 150. As adoptions decrease emissions increase converging to a value higher than their initial level. Even if according to our deterministic analysis we should expect a green transition, in the true random system such a transition represents only a transient short run phenomenon since in the long run emissions turn out to be higher than they were initially. Clearly, due to the metastable properties of the stochastic dynamics, inferring the evolution of adoption from a deterministic setting may be highly misleading, thus understanding under which conditions a green transition may effectively occur is not simple at all.

Our previous analysis shows that even if the conditions supporting a low-carbon transition are in place, agents' adoption decisions may not result in long run environmental improvements as such a transition may represent only a transient phase at the end of which the economy will return to a high-carbon intensity state. It is thus natural to wonder whether it is possible to improve long run environmental outcomes through some specific policy interventions, and subsidies are a natural candidate in this context. A publicly-provided subsidy, $\tau > 0$, aimed at stimulating green adoptions affects the economic component of agents' utility as follows: $\epsilon_i = b + \epsilon_i + \tau$, such that in our deterministic

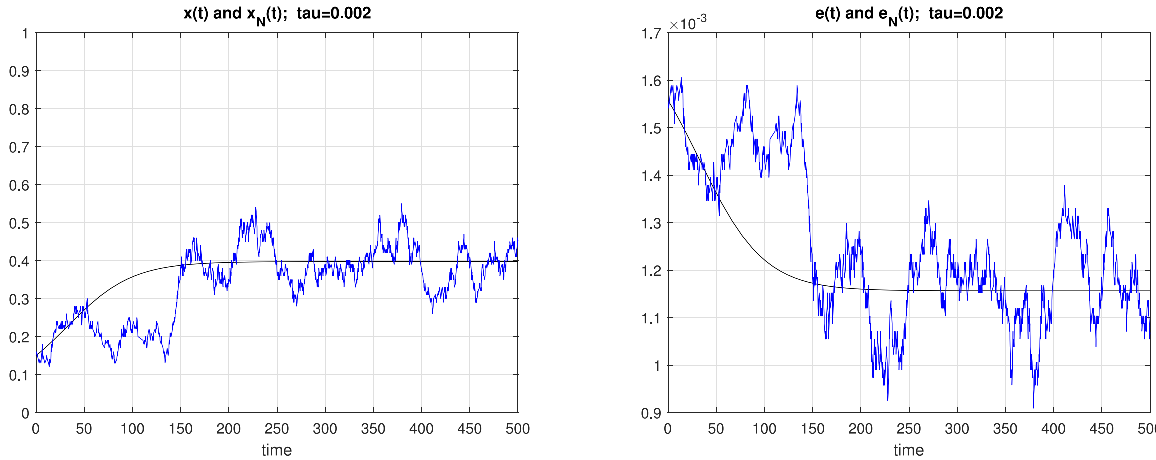

Fig. 2. Dynamics of the adoption rate (left) and emissions (right) in the deterministic (black) and stochastic (blue) settings in the case of a small subsidy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

asymptotic approximation the evolution of the adoption rate is given by the following equation:

$$\dot{x}_t = (1 - x_t)\eta(h + \tau + J x_t) - \delta x_t \tag{9}$$

Apart from increasing the equilibrium adoption rate, a subsidy (even a small one) allows to stabilize the stochastic fluctuations in the random system ruling out out-of-equilibrium dynamics. By relying on the same parameterization earlier employed, Fig. 2 compares the time evolution of adoption (left) and emissions (right) in the deterministic (black curve) and stochastic (blue curve) settings in the case of a small subsidy,[3] which has been set as $\tau = 0.002$. Different from what we have seen in Fig. 1, now the stochastic adoption trajectory continues to fluctuate around the deterministic one, showing convergence to the equilibrium $\overline{x}_H$; in this case the adoption trend is positive while the emissions trend is negative suggesting that in the long run emissions will effectively be lower than their initial level. This suggests that by properly tailoring the size of the subsidy it is possible to ensure that a green transition is associated with a permanent reduction in the carbon intensity generating long run environmental improvements.

Our analysis thus far has allowed us to identify two major issues which may affect the effective transition to a low-carbon economy. Indeed, even if the conditions consistent with a green transition are met, such a transition does not necessarily need to occur, because of path-dependency and metastability. Path-dependency implies that the legacy of past adoptions may affect future adoptions, precluding a reductions in emissions unless the initial adoption rate exceeds a tipping point, and such a tipping point determines the probability of the success of a low-carbon transition. Metastability implies instead that the uncertainty induced by the complex interactions between social and environmental factors may generate out-of-equilibrium dynamics leading a green transition to represent only a short run phenomenon not resulting in an effective reduction in long run emissions; this decreases the probability of the success of a low-carbon transition with respect to the level determined by path-dependency considerations. Public policy in the form of a subsidy though can solve both these issues, and even a small subsidy may be effective in promoting a green transition by decreasing the tipping point and ruling out out-of-equilibrium dynamics.

[3] The size of the subsidy required to stabilize the stochastic fluctuations in the random system depends on the other parameter values, but since we are relying on a numerical analysis in this context we cannot quantify exactly how large such a subsidy needs to be. Therefore, in our discussion of a "small" subsidy we are referring to a subsidy just enough to rule out out-of-equilibrium dynamics.

3. Network and multiplexity

An effective transition to a low-carbon economy is ultimately a geographical process since it involves a substantial change in the spatial patterns of economic and social activities (Bridge et al., 2013; Siksnelyte-Butkiene et al., 2022). In our previous analysis we have been unable to discuss this matter since our benchmark framework entirely abstracts from a spatial dimension, which nevertheless plays an important role in determining agents' adoption decisions through both environmental and social links. In order to understand how our results may change by allowing for spatial considerations, we now introduce a network structure into our baseline model (Newman, 2010; Kollmann et al., 2021). The network represents the global economy in which the nodes represent the local economies which compose it, and local economies within the network are interconnected by multiplex ties. Since pollution is transboundary the emissions generated in one single local economy affect other local economies as well, thus the adoption decisions of agents located in different local economies are all interrelated as the relevant environmental driver of the green technology adoption is the overall emissions level within the global economy (Ansuategi and Perrings, 2000; La Torre et al., 2021). Moreover, since in modern economies information spreads widely and fast through social media and other communication means imitation effects may extend outside the single local economy such that agents' adoption decisions in different local economies are all interrelated also because the relevant social driver of their choice is the overall adoption rate within the global economy (Berger and Milkman, 2012; Zhu et al., 2020).

For the sake of simplicity we present our extended framework directly in terms of its deterministic asymptotic approximation. We consider a spatial setup where a set of locations (i.e., local economies) form a network (i.e., global economy). Each location (a node on the graph) is characterized by a degree which measures the number of locations it is interconnected to. Following the complexity science literature (Barthélemy et al., 2005; Barrat et al., 2008), different local economies are located on a graph characterized by a certain degree distribution p^k, whose average $\lambda > 0$ measures the average number of connections among locations. Therefore, this parameter captures the intensity of the interconnections between agents across locations and the extent to which spatial interactions within the network matter in determining individual agents' adoption choices. In particular, due to the transboundary nature of pollution and the wide spread of information, the probability that an agent in a location with degree k adopts the green technology depends on the social and environmental utility components as follows: $s_t^k = c v_t$ and $e_t^k = e - e(1-\psi)v_t$, representing the overall adoption rate and the overall emissions in the network, respectively. In the previous expressions, $v_t = \sum q^k x_t^k$ measures the average (across locations) share of agents deciding to adopt the green technology with q^k representing the excess degree distribution related to the distribution p^k, and such an average adoption rate on the one hand increases agents' conformism motive as agents wish to imitate the behavior of other agents in the network and on the other hand decreases emissions by reducing the ecological footprints within the network. This formulation is based on the so-called *degree based approach* (see Barthélemy et al., 2005), and it states that through both the social and environmental channels all agents in locations with degree k have the same likelihood of adopting, independent of their exact location, and such a probability depends on the degree of the neighborhood, k, multiplied by the probability that a directly connected agent adopts, and this latter probability depends on v_t (through social and environmental considerations). Accounting for such spatial interconnections through the social and environmental channels, the evolution of the share of adopting agents residing in a location with degree k and emissions in a location with degree k are respectively given by the following equations:

$$\dot{x}_t^k = (1 - x_t^k)\eta \left(b + \frac{k}{\lambda} c v_t + \frac{k}{\lambda} e_t^k\right) - \delta x_t^k \quad (10)$$

$$e_t^k = e - e(1-\psi)v_t, \quad (11)$$

where the term $\frac{k}{\lambda}$ generalizes our benchmark a-spatial model to account for the influence of transboundary (environmental and social) effects in agents' adoption decisions. By plugging (11) into (10) the green adoption rate in a location with degree k can be rewritten as follows:

$$\dot{x}_t^k = (1 - x_t^k)\eta \left(\tilde{h}(k) + \tau + \tilde{J}(k) v_t\right) - \delta x_t^k, \quad (12)$$

where $\tilde{h}(k) \equiv b + \frac{k}{\lambda} e$ and $\tilde{J}(k) \equiv \frac{k}{\lambda} c - \frac{k}{\lambda} e(1-\psi)$ represent the spatial effective benefit from adoption and the spatial effective degree of conformism, respectively. Such parameters differ from their a-spatial counterparts, h and J, because of the presence of the $\frac{k}{\lambda}$ term which captures the spatial interrelations across locations (via environmental and social factors) within the network and clearly depends on k and λ. The higher the degree, k, the higher the probability that agents' decisions are influenced by what is happening within the whole network. The higher the average degree of the network, λ, the smaller the effect of a single location on the individual agent's adoption decision. Indeed, if all locations have the same degree ($k \equiv \lambda$), our extended model in (12) reduces to our benchmark a-spatial model in (9); in fact, in this case, $\tilde{h}(k) = h$, $\tilde{J}(k) = J$ and $v_t = x_t$, such that the network is an exact replica of all the identical locations that compose it. To simplify the comparison with what we have discussed in the previous section, rather than commenting on what happens in a single location it may be convenient to focus on the proportion of agents adopting the green technology and the emissions level within the whole network, which can be obtained as the weighted average of all x^k, that is $x_t = \sum_{k=0}^{\infty} p^k x_t^k$ and $e_t = \sum_{k=0}^{\infty} p^k e_t^k$, respectively.

As in our benchmark case, we start by analyzing what happens in a deterministic approximation of the random dynamics in which uncertainty does not play any role, and in particular we wish to understand how the network structure modifies our previous conclusions. Unfortunately, analytical results cannot be derived since (12) characterizes a system of k differential equations, but we can nevertheless determine some sufficient conditions ensuring the existence of unique or multiple equilibria. This is summarized in the following proposition (a sketch of its proof is presented in Appendix).

Proposition 4. *Consider $x_t = \sum_{k=0}^{\infty} p^k x_t^k$, where x_t^k is described by (12) for all k. The following situations may apply:*

(i). if $\tilde{h}(k) + \tau + \tilde{J}(k) \le 0$ for all k such that $q^k > 0$, then there exists a unique equilibrium $\bar{x} = 0$;
(ii). if there exists $\bar{k} > 1$ such that for $k < \bar{k}$, $\tilde{h}(k) + \tau + \tilde{J}(k) \le 0$, whereas for $k \ge \bar{k}$, $\tilde{h}(k) + \tau + \tilde{J}(k) > 0$ and, moreover, $\tilde{h}(k) + \tau \le 0$, then there may coexist multiple equilibria $\bar{x}_L = 0$ and $\bar{x}_H > 0$;

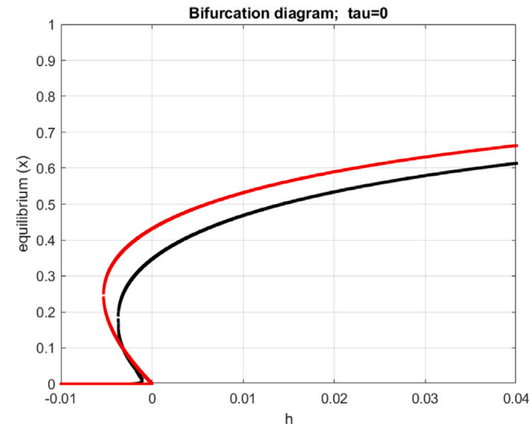

Fig. 3. Bifurcation diagram in the $(h, \bar{x})$ plane, both in the spatial (black) and a-spatial (red) settings. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(iii). if there exists $\bar{k} > 1$ such that $\tilde{h}(k) + \tau > 0$, then there exists a unique equilibrium $\bar{x} > 0$.

Proposition 4 states that for different values of the spatial effective benefit from adoption and the spatial effective degree of conformism there may exist a unique or multiple equilibria, similar to what we have discussed in the previous section (see Proposition 1), but it does not determine the value of the equilibria different from the zero adoption outcome. Moreover, since the spatial effective benefit and the spatial effective degree of conformism depend on k there are k different values of these parameters, thus understanding clearly what is the parameter region in which unique or multiple equilibria arise is not straightforward, thus it may be convenient to rely on a graphical illustration. Specifically, we represent graphically the possible equilibria through a bifurcation diagram in which we show how the number and the value of the equilibria change with the effective benefit h (and not with the spatial effective benefit $\tilde{h}(k)$ as stated in Proposition 4, in order to simplify the comparison with what we have discussed in the previous section). Fig. 3 compares the equilibrium outcomes in our spatial (black curve) and a-spatial (red curve) frameworks (by focusing on the $\tau = 0$ case, again to ease the comparison with our previous results), showing that qualitatively the two settings yield the same results: when h is negative and large in absolute value there exists a unique equilibrium associated with no adoptions, when h is positive there exists a unique equilibrium associated with positive adoptions, and when h is negative and small in absolute value there exist multiple equilibria in which the intermediate equilibrium separates the basins of attraction of the low and high equilibria, characterized by no and positive adoptions, respectively (see Proposition 1). There exist two important quantitative differences though. (i) In the $h > 0$ case the equilibrium adoption level is smaller and thus emissions are larger in the spatial framework than in the a-spatial one. (ii) The parameter region in which multiple equilibria coexist is smaller in the spatial setting than in the a-spatial one, and in such a region the value of the tipping point is larger and that of the high equilibrium is smaller in the spatial context. This suggests that whatever we have earlier discussed in the previous section to a large extent applies also in the presence of spatial interactions. However, we can also conclude that since in this context the tipping point is larger than in the a-spatial setting, in the parameter region in which multiple equilibria coexist, the probability of a low-carbon transition is smaller in the spatial framework than in the a-spatial one (see Proposition 3).

In order to understand the role of different levels of spatial interactions on adoptions and emissions within the network, we now proceed with a numerical analysis. First, we specify the degree distribution as a Poisson distribution where λ measures both its average and variance. We keep relying on the same parametrization consistent with the

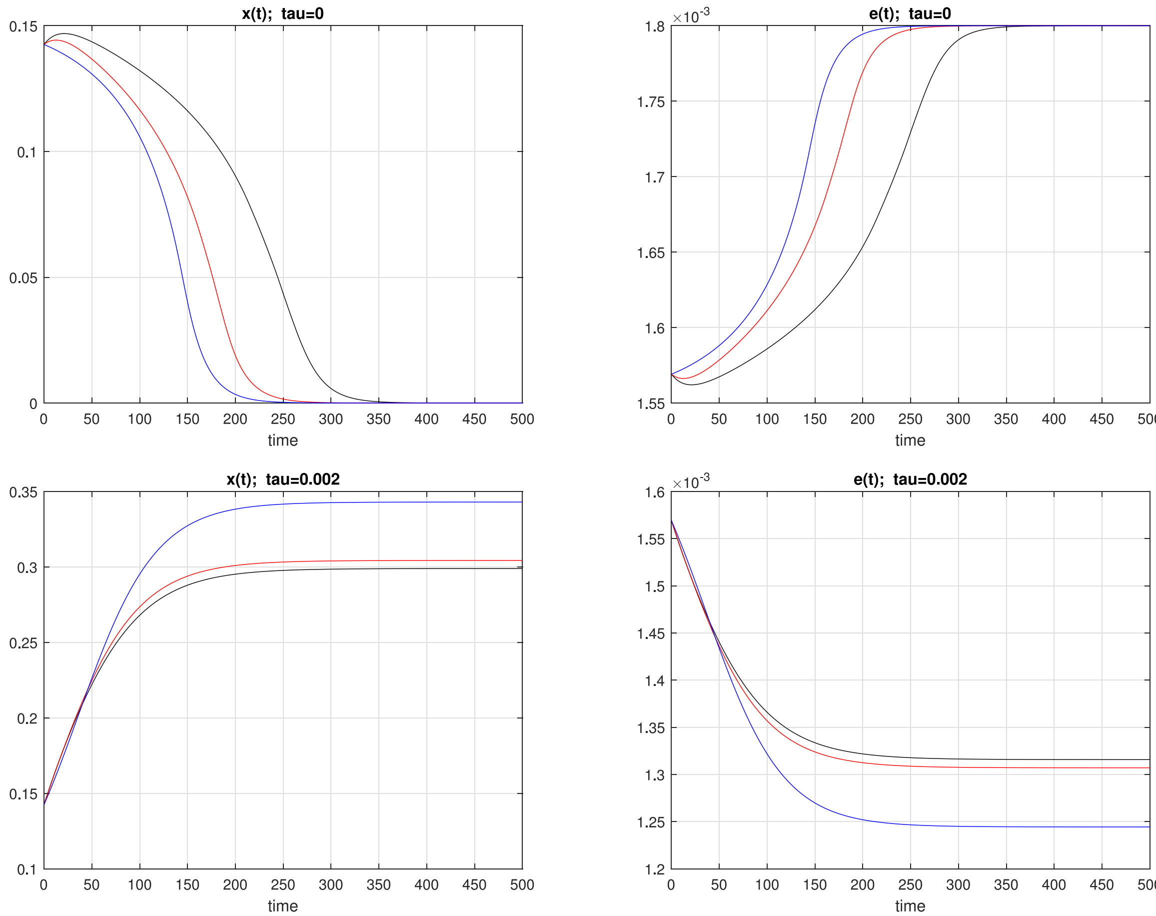

Fig. 4. Dynamics of the adoption rate (left) and emissions (right) in the deterministic setting in the $\tau = 0$ (top) and $\tau = 0.002$ (bottom) cases, whenever spatial interactions involve only environmental (blue), only social (red) and both environmental and social (black) outcomes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

possibility of a low-carbon transition that we have employed in the previous section ($0 > h > \hat{h}_1$), while we set $\lambda = 3$. It is possible to show though that changes in λ do not affect qualitatively our conclusions and a lower λ will lead to a lower long run adoption rate and thus higher emissions. Second, we distinguish three possible specifications of the model that account for different ways in which the spatial dimension (k) interferes with the adoption process (h, J). Specifically, the case in which spatial interactions involve: (i) only environmental outcomes, namely $\tilde{h}(k) \equiv b + \frac{k}{\lambda}e$ and $\tilde{J}(k) \equiv c - \frac{k}{\lambda}e(1-\psi)$; (ii) only social outcomes, namely $\tilde{h}(k) \equiv b + e$ and $\tilde{J}(k) \equiv \frac{k}{\lambda}c - e(1-\psi)$; (iii) both environmental and social outcomes, namely $\tilde{h}(k) \equiv b + \frac{k}{\lambda}e$ and $\tilde{J}(k) \equiv \frac{k}{\lambda}c - \frac{k}{\lambda}e(1-\psi)$. These three specifications allow us to disentangle the relative impact of spatial effects on the outcome of the model (x_t and e_t), in terms of the different behavioral motives in the adoption choice. Fig. 4 illustrates the deterministic dynamics of the adoption rate (left panels) and emissions (right panels) in the $\tau = 0$ (top panels) and $\tau = 0.002$ (bottom panels) cases, and under the three specifications just described: (i) spatial interactions involve only environmental outcomes (blue curve); (ii) only social outcomes (red curve); (iii) both environmental and social outcomes (black curve).

By comparing the top and bottom panels with the black curves in Figs. 1 and 2, respectively, we can observe that the presence of spatial interactions completely changes the adoption and emissions patterns. With no subsidy, while in an a-spatial setting adoptions gradually increase to allow for a gradual decrease in emissions (see Fig. 1) in our spatial network adoptions monotonically decrease converging to zero such that emissions increase and turn out in the long run to be higher than their initial level, and this result holds true even if the initial adoption level exceeds the (a-spatial) tipping point (i.e., $x_0 > \overline{x}_M$) and independent of the type of spatial interactions considered. The type of spatial interactions affects though the speed of adoptions fallout and emissions growth, which are fastest when spatial interactions involve only environmental factors (specification (i)) and slowest when they involve both environmental and social factors (specification (iii)). With a small subsidy, we observe a gradual increase in adoptions and decrease in emissions both in the a-spatial and spatial frameworks, but the long level of adoptions within the network is lower and thus the long run level of emissions are higher than in the a-spatial context (see Fig. 2), and this is true independent of the type of spatial interactions considered. The type of spatial interaction affects the magnitude of the differences between the spatial and a-spatial settings, which are smallest when spatial interactions involve only environmental factors (specification (i)) and largest when they involve both environmental and social factors (specification (iii)). In particular, when spatial interactions are due both to environmental and social factors the long run adoption rate within the network is about 10% smaller and thus long run emissions are about 15% larger than in the a-spatial context.

We now introduce uncertainty in the analysis in order to understand whether and how the network structure interacts with the metastable properties of the stochastic dynamics. We focus on the fully-fledged network framework in which spatial interactions involve both environmental and social factors (specification (iii)). Fig. 5 compares the time evolution of adoption (left panels) and emissions (right panels) in the deterministic (black curve) and stochastic (blue curve) settings, whenever $\tau = 0.002$ (top panels) and $\tau = 0.004$ (bottom panels). The top panels analyze the implications of uncertainty in the case of a small subsidy, which in our previous a-spatial analysis we have

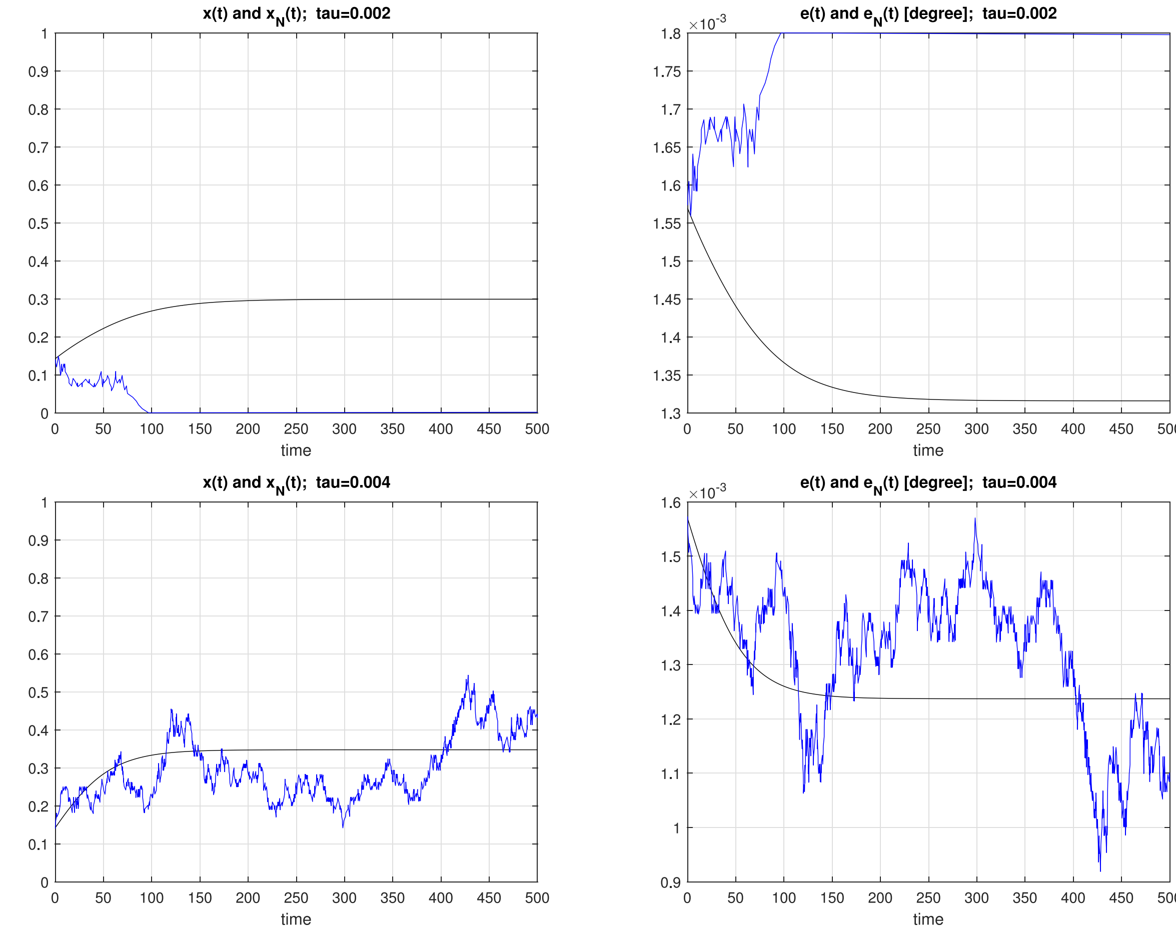

Fig. 5. Dynamics of the adoption rate (left) and emissions (right) in the deterministic (black) and stochastic (blue) settings in the case of a low (top) and high (bottom) subsidy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

seen being enough to fix the out-of-equilibrium issues leading the low-carbon transition to represent only a short run transient phase after which emissions turn high again (see Fig. 2). However, the presence of spatial interactions changes completely our conclusions as the same subsidy earlier considered is not enough to avoid metastability to bring adoptions to converge to zero and thus emissions to increase, and actually we observe that a low-carbon transition does not occur even in a transient form since adoptions decrease and emissions increase since time 0. The bottom panels show the effects of a large subsidy (i.e., with a double size with respect to the previous one) which instead is effective in stabilizing the stochastic fluctuations in the random system ensuring an adoption and emissions pattern consistent with a permanent green transition. This result shows that the intensity of the policy measures required to effectively support a low-carbon transition substantially increases when we take into account the presence of spatial interactions.[4]

On top of the path-dependency and metastability issues discussed in our benchmark model, our analysis in a spatial network context has allowed us to identify another potential problem affecting the effective transition to a low-carbon state, namely spatial interactions. Indeed, the presence of spatial interactions (due to social factors, environmental factors, or both) tends to reduce adoption increasing thus emissions, nontrivially interacting with tipping points and out-of-equilibria dynamics. Spatial interactions may increase the tipping point meaning that, compared to what we have earlier discussed in our previous a-spatial analysis, a higher initial adoption rate may be needed to generate a reduction in emissions, reducing thus the likelihood of a green transition to take place. Spatial interactions may also reduce the effectiveness of public policy suggesting that, again compared to what we have earlier discussed in our previous a-spatial analysis, a higher subsidy may be required to ensure that a green transition effectively results in lower long run emissions. This suggests that assessing the conditions under which green transitions may occur is all but trivial and performing this task without properly quantifying the extent of spatial interactions may be highly misleading, since the intensity of public policy determined by abstracting from spatial considerations may not be enough to promote a greener future.

4. Conclusion

The growing need for climate mitigation has increased the demand by both private individuals and public institutions for a low-carbon future. However, understanding how to design policies to favor a green transition is not simple since several factors may limit their effectiveness. In particular, the uncertain and complex characteristics of energy systems play a key role in determining the eventual success of low-carbon transitions. Our paper aims to shed some light on the

[4] As mentioned earlier, from our numerical analysis we cannot quantify exactly the required size for a subsidy to stabilize the stochastic fluctuations in the random system. Therefore, in our discussion we are referring to a subsidy as "small" if it is just enough to rule out out-of-equilibrium dynamics in the absence of spatial interactions, and as "large" if it takes a value large enough to rule out out-of-equilibrium dynamics even in the presence of spatial interactions. Even if this creates some problems in interpreting in quantitative terms the relative size of small and large subsidies, we believe that from a qualitative point of view our conclusions are extremely clear and useful to characterize the policy implications of spatial interactions.

possible problems associated with such uncertainty and complexity along with the potential strategies to overcome them. Specifically, we analyze a discrete choice agent-based model where heterogeneous utility-maximizing agents optimally decide whether to adopt a green technology by accounting for social and environmental considerations. The decision to adopt is positively related both to the share of individuals adopting and the level of emissions, thus as some agents adopt the importance of social factors strengthens while that of environmental issues weakens, generating unclear effects on the adoption rate and thus on the likelihood that a low-carbon transition effectively takes place.

We characterize the determinants of the success of such a transition, emphasizing that even if the favorable conditions are met, the green transition may not result in long run environmental improvements because of path-dependency and metastability. Public policy may solve these problems by increasing through subsidies the incentive for single agents to adopt, ensuring thus the achievement of a permanent low-carbon state. By extending the analysis to a spatial network characterized by multiplexity in which the transboundary nature of pollution and the wide spread of information represent different layers of interrelations across economies, we show that spatial interactions negatively affect agents' adoption incentive yielding detrimental environmental consequences and reduce the effectiveness of public policy by interacting in a nontrivial way with path-dependency and metastability. Our analysis suggests thus that determining environmental policy without properly quantifying spatial interactions may lead to misleading conclusions, compromising the likelihood to eventually achieve a low-carbon state.

To the best of our knowledge, ours is the first paper trying to account for the implications of uncertainty and complexity on low-carbon transitions from a policy perspective. In order to present our arguments in the simplest and most intuitive way we have analyzed a stylized and analytically tractable agent-based model in which heterogeneity is rather limited. In reality heterogeneity involves a range of agents' characteristics which should be properly accounted for in order to truly understand how to design effective policy measures to support green transitions. Extending the analysis along this direction is left for future research.

CRediT authorship contribution statement

Simone Marsiglio: Writing – original draft, Formal analysis, Conceptualization. **Marco Tolotti:** Writing – original draft, Formal analysis, Conceptualization.

Appendix. Technical appendix

Proof of Proposition 1. The possible equilibria of the variable x are related to the (stable) steady states of (8). Since $\eta(\cdot)$ can take value 0, 1 or $h + Jx$, it is not difficult to see that the possible equilibria are $\bar{x} = 0$ (when $\eta(\cdot) = 0$), $x_\delta = \frac{1}{1+\delta}$ (when $\eta(\cdot) = 1$), and $x_{+,-} = \frac{J-h-\delta\pm\sqrt{[J-h-\delta]^2+4Jh}}{2J}$, when the argument of η takes values in $(0,1)$. Depending on the values of the parameters, one (or more than one) of these situations may happen. Specifically, the equilibrium can be unique or three of them coexist. In this latter case, the intermediate one is unstable ant the two extremese are (locally) stable. In order to study existence of the different equilibria, we introduce some relevant values for the parameter h: $\widehat{h}_1 = 2\sqrt{J\delta} - J - \delta$ and $\widehat{h}_2 = 1 - \frac{J}{1+\delta}$; note that $\widehat{h}_1 < 0$ and $\widehat{h}_1 < \widehat{h}_2$.

Let us start by the extreme cases. If $h + Jx \le 0$, then $x = 0$ is the equilibrium. This happens if and only if $h \le 0$. We infer that $h \le 0 \implies \bar{x} = 0$ is an equilibrium. In case $h + Jx \ge 1$, then x_δ is an equilibrium. Substituting such value in the equation, we obtain that $h \ge \widehat{h}_2 \implies x_\delta$ is an equilibrium. Note that the two extreme equilibria seen so far may also coexist in case $\widehat{h}_2 \le h \le 0$.

We now discuss the existence of $x_{+,-}$. To this aim, we need to check that the argument of the square root is positive and that $0 < x_{-,+} \le 1$. Concerning x_-, after some algebraic calculations, we find that this happens if and only if $\widehat{h}_1 < h < 0$. As far x_+ is concerned, a similar argument shows that x_+ exists if and only if $h > \widehat{h}_1$. Moreover, we need also to impose that $h < \widehat{h}_2$, otherwise it can be proved that $x_\delta < x_+$ and this makes impossible for the system to reach the larger equilibrium x_+. Therefore, the final existence condition for x_+ is $\widehat{h}_1 < h < \widehat{h}_2$.

Summarizing, we see that a few situations related to h can happen: if $h < \widehat{h}_1$, only $\bar{x} = 0$ is an equilibrium. In case $h > 0$, the equilibrium is again unique but now $x = 0$ is excluded. The prevailing equilibrium is $\bar{x} = \min\{x_+, x_\delta\}$ and this depends on the fact that h is smaller or larger than $\widehat{h}_2$. In the remaining range for h, namely when $\widehat{h}_1 < h < 0$, three steady states coexist: $\overline{x}_L = 0$, $\overline{x}_M = x_-$ and $\overline{x}_H = \min\{x_+, x_\delta\}$. Again, the larger equilibrium depends on the fact that h is smaller or larger than $\widehat{h}_2$. In all those situations, it is not difficult to show that the intermediate equilibrium $x_M = x_-$ is locally unstable, whereas the extreme ones are stable.

Proof of Proposition 2. According to Proposition 1, a transition towards a situation where the prevailing equilibrium has positive adoption states ($x > 0$) is possible if and only if $h > \widehat{h}_1$.

Proof of Proposition 3. When $0 > h > \widehat{h}_1$, two locally stable equilibria coexist, namely, $\bar{x}_L = 0$ and $\bar{x}_H = \min\{x_\delta, x_+\}$. Depending on the initial condition $x(0) = x_0$, the trajectory x_t will eventually reach one of them. More specifically, the prevailing one depends of the fact that x_0 is smaller or larger that the intermediate equilibrium, $\bar{x}_M = x_-$. In fact, the trajectory cannot overpass the locally unstable equilibrium. In this respect, we can say that $\bar{x}_M$ separates the basins of attraction of the two locally stable extreme equilibria. Suppose now that there is no perfect knowledge on x_0; we just know that x_0 is a random variable with distribution function G. The probability of reaching the large equilibrium $\bar{x}_H$ is equivalent to the probability of laying in the basin of attraction of such equilibrium. As said, this is related to the value of $\bar{x}_M$. In fact, $\mathbb{P}(x_0 > \bar{x}_M) = 1 - G(\bar{x}_M)$.

Proof of Proposition 4. Thanks to (12), we can derive the (unique) equilibrium for x^k, given an equilibrium value of v:

$$x^k(v) = \frac{\eta(v,k)}{\delta + \eta(v,k)},$$

where, with a slight abuse of notation, we put evidence on the fact that now η depends on k through $\tilde{h}(k)$ and $\tilde{J}(k)$. Since $v = \sum_{k=0}^{+\infty} q^k x_t^k$, v^* is an equilibrium if and only if:

$$v^* = \sum_{k=0}^{+\infty} q^k x^k(v^*) := F(v^*).$$

Once v^* is determined, it follows that:

$$x^* = \sum_{k=0}^{+\infty} p^k \frac{\eta(v^*,k)}{\delta + \eta(v^*,k)}.$$

Therefore, we restrict our attention to the determination of the equilibrium values for v.

(i) If $\tilde{h}(k) + \tau + \tilde{J}(k) \le 0$ for all k such that $q^k > 0$, then $v = 0$ ($x = 0$) is the unique equilibrium. In fact, there is no value v that makes $F(v)$ strictly positive.

(ii) If $\tilde{h}(k) + \tau \le 0$ for all k such that $q^k > 0$, then $\eta(v,k) = 0$ for all relevant values of k; therefore, $F(v) = 0$ for all v and $v = 0$ (equivalently, $x = 0$) is an equilibrium. Moreover, if there exists $\bar{k}$ such that for $k < \bar{k}$, $\tilde{h}(k) + \tau + \tilde{J}(k) \le 0$, whereas for $k \ge \bar{k}$, $\tilde{h}(k) + \tau + \tilde{J}(k) > 0$, then a positive solution to $v = F(v)$ may exist. First of all, note that both $\tilde{h}$ and $\tilde{J}$ are increasing in k, so the assumption is satisfied for suitable values of the parameters b, c, e, ψ, δ and λ. Having said that, consider that:

$$F(v) = \sum_{k \ge \bar{k}} q^k \frac{\tilde{h}(k) + \tau + \tilde{J}(k)v}{\delta + \tilde{h}(k) + \tau + \tilde{J}(k)v}. \tag{13}$$

A natural upper bound for $F(v)$ is $\frac{1}{1+\delta}$, since by definition $\eta(v,k) \leq 1$. On the other hand, since both $\tilde{h}$ and $\tilde{J}$ are increasing in k, also the RHS of (13) is increasing in k, therefore, we have that:

$$F(v) \geq \bar{F}(v) := \sum_{k\geq\bar{k}} q^k \frac{\tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v}{\delta + \tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v} = \bar{q} \cdot \frac{\tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v}{\delta + \tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v},$$

where $\bar{q} = \sum_{k\geq\bar{k}} q^k$. Depending on the parameters, the following fixed point equation

$$v = \bar{q} \cdot \frac{\tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v}{\delta + \tilde{h}(\bar{k}) + \tau + \tilde{J}(\bar{k})v}$$

admits a solution $v^\ell \in (0, \frac{1}{1+\delta})$. Therefore, in this case we have that:

$$F(v) \geq \bar{F}(v^\ell) = v^\ell > 0.$$

Summarizing, since F is continuous and defined on the compact set $[v^\ell, \frac{1}{1+\delta}] \in (0,1)$, thanks to Brewer's fixed point theorem, there exists at least one value $v \in (v^\ell, \frac{1}{1+\delta})$ such that $v = F(v)$. This, together with (i), proves the existence of multiple equilibria for v, under these assumptions on the parameters.

(iii) As soon as $\tilde{h}(k) + \tau > 0$ for some k, $v = 0$ cannot be a solution of $v = F(v)$, since $F(0) > 0$. On the other hand, since $F(v) \leq \frac{1}{1+\delta}$ for all the values of the parameters, a positive solution $v \leq \frac{1}{1+\delta}$ must exist. Being F monotone, such solution is unique.

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