COMPETITIVE DIFFUSION AND SUSTAINABILITY TRANSITIONS: THE CASE OF PLASTICS RECYCLING TECHNOLOGIES

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Competitive diffusion and sustainability transitions: the case of plastics recycling technologies

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Abstract

Climate change calls for a transition to a more sustainable economy. Incumbent technologies pose a barrier to the diffusion of innovative solutions. Furthermore, the benefits of novel sustainable practices, such as recycling, can be offset by the adoption of obsolete polluting technologies. Understanding the mechanism of competitive diffusion is crucial for designing policies that favour promising but underdeveloped technologies. We propose an agent-based model where adoption occurs in a social network by word-of-mouth, in a percolation framework. We study how learning affects competitive diffusion and find that small differences in technologies' costs lead to large differences in their diffusion sizes. In addition, increasing the number of early adopters can back-fire and hinder overall diffusion. We calibrate the model to data on plastic waste recycling, where alternative solutions such as mechanical and physical/chemical technologies compete for a new market. Green public procurement, tax exemption and R&D boost are implemented for triggering sustainable transitions. The direction of technical change is discussed, as well as the role of policymakers in creating a shift in the plastic value chain.

JEL classification: C66, O33, Q55.

Keywords: Agent-based modeling, Learning curves, Mission-oriented policies, Networks, Percolation.

1 Introduction

Climate change is undeniably a global issue of the utmost importance, presenting a myriad of challenges that demand structural changes and collective efforts. Transitioning to renewable energy sources, carbon sequestration strategies, and sustainable practices are essential steps towards a resilient and sustainable future. More generally, the mitigation of the effects of climate change requires a multifaceted approach encompassing international cooperation, sustainable development, and the adoption of innovative technologies. But eco-innovations alone are not enough for climate change mitigation (Kesidou et al., 2024). Empirical studies have shown that often the benefits of eco-innovations strongly depend on the efficient use of materials and energy through recycling, re-manufacturing or refurbishing (Murray et al., 2017; Durán-Romero et al., 2020). The Waste Packaging Directive of the European Commission has estimated a potential reduction of 443 million tonnes of GHG between 2014 and 2030 (European Commission, 2014, 2020). Our paper focuses on the competition dynamics of technologies for plastics recycling at different stages of development (mature vs. emerging technologies).

In a context where *history matters*, the diffusion and competition of innovations drive structural changes in the economy and society (David, 1985; Arthur, 1989; Dosi and Nelson, 2013). More precisely, the cumulative nature of capital and knowledge embodied in workers creates strong path dependencies for firms (Hepp, 2022). Potential sources of lock-in relating to technology, markets, industrial and organizational value chains have been identified (Cecere et al., 2014; Brenner and zu Jeddeloh, 2023; Mundt et al., 2023). Path dependency is driven by self-reinforcing processes with a state of lock-in, from which it is difficult to escape. This lock-in can lead to persistent inefficiencies, by preventing the system from evolving towards better alternatives. 'Carbon lock-in', or the persistence of an unsustainable economic system based mainly on high-carbon technologies, is a significant example of being trapped in a Pareto-dominated state caused by a path-dependent process (Foxon, 2011; Seto et al., 2016; Korhonen et al., 2018). However, when it comes to the diffusion of their preferred technological trajectory, actors within the economic system do not act neutrally, which may affect the existing 'carbon lock-in' in various ways (Barbault et al., 2023; Rödl et al., 2022).

Thus, social structure is a key driver of the diffusion process, responsible for nonlinear patterns involving sharp transitions from a regime of no diffusion to a regime of diffusion. In particular, the academic literature has demonstrated the importance of nonlinear diffusion matters for the adoption of innovative products or behaviours by potential adopters. This non-linearity arises from the structure and heterogeneity of individual preferences and social or economic connections. (Janssen and Jager, 2002; Cowan and Jonard, 2004; Young, 2006; Schilling and Phelps, 2007; Jackson and Yariv, 2007; Jackson et al., 2008; Banerjee et al., 2013; Lazaric et al., 2020). Furthermore, processes of social diffusion, such as those involving innovative products and technologies, are further complicated by the evolving nature of the entities being diffused. As products evolve and technologies improve during the diffusion process, these changes can have a significant impact on the dynamics and outcomes of diffusion (Cantono and Silverberg, 2009) and specifically, on the recycling dynamics for both consumers and producers (Brouillat and Oltra, 2012).

Innovative technologies usually enter in a market where mature technologies are already in use by a large customer base. Technologies for material recycling represent a special case. When structural economic changes occur, such as those triggered by the introduction of recycling technologies, new markets emerge and become the battleground for different technological options. Here, the competition is at ground zero, with a large number of potential adopters, and little adoption so far. Different technologies are at different stages of their respective learning curves, with innovative technologies competing with mature ones. This scenario is particularly relevant for sustainable innovations, which are often cited to combat climate change. Our working example is the plastics recycling market, in which alternative solutions exist such as mechanical recycling, physical recycling and chemical recycling and represent diverse competing technologies at different stages of development.

In this paper we study the competitive diffusion of technologies in a new market, proposing a calibrated agent-based model based on a percolation framework, extending Zeppini and Frenken (2018). Although percolation was originally developed in physics (Stauffer and Aharony, 2018), it can be effectively interpreted through the economic concept of reservation price and has shown to accurately describe the mechanisms and phenomena of innovation diffusion in social systems (Solomon et al., 2000; Hohnisch et al., 2008; Cantono and Silverberg, 2009; Konc and Savin, 2019; Tur et al., 2018, 2024). From a methodological perspective, agent-based modelling is a powerful tool for describing dynamics, particularly with the influence of agents heterogeneity and network structure on innovation diffusion processes (Kiesling et al., 2012; Balint et al., 2017; Zhang and Vorobeychik, 2019; Ramkumar et al., 2022).

In Zeppini and Frenken (2018)), consumers adopt an innovative product by consumers through word-of-mouth in a social network. Consumers are characterized by their reservation prices, which represent their maximum willingness to pay and which they use to evaluate the product, once they have received information about it. Information is local: a consumer is informed if someone they know has adopted the product. A critical price is key to creating a jump in demand among consumers, leading to a transition from a no- diffusion to a diffusion regime. We extend this framework to include the competitive diffusion of substitute technologies with learning in a network of firms representing potential adopters. Multiple diffusion processes within the same network are crucial element for understanding the role of economies of scale in the spread of innovation, as the market share of each competing innovation impacts the individual adoption decision (Zeppini and Van Den Bergh, 2020; Geels and Ayoub, 2023). Additionally, we introduce technological change, whereby the cost of a technology is affected by learning and adoption rates, rather than being constant. Learning decreases the cost of technology through adoption, thereby fostering further adoption.

In our simulations, we focus on the specific scenario where the competition takes place between a mature technology and an emerging one. The latter is characterized by a higher learning rate, as well as a higher initial cost. These features allow our model to be empirically grounded, and are particularly relevant for several cases of technology competition linked to environmental sustainability, the most notable example being power generation (Zeppini and Van Den Bergh, 2020; Way et al., 2022). We calibrate the model to the case of recycling technologies for plastic waste, one of the 'grand challenges of the 21st century' in relation to climate change (Sheldon and Norton, 2020). Currently, there are standard recycling technologies as well as more advanced, so-called emerging technologies. These technologies differ in terms of maturity, their costs (Bachmann et al., 2023), their performance (Volk et al., 2021) and their legitimacy (Zepa et al., 2024).

Emerging technologies are often developed in environments that are relatively 'protected' from market selection pressures. Within these spaces, or 'niches', innovations are improved and are made viable through a process of learning (Smith et al., 2010). This can result in significant changes and a transition to a new regime. While some emerging technologies manage the move from the initial niche level, in other cases attempts to diffuse to regime level are hampered by several obstacles (Geels, 2011).

Our analysis of the model proposed is policy-oriented. We examine how different policy interventions shape technologies' diffusion and competition. Various policy instruments and strategies exist, with the aim of achieving a balance between different objectives, such as environmental and economic performance (Brouillat et al., 2018; Dosi et al., 2020; Rengs et al., 2020; Polonsky et al., 2022; Wijayasundara et al., 2022). These include market-based mechanisms, such as environmental taxes and innovation policies that foster the development and diffusion of clean technologies, and green public procurement, which serves as demand-side policy tool boosting the desirability of innovative activities by direct and selective interventions enabling new productions and markets (Crespi and Guarascio, 2019). Mission-oriented policies (Mazzucato, 2018) stand out as an integrated and strategic approach. These policies consist of a coordinated package of instruments aimed at tackling specific environmental or climate-related challenges (Miedzinski et al., 2019; Edler et al., 2025). Rather than addressing issues in isolation, mission-oriented policies combine different measures such as regulatory frameworks, financial incentives and research initiatives. This holistic approach ensures that different interventions work together to achieve long-term sustainability goals. Mazzucato (2018) suggests that measures supporting mission-oriented research and innovation are particularly effective in steering innovative activities towards sustainable developments.

Similarly, Rengs et al. (2020) emphasize the importance of combining existing tools for directing technical change towards sustainability. Policy makers may decide on policy package including various types of tax, subsidies to lower the price of low-carbon technologies, and subsidies, or green procurement. These "climate policy packages" enable structural changes and can boost the diffusion of sustainable technologies. In their model, each policy instrument is observed separately and combined to assess the robustness of each kind of intervention.

We focus on three different policies designed to encourage the recycling of plastics: Tax exemptions for recycled plastics; R&D boosts for green recycling technologies, and green public procurement. We performed a scenario analysis to assess the effects of each policy against a business -as-usual (BAU) scenario. In our simulations tax exemptions are the most effective intervention in terms of the final diffusion of recycled plastics, while green public procurement mostly promotes the emergent chemical recycling technology, at the expense of the overall plastic recycling diffusion. Combined implementation of the three policy channels has the greatest impact on both the overall diffusion of plastic recycling and the diffusion of greener chemical recycling. This demonstrates the synergistic effect of policy interventions, whereby a portfolio of policies achieves a greater impact than each policy alone (Zeppini and van den Bergh, 2025).

The main results and contributions of this paper are as follows. Firstly, we show how the phase transition that is characteristic of diffusion processes translates into non-linear patterns of competitive diffusion. Near to the percolation threshold, slight variations in technologies' costs result in significant differences in their respective market shares. In the case of competition between a *mature* technology and an *emerging* one, endogenous learning from technological progress can reverse market shares.

Secondly, the interplay of endogenous learning and initial adopters leads to a counterintuitive result: increasing the number of initial adopters of both competing technologies can result in a smaller diffusion size of overall. Also the other way around can occur, in a symmetric fashion: lowering the number of initial adopters can lead to a larger final diffusion size. This means that policies designed to boost adoption in the early stages of diffusion are not necessarily the best option. In fact, maintaining low diffusion at the outset can result in a higher level of diffusion later on, thanks to learning processes. The intuition is that adoption occurring too early 'steals' potential adopters from the most promising innovative technology. Learning needs to occur before too many adopters have made their choice, so that positive network externalities can deliver their beneficial effects on final diffusion.

We calibrate our model to the case study of recycling technologies for Polyethylene Terephthalate (PET) plastics. An investigation of different scenarios of policy intervention shows the strong synergy potential of policies when they address competitive diffusion processes: the non-linearity of diffusion translates into a multiplier effect. When *Tax exemptions*, *R&D boosts* and *Green public procurement* are introduced in concert, the outcome is not only an addition of each separate beneficial effect, but a multiplicative effect both in overall diffusion of recycling as well as market penetration of the desirable sustainable solution (chemical recycling).

The paper contributes to the scrutiny of shifts during the diffusion of recycling technologies, which have the potential to cause structural changes to the technological landscape. Whenever novel technologies and business models are introduced, such as waste recycling, we observe the competitive diffusion of different solutions at various stages of technical development. The interplay of various factors, including social structure, learning, initial adopters and policy interventions, results in highly nonlinear outcomes that have significant effects on collective behaviours.

The framework proposed is relevant more in general to the study of societal shifts and structural economic change that encompass multiple economic diffusion processes, and in particular to instances of social change that underlie the Sustainable Development Goals of United Nations:[1] whenever novel practices and business models are proposed, such as waste recycling, we observe the competitive diffusion of different solutions, at different stages of their technical development, and the interplay of different dimensions as social structure, learning, initial adopters, and policy interventions lead to highly non-linear outcomes, also with huge opportunities for policy making.

The paper is organised as follows. Section 2 presents the modelling framework. Section 3 describes diffusion results comparing the Small World and the Scale Free networks. Section 4 explains how our model captures a set of stylized empirical facts from the current landscape of plastics recycling technologies. Section 5 presents simulations of our model calibrated to the case study of PET plastics. Section 6 concludes.

2 Diffusion model framework

2.1 Percolation

We model the competitive diffusion of technologies in a network of potential adopters (firms) within a percolation framework, extending Zeppini and Frenken (2018). In our model competition is triggered by the advent of a novel practice, or process, in the value chain of a given sector. Our working example is plastic recycling technologies. Multiple technologies are available and enter in competition while diffusing into a social network of producers. The latter are informed about the available technology only locally, through word-of-mouth from a directly connected adopter. Besides information, the adoption decision is governed by preferences. These are described as a willingness-to-pay, or reservation cost (or price), expressing the valuation of the technology by an agent. In other words, this reservation cost is the maximum price that an agent is willing to pay to adopt the technology. If the technology price is below the reservation cost, the informed agent adopts, otherwise it does not. Each agent can adopt only one technology, and once this happens, adoption of any other technology by the agent is precluded.

Agents, i.e. potential adopters, are heterogeneous in their preferences. In a population of size N, the reservation cost of agent $i \in \{1, \dots, N\}$ is a random number c_i following a given distribution. For simplicity, we consider a uniform distribution of agents' reservation costs, with $c_i \sim U[0, 1]$.[2] Accordingly, technology prices take values in the range $[0, 1]$. When the price of a technology is 0, any agent would adopt, while a price equal to 1 refers to an infinitely costly technology, that no agent would adopt.

The initial conditions (time $t = 0$) in our model are set by the advent of a new phase or step in the value chain of a given industrial sector emerging, such as a process of recycling for a given material used in the production of different items, e.g. plastics. This is the event that triggers the competition of different solutions, or technologies, for the appropriation of a new market. At $t = 0$, for each technology j, there

[1]The 17 Sustainable Development Goals (SDG) of UN can be found at https://sdgs.un.org/goals.

[2]A uniform distribution of agents' reservation price, or more generally nodes' acceptance level, is customary in models of diffusion on networks. An exception is Tur et al. (2018).

are $n_0^j << N$ initial adopters (*seeds*). Initial adopters immediately transmit information about the adopted technology - including its cost - to their neighbours, and allow for the diffusion process to start.

During the diffusion process, competing technologies improve, with technical progress described by a learning curve: the cost of a technology decreases over time. Technical progress is endogenous, as the c_t^j curve slopes down with the total number of adopters of the technology. If a potential adopter with reservation price c_i is informed about the technology j at a given time t, adoption occurs if $c_i > c_t^j$.

In summary, potential adopters adopt a technology when two conditions are met: 1) they learn about the existence and cost of a technology from a neighbour who has already adopted it, and 2) the cost of the technology does not exceed their *reservation cost*. The crucial aspect of this model is that only adopters can pass information about the technology to their neighbours. In the case of competing diffusing technologies, if potential adopters learn simultaneously about two technologies having a cost lower than their c_i, they randomly choose one to adopt.

In a percolation model the diffusion process is determined by the network topology of the graph defined by our potential adopters as nodes and their social links, and by the random values describing the nodes' acceptance levels, i.e. the reservation cost values, in our case. Nodes with too low reservation price 'block' information spreading, and can *de-facto* be removed from the network, together with their links. Put differently, drawing nodes' *reservation costs* from a given distribution is tantamount to randomly *deactivating* nodes and their links. The resulting network made of the remaining nodes is called the *operational network*. Diffusion only takes place in the operational network. Technical progress enriches this picture, as the operational network is not static, but it is enlarging with adoption events. What follows is a detailed description of the two main drivers of diffusion: the learning dynamics of technical progress and the network topology.

2.2 Learning

Competing technologies are improving during the diffusion process. We choose to model technological progress in an endogenous fashion, with the cost of technologies decreasing in the number of adopters. This choice responds to the strong empirical evidence that costs of technologies decrease with cumulative production (Nagy et al., 2013). As the time scale of technological change is usually slower than the technology diffusion process, the cost of each diffusing technology depends on a *slowly decaying factor* with a learning rate that can be used to calibrate the model to a given technology or industrial sector. Let n_t^j be the number of adopters of technology j at time t, and r^j its *learning rate*. At a given time $t > 1$ the cost of technology j is

$$c_t^j = c_{t-1}^j \cdot \left(\frac{n_t^j}{n_{t-1}^j} \right)^{-r^j}. \tag{1}$$

The number of adopters can only increase in our model, so that $n_t^j > n_{t-1}^j$, and $c_t^j < c_{t-1}^j$. Equation (1) describes a cost decreasing with cumulative adoptions, as the relative cost reduction c_t^j / c_{t-1}^j depends on the number of adopters added on time t, in line with the relevant literature (Cantono and Silverberg, 2009; Lafond et al., 2018; Way et al., 2022).[3]

2.3 Networks

In our model, firms that adopt diffusing technologies are embedded in a network of social and economic relationships. Such relationships can be partnerships, collaborative alliances, or simply social connections between competitors. We assume that these links act as channels for exchanging knowledge about existing technologies that are relevant to their business (Grandori and Soda, 1995; Ozman, 2009). The links are assumed to be static and undirected. According to the percolation model of diffusion, information about a given technology is passed along the network's links following adoption events among connected firms.

[3] In particular, at every time step the cost relative reduction is equal to the relative increase in the number of adopters multiplied by the learning rate: $\frac{c_t^j}{c_{t-1}^j} = \left(\frac{n_t^j}{n_{t-1}^j} \right)^{-r^j}$, then $\ln \frac{c_t^j}{c_{t-1}^j} = -r \ln \frac{n_t^j}{n_{t-1}^j}$. Computing the differential of this equation we obtain $\frac{dc_t}{c_t} = -r \frac{dn_t}{n_t}$.

We consider two graph topologies that are commonly used to describe large-scale economic and social networks. Firstly, we consider the Watts-Strogatz Small World network (Watts and Strogatz, 1998). This network topology is characterized by clusters, where groups of nodes are connected in several triadic structures. As a result, with high probability two connections of one node are also connected directly to each other. This topology is generated starting from a regular lattice (e.g. a circular network where nodes are located on a circle and each node is connected to its left and right neighbours[4]) and perturbing the lattice with a rewiring process, where a node is rewired to another one randomly, with a small probability. The resulting Small World network presents a high clustering degree, measured in terms of density of triadic structures, just slightly lower than the starting regular lattice, and a low average path length, typical of fully random networks. The literature on the diffusion of knowledge and innovation among firms in diverse industries, utilizing data on strategic inter-firm alliances, reveals that alliances and knowledge networks exhibit traits akin to the Watts-Strogatz Small World Network model. This pattern is consistent across various industries, including aerospace, automotive, chemicals, pharmaceuticals, and technology (Schilling and Phelps, 2007).

The second graph topology that we study with our model is the Barabási–Albert Scale Free Network (Barabási and Albert, 1999). This graph topology is characterised by a power-law degree distribution of connections between firms. In particular, numerous links are concentrated among selected few firms that function as hubs, while many firms have very few connections. Empirical studies suggest that the Barabási–Albert Scale Free network accurately reflects the structural and topological characteristics of many real-world networks, including supply chains and inter-firm networks in sectors such as automotive, food supply, pharmaceuticals, and electronics (Okamura and Vonortas, 2006; Perera et al., 2017).

The following section reports simulation experiments for a Small World network with a rewiring probability of 1%. The analysis for other instances of Small World networks and for Scale Free networks is reported as robustness checks in appendices B and D.

3 Model simulations

We focus on the case of two competing technologies, simulating our model for various scenarios and parameters combinations. Multiple simulation runs were conducted for each combination, and the results were analysed looking at the final total adoption size (number of adopters), the number of adopters of each technology, and the diffusion time (i.e. the total number of time steps needed for the diffusion process to terminate). For the Watts-Strogatz Small World network, we used a rewiring probability of 1%, while for the Barabási–Albert Scale Free we used a parameter of preferential attachment of links equal to 2 (two links for each added node in the network formation process). The average connectivity in both network structures is equal to 4. The main focus of our simulation experiments are, first, the technologies' initial cost, that takes values in the range $\{0.05, 0.1, 0.15, ..., 1\}$, and, second, the technologies learning rate, with values $\{0, 0.01, 0.02, ..., 0.2\}$. Finally, we examine the role of the number of initial adopters with two initial conditions: 0.1% and 0.5% of the population. Table 1 summarises the parameters' space of our model simulations.

[4]Depending on the desired connectivity, only the nodes immediately on the right and left can be connected to a given node, or two nodes on each side, and so on.

Model Parameters	**Description**
Number of technologies	2
Number of firms	10000
Number of links	20000
Average connectivity	4
Technology's initial cost	{0.05, 0.1, 0.15, ... , 1}
Learning rate	{0, 0.01, 0.02, ... , 0.2}
Proportion of initial adopters	0.1%, 0.5%
Time horizon	1000

Table 1: Model settings and parameters space for the simulation of the diffusion model for two competing technologies. These values are used for both topologies considered, the Watts-Strogatz Small World and the Barabási–Albert Scale Free network.

3.1 Competitive diffusion

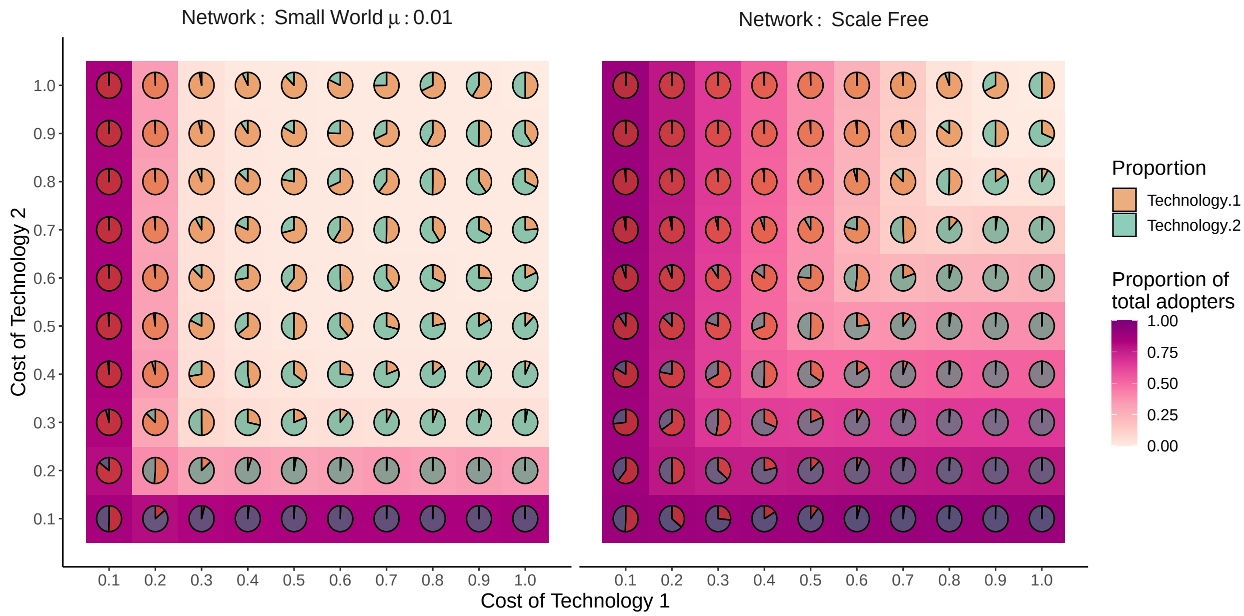
Our initial analysis centres on the competitive diffusion of technologies in the absence of learning (technological progress). This analysis lays the groundwork for our main analysis of the interplay between competitive diffusion and learning curves. A competitive diffusion process demonstrates how critical transitions in diffusion on networks extend to competitive diffusion. Around the percolation threshold in particular, small differences in the cost of the two technologies can lead to significant differences in their final market shares. We ran simulation experiments comprising 100 runs, computing average values for overall diffusion size and market share of the two competing technologies across runs. In Appendix A, we report the distribution of simulation standard errors.

Figure 1 shows the average diffusion size (heat map colours) and the market shares (pie charts) of the two technologies, for different costs combinations. The left panel is for a Small World network with rewiring probability 1%, while the right panel has results for a Scale Free network, which has been generated with 2 new links for every added node. In Appendix B, we report the results for different network configurations, and different numbers of initial technology adopters (see Figure 10).

From the results of Figure 1, we make the following observations. There is a percolation threshold in the two-dimensional space defined by the technologies' costs, which clearly separates a *diffusion regime* region (bottom left) and a *no-diffusion regime* region. As technologies are identical in this model setting, the diffusion and no-diffusion regimes regions are symmetric with respect to the 45^o degrees line. The threshold effect is relatively more pronounced for the Small-World network, with a sudden change of overall diffusion between cost values of 0.1 and 0.3. We measure the percolation threshold as the technologies' cost level at which the overall diffusion size experiences the highest increase compared to the next cost value. For networks of infinite size, the simulations would have a sharp discontinuity at the percolation threshold, indicating a sudden transition between the diffusion and no-diffusion regimes. An alternative way to measure the percolation threshold is to identify for the cost at which the diffusion takes the longest time. The diffusion time peaks at the percolation threshold, which is a characteristic pattern of second-order phase transitions in physical systems. In Appendix C, we report the average simulation diffusion time for various costs of technologies (Figure 11). This approach allows to precisely locate the critical value of the cost that separates the two regimes (phases) of diffusion and no-diffusion. The two measurement methods are consistent, and produce the same percolation threshold value.[5] Based on this analysis the percolation threshold is around $\{c_0^1, c_0^2\} = \{0.2, 0.2\}$ in the Small World network, and $\{c_0^1, c_0^2\} = \{0.75, 0.75\}$ in the Scale Free network. In the Scale Free, the percolation is much smoother compared to the Small World network. We have run simulations also in different Small Worlds networks, namely with higher and lower values of the rewiring probability. Results for different settings of network structure are reported in Appendix B.

In general, simulations show that around the percolation threshold the market shares of the two competing

[5]The percolation threshold of Small World networks of infinite size can be evaluated implicitly (Newman and Watts, 1999; Zeppini and Frenken, 2018). The values that we obtain using our measurement methods match these theoretical values, within the experimental errors.



(a) Average proportion of total adopters (pink colour shade) and average proportion of adopters of each of the two technologies (pie charts), obtained over 100 replications for each parameters combination.

Estimate	Network	SEM			
		Mean	Median	Min	Max
Proportion of total adopters	*Small World*	0.002	0.001	0.000	0.010
	Scale Free	0.001	0.001	0.000	0.002
Proportion of adopters of Technology 1	*Small World*	0.004	0.004	0.000	0.016
	Scale Free	0.007	0.004	0.000	0.030

(b) Descriptive Statistics of the obtained Standard Error of the Mean (SEM) of the presented estimates.

Figure 1: Competitive diffusion in a Small World network (left) and in a Scale Free network (right), with $N = 10000$ nodes, average connectivity 4, and 10 seeds for each technology (0.1% of nodes are initial adopters).

technologies are highly sensitive to marginal differences in cost. In the Small World network, the two scenarios identified by cost values $\{c_0^1, c_0^2\} = \{0.2, 0.2\}$ and $\{c_0^1, c_0^2\} = \{0.3, 0.2\}$, result in very different outcomes. The first one is characterised by almost equal market shares, in the second scenario, where Technology 2 is 33% cheaper than Technology 1, Technology 2 obtains a market share of 87%. In the scenario $\{c_0^1, c_0^2\} = \{0.25, 0.2\}$, Technology 2 is just 20% cheaper but ends with conquering 73% of the market. We obtain a similar result in the Scale Free network: in the scenario with costs $\{c_0^1, c_0^2\} = \{0.8, 0.7\}$, Technology 2 obtains 88% of potential adopters, compared to quasi-equal market shares in the scenario $\{c_0^1, c_0^2\} = \{0.7, 0.7\}$, in which the cost of Technology 1 is only 12.5% lower.

3.2 Competing diffusion with learning

We now introduce technological progress from a learning dynamic of technologies and study the interplay between learning and competitive diffusion of technologies. As before, the competing diffusion model describes technologies that battle for conquering a new market, such as the recycling market in our working example. The extension of this part of the model is an endogenously decreasing technology cost. To keep the analysis simple, we consider the case where only one technology has a positive learning rate. This setting describes the competition between a mature technology, for which costs are not substantially decreasing anymore, and an emerging innovative technology, which still attracts R&D investments and is improving during its diffusion process. Hereafter, we will call the former the *mature* technology, and the latter the *emerging* technology.

In our simulations we focus on a range of technologies' initial cost values located around the percolation threshold, as this represents the most interesting range, also for policy considerations. We consider cases where the difference between the initial costs of the two technologies is relatively small, and assume the *emerging* technology as being initially the most expensive.[6] We thus analyse the three following scenarios:

1. the cost of the learning technology is at the percolation threshold, that we call *"Both technologies initially in the diffusion regime"*;
2. the cost of the mature technology is at the percolation threshold, that we call *"Only the mature technology initially in the diffusion regime"*;
3. both costs are higher than the percolation threshold, that we call *"Both technologies initially outside the diffusion regime"*.

In the Small-World network with a percolation threshold at $\{c_0^1, c_0^2\} = \{0.2, 0.2\}$, the first, second and third scenario are obtained by setting $\{c_0^1, c_0^2\} = \{0.2, 0.15\}$, $\{c_0^1, c_0^2\} = \{0.25, 0.2\}$ and $\{c_0^1, c_0^2\} = \{0.3, 0.25\}$, respectively.

Finally, we study the effect of initial adopters - the seeds of simulation. We consider two different initial levels, 0.1% in and 0.5% initial adopters, randomly and uniformly distributed across the two technologies. Remember that both mature and emerging technology start competing for a novel market such as recycling. This dimension of analysis is highly policy relevant, as it can describe efforts to promote a novel sustainable technology.

Figure 2 shows the average final diffusion sizes (bottom panels) and market shares of the emerging technology (upper panels), as a function of its learning rate. The two curves represent two different numbers of initial adopters, a rate of 0.1% (light pink), and a rate of 0.5% (dark pink). The three panels from left to right relate to the different combinations of initial costs, with the emerging technology always starting as the most expensive option. In Appendix D, we report the results for other network configurations.

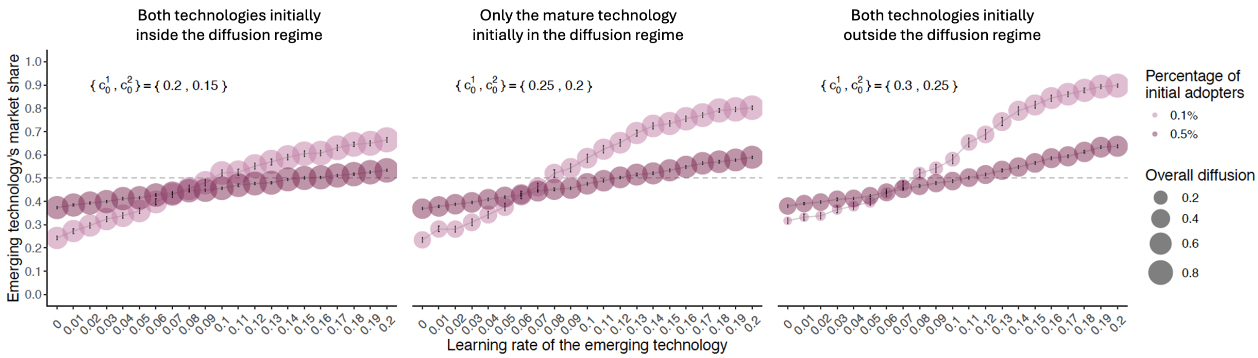
The results presented in Figure 2 highlight the existence of a tipping point in terms of market leadership. For a sufficiently high learning rate, the market environment, initially favouring the cheaper mature technology, shifts to favour the emerging technology. This tipping point is observed when the curve representing the market share of the emerging technology crosses the 0.5 threshold. This occurs at a lower learning rate when the learning technology is initially outside the diffusion regime. For example, starting with 0.1% initial adopters (light pink curve), the reversal of market dominance is observed at a learning rate of 0.1 in the left panel and 0.08 in the central and right panels.

Most importantly, the simulations show a counter-intuitive result: a smaller number of initial adopters may result in greater diffusion. We see this clearly in the lower panels of Figure 2, when the learning rate of the emerging technology is large enough. The effect is particularly strong when the emerging technology is initially outside the diffusion regime (middle panel) and when they are both initially outside the diffusion regime (right panel). While a larger number of initial adopters is beneficial for diffusion when the learning rate is low, it hinders diffusion when the learning rate of the emerging technology is relatively high (recall that initial adopters are uniformly distributed across the two technologies).

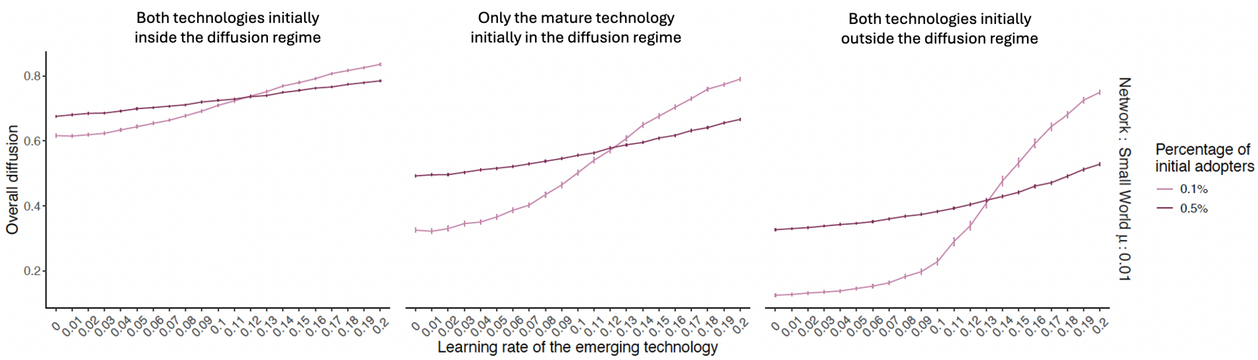
Learning is characterized by a critical threshold above which the innovative and initially more costly technology takes off in terms of diffusion, and outperforms the mature technology (upper panels of Figure 2). The overall diffusion size shows a tipping point pattern especially for the case with a relatively low number of early adopters (lower panels of Figure 2). The surprising implication is that less initial adopters favour total diffusion, when the learning rate of the innovative technology is large enough. In our simulations this occurs when the learning rate of the emerging technology is above 0.11 in the scenario of lower initial costs (left panel), above 0.12 in the scenario of middle values for the initial costs (central panel) and above 0.13 for the scenario of relatively high initial costs (right panel).

The counter-intuitive result is explained by limited access to potential adopters of the emerging technology due to the early adoption of the mature technology. If too many people adopt the mature technology, there are not enough potential adopters left, which hinders the spread of information about the innovative one. The

[6] This assumption has wide empirical validity, well beyond our working example of technologies for plastic recycling (more on this case in Sections 4 and Section 5). For instance, it is the case of solar photovoltaic vs onshore wind power (IRENA 2025, Renewable power generation costs in 2024, International Renewable Energy Agency).



(a) Final share of the emergent technology as a function of its learning rate, for two levels of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes (left to right). The size of the circle measures total diffusion.



(b) Total diffusion of both competing technologies as a function of the learning rate of the emerging one, for two levels of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes (left to right).

Figure 2: Simulated competing diffusion in a Small World network ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4. The horizontal axis reports the learning rate of the emergent technology. In each graph the two sets of points refer to two different numbers of initial adopters. Each data point is an average over 500 replications in each parameters combination, and the bars measure the standard error.

emerging technology, which has superior potential, is unable to improve while it follows its learning curve. Consequently, overall diffusion is limited. If large-scale adoption occurs too early, fewer potential adopters will be available to drive down the cost of the novelty. Conversely, if diffusion occurs at a slower pace, more firms will be available to adopt the emerging technology when its cost is relatively low.

In terms of diffusion dynamics, the emerging technology provides a slowly changing parameter which 'spans' the cost space. The non-linear diffusion patterns, particularly in the centre and right panels of Figure 2, reproduce the phase transition of percolation in the learning rate space. If the emerging technology can reach enough nodes in its diffusion, it can 'cross' the percolation threshold and eventually reach far more adopters than a static technology would.

This unexpected result has huge implications for technological change and environmental sustainability. In new market sectors - such as recycling - where alternative technologies are considered, the diffusion of competing technologies may lead to dramatically different results, depending on whether innovative and sustainable technologies can take off, or more mature and less sustainable technologies prevail. For sustainability goals, it is desirable to allow a 'niche' technology with relatively high learning potential to develop, even if it is more expensive. As adoption is necessary for learning, it is beneficial to long-term sustainability goals if adoption does not occur too quickly in the short term. There is notable historical evidence for this: for example, in the early stages of the videocassette market, the VHS format ultimately prevailed despite experts deeming the alternative format Betamax superior (Arthur, 1990). A technology is not adopted based on its intrinsic qualities; rather, it becomes superior through adoption, which gives early adopters decisive weight in the competition process thanks to network externalities.

4 Empirical evidence from plastics recycling

Rising awareness of the climate challenge has forced governments and supra-governmental bodies to prioritize environmental sustainability, with the United Nations being the most notable example (UNFCCC, 2023). In particular, "Sustainable Consumption and Production" is the 12^{th} of the United Nations' 17 Sustainable Development Goals.[7] Within this general goal, waste recycling plays a crucial role.

Introducing recycling stages into the value chain opens new markets and technological frontiers, prompting the consideration of various solutions for the first time. In this scenario, we see different technologies competing at the early stages of a diffusion process. It is important to note that the situation with recycling technologies differs from the usual scenario in which an innovative technology, product or process emerges and competes with existing ones. Here, competing technologies can be at different stages of maturity, but they are all applied to the new task of recycling at around the same time. This provides a unique opportunity to study the competitive diffusion of innovation.

4.1 The plastics waste issue

Plastics waste is one of the "grand challenges" of climate change. Plastics have enabled numerous improvements, such as lightness of materials, food safety and medical supplies, and are characterized by robustness and durability. However, it is precisely these same properties that present an issue when it comes to recyclability. If they are not recycled, plastics can persist as harmful pollutants in the environment. The OECD's projections suggest that, under current policies, the global use of plastics could almost triple by 2060, with half of all plastic waste still being landfilled and less than a fifth being recycled (OECD, 2022).

There are two options to tackle this issue. The first involves reducing plastic usage and replacing it with alternative materials. The second option involves the circularity of plastics by 'optimizing' their recycling. This departs from the linear approach to plastic production, where extraction represents the primary source of new materials. Extending the lifespan of materials already extracted reduces the need for further extraction. Enhanced circularity not only helps combat climate change but also addresses emerging issues with growing land use concerns, such as landfills and raw material sourcing for bio-based plastics.

In the context of circularity, recycling is necessary to provide output quality comparable to that of virgin plastics, so that it is suitable for sensitive uses such as food packaging, toys or medical instruments. Indeed, the use of recycled plastics in such high requirements products needs to be strictly regulated by laws (Geueke et al., 2018) to prevent the presence of hazardous chemicals or legacy additives (Chen et al., 2009; Samsonek and Puype, 2013; Ionas et al., 2014; Li et al., 2019).

4.2 Mature and emerging technologies

The main options for recovering plastic waste are *mechanical* recycling, *physical* recycling, *chemical* recycling and *energy recovery*. Mechanical recycling involves using separation, crushing, heat and extrusion to melt used plastic waste and ultimately create recycled plastic pellets. This process transforms plastic waste into secondary raw materials with minimal alteration to the polymer's chemical structure. However, the resulting materials are generally of lower quality and purity than virgin plastics (Geueke et al., 2018; Schyns and Shaver, 2021) and are therefore mostly intended for 'down-cycling'. Nevertheless, it is the most widespread and developed recycling technology (Plastics Europe, 2022).

Physical and chemical recycling are considered as more advanced technologies. Physical recycling, which involves processes such as dissolution, is a solvent-based method that allows for the separation of additives and undesired substances, and the recovery of plastic materials without altering the polymer's chemical structure. In contrast, chemical recycling involves depolymerizing polymers, i.e. breaking them into their molecular components.[8] These advanced technologies offer a higher potential for recovered quality comparable to that of virgin materials, making them suitable for sensitive applications. Arena and Ardolino (2022) classify the main recycling processes according to their industrial maturity, categorizing them as either traditional or

[7] United Nations, Department of Economic and Social Affairs, Sustainable Development goal n.12: Ensure sustainable consumption and production patterns, https://sdgs.un.org/goals/goal12.

[8] Chemical recycling is also referred to as 'feedstock' recycling in the industry and its specialised literature.

emerging. Mechanical recycling is categorized as a traditional process, while physical recycling and certain chemical recycling processes are described as emerging. A technology's level of development and maturity can also be described using the Technology Readiness Level (TRL) scale (Mankins, 1995, 2009). Among recycling technologies, mechanical recycling technology currently has the highest TRL (Schwarz et al., 2021). Indeed, mechanical recycling has a TRL of 9, whereas the main chemical and physical recycling technologies have a TRL ranging between 3 and 8 (Arena and Ardolino, 2022). In 2022, chemical recycling of post-consumer plastic waste accounted for only 0.1% (±0.1Mt) of European plastics production and less than 0.1% of global plastics production (Plastics Europe, 2022).

4.3 Emerging technologies are more costly

Emerging technologies such as physical and chemical recycling technologies offer higher potential in terms of quality and purity of the obtained recycled material, but this comes at a higher cost. Arena and Ardolino (2022) compare the costs associated with different recycling technologies and indicate that while for mechanical recycling the cost is in the *Low* category, for the main chemical and physical recycling technologies the cost varies between *Medium-High* and *Very-high*. Chemically recycled polymers can even be more expensive than virgin materials, due to the cost of the raw materials involved and capital investment. For example, it has been calculated that for a PET chemolysis facilities to be economically viable a minimum throughput of 1.5×10^4 tonnes per annum is required (George and Kurian, 2014).

4.4 Innovation in recycling technologies is increasing

Dussaux and Agrawala (2022) investigated how the number of patents for environmentally relevant plastic technologies has changed between 1990 and 2017. They observed that most of circular plastic innovation was in technologies aimed at enhancing plastic waste recycling. They also show that mechanical recycling and plastic waste sorting account for the largest proportion of plastic waste recycling innovation. Conversely, innovation in plastic-to-plastic chemical recycling is among the least significant. Nevertheless, most of the technologies considered present comparable growth rates. The average annual growth rates between 1995 and 2017 for mechanical recycling and plastic-to-plastic chemical recycling were 7.3% and 5.2%, respectively. Furthermore, they observe that innovation in plastic-to-plastic chemical recycling accelerated towards the end of the study period, with growth rates reaching 11% per year between 2008 and 2017.

The number of scientific articles on advanced recycling technologies has increased over the last decade (Davidson et al., 2021; Khatun et al., 2021; Armenise et al., 2021; Zepa et al., 2024). Davidson et al. (2021) examined how the publication results of mechanical, chemical and feedstock recycling have changed over the last decade. They found that the number of papers published per year increased from 7 to 29 for mechanical recycling and from 23 to 36 for chemical recycling between 2010 and 2019. On several occasions, the number of papers on chemical and feedstock recycling, and sometimes chemical recycling alone, surpassed the number of papers on mechanical recycling, as was the case in 2019. Similarly, Khatun et al. (2021) conducted a bibliometric analysis of research trends in selected chemical recycling technologies for plastics between 1990 and 2020. At the heart of the chemical recycling process is pyrolysis, the technology on which more than 88% of publications focus. The number of publications on pyrolysis has steadily increased over the past 30 years. From 2015 to 2020, this growth accelerated, increasing by a factor of 2.5. Armenise et al. (2021) conducted a bibliometric survey focusing specifically on plastic waste recycling by pyrolysis between 2001 and 2020. They observed an increase in the number of publications related to this recycling technology, with an even higher rate of increase since 2016.

5 Simulation of the calibrated model

5.1 Calibration

We focus on PET (Polyethylene terephthalate) plastics. The two main recycling technologies for this polymer are mechanical and chemical (Joseph et al., 2024). Although data on the relevant dimensions of PET plastic recycling is sparse and heterogeneous, we can identify some stylized facts for a calibration of the model.

Uekert et al. (2023) provide estimates of the minimum selling price (MSP) for different PET recycling technologies. We use these MSPs as proxies for the cost parameter in our model. We normalize the MSPs so that they fall within the interval [0, 1], setting the upper bound at 1 and corresponding this to the highest MSP, which is that of the enzymatic hydrolysis recycling technology. The same study considers different chemical recycling technologies. We select glycolysis as a representative of chemical recycling, as it was estimated to display the best economic and environmental performance. Within our normalised scale, the estimated costs obtained are 0.27 for mechanical recycling and 0.48 for chemical recycling.

In terms of the initial adoption rates of the two technologies, we will use the figures for plastics in general as an approximation for PET plastics. These numbers are taken from Plastics Europe's biennial report, The Circular Economy for Plastics – A European Analysis (Plastics Europe, 2024). The report estimates that, in 2022, the production of mechanically recycled (post-consumer) plastics represented 13.2% of the total European production of plastics, while the production of chemically recycled plastics represented 0.1%. Plastics Europe (2023) provides similar estimates at a global level for the same year: 8.9% for mechanical recycling (post-consumer) and less than 0.1% for chemical recycling.

As for the learning rates of both technologies, we could not find in the literature precise estimates. We thus rely on Daugaard et al. (2015) who provide general estimates of learning rates of bio-refinery processes, such as gasification and pyrolysis, which are processes also used in chemical recycling of plastics. These estimates range from 5% to 20%. We choose to consider the median of this range, 12.5%, as an approximation of the learning rate of chemical recycling technology. For mechanical recycling, a more mature and established technology, we consider a learning rate of 2%. We also run a sensitivity analysis by simulating the model for a range of additional values.

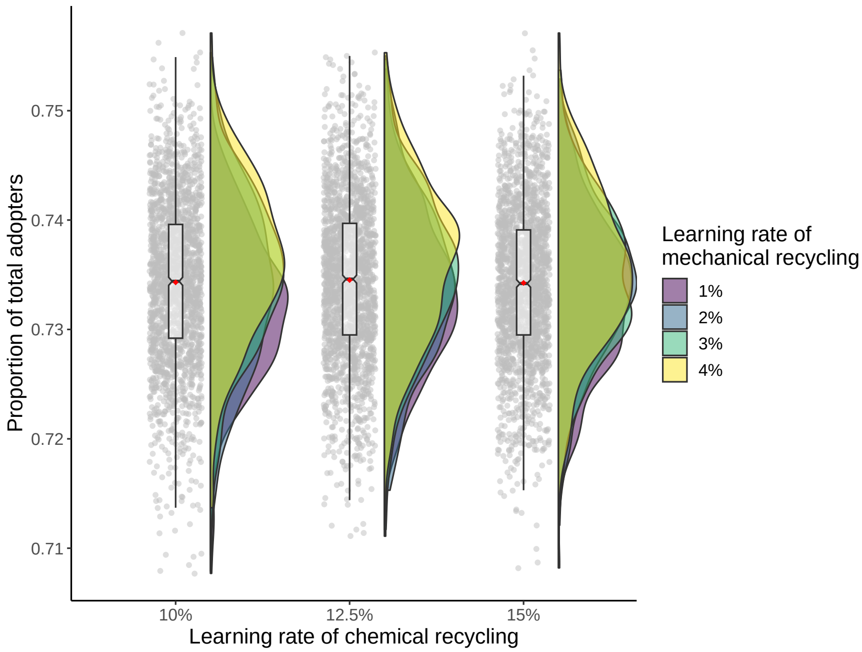
Concerning the network topology, we consider the Small World which accurately reflect the structure of the PET-based product manufacturing industry. Indeed, the Small World network effectively captures both the inter-connectivity and the diversity of the social and knowledge dynamics of this industry. The homogeneity of these potential adopters of recycled PET, who are generally similar in size and influence, and often operate in an oligopolistic market, creates tightly-knit clusters with overlapping networks of influence. Whyle these producers typically belong to small ecosystems, the diversity of products within the PET industry leads to interactions across different, overlapping clusters.

5.2 Scenarios analysis

We use the calibrated model to define and analyse a number of scenarios. First, we investigate the BAU (*Business-as-usual*) scenario. Then, we focus on three policies aimed at promoting chemical recycling, that we introduce separately, and in combination.

5.2.1 BAU scenario

The BAU scenario corresponds to the calibrated model without any policy intervention, with a learning rate of 1% for the mechanical recycling and 12.5% for chemical recycling. Figure 3a shows the distribution of total adoption rate for chemical and mechanical recycling combined, for different values of learning rates of these two technologies. Figure 4a shows the proportion of adopters of chemical recycling out of the total adopters. The model simulations converge to an average total adoption rate around 74% in the Scale Free network and 73% in the Small World network, out of which only less than 1% adopt chemical recycling. There is little difference between the distributions for the various tested learning rates. We present also the outcomes of an analysis of variance model, both for the proportion of total adopters (Figure 3b) and for the proportion of adopters of chemical recycling (Figure 4b). In these tables we report a partial eta squared (η^2) test. No significant effects were observed, except for the learning rate of mechanical recycling on the proportion of total adopters. However, the corresponding effect size is small (0.02).

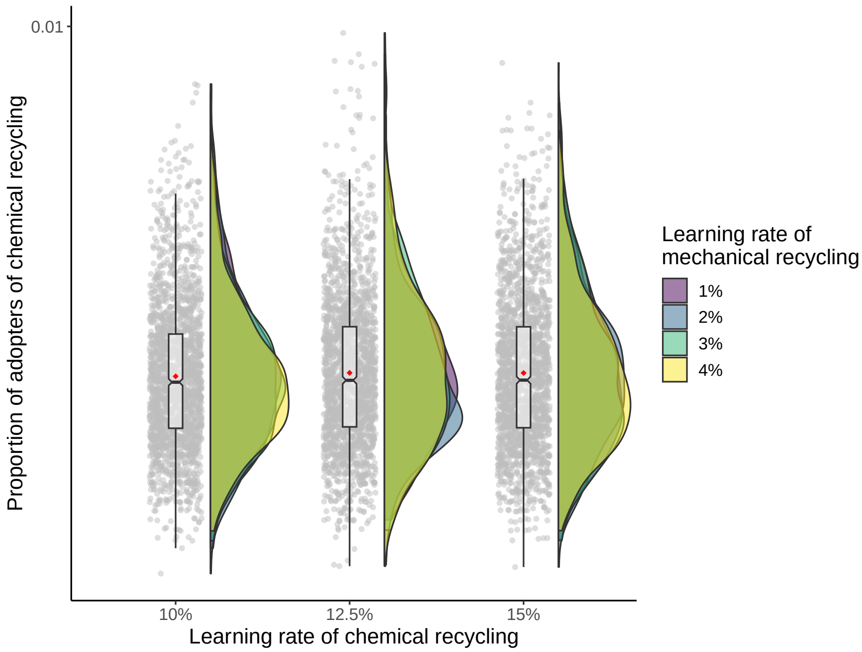


(a) Distribution of total adoption rate for chemical and mechanical recycling combined represented using boxplots (red diamonds: mean) and kernel probability density plots.

	Df	Sum Squares	Mean Squares	F value	Pr(>F)	η^2 (partial)
Learning rate of chemical recycling	2	0.00	0.00	0.74	0.4777	< 0.001
Learning rate of mechanical recycling	3	0.00	0.00	48.97	< 0.001	0.02
Residuals	5994	0.32	0.00			

(b) Summary of Analysis of Variance Model

Figure 3: BAU Scenario. Proportion of total adopters of the two competing recycling technologies for three different learning rates of chemical recycling and four different learning rates of mechanical recycling, in Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4. In the BAU Scenario, mechanical recycling has an initial cost of 0.27 and an initial adopters rate of 13.2%, and chemical recycling has an initial cost of 0.48 and an initial adopters rate of 0.1%. Simulated data are obtained over 500 replications for each parameters combination.



(a) Distributions of the proportion of chemical recycling adoption out of total adopters, represented using boxplots (red diamonds: mean) and kernel probability density plots.

	Df	Sum Squares	Mean Squares	F value	Pr(>F)	η^2 (partial)
Learning rate of chemical recycling	2	0.00	0.00	1.36	0.2555	< 0.001
Learning rate of mechanical recycling	3	0.00	0.00	0.55	0.6463	< 0.001
Residuals	5994	0.01	0.00			

(b) Summary of Analysis of Variance Model

Figure 4: BAU Scenario. Proportion of adopters of the chemical recycling technology for three different learning rates of chemical recycling and four different learning rates of mechanical recycling, in Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4. In the BAU Scenario, mechanical recycling has an initial cost of 0.27 and an initial adoption rate of 13.2%, while chemical recycling has an initial cost of 0.48 and an initial adoption rate of 0.1%. Simulated data are obtained over 500 replications for each parameters setting.

5.2.2 Tax exemption

The idea behind tax exemption is that, since tax was applied during initial production, it is reasonable to exempt them from further taxation when they are reused or recycled. We implement tax exemptions as a negative tax added to the initial cost of a recycling technology, and consider the following two cases:

- 10% : corresponds to an exemption of half of the tax amount for both products. The initial cost c_0^j is thus decreased by 10% for $j = 1, 2$.
- 20% : corresponds to an exemption of the whole tax for both products. The initial cost c_0^j is thus decreased by 20% for $j = 1, 2$.

Figure 5 shows the results obtained in the two cases in terms of both overall diffusion and proportion of the chemical recycling technology. These results demonstrate that reducing the tax has a positive impact on

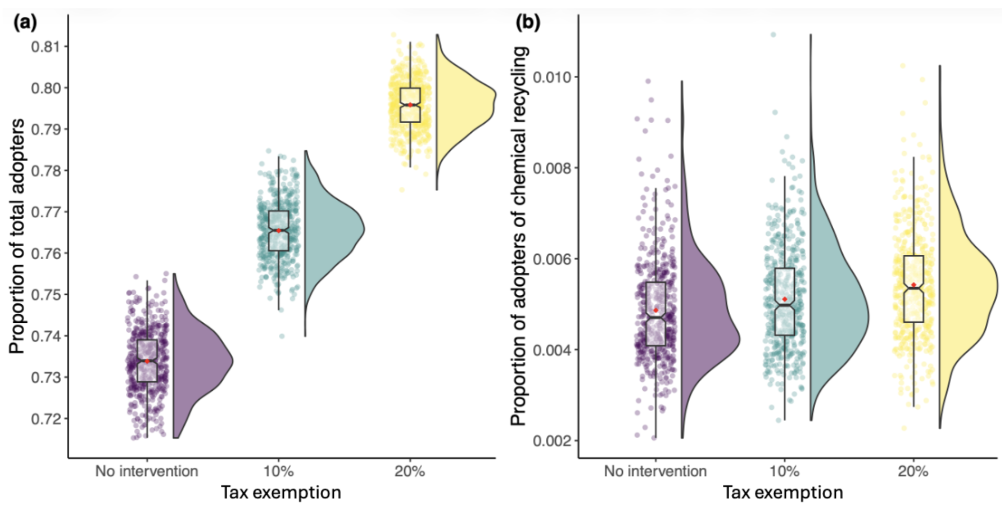


Figure 5: Tax Exemption Scenario. Distributions of the proportion of **(a)** total adopters and **(b)** adopters of chemical recycling, in Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4, represented using boxplots (red diamonds: mean) and kernel probability density plots. Simulated data are obtained over 500 replications for each parameters combination.

overall diffusion, increasing it by approximately 3 and 6 percentage points for partial and full tax exemptions, respectively. However, the effect of the intervention on the diffusion of the emerging technology is negligible. Thus, the increase in overall diffusion is mainly driven by an increase in the adoption of mechanical recycling, the technology that benefits most from the cost reduction in this scenario. The aspired positive effect of this cost reduction on the diffusion of the emerging technology is hindered by its very low initial adoption rate.

5.2.3 R&D boost

The R&D boost scenario refers to a situation where the government actively promotes research and development in the emerging green technology. This could involve various forms of support aimed at accelerating innovation in this technology. This scenario is implemented by setting higher learning rates for chemical recycling at $t = 0$. We consider the following cases: 25%, 50%, 100% and 200%, corresponding to a multiplication of the BAU learning rate of chemical recycling by a factor 1.25, 1.5, 2 and 3, respectively.

Figure 6 shows the results obtained in the different cases in terms of overall diffusion and the proportion of chemical recycling technology. However, we do not observe any effect of the intervention on either dimension. This may be due to the very low initial level of adoption of the emerging technology, which leaves little room for it to benefit from learning dynamics.

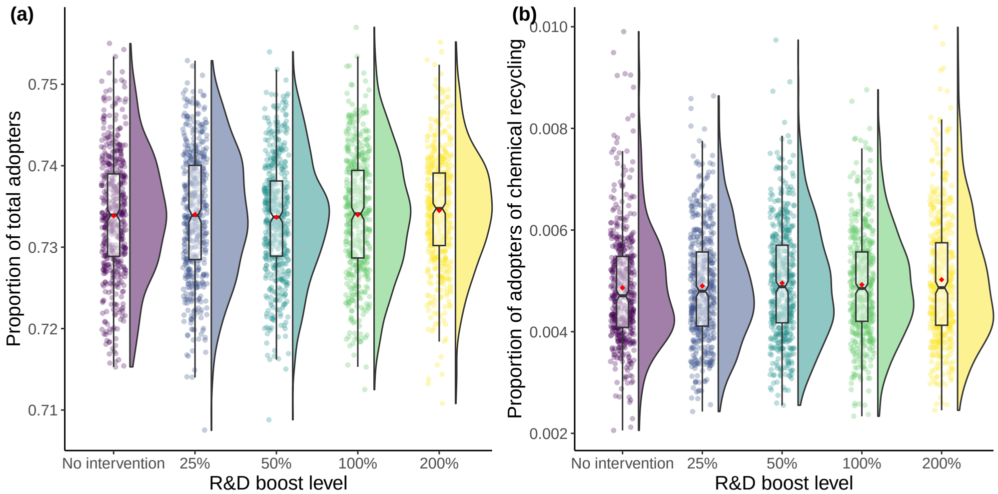


Figure 6: R&D boost Scenario. Distributions of **(a)** total adopters and **(b)** adopters of chemical recycling proportions in the R&D boost Scenario for Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4, represented using boxplots (red diamonds: mean) and kernel probability density plots. Simulated data are obtained over 500 replications for each parameters combination.

5.2.4 Green public procurement

Green public procurement (GPP) is a process where public authorities seek to procure goods, services and works with a reduced environmental impact throughout their life cycle. It helps to drive the market towards more sustainable solutions by using the significant purchasing power of governments to support green innovations. This policy tool involves for instance authorities implementing minimum requirements that encourage producers to shift from certain products or technologies to others. In the GPP scenario for plastic recycling, this means encouraging early adopters to switch from mechanical to chemical recycling. The following cases are implemented: 25%, 50% or 75% of the initial adopters of mechanical recycling switching to chemical recycling at time $t = 0$.

Simulations results are in Figure 7, with overall diffusion on the left panel and the proportion of chemical recycling adopters on the right panel. This policy intervention is the only one that significantly increases the level of adoption of chemical recycling, allowing it to reach on average 17%, 37%, and 63% of the total adopters in the four cases analysed (remember, these are proportions out of all adopters of recycling technology combined). However, this has a negative effect on overall diffusion, reducing it by about 3, 8 and up to 14 percentage points for switching levels of 25%, 50% and 75%, respectively.

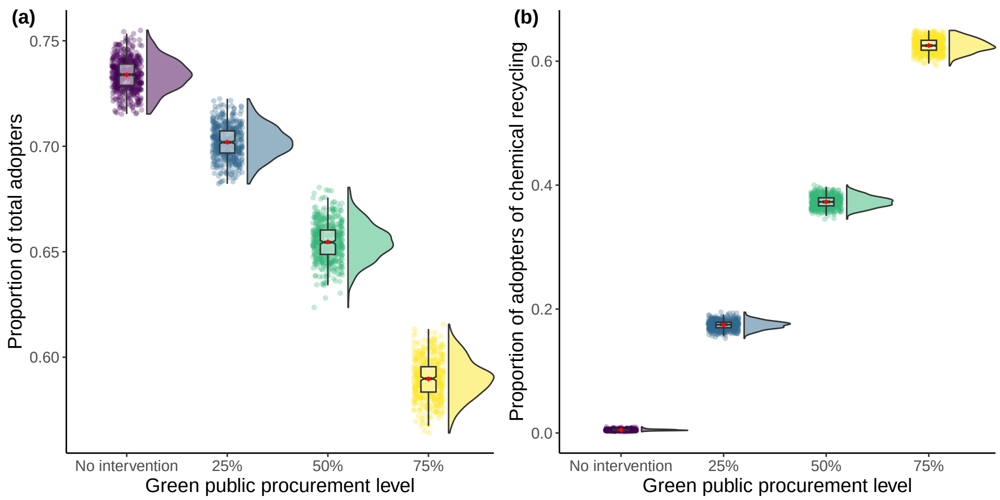


Figure 7: Green public procurement Scenario. Distributions of the proportion of **(a)** total adopters and **(b)** adopters of chemical recycling for four switching levels of the Green public procurement Scenario (BAU, 25%, 50% and 75%) in Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4, represented using boxplots (red diamonds: mean) and kernel probability density plots. Simulated data are obtained over 500 replications for each parameters combination.

5.3 Summary analysis and Golden Scenario

The effects of the three policies are summarised in Table 2. In relative terms, the R&D scenario is the least effective. The Tax exemption scenario raises overall diffusion but fails to promote the diffusion of the emerging green technology (chemical recycling). Green public procurement enhances the diffusion of the emerging green technology, but this comes at the cost of lower overall diffusion.

	Effect on	
Policy	**Overall diffusion**	**Proportion of the emerging green technology**
Tax exemption	$\nearrow$	Negligible
R&D boost	Negligible	Negligible
Green public procurement	$\searrow$	$\nearrow$

Table 2: Summary of the effects of different policy interventions on the overall diffusion and on the final proportion of the emerging green technology (chemical recycling)

We conclude with simulations showcasing a Golden scenario, where the three policies above are combined together. The results, presented in Figure 8, show that when policies are combined, the negative effects of Green public procurement (GPP) are offset by the positive effects of tax exemption. However, this only occurs for low levels of GPP. Otherwise, the negative effect of GPP on overall diffusion prevails. R&D boost has a negligible role, except at high levels of GPP. As for the emerging technology, the positive effect observed in the GPP scenario is maintained in the Golden scenario, with even higher levels of diffusion attained. The latter observation means that for some parameters' settings there is a synergetic mechanism of policies combination. This is reported in Table 3, that shows when a given combination of policies provides larger overall diffusion of recycling technologies combined with respect to the BAU scenario. We observe that when Green public procurement promotes too much (75%) the emerging technology, overall diffusion is always lower. For moderate Green public procurement (50%) overall diffusion is higher only for a complete tax exemption. For low levels of Green public procurement, instead, we always obtain a larger overall diffusion. The latter combination results then as the best one, as long as the ultimate goal is to both promote recycling technologies in general, and possibly favour the 'greener' and emerging technology of chemical recycling.

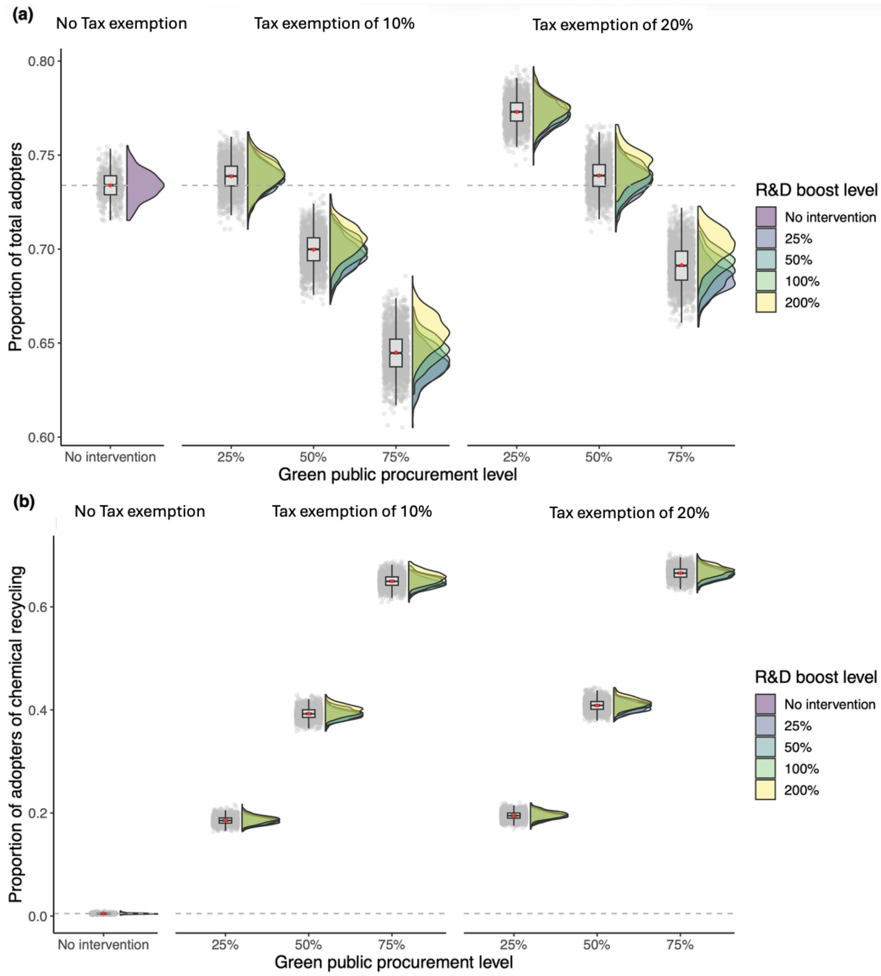


Figure 8: Golden Scenario. Proportion of **(a)** total adopters and **(b)** adopters of chemical recycling, obtained over 500 replications for each parameters combination, in Small World networks ($\mu = 0.01$), with $N = 10000$ nodes and average connectivity 4, represented using Boxplots (Red diamonds: mean) and Kernel probability density plots.

		Green Public Procurement level					
		25%		50%		75%	
		Tax exemption					
		10%	20%	10%	20%	10%	20%
R&D boost level	25%	↗	↗	↘	↗	↘	↘
	50%	↗	↗	↘	↗	↘	↘
	100%	↗	↗	↘	↗	↘	↘
	200%	↗	↗	↘	↗	↘	↘

Table 3: Summary of the effects of the different combinations policy interventions on the overall diffusion

6 Discussion and conclusions

We propose a percolation model to study the effect of technological progress on competitive innovation diffusion. First, we find that in the absence of technological change, small differences in the costs of the technologies can lead to important differences in diffusion size shares. We then introduce technological change and focus on scenarios where only one of the two technologies experiences technological progress, to illustrate the case of emerging technologies competing with more mature technologies. This scenario is reasonably representative of technological competition in the early stages of diffusion of innovative practices such as recycling, and in particular plastics recycling.

Our main finding is that a high number of early adopters of both competing technologies can be detrimental to the overall diffusion process, as well as to the emerging technology, which is the one with higher potential. Indeed, early adoption of mature technology blocks access to potential adopters of the emerging technology. Our model provides a bottom-up explanation within the dynamics of competitive diffusion in networks. Moreover, we find that technological change can reverse market shares in favour of the emerging technology, even if it is initially more costly.

We further calibrate our model to the case study of PET plastic recycling technologies and examine the forecasts of different scenarios involving policy interventions aimed at promoting the diffusion of the chemical recycling technology. Our findings indicate that reducing taxes on both competing technologies is the only policy that effectively promotes the overall diffusion of recycling. Additionally, green public procurement is the only instrument that succeeds in stimulating competition by increasing the share of the emerging green technology, but this comes at the cost of lower diffusion of recycling technologies. When the policies interventions are combined, the greatest potential for diffusion is found at low levels of green public procurement, where the negative effect of green public procurement is outweighed by the positive effect of the tax exemption. The trade-off between total diffusion and the diffusion of the emerging technology is also observed when the different policies are combined. Our results have several implications, which will now be discussed.

6.1 Direction given by policy makers

Along with Mazzucato (2018), mission-oriented policy instruments are important and can redirect the technological change. However, policymakers should make choices about the direction of change to be implemented. Indeed, what kind of landscape for recycling technologies is maintained depends on the direction chosen. In short, can policy makers only act on the emerging technology with green procurement at the expense of the overall diffusion, or can they take the process one step further in the circular economy by promoting both recycling technologies with reduced taxes? This policy choice depends on the existing regulation, the macroeconomic context, the structural changes in the plastic value chain, but also on the possibility to implement green procurement. The latter tool is not neutral and may encounter resistance, as shown in Australia when trying to implement green procurement for recycled materials (Wijayasundara et al., 2022).

6.2 Resistance for preserving *status quo* and installed base

Policy makers can redirect the landscape for recycling technologies towards a sustainable transition, but they may face resistance in doing so. Indeed: "*The challenges faced by clean technologies are therefore seldom just technical; they are political (and social) and include a need for greater commitments of patient capital by governments and businesses around the world. R&D works, but it is not enough. Nurturing risky new industries requires support, subsidy and long-term commitments to manufacturing and markets as well*" (Mazzucato et al. (2015), pp. 149-150).

This resistance may exist to avoid structural changes along the plastics value chain and to avoid a costly sustainable transition. For example, resistance to structural change is illustrated by the concept of the 'installed base', which is the accumulation of old technologies that maintain the status quo and the dominant position of mature technologies and infrastructures (Greenstein, 1993). A growth regime with a larger installed base increases the chances of achieving a dominant market position through the mechanisms of economies of scale and decreasing cost conditions. Within the plastic value chain, this explains the few incentives for changing the dominant regime and the high switching costs of the emerging technology. The latter remains contested, with lack of alignment between actors (Zepa et al., 2024), resulting in a technological lock-in. In addition, productivity gains along the global plastic value chain provide strong incentives to continue investing in current infrastructures and preserving short-term profits, rather than disrupting the current pattern in the recycling landscape (Mundt et al., 2023).

6.3 Lock in nested in the plastic value chain

Lock-ins are difficult to remove when they are found in several steps of the value chain, creating diverse sources of inertia. Indeed, lock-ins are stubbornly entrenched across the domains of production, markets, waste management, industry organization, and governance: "*The complexity of plastic value chains is striking in comparison to other energy- and emissions-intensive material industries. This is manifested in the variety of interconnected processes and companies in petrochemical clusters, huge diversity of plastics, and omnipresence of both short- and long-lived products across all domains of modern life. As a result, the fossil lock-in is very strong. The pathways are also complex and certain measures sometimes in conflict [...] This complexity, including uncertainty concerning the effectiveness of measures and conflicting interests across value chains, hampers the envisioning of zero emission futures and how to get there*" (Bauer et al., 2022, p. 372).

In this context, policymakers have an opportunity to act and reverse the current situation. However, they should be aware of the path dependency effect and the risks involved in promoting innovation, even if they encounter resistance, in order to move the global plastic value chain forward. A policy package of tools could facilitate this shift and adapt outcomes to various institutional contexts, providing a means of responding to resistance and introducing novelties within the plastic value chain. As Hepp (2022) demonstrated, the success of any policy intervention also depends on timing and the ability to implement interventions at the 'right' moment.

Appendix A Simulations standard errors

When studying competitive diffusion without learning (Section 3.1), for each setting of the model's parameters we run simulation experiments of 100 runs. Since we have two random data generating processes in our model, the formation of the initial network of firms and the extraction of firms' reservation costs, the output of different simulations runs is a set of random numbers. We keep track of the final total diffusion size and of technologies' market shares, as well as of the diffusion time (i.e. the total number of time steps needed by the diffusion process to terminate), at the end of each single diffusion process run. Thus, for each setting of the model's parameters, we obtain a series of 100 observations of these variables. In addition to the descriptive statistics reported in Figure 1b, here below we show the distribution of the standard errors of the mean for both the total fraction of adopters (left panel of Figure 9), and the market shares of one of the two technologies (right panel of Figure 9), from which the market share of the competing technology can directly be deduced as the two add up to one.

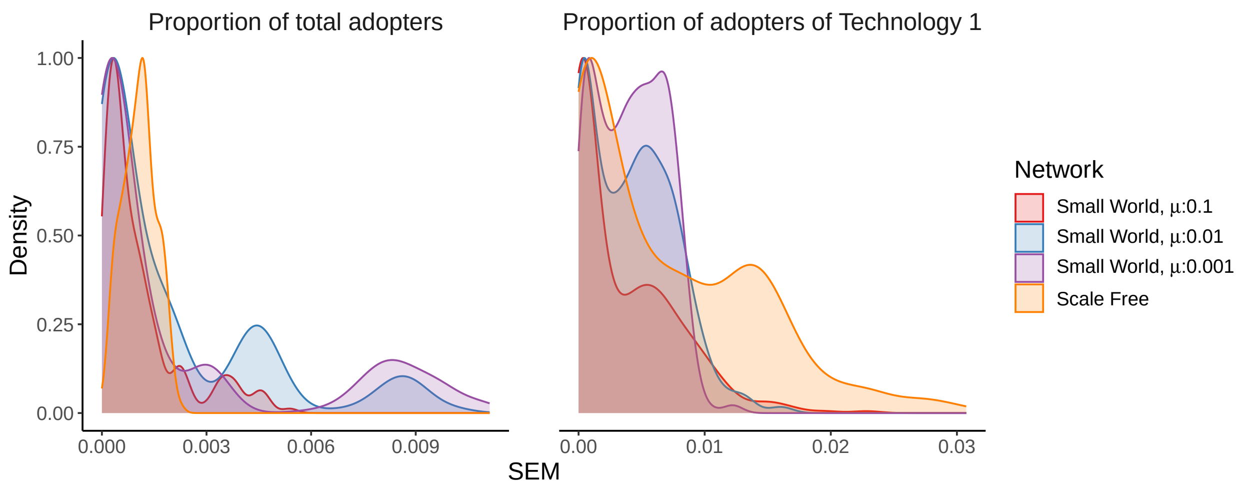


Figure 9: Standard error of the mean (SEM) of the proportion of total adopters and of adopters of Technology 1, obtained over 100 replications for each parameters combination in Small World network and in Scale Free network, with $N = 10000$ nodes, average connectivity 4, and 10 seeds for each technology.

For the overall diffusion size our simulations present a very small error, with the majority of probability mass of its error below 0.002. The error of the technologies market shares is one order of magnitude larger, with most of probability mass below an error of 0.01. We consider these orders of magnitude acceptable as the variables of interest in our study are market shares, with range $[0, 1]$.

Appendix B Comparative analysis of competitive diffusion in three Small World networks and in a Scale Free network

In this appendix we report a spectrum of simulation results for different settings of the competitive diffusion model, including the setting considered in the main analysis of the paper. In particular, we have considered different Small World networks with more or less degree of randomness, by varying the rewiring probability (μ) used to generate the network. Indeed, in addition to $\mu = 0.01$, we investigate the cases of $\mu = 0.1$ and $\mu = 0.001$. This allows us to compare results in different Small World networks. We have also studied competitive diffusion in Scale Free networks.

Figure 10 uses heatmaps to show average diffusion size and market shares of the two technologies, for different cost combinations, in the different networks. We see how the percolation threshold of overall diffusion shifts depending on the rewiring probability of the Small World network: in a Small World with rewiring probability 10% ($\mu = 0.1$) the percolation threshold is around a technology cost of 0.5, for both technologies, symmetrically. Conversely, in the Small World with rewiring probability of 0.1% ($\mu = 0.001$) the percolation threshold is near zero cost,[9] with a no-diffusion regime that encompasses almost the entire cost range.

The Scale Free network is relatively more efficient for diffusion, with a remarkably smooth transition between diffusion and no-diffusion regimes. For Small-World networks, besides specific differences in terms of the cost critical value separating diffusion regimes, results regarding competitive diffusion are qualitatively similar and robust: around the critical threshold there are huge differences in terms of technologies market shares, so that small differences in costs result in large differences of the final diffusion in relative terms.

[9]Note that previous work (Newman and Watts, 1999; Zeppini and Frenken, 2018) find that in such network of infinite size, the percolation threshold is around 0.06.

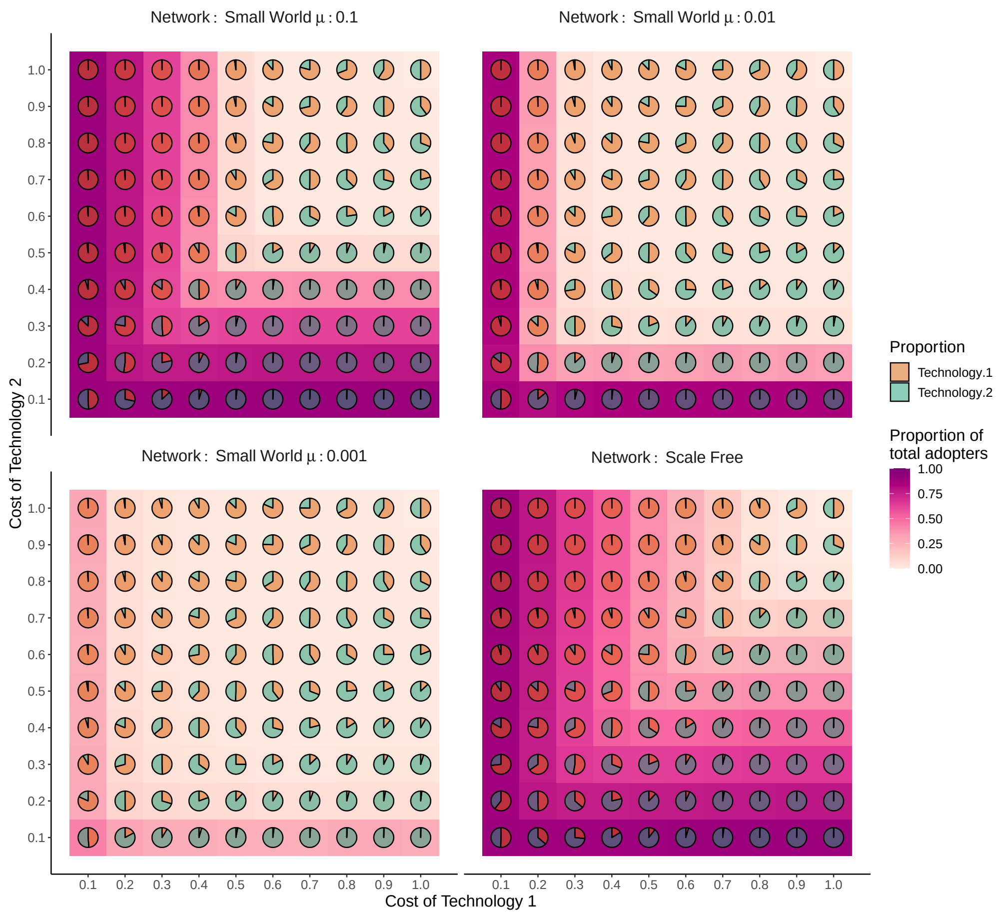


Figure 10: Average proportion of total adopters (pink colour shade) and average proportion of adopters of each of the two technologies (pie charts), obtained over 100 replications for each parameters combination, in different networks, with $N = 10000$ nodes, average connectivity 4, and 10 seeds for each technology.

Appendix C Diffusion Time

When studying competitive diffusion without learning (see Subsection 3.1), in each simulation we have also recorded the time needed for the diffusion process to conclude. In our model, the diffusion process terminates if no more new adoption occurred in the last times step, meaning that diffusion reached the final state where all connected potential adopters with reservation cost low enough have adopted one or the other technology, or if the time horizon limit of 1000 time steps is reached. Note that the latter happened in only 7 out of 160000 observations[10]. The diffusion time reported below in Figure 11 presents a non-monotonic pattern, with a peak located at the percolation threshold. As a matter of fact, the distribution of diffusion times is a handy tool for locating the percolation threshold.

[10] 20 initial costs for Technology 1 x 20 initial costs for Technology 2 x 4 networks x 100 runs = 160000 observations

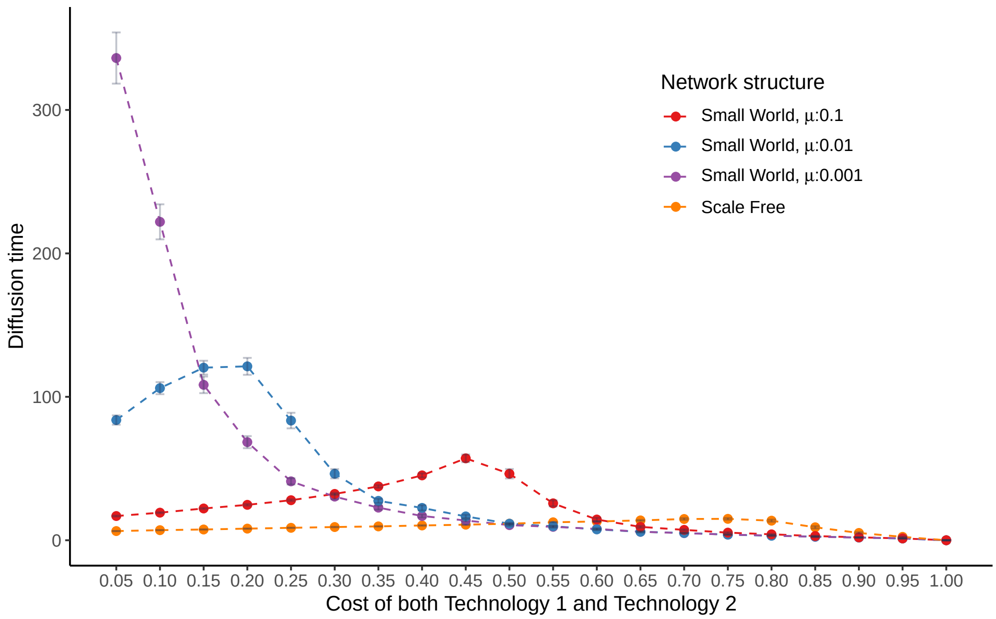


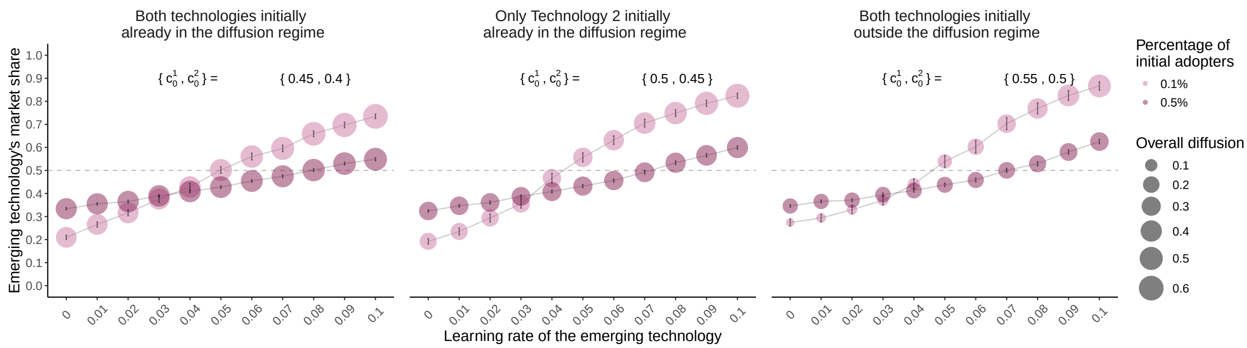
Figure 11: Diffusion time at different prices (equal prices between the two technologies), obtained over 100 replications in different networks, with $N = 10000$ nodes, average connectivity 4, and 10 seeds for each technology.

Appendix D Robustness check of competitive diffusion and learning

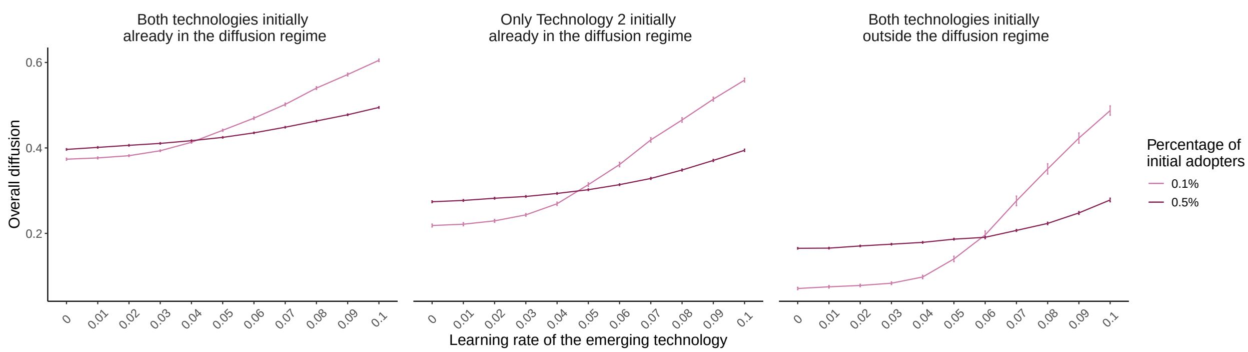
We have conducted further simulation experiments with different network structures for the the model featuring an interplay between learning and competition, as a robustness checks of Section 3.2. We have considered a Small-World network with $\mu = 0.1$ (in the main analysis we have $\mu = 0.01$) and a Scale Free network.

D.1 Small World networks with $\mu = 0.1$

Figure 12 shows the average final diffusion sizes and market shares of learning technology, for the different initial costs combinations and learning rates while manipulating the number of initial adopters. Thus, in addition to a rate of 0.1%, we also consider a rate of 0.5%. The results are in line with those obtained for the Small World with $\mu = 0.01$. The main difference is that lower learning rates are required to observe an inverse situation in terms of market share of the learning technology.



(a) Technology competition: average proportion of adopters of the learning technology for two different numbers of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes. The bars are two times the standard error of the mean (SEM). Dots sizes represent the average proportion of total adopters.



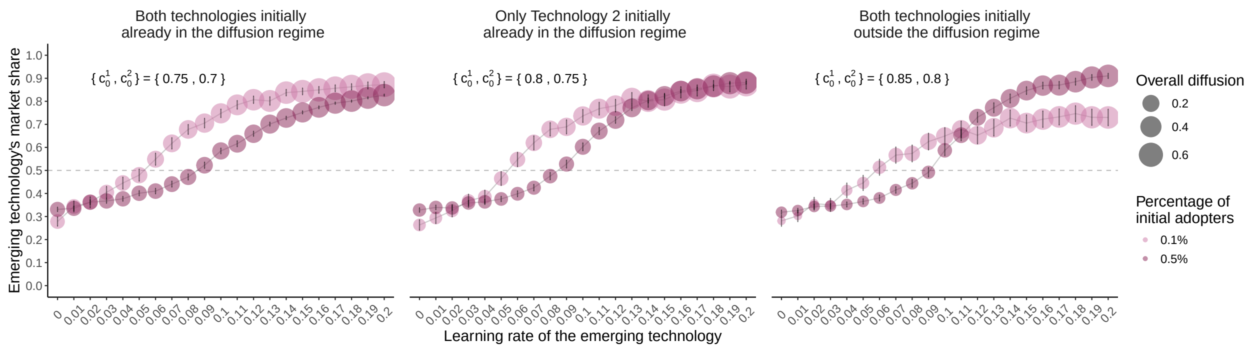
(b) Overall diffusion: average proportion of total adopters (represented in **(a)** by the dots sizes) for two different numbers of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes. The bars are two times the standard error of the mean (SEM).

Figure 12: Effect of both learning and the number of initial adopters on diffusion size and market shares in Small World network ($\mu = 0.1$), with $N = 10000$ nodes, average connectivity 4. The estimates are obtained over 500 replications for each parameters setting.

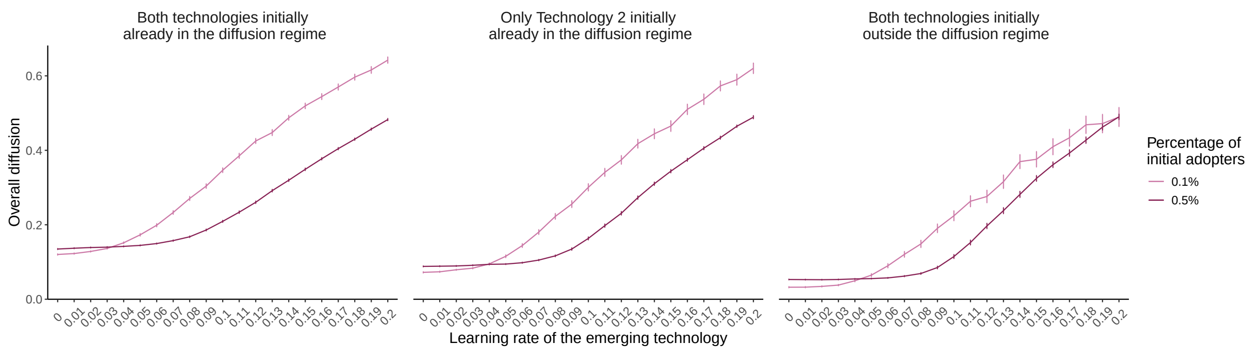
D.2 Scale Free network

In a Scale Free network we obtain slightly different patterns, but the main results remain, as shown in Figure 13. In particular, less initial adopters are again beneficial to overall diffusion, even for a larger range of learning rates of the innovative technology. In all three scenarios of technologies starting inside or outside the diffusion regime, the final diffusion size is larger with less initial adopters for a learning rate of the innovative technology just above 0.04.

Another difference of Scale Free networks is that in the third scenario, when technologies start outside the diffusion regime, for a very high learning rate the difference in final diffusion size shrinks, and it is basically the same, irrespective of the number of initial adopters. It seems that in this case the innovative technology spreads too quickly and self-prevent to achieve lower cost levels that would have attracted more adoption.



(a) Technology competition: average proportion of adopters of the learning technology for two different numbers of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes. The bars are two times the standard error of the mean (SEM). Dots sizes represent the average proportion of total adopters.



(b) Overall diffusion: average proportion of total adopters (represented in **(a)** by the dots sizes) for two different numbers of initial adopters (0.1% in light pink, 0.5% in dark pink), in three different diffusion regimes. The bars are two times the standard error of the mean (SEM).

Figure 13: Effect of learning and initial adopters on diffusion size and market shares in Scale Free networks (generated with two links for each new node), with $N = 10000$ nodes and average connectivity 4. Results are obtained over 500 replications for each parameters setting.

References

Arena, U. and Ardolino, F. (2022). Technical and environmental performances of alternative treatments for challenging plastics waste. *Resources, Conservation and Recycling*, 183:106379.

Armenise, S., SyieLuing, W., Ramírez-Velásquez, J. M., Launay, F., Wuebben, D., Ngadi, N., Rams, J., and Muñoz, M. (2021). Plastic waste recycling via pyrolysis: A bibliometric survey and literature review. *Journal of Analytical and Applied Pyrolysis*, 158:105265.

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal*, 99(394):116–131.

Arthur, W. B. (1990). Positive feedbacks in the economy. *Scientific american*, 262(2):92–99.

Bachmann, M., Zibunas, C., Hartmann, J., Tulus, V., Suh, S., Guillén-Gosálbez, G., and Bardow, A. (2023). Towards circular plastics within planetary boundaries. *Nature Sustainability*, 6(5):599–610.

Balint, T., Lamperti, F., Mandel, A., Napoletano, M., Roventini, A., and Sapio, A. (2017). Complexity and the economics of climate change: a survey and a look forward. *Ecological Economics*, 138:252–265.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341(6144):1236498.

Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.

Barbault, L., Brette, O., Lazaric, N., Massardier, V., and Revest, V. (2023). Bio-based plastics: a 'sustainable' alternative for the plastic industry? *International Journal of Environmental Sciences & Natural Resources*, 31(5).

Bauer, F., Nielsen, T. D., Nilsson, L. J., Palm, E., Ericsson, K., Fråne, A., and Cullen, J. (2022). Plastics and climate change breaking carbon lock-ins through three mitigation pathways. *One Earth*, 5(4):361–376.

Brenner, T. and zu Jeddeloh, S. (2023). Path dependence in an evolving system: a modeling perspective. *Cliometrica*, pages 1–36.

Brouillat, E. and Oltra, V. (2012). Dynamic efficiency of extended producer responsibility instruments in a simulation model of industrial dynamics. *Industrial and Corporate Change*, 21(4):971–1009.

Brouillat, E., Saint Jean, M., and Arfaoui, N. (2018). "reach for the sky": modeling the impact of policy stringency on industrial dynamics in the case of the reach regulation. *Industrial and Corporate Change*, 27(2):289–320.

Cantono, S. and Silverberg, G. (2009). A percolation model of eco-innovation diffusion: the relationship between diffusion, learning economies and subsidies. *Technological Forecasting and Social Change*, 76(4):487–496.

Cecere, G., Corrocher, N., Gossart, C., and Ozman, M. (2014). Lock-in and path dependence: an evolutionary approach to eco-innovations. *Journal of Evolutionary Economics*, 24:1037–1065.

Chen, S.-J., Ma, Y.-J., Wang, J., Chen, D., Luo, X.-J., and Mai, B.-X. (2009). Brominated flame retardants in children's toys: concentration, composition, and children's exposure and risk assessment. *Environmental Science & Technology*, 43(11):4200–4206.

Cowan, R. and Jonard, N. (2004). Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28(8):1557–1575.

Crespi, F. and Guarascio, D. (2019). The demand-pull effect of public procurement on innovation and industrial renewal. *Industrial and Corporate Change*, 28(4):793–815.

Daugaard, T., Mutti, L. A., Wright, M. M., Brown, R. C., and Componation, P. (2015). Learning rates and their impacts on the optimal capacities and production costs of biorefineries. *Biofuels, Bioproducts and Biorefining*, 9(1):82–94.

David, P. A. (1985). Clio and the economics of qwerty. *The American Economic Review*, 75(2):332–337.

Davidson, M. G., Furlong, R. A., and McManus, M. C. (2021). Developments in the life cycle assessment of chemical recycling of plastic waste–a review. *Journal of Cleaner Production*, 293:126163.

Dosi, G. and Nelson, R. R. (2013). The evolution of technologies: an assessment of the state-of-the-art. *Eurasian business review*, 3(1):3–46.

Dosi, G., Roventini, A., and Russo, E. (2020). Public policies and the art of catching up: matching the historical evidence with a multicountry agent-based model. *Industrial and Corporate Change*.

Durán-Romero, G., López, A. M., Beliaeva, T., Ferasso, M., Garonne, C., and Jones, P. (2020). Bridging the gap between circular economy and climate change mitigation policies through eco-innovations and quintuple helix model. *Technological Forecasting and Social Change*, 160:120246.

Dussaux, D. and Agrawala, S. (2022). Quantifying environmentally relevant and circular plastic innovation: Historical trends, current landscape and the role of policy. *OECD Environment Working Papers, No. 199*.

Edler, J., Matt, M., Polt, W., and Weber, M. (2025). Transformative mission-oriented sti policy: Theoretical and conceptual rationales, intervention logics and challenges of an emerging type of sti policies. In *Transformative Mission-Oriented Innovation Policies*, pages 16–35. Edward Elgar Publishing.

European Commission (2014). Questions and answers on the commission communication "towards a circular economy" and the waste targets review.

European Commission (2020). A new circular economy action plan for a cleaner and more competitive europe. communication from the commission to the european parliament, the council, the european economic and social committee and the committee of the regions.

Foxon, T. J. (2011). A coevolutionary framework for analysing a transition to a sustainable low carbon economy. *Ecological Economics*, 70(12):2258–2267.

Geels, F. W. (2011). The multi-level perspective on sustainability transitions: Responses to seven criticisms. *Environmental Innovation and societal Transitions*, 1(1):24–40.

Geels, F. W. and Ayoub, M. (2023). A socio-technical transition perspective on positive tipping points in climate change mitigation: Analysing seven interacting feedback loops in offshore wind and electric vehicles acceleration. *Technological Forecasting and Social Change*, 193:122639.

George, N. and Kurian, T. (2014). Recent developments in the chemical recycling of postconsumer poly (ethylene terephthalate) waste. *Industrial & Engineering Chemistry Research*, 53(37):14185–14198.

Geueke, B., Groh, K., and Muncke, J. (2018). Food packaging in the circular economy: Overview of chemical safety aspects for commonly used materials. *Journal of Cleaner Production*, 193:491–505.

Grandori, A. and Soda, G. (1995). Inter-firm networks: antecedents, mechanisms and forms. *Organization Studies*, 16(2):183–214.

Greenstein, S. M. (1993). Did installed base give an incumbent any (measureable) advantages in federal computer procurement? *The RAND Journal of Economics*, pages 19–39.

Hepp, J. (2022). Being small at the right moment: Path dependence after a shift in the technological regime. *Industrial and Corporate Change*, 31(2):464–499.

Hohnisch, M., Pittnauer, S., and Stauffer, D. (2008). A percolation-based model explaining delayed takeoff in new-product diffusion. *Industrial and Corporate Change*, 17(5):1001–1017.

Ionas, A. C., Dirtu, A. C., Anthonissen, T., Neels, H., and Covaci, A. (2014). Downsides of the recycling process: harmful organic chemicals in children's toys. *Environment International*, 65:54–62.

Jackson, M. O. et al. (2008). *Social and economic networks*, volume 3. Princeton university press Princeton.

Jackson, M. O. and Yariv, L. (2007). Diffusion of behavior and equilibrium properties in network games. *American Economic Review*, 97(2):92–98.

Janssen, M. A. and Jager, W. (2002). Stimulating diffusion of green products. *Journal of Evolutionary Economics*, 12:283–306.

Joseph, T. M., Azat, S., Ahmadi, Z., Jazani, O. M., Esmaeili, A., Kianfar, E., Haponiuk, J., and Thomas, S. (2024). Polyethylene terephthalate (pet) recycling: a review. *Case Studies in Chemical and Environmental Engineering*, page 100673.

Kesidou, E., Krammer, S. M., and Wu, L. (2024). Subnational institutions, firm capabilities and eco-innovation. *Industrial and Corporate Change*, 33(6):1460–1486.

Khatun, R., Xiang, H., Yang, Y., Wang, J., and Yildiz, G. (2021). Bibliometric analysis of research trends on the thermochemical conversion of plastics during 1990–2020. *Journal of Cleaner Production*, 317:128373.

Kiesling, E., Günther, M., Stummer, C., and Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, 20:183–230.

Konc, T. and Savin, I. (2019). Social reinforcement with weighted interactions. *Physical Review E*, 100(2):022305.

Korhonen, J., Honkasalo, A., and Seppälä, J. (2018). Circular economy: the concept and its limitations. *Ecological Economics*, 143:37–46.

Lafond, F., Bailey, A. G., Bakker, J. D., Rebois, D., Zadourian, R., McSharry, P., and Farmer, J. D. (2018). How well do experience curves predict technological progress? a method for making distributional forecasts. *Technological Forecasting and Social Change*, 128:104–117.

Lazaric, N., Le Guel, F., Belin, J., Oltra, V., Lavaud, S., and Douai, A. (2020). Determinants of sustainable consumption in france: the importance of social influence and environmental values. *Journal of Evolutionary Economics*, 30:1337–1366.

Li, Y., Chang, Q., Duan, H., Liu, Y., Zhang, J., and Li, J. (2019). Occurrence, levels and profiles of brominated flame retardants in daily-use consumer products on the chinese market. *Environmental Science: Processes & Impacts*, 21(3):446–455.

Mankins, J. C. (1995). Technology readiness levels. *White Paper, April*, 6(1995):1995.

Mankins, J. C. (2009). Technology readiness assessments: A retrospective. *Acta Astronautica*, 65(9-10):1216–1223.

Mazzucato, M. (2018). Mission-oriented innovation policies: challenges and opportunities. *Industrial and corporate change*, 27(5):803–815.

Mazzucato, M. et al. (2015). The green entrepreneurial state. *The politics of green transformations*, 28:9781315747378–9.

Miedzinski, M., Mazzucato, M., and Ekins, P. (2019). A framework for mission-oriented innovation policy roadmapping for the sdgs: The case of plastic-free oceans.

Mundt, P., Savin, I., Cantner, U., Inoue, H., and Vannuccini, S. (2023). Peer effects in productivity and differential growth: a global value-chain perspective. *Industrial and Corporate Change*, 32(6):1267–1285.

Murray, A., Skene, K., and Haynes, K. (2017). The circular economy: an interdisciplinary exploration of the concept and application in a global context. *Journal of business ethics*, 140:369–380.

Nagy, B., Farmer, J. D., Bui, Q. M., and Trancik, J. E. (2013). Statistical basis for predicting technological progress. *PloS one*, 8(2):e52669.

Newman, M. E. and Watts, D. J. (1999). Scaling and percolation in the small-world network model. *Physical review E*, 60(6):7332.

OECD (2022). Perspectives mondiales des plastiques scénarios d'action à l'horizon 2060. Accessed: 2023-02-24.

Okamura, K. and Vonortas, N. S. (2006). European alliance and knowledge networks. *Technology Analysis & Strategic Management*, 18(5):535–560.

Ozman, M. (2009). Inter-firm networks and innovation: a survey of literature. *Economic of Innovation and New Technology*, 18(1):39–67.

Perera, S., Bell, M. G., and Bliemer, M. C. (2017). Network science approach to modelling the topology and robustness of supply chain networks: a review and perspective. *Applied Network Science*, 2(1):1–25.

Plastics Europe (2022). The circular economy for plastics – a european overview 2022.

Plastics Europe (2024). The circular economy for plastics – a european analysis 2024.

Polonsky, M. J., Wijayasundara, M., Noel, W., and Vocino, A. (2022). Identifying the drivers and barriers of the public sector procurement of products with recycled material or recovered content: A systematic review and research propositions. *Journal of Cleaner Production*, 358:131780.

Ramkumar, S., Mueller, M., Pyka, A., and Squazzoni, F. (2022). Diffusion of eco-innovation through inter-firm network targeting: An agent-based model. *Journal of Cleaner Production*, 335:130298.

Rengs, B., Scholz-Wäckerle, M., and van den Bergh, J. (2020). Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages. *Journal of Economic Behavior & Organization*, 169:332–368.

Rödl, M. B., Åhlvik, T., Bergeå, H., Hallgren, L., and Böhm, S. (2022). Performing the circular economy: How an ambiguous discourse is managed and maintained through meetings. *Journal of Cleaner Production*, 360:132144.

Samsonek, J. and Puype, F. (2013). Occurrence of brominated flame retardants in black thermo cups and selected kitchen utensils purchased on the european market. *Food Additives & Contaminants: Part A*, 30(11):1976–1986.

Schilling, M. A. and Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53(7):1113–1126.

Schwarz, A., Ligthart, T., Bizarro, D. G., De Wild, P., Vreugdenhil, B., and Van Harmelen, T. (2021). Plastic recycling in a circular economy; determining environmental performance through an lca matrix model approach. *Waste Management*, 121:331–342.

Schyns, Z. O. and Shaver, M. P. (2021). Mechanical recycling of packaging plastics: A review. *Macromolecular Rapid Communications*, 42(3):2000415.

Seto, K. C., Davis, S. J., Mitchell, R. B., Stokes, E. C., Unruh, G., and Ürge-Vorsatz, D. (2016). Carbon lock-in: types, causes, and policy implications. *Annual Review of Environment and Resources*, 41:425–452.

Sheldon, R. A. and Norton, M. (2020). Green chemistry and the plastic pollution challenge: towards a circular economy. *Green Chemistry*, 22(19):6310–6322.

Smith, A., Voß, J.-P., and Grin, J. (2010). Innovation studies and sustainability transitions: The allure of the multi-level perspective and its challenges. *Research Policy*, 39(4):435–448.

Solomon, S., Weisbuch, G., de Arcangelis, L., Jan, N., and Stauffer, D. (2000). Social percolation models. *Physica A: Statistical Mechanics and its Applications*, 277(1-2):239–247.

Stauffer, D. and Aharony, A. (2018). *Introduction to percolation theory*. CRC press.

Tur, E. M., Zeppini, P., and Frenken, K. (2018). Diffusion with social reinforcement: the role of individual preferences. *Physical Review E*, 97(2):022302.

Tur, E. M., Zeppini, P., and Frenken, K. (2024). Diffusion in small worlds with homophily and social reinforcement: A theoretical model. *Social Networks*, 76:12–21.

Uekert, T., Singh, A., DesVeaux, J. S., Ghosh, T., Bhatt, A., Yadav, G., Afzal, S., Walzberg, J., Knauer, K. M., Nicholson, S. R., et al. (2023). Technical, economic, and environmental comparison of closed-loop recycling technologies for common plastics. *ACS Sustainable chemistry & engineering*, 11(3):965–978.

UNFCCC (2023). Secretary-general's statement at the closing of the un climate change conference cop28.

Volk, R., Stallkamp, C., Steins, J. J., Yogish, S. P., Müller, R. C., Stapf, D., and Schultmann, F. (2021). Techno-economic assessment and comparison of different plastic recycling pathways: A german case study. *Journal of industrial ecology*, 25(5):1318–1337.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of 'small-world'networks. *Nature*, 393(6684):440–442.

Way, R., Ives, M. C., Mealy, P., and Farmer, J. D. (2022). Empirically grounded technology forecasts and the energy transition. *Joule*, 6(9):2057–2082.

Wijayasundara, M., Polonsky, M., Noel, W., and Vocino, A. (2022). Green procurement for a circular economy: What influences purchasing of products with recycled material and recovered content by public sector organisations? *Journal of Cleaner Production*, 377:133917.

Young, H. P. (2006). The diffusion of innovations in social networks. *The economy as an evolving complex system III: Current perspectives and future directions*, 267:39.

Zepa, I., Grudde, V. Z., and Bening, C. R. (2024). Legitimising technologies for a circular economy: Contested discourses on innovation for plastics recycling in europe. *Environmental Innovation and Societal Transitions*, 50:100811.

Zeppini, P. and Frenken, K. (2018). Networks, percolation, and consumer demand. *Journal of Artificial Societies and Social Simulation*, 21(3).

Zeppini, P. and Van Den Bergh, J. C. (2020). Global competition dynamics of fossil fuels and renewable energy under climate policies and peak oil: A behavioural model. *Energy Policy*, 136:110907.

Zeppini, P. and van den Bergh, J. C. (2025). Did covid-19 help or harm the climate? modeling long-run emissions under climate and stimulus policies: P. zeppini and j. c jm van den bergh. *Journal of Evolutionary Economics*, 35(4):721–757.

Zhang, H. and Vorobeychik, Y. (2019). Empirically grounded agent-based models of innovation diffusion: a critical review. *Artificial Intelligence Review*, 52:707–741.

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