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1 to a low-carbon economy requires moving to the producti
energy- and material-intensive than current practices. This may prov

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Let us illustrate such uncertainty with an example. As simple as it may seem, it is not obvious to compare the environmental impact of washing dishes by hand or using a dishwasher. A Google search of ‘dishwasher vs hand washing environment’ returns millions perspectives and answers. This is because such comparison requires a life cycle analysis of all components used in hand and machine washing, i.e. studying where the metal comes from, how it is assembled, or how the detergent is produced, as well as an assessment of how consumers employ each component and how each of them impacts on the environment. On top of this, small behavioral changes can influence producer choice and changes in technical features (e.g. energy efficiency and cost), which in turn influence consumer behavior, and so on.

Such technological and behavioral complexities have been largely ignored in climate policy discussions. They can be studied with evolutionary-economic models that employ an agent-based modelling (ABM) approach. Following the ABM approach, macroeconomic outcomes emerge from interactions between large numbers of distinct agents in distinct networks (Tesfatsion, 2006). In ABM, agents are modelled as independent entities having their individual objectives, preferences, knowledge, who perceive and adapt to changes in the environment. They are often described by rules that can accommodate a variety of boundedly rational behaviors, but also include rational behavior and utility maximization. The interactions between agents and the feedbacks from aggregate emerging outcomes, are the sources of nonlinear dynamics and of further emergent phenomena. Evolutionary ABM have proved capable of explaining a number of stylized facts, which traditional economic approaches rule out as ‘out-of-equilibrium’ properties such as the cascades of bankruptcies of firms and banks or business cycles. Such models have been widely adopted in modelling industrial dynamics and technological change (Malerba and Orsenigo, 1997; Janssen and Jager, 2002; Oltra and Saint Jean, 2009; Windrum et al., 2009b,a; Safarzyńska and van den Bergh, 2010), economic growth (Dosi et al. (2010); Cincotti et al. (2010); Ciarli et al. (2018)), or the cascades of bankruptcies in financial markets (Tedeschi et al., 2012; Thurner and Poledna, 2013).

Over the last two decades, evolutionary ABM have achieved an increasing attention in modeling different aspects of sustainability transitions. For instance, the coevolutionary models discussed in Section 2, have offered important insights on how to unlock the market, where evolving consumers preferences affect the direction towards which firms innovate. More recently, authors have combined evolutionary models with energy markets and/or climate modules (e.g. Gerst et al., 2013; Wolf et al., 2013; Ponta et al., 2018; Lamperti et al., 2018) to study interactions of different sub-systems in the economy and how they can generate a systemic risk, or can amplify damages from climate change.

In this paper we focus on, and extend, a toy-model by Windrum et al. (2009a) that explains how the interactions between consumers, between firms, between consumers and firms, and between technological components may influence the environmental impact of consumption and related production (Section 3). Before presenting and discussing the model, Section 2 provides a brief overview-3 ( )]Tuhe enolutionary knowledge about sustainability transition. Section 4 concludes and proposes extension to the toy model.

2. A Selected Literature Review

Evolutionary-economic models can provide important insights to modelling sustainability transitions (Ciarli and Savona, 2019; see Safarzynska et al. (2012) for a review of policy oriented evolutionary-economic models; and Balint et al. (2017), Lamperti et al (2019) and Hafner et al. (2020) for overviews of evolutionary ABM). In this section, we discuss how technological change, evolving preferences and consumer-producer interactions (co-evolution) are modelled in evolutionary-economic theories, and discuss their relevance to understand sustainability transitions.

Industry dynamics models explain economic and organizational change as a result of evolutionary forces acting on the population of firms: innovations introducing new varieties to the population and selection causing differential growth of firms. In such models, heterogeneous firms actively search technological landscapes for better solutions or to imitate frontier technologies (Nelson and Winter 1982). New technologies and products can emerge at any time. Most early industry models depict products (technologies) as defined over one or two dimensions such as quality and cost. However, transitions to sustainability generally involve changes in large technological systems or complex technologies embodying many technical components, where different sub-technologies co-evolve. This creates a challenge as changes in one sub-technology, for instance improving the technical characteristic of a single component, may negatively affect the functioning of other components, reducing the overall performance of the technology. Examples of non-modular technologies are numerous: cars, aircrafts, or computers combine different technological solutions in a single product. A particularly well known way to represent interdependencies between sub-technologies is to use the NK-model originally developed in the context of biological evolution (Kauffman and Johnsen, 1991; Kauffman, 1993). It has been shown that as the complexity of technologies increases, as a function of the interdependence between its components, it becomes more difficult to find an element to be improved (Kauffman, 1993; Auerswald et al., 2000). Optimizing the performance of non-modular technologies is inherently difficult because the 'fitness landscape' consists of many local optima. Building on the concept of fitness landscapes underlying the NK-model, Alkemade et al. (2009) study transitions pa

The important insights from this line of research is that maintaining diversity of technologies options is important to prevent lock-in to a single technology that initially looks promising, but overtime may turn sub-optimal.

Diversifying investments in technological options allows also for combining existing technologies and ideas, which is widely recognized as an important source of innovation (Tsur and Zemel, 2007; Weitzman, 1998). Here, experimenting with variations of existing technologies may contribute to knowledge creation. However, maintaining the diversity of options is generally expensive for a single firm, and at the same time the benefits from each innovation are uncertain (Safarzyńska and van den Bergh 2010,2013).

Zeppini and van den Bergh (2011) focus on the trajectory of technologies as an outcome of firm innovation. They extend Arthur (1989) lock-in model introducing the possibility of innovating by recombining technologies from different trajectories. The two competing technologies are green and brown, which are substitutes. The authors show that the recombination of the technologies may offer hybrid technological pathways, with lower environmental impact than that of incumbent technologies.

Most evolutionary models of industrial dynamics reduce the consumer side to a static selection environment, while assuming that the processes of innovation, creation, and selection are independent. Theories of 'technological push' emphasizes the role of market forces in the process of change. They rely on the one-way causal determination from science to technology and production, largely ignoring the role of economic factors in the process of change (Dosi, 1982). In turn, theories of 'demand-pull' assume that the market is capable of signaling consumer needs through the relative movements in prices and quantities and consequently of pulling the innovative activities of producers in a particular direction of search. Both approaches are criticized for offering a partial explanation of market dynamics and technological change. Many successful innovations, which seem to be unrelated to user needs (e.g. innovation emanating from blue-sky research), stem from user-producer interactions (Mowery and Rosenberg, 1979).

A number of evolutionary models have been proposed to study technological change as a result of the co-evolution of technologies on the supply side and of consumer preferences on the demand side. In models of demand-supply co-evolution, the substitution of an incumbent by a new technology relies on the pace of technological change and evolving consumers preferences. For instance, Windrum and Birchenhall (1998) propose a formal model of demand-supply coevolution to examine determinants of technological succession. In their framework, firms offer products to satisfy clients in consumer classes, to which they are randomly assigned. In addition, firms engage in product innovation to attract new consumers. Consumers move between consumer classes depending on the relative attractiveness of products offered by incumbent firms. They imitate the consumption choices of their peers, if

technology components, for the emergence of less polluting products. In Section 3.8 we extend the model to capture the uncertainty rooted in the technological change towards more sustainable goods. We add the interaction between several components of a technology, which makes the exploration of technological landscape complex, reducing the relevance of the expectations on future technological trajectories for consumer choice. The uncertainty for both producers and consumers increases with the complexity of the technology, as firms discover information about the technology while exploring it. Such uncertainty may not allow to fully exploit the technology green potential, if firms randomly start on a search path that leads to local optima, where the global optimum is the most sustainable technology in a given technological paradigm. The more complex and newer is the technology, the higher the chance for a firm to follow a suboptimal research strategy and lock-in in local optima; and the higher the chance for consumer to lower their expectations about the green potential of the new technology.

We use this model as it captures several features that apply to the co-dynamics between consumers and producers that are crucial to understand how firms improve the environmental impact of their goods, and the process of their adoption. Innovation in this model is the outcome of a co-learning process between producers and consumers. The model is also quite flexible: it can be easily extended to capture more sophisticated firm and consumer behavior, to add more sectors, such as finance or energy, and to include a macroeconomic account.

The model features two types of interacting agents: firms and final consumers. Firms produce a good with a vector of product characteristics that define its use properties (Lancaster, 1966a), a price and an environmental impact (from consuming it). Firms target a given consumer class, endowed with given preferences. Firms can improve the feature of the goods that they produce through innovation, which may affect its cost (therefore price), quality (the vector of characteristics), or the environmental impact of consuming it. Environmental impact in the model is a property of the good, which depends on its 'environmental fitness', rather than a property of the production process (as more commonly analyzed in the literature). Because pollution depends on the goods purchased, consumers are concerned about the pollution externality of using a given good, rather than about the technology to produce it. Environment caused by using a good. Within a class, consumers are homogeneous. This introduces in the model the crucial difference between individual and collective benefits of individual choices. The actions of a small number of environmentalists through consumption may have a small impact on the stock of pollution, unless their action is imitated by similar consumers. Two opposite outcomes may occur: classes of environmentalist consumers manage to attract consumers that are initially less concerned about the polluting features

the characteristics (T&) and of the stock of pollution ( ). Each firm produces a heterogeneous good (Section 3.2), therefore we index a good's feature with that of the producing firm Ê. Formally, a class utility is expressed as:

Qß Ÿ = R k Ì L ÜÜ o + @ T& + A k (O) & o (1)

where I Ÿ is the budget constraint of all individuals in class j. The three terms of the class utility function have the following form:

R Ÿ = Ù Ÿ ¥ I Ÿ F L ç ? ,5Ü Ê L ç ? ,5Ü < I Ÿ

@ Ÿ = Ã Û Ð õ Ú Ÿ Û ¥ T ç ? ,5Û Ü (2)

A Ÿ = J Ÿ (c ¾ k æ 7, -O ? æ -7) / (5 ?) Ê ⊖ ' (O)

where Ù Ÿ and > Ÿ Û are the consumer preferences with respect to the price and quality of the good (determined by a vector of characteristics T&).

The first component of Q Ÿ simply represent a consumer preference for saving (in a given class j). The price of the good L Ü is relatively more relevant the lower is the consumer budget constraint. In other words, the preference for savings decreases with the budget constraint: consumers in wealthy classes are less influenced by prices in their purchasing decision.

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performance, in this model we only refer to the features of the good they produce, and not to a firm production process.

The expected environmental fitness of a firm (i.e. of the product produced) ' $_{Y}$(Q$_{j}$) is a combination of the fitness of the best technology available in the market (Q(Y)) in a given time period (t)[1] and the firm environmental fitness (Q T$_{j}$&:

$$' _{Y}(Q_{j}) = ß^{ã}_{Y} \frac{æ(e æ\&)_{j}}{5 > (æ) ? æ(e æ\&)_{j}} \quad (3)$$

where $ß^{ã}_{Y}$ Ð[0,1] is a weight that consumers attach to the current environmental impact of design E[6] relative to the technological promise of the most recent paradigm Q(Y) (note that a design (T$_{j}$&

relatively lower utility. In other words, a class that is well catered by existing goods (i.e. goods that balance the trade-offs between the direct, indirect, and environmental preferences of that consumer class), experiences a higher average utility than a class that is not well catered for by the existing goods.

Formally, the movement of individual consumers across classes is modelled as a replication dynamics. Classes with above-average utility, grow as a proportion of the total population, while classes with below-average utility decline. As a result, the combination of preferences in the population also change, moving towards the preference of the classes that grow in number of consumers (the total population is fixed). In turn, this change in consumer population (and average preferences) also changes the signal for firms, which may need to adapt their innovation behavior to accommodate the changing distribution of consumer preferences. Because with a pure replicator dynamics only one class is likely to survive in the limit, which would also lead to a single dominant design, and a single firm dominating the whole market, we use a 'tamed' replicator (Wirkierman et al. (2018)): an intensity parameter β tempers the strength of selection, allowing a number of classes with similar utility to have the same share $s_{j,t}$ of total consumers N.

The number of consumers $N_{j,t} = s_{j,t} N$ in each class j is computed as a ratio $s_{j,t}$ of the total number of individual consumers:

$$s_{j,t} = s_{j,t-1} \frac{\bar{u}_{j,t-1}^{\beta}}{\sum \bar{u}_{j,t-1}^{\beta}} \tag{5}$$

where $\bar{u}_j$ is the average utility of class j:

$$\bar{u}_{j,t} = \max\left(\epsilon, \frac{\bar{u}_{j}}{\bar{U}_{t}}\right) \tag{6}$$

$\bar{U}_{t-1}$ is the average utility across all classes; $u_{i,j,t}$ is the utility of a single consumer i in class j; and ϵ is a small parameter allowing each class to survive through time, so that it can be populated again, in case it becomes attractive when its fitness change (e.g. because of a change in the technological paradigm).

In each time period, consumer classes access the market in random order (a different one in each period). When it is their turn, each consumer in a class select the firm that best satisfies their utility. To simplify, we assume that each consumer buys one unit of the selected good. Firms use their inventories and finished goods to match the demand from a class. When they run out of inventories -1 (s)1 Tc 0da [(thp)-1 (s) purchasing options. When consumers do not consume for one of these reasons, their utility comes from saving, or consuming the budget on a different market: $U_{j} = \overline{U}$.

3.2. Supply

We model F firms indexed by i producing an heterogeneous good, with different use characteristics, to satisfy one unique consumer need. Firms are initially homogeneous, endowed with the same market share and capital, the only factor of production. Production is kept to its simplest form, to allow focusing on the innovation process, industrial dynamics, and the interaction with consumers. As times goes by, firm market shares depend on the relation between consumer preferences, the price, quality and environmental fitness of the produced good. To produce the good firms invest in capital, which defines their production capacity. Depending on the relation between production and demand, firms accumulate non-perishable inventories, which are carried on from one period do the next. Firms innovate in order to improve their good, but depending on the market signal they receive from the consumers buying from them, they may follow different innovation paths in the technological landscape. Firms that do not manage to maintain a sufficient amount of capital exit the market.

Firms define a target level of output (Y^D_t) as a linear combination between consumer demand ($D_{i,t}$) and actual sales ($S_{i,t} = \min(D_{i,t}, INV_{i,t-1})$), which cannot be higher than the available inventories $INV_{i,t-1}$:

$$Y^D_t = \alpha^D D_t + (1 - \alpha^D) S_t \qquad (7)$$

where $\alpha^D \in [0,1]$ allows to adjust smoothly to changes in demand and avoid sudden oscillations.

Given Y^D_t and the financial constraint, a firm may (dis)invest, according to the following rule:

$$I_{i,t} = \begin{cases} \alpha^K \min\{Y^D_{i,t} - K_{i,t-1}, FR^D_{i,t}\} & \text{if } Y^D_{i,t} > K_{i,t-1} \\ -\alpha^K \min\{K_{i,t-1} - Y^D_{i,t}, K_{i,t-1}\} & \text{if } Y^D_{i,t} < K_{i,t-1} \end{cases} \qquad (8)$$

where $\alpha^K \in [0,1]$ represents potential physical constraints in changing production levels in the short run. Firms invest when the target output is above the available capital, otherwise they disinvest and sell capital. When they invest, the amount is the minimum between the capital needed to achieve the desired level of output, and the financial constraint, the sum of the cumulated financial resources and last period profits: $FR^D_{i,t} = FR_{i,t-1} + \pi_{i,t}$. When output decrease and a firm needs to disinvest, they sell the difference between the available capital and the capital required to produce Y^D_t – unless the difference is larger than the available capital, in which case they sell only the remaining capital available.

Changes in the capital stock then depend on the above investment rule and the financial resources in t:

$$K_{i,t} = \begin{cases} K_{i,t-1} + I_{i,t} & \text{if } FR^D_{i,t} > 0 \\ \max\{K_{i,t-1} + FR^D_{i,t}, 0\} & \text{if } FR^D_{i,t} < 0 \end{cases} \qquad (9)$$

As a result of the investment, the stock of financial resources that will be available in the following periods also changes:

$$S_{ç\ddot{U}} = S^{\hat{U}}_{ç\ddot{U}} F \ k \ G_{ç\ddot{U}} F \ G_{ç?,5\ddot{U}} o \tag{10}$$

independently. When this is the case, firms can improve each characteristic independently from the others. The choice to innovate in one or the other direction, is driven by the trade-off between improving the characteristic and improving its environmental fitness (as we discuss in Section 3.4 below).

The environmental impact of consuming the good produced by firm i is a decreasing function of environmental fitness, with a steeper slope for intermediate levels of fitness:[3]

$$Þ_{U} = \frac{à}{5 > d\frac{Þkã\&\hat{O}o7\,Þ}{,}\,h} \qquad (16)$$

where Þ is the maximum environmental impact of a good; Q is the minimum level of fitness attainable; and î is a parameter that defines the rate at which an improvement in the environmental fitness of the good reduces its impact on pollution. The function is similar to a logistic. In the beginning, innovation is exploratory and yields marginal improvements to the environmental fitness: for very low levels of fitness, a fitness increase has a small impact in reducing the pollution impact of the good. As R&D activities continue, innovation manages to make larger steps, and improvement in fitness reduce the impact of using the good on the environmental sustainability. As the fitness reaches closer to its maximum, i.e. its maturity, returns to R&D to reduce the impact on the environment slow down. In other words, although increases in fitness are perceived by consumers in the same positive way, their impact on pollution differs for different phases of the innovation process, which come with different opportunities.

3.4. Innovation

As explained in Section 3.1, consumers choose goods depending on their utility, which depends on three features of the good produced by firms: the price, the vector of characteristics, and the environmental impact caused by its use. Firms have an incentive to reduce the price, increase the quality of its characteristics, and increase the environmental fitness. But they face trade-offs.

We assume that all firms undertake R&D in each period to modify the characteristics of the produced good, within a given paradigm. Modifying a characteristic has three effects: (i) changes the quality of the good, (ii) its cost (see Eq. 12) and (iii) the environmental fitness (see Eq. 15). We model innovation in two steps. In the first step, firms invest in R&D to innovate ('mutation'), attempting to change one characteristic. In the second step, firms assess this change, taking into account the preferences of the consumers in the class that they target (assigned at the outset and fixed throughout the firm's life time), and how the change modifies the trade-offs between quality, cost and environmental fitness ('evaluation'). Firms decide whether to retain the innovation(s) depending on the expected changes in the demand of the consumer class that they target.

Mutation

For simplicity we assume that R&D does not depend on firm revenues. All firms attempt an innovation, in each time period, on one random product characteristic h. There is a small probability • that the innovation is successful and results in a mutation of the position $T_{ŲÛ}$ of characteristic h on the technological landscape. When the innovation is successful, the firm draws a random number from a Standard distribution that defines the extent of the change of characteristic h:

$$¿ T_{ŲÛ} = 0\,(0,1) \cdot æ \qquad (17)$$

where æ is a parameter that allows to measure how local is the innovation process. If successful, as a result of R&D a one bit mutation then occurs: a change in the value of $T_{ŲÛ}$ by a factor $¿ T_{ŲÛ}$.

Evaluation

If R&D was successful for at least one

Incumbent firms are also constrained by their target class: we assume that a firm cannot swi

A rate of pollution decay is implicit in the relationship between environmental fitness and impact (eq 16).

3.6.

alerted to pollution, when close to their tolerance threshold, marginal changes in fitness have a large impact on utility, offsetting reductions in the product characteristics. Consumers enjoy a higher utility, on average, with less performing, more environmental goods.

In the basic version of the model we also observe market concentration, with the economy converging to oligopoly, even when firms compete on several co-existing paradigms. This is partly driven by consumers concentrating in few classes, reducing market differentiation. However, demand concentration is not a necessary condition in our model, as firms manage to target different classes with the same technology.

As expected, increasing the average relevance of environmental preferences across consumer classes reduces pollution. However, in our model this also has a perverse effect. Because the environmental component of the utility function is conditional on the potential environmental fitness of a technology (in a paradigm), for extremely high average environmental preferences firms may be better off exploiting the current paradigm and increase the value of product characteristics, rather than moving to new paradigms, where they will be punished for being too far from the potential frontier. In other words, if consumers expect a high environmental performance from a new technological paradigm, and they also have high preferences for environmental fitness, no firm has an incentive to move to the new technological paradigm, because by the time they manage to introduce incremental innovations, they would not be able to compete with firms performing at the edge of the older paradigm. This sounds familiar with many experimental green technologies, that require public support to attract private investors.

Aside from the average preferences, for a given low level of average environmental preferences across classes, higher heterogeneity of preferences across classes also reduces the pollution stock. This is because consumer classes with high environmental preferences, on average, attract more consumers, as they enjoy a higher utility when firms increase the environmental performance of their good. 'Eco-warriors' experience a larger utility, attract consumers that are less sensitive to the environment, increasing the demand for more eco innovations. When compared, the average environmental preference has a stronger impact on reducing pollution in our model, than the heterogeneity among consumer classes.

The model also shows that the positive effect of environmental preferences occurs when consumer preferences for product characteristics are sufficiently low. When there is a high trade-off between the use characteristics and the environmental fitness of a good, the former may prevail, reducing firm incentive to innovate towards environmental fitness. The preference for the product characteristics play a negative role on pollution abatement also when the average is relatively low, but the heterogeneity across consumer classes is high. With a very heterogenous population (with respect to their preferences for the use characteristics), firms have the option to focus on either the use characteristics or the environmental fitness of their good, which holds back environmental innovations.

With respect to the willingness to pay for improved environmental fitness, we find that the level of pollution depends on the distribution of consumer preferences with regards to the trade-off between environmental and price preferences. The larger the difference between price and environmental preferences, the higher the level of pollution. In other words, in the presence of consumer classes that are highly sensitive to price differences (high price elasticity), even the presence of consumer classes highly sensitive to pollution does not help reducing the environmental impact of consumption. When this is the case, firms target two different niches of consumers with old (low price and more polluting) and new technologies (high price and less polluting). The presence of the class of environmentally sensitive consumers, with their quota of green consumption, help maintaining pollution to a level that is low enough to allow firms to keep producing polluting goods for classes that prefer (or can afford only) cheaper goods.

3.8. Model extension: coordination and technological complexity

So far, we have assumed that the environmental impact of each product characteristic is perfectly modular. That is, it suffice for a firm to increase the environmental fitness of one

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Second,

influence the results, for example by exploring a wider space of the technological landscape, reducing the lock-in to optimal solutions? Regulations may also increase the coordination between producers of different component of final goods, for example by setting causes existing computers to become quickly outdated, generating e-waste. Firms in the computer and software industry do not search to coordinate actions to reduce e-waste, and therefore the impact of computers on the environment. Instead, they focus on the innovation in product characteristics, to appeal to most consumers, who have little information and rather uncertain exactions about the environmental impact of computers.

The model misses several relevant aspects that may allow to address the complexity and that suggest useful extensions for policy making. For instance, R&D has no cost in this version of the model, which may make firms incentives to move to a new paradigm even lower. Unless the demand or policy constraints are large enough. We encourage the use of the code in the modular LSD application[6]

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A Initialization

We set up a benchmark configuration with average values of the critical parameters (Table 1). Consumers preference toward the environmental sustainability of goods ( ) is fixed and equal across consumer classes; similarly for indirect preference ( ); direct preferences toward each product characteristic (ι_h) are randomly drawn from a uniform distribution that is also equal across classes. In sum, benchmark results are an outcome of a random selection between consumer classes, which occurs as their preferences randomly change through time as classes that enter the market bring novelty in consumption tastes; rather than an outcome of a selection on environmental preferences.

We run simulations with a population of 25 firms and 500 consumers divided into 100 consumer classes, all fixed through time. Both firms and classes start with equal endowments and equal share of sales and consumers respectively. We run each setting for 3000 time periods. Unless differently stated in the text, all result present average simulation outcomes over 10 different runs: after a preliminary analysis of the model we have considered this a good tradeoff between results verification and computational effort. The interested reader may refer to Windrum et al. (2009a) for a sensitivity analysis.

Table 1: Parameters setting

Par/ 8 = ÇN	Description	Value
%	total number of consumers in the economy	500
f	replicator tamed parameter	5
Ýè	minimum survival term	0.02
I Ý	Endowment	10
ÙÝ	Indirect utility preference	0.5
ÚÝÛ	Preferences for product characteristics	U [0.1,0.3]
ßÝt.522e5	Preference for environmental sustainability (discount rate)	(o51 (r)- 26 (e)]

å	Mark–up	0.1
Þ	Maximum environmental impact of goods	1
î	Speed of impact reduction of a fitness increase	2
á	Probability of success of innovation on one characteristic	0.2
æ	Mutation weight	0.2
ê Ó	Peak variance that allows to open a new window of opportunity	0.005
ì Ó ÆÜá	Minimum number of periods needed to discover a new techno-environmental paradigm	100
ì Ó ÆÔë	Maximum number of periods needed to discover a new techno-environmental paradigm	50
¿ Ð	Change in the maximum level of environmental fitness across paradigms	0.5
Ì Ñ	Variance of the technological change of the environmental landscape	0.3
¾‰	Minimum number of consumers below which a class is repla	2
¾	Minimum amount of capital below which firm is replaced	0.2
Î˜ y•"	Minimum number of periods between two firms and consumers turnovers	10
Î˜ y‡ž	Maximum number of periods between two firms and consumers turnovers	20
¼ y•"	Minimum value consumer preferences toward product characteristics	0.1
¼ y‡ž	Maximum value consumer preferences toward product characteristics	0.3
t	Number of user characteristics in any design in any paradigm	3
ž y•"	Minimum value of a product characteristic in the first period	0.1
ž y‡ž	Maximum value of a product characteristic in the first period	2.5
	Technological complexity	
‡•,ž	Environmental fitness interaction term: the effect of a change in TÛ on the fitness of TÛ	7[=ÆÜá==ÆÔ]ë
‡ y•"	Minimum value of the product characteristics environmental fitness interaction	tested
‡ y‡ž	Maximum value of the product characteristics environmental fitness interaction	tested

Notes. Fitted polynomial regression between different initial values of $\tau_{i,0}$ and the average distance between each characteristic and their optimal position (the one that attains maximum environmental fitness) across characteristics and firms. The average is further averaged across the 3000 time periods. The full fitted line (and hollowed circles) represents the simple average; the dash fitted line (and crosses) is the weighted average, using firm market share as weights

Figure 2: Relation between complexity ($\tau_{i,0}$) and the average distance of product characteristics with respect to their optimal position

Notes. Fitted polynomial regression between different initial values of $\tau_{i,0}$ and the minimum level of good's environmental fitness accepted by consumers ($\underline{s}$) at the end of given periods. The red crosses are used to plot the relation after 250 periods; the green circles with crosses are used to plot the relation after 380 periods; the blue hollowed circles are used to plot the relation at the end of the simulation (3000).

Figure 3: Relation between complexity ($\tau_{i,0}$) and the minimum level of good sustainability accepted by consumers

0.0 0.2 0.4 0.6 0.8 0.0 0.2 0.4 0.6 0.8 a (technological complexity)
a (technological complexity)

(a) Average

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