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Efficiency traps beyond Climate Change

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Main Text

Summary

Higher levels of economic activity are often accompanied by higher energy use and consumption of natural resources. As fossil fuels still account for 80% of the global energy mix, energy consumption remains closely linked to greenhouse gas emissions and thus to climate change. Under the assumption of sufficiently elastic demand, this reality of global economic development based on permanent growth of economic activity, brings into play the Jevons Paradox, which hypothesises that increases in the efficiency of resource use leads to increases in resource consumption. Previous research on the rebound effects has limitations, including a lack of studies on the connection between psychological processes and environmental consequences. This paper develops a mathematical model and computer simulator to study the effects of micro level exploration-exploitation strategies on efficiency, consumption, and sustainability, considering different levels of direct and indirect rebound effects. Our model shows how optimal exploration-exploitation strategies for increasing efficiency can lead to unsustainable development patterns if they are not accompanied by demand reduction measures, which are essential for mitigating climate change. Moreover, our paper speaks to the broader issue of efficiency traps beyond climate change by highlighting how indirect rebound effects driven by adverse behavioural responses not only affect greenhouse gas emissions but also resource consumption in other domains. By linking these issues together, our study sheds light on the complexities and interdependencies involved in achieving sustainable development goals.

Introduction

Economic growth is often associated with an increase in energy use (Stern, 2004; Ockwell, 2008; Kais et al., 2016; Sadraoui et al., 2019) and resource consumption (Bringezu et al., 2004; UN, 2011). As fossil fuels still account for 80% of the global energy mix (Abas et al., 2015; EESI, 2021), energy consumption remains closely linked to greenhouse gas emissions and thus to climate change. In this context, the goal of sustainability is to ensure long-term habitation on Earth by preserving natural resources and maintaining ecological balance. This goal has been widely acknowledged by governments and organizations worldwide. The United Nations'

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Sustainable Development Goals (UN, 2015) have set the target to implement energy efficiency improvements in order to promote sustainable development. However, efforts to achieve this goal, through technical innovations motivated by increased efficiency, is often frustrated due to the rebound effect (Binswanger, 2001; Azevedo et al. ,2014; and Santarius and Soland, 2018). These rebound effects occur when an increase in resource and energy efficiency is offset by adverse behavioral responses, leading to increased consumption rather than decreased consumption.

Under the assumption of sufficiently elastic demand, this reality of global economic development based on permanent growth of economic activity, brings into play the Jevons Paradox, which hypothesises that increases in the efficiency of resource use leads to increases in resource consumption (Jevons, 1866). Surprisingly, policy makers remain relatively unaware of these issues, with governments, green-focused political parties, and NGOs tending to believe that efficiency gains lower consumption and thus mitigate deleterious environmental impacts. Yet, when resource and energy efficiency is offset by adverse behavioral responses, the actual savings in energy use, emissions, or other environmental impacts are lower than expected (Sorrell, 2007; Guerra and Sancho, 2010; Chitnis et al., 2013; Thomas and Azevedo 2013a, 2013b; Santarius and Soland, 2018).

Recent evidence demonstrates that absolute decoupling is possible. 18 developed nations feature reductions of GHG emissions accompanied by growing GDP (Le Quéré et al., 2019). This is largely driven by an increasing share of renewable energy in the electricity mix. This would be in accordance with the predictions of the environmental Kuznets curve (EKC), which hypothesises that environmental degradation tends to worsen as economic growth occurs until average income reaches a certain point beyond which environmental degradation would decrease (Yasin, Ahmad & Chaudhary, 2021). However, this trend is not pervasive and not fast enough to make a difference to break increasing global GHG emission trajectories (Lamb et al., 2021). Other analysis suggests that renewables energies, while underestimated in their potential (Creutzig et al., 2017), cannot completely substitute for fossil fuels before 2050 if not accompanied by global reductions in energy demand (Creutzig et al, in review). Furthermore, even with the most positive outlook, other studies question the feasibility of completely breaking the link between GDP and resource consumption (Hickel & Kallis, 2020). Similarly, a 2020 review of 835 empirical studies reached a similar conclusion: solely relying on decoupling is insufficient to meet climate goals and reduce resource consumption in absolute terms (Haberl et al., 2020). In this context, carbon emissions are not consistently decreasing according to the EKC, and there is little consensus on whether the EKC with respect to CO2 emissions has been validated (Uchiyama, 2016; Galeotti, Lanza, & Pauli, 2006).

The quantification of rebound effects is commonly accomplished by measuring carbon dioxide (CO_2) emissions, greenhouse gas (GHG) emissions, or energy use. The magnitude of the estimated rebound effects, measured as GHG emissions, has been demonstrated to vary considerably. Although rebound effects ranging from zero to 100% are the most common, backfire effects (rebound effects > 100%) are also frequently observed (Reimers et al., 2021). Rebound effects can be broken down into direct and indirect rebound effects, particularly at the consumer level (Sorrell, 2007; Santarius et al., 2016). A direct rebound effect occurs when an increase in the efficiency of energy service provision leads to an increase in the demand for such a service by consumers. For example, when a household replaces their less energy-efficient boiler with a more energy-efficient one, they may enjoy lower heating costs and consequently choose to maintain a higher room temperature, leading to a direct rebound effect (Chitnis et al., 2014). In contrast, an indirect rebound effect occurs when consumers react to an energy efficiency improvement or a sufficiency-related behavioral change by increasing consumption in another area. For instance, they may use the cost savings from a new, more energy-efficient boiler to fund a holiday abroad, which, in turn, generates increased emissions (Chitnis et al., 2014).

The present study introduces a versatile model capable of estimating parameters for a broad range of case studies pertaining to diverse resource domains such as electricity, lighting, transport, heating, food, among others. The model can be applied to various metrics such as GHG-based energy consumption, primary energy consumption, and material consumption (e.g., metals, non-metallic minerals, biomass, and fossil energy carriers) at different levels of rebound effect. Previous studies have reported a significant variation in the estimated rebound effect (%) (Chitnis, 2014). For example, Lenzen and Dey (2002) reported a rebound effect of

45-123% in food and heating, Alfredsson (2004) reported 7-300% in food, travel, and utilities, Brannlund et al. (2007) 120-175% in transport and utilities, Mizobuchi (2008) 12-38% in transport and utilities, Kratena and Wuger (2008) 37-86% in transport, heating, and electricity, Druckman et al. (2011) 7-51% in transport, heating, and food, Thomas and Azevedo (2013) 7-25% in transport and electricity, and Murray (2013) 4-24% in transport and lighting. Given the wide variation in regions, resource domains, metrics and rebound effects reported in previous research, the proposed model holds particular significance as a parameter estimation tool that can be used to estimate the values of the unknown exploration-exploitation parameters that best fit the observed data. This tool is particularly valuable in the generation of hypotheses concerning the interdependencies and feedback mechanisms that exist among resources and their influence on the global system, regardless of the physical units employed. The distinct representation of three sequential resource domains and its corresponding dynamics facilitates the evaluation of cascading effects resulting from changes in one domain on the others, thereby enabling robust policy formulation and scenario analysis.

Previous studies on the relationship between how people make decisions and their impact on the environment have shortcomings. There is a limited amount of research that looks at the connection between psychological processes and environmental consequences (Reimers et al., 2021). The theory of moral licensing (Blanken et al., 2015; Miller and Effron, 2010; Monin and Miller, 2001) offers a promising starting point and initial evidence of psychological-based rebounds. However, while there is a significant amount of research on licensing effects in relation to climate-related behaviour, studies that specifically measure the extent of spillover effects on energy consumption or emissions are limited. Furthermore, as Reimers et al. (2021) suggests, research on rebound effects tends to only examine within-domain (Catlin and Wang, 2013; Ma et al., 2019) or cross-domain effects (e.g. Truelove et al., 2016), but not both. Additionally, there is a lack of modelling research that formalises and quantifies the negative impact of individual's actions on resource consumption at the systemic level.

Exploration-exploitation models are a class of reinforcement learning models that provide a framework for balancing the exploration of new strategies with the exploitation of currently effective ones (Hills, 2015; Bergel-Tal et al., 2014; Toyokawa et al., 2014; Katz et al., 2015). In decision making, exploration refers to the process of trying out new options or strategies, while exploitation refers to the process of maintaining the best known option or strategy currently available. Exploration-exploitation models can provide a useful framework for studying issues related to consumption and sustainability by treating efficient resource utilization as a search problem where populations can either exploit known solutions or explore for more efficient opportunities elsewhere. These models can help balance the trade-off between trying out new methods to conserve resources and using currently effective methods (Mao et al., 2016). Moreover, exploration-exploitation models can also be applied to the analysis of consumption behavior (Mason & Grijalva, 2019), which is a crucial factor in the promotion of sustainable consumption patterns. However, models of reinforcement learning applied to resource consumption and environmental conservation are relatively rare, and their use has been directed more towards social learning and optimisation (Hills, 2015; Bergel-Tal et al., 2014; Toyokawa et al., 2014, Yogeswaran et al., 2012). Studies have demonstrated that exploration-exploitation models are valuable in examining resource consumption and sustainability, because they can help to understand how agents, such as individuals or organizations, make decisions about allocating resources in uncertain environments (Frankenhuis et al, 2019; Dalamagkidis et al, 2007). By studying these models, researchers can gain insight into how different factors, such us resource scarcity or regulatory policies, affect resource consumption and sustainability.

In this paper, we ask: What is the consequence of exploration-exploitation dynamics on long-term resource consumption? Using a combination of mathematical and computational modelling, where we study the aggregated effects of micro level strategies on efficiency, consumption, and sustainability, our model allows us to investigate different levels of direct and indirect rebound effects across resource domains. We formalise the Jevons' paradox at a systemic level, demonstrating how efficiency-driven decision-making strategies can lead to unsustainable development patterns. Our results speak to questions such as whether the climate and resource consumption crisis can be solved by increased efficiency alone, or under what conditions pursuing efficiency without demand adjustments could become a trap that leads to environmental collapse.

Methods

We first describe the exploration-exploitation dynamic and explain how we compute efficiency. We then describe how we compute resource consumption at the population level as well as the computation of existing resources and the sustainability index. Finally, we present a table with the combinations of parameter values examined.

The model

The exploration-exploitation dynamic:

We consider a population of agents in which agents must decide at each time step between two possible complementary development strategies:

(i) Exploration, which allows agents to improve their current knowledge by searching for new solutions, allowing them to make more informed decisions in the future.
(ii) Exploitation, which refers to the use of already existing solutions. This strategy leads to efficiency stagnation.

Let's consider a vector of possible actions $K = \{1, \ldots, k\}$ where $K \in N^{+}$. We model action selection using a *N*-armed bandit problem that consists of a number of real distributions of efficiency $E = \{e_1, \ldots, e_k\}$, each of them associated with a reward $M = \mu_1, \ldots, \mu_k$. We assume that agents have a strong preference for maximising efficiency so that when they find a more efficient action they receive a higher reward. The initial probability distributions of the efficiency corresponding to each action are different and unknown to the agents. The efficiency of an action chosen by a given agent after T time steps is given by the following equation:

$$E_{akt} = 1 - (T\mu^{*} - \sum_{t=1}^{T} \mu_{akt})$$

where μ^{*} stands for the maximal reward mean and μ_{atk} is the reward obtained by an agent when using action k at time t. Since the real efficiency distributions of the system are predefined at the outset, the maximum efficiency of the model is reached when agents obtain the maximum reward. This will allow us to relate the consequences of the maximisation model to the consumption of resources in different rebound effect scenarios.

In order for agents to decide which action to choose, actions have a value. The value of an action is defined as the expected efficiency of that action out of the set of all possible actions. Since the agent does not know the value of selecting an action, we use the sample mean to estimate the expected efficiency:

$$E(E_{akt}) = \frac{\sum_{t=1}^{T} \mu_{akt}}{n_{kt}}$$

where n_t is the number of times action *k* was taken before time *t*. This function allows agents who decide to exploit their current knowledge to choose the action that has the most efficiency associated with it, namely $max\ k_t$.

We use a simple algorithm to balance exploration and exploitation, in such a way that the mathematical optimisation can yield locally optimal solutions that approximate a globally optimal solution. At each time step, agents take either the action that seems to be optimal ($max\ k_t$) with probability (1-ε) (i.e. exploitation), or a random action with probability ε (exploration). In this context, $\varepsilon = 0$ means full exploitation, and $\varepsilon = 1$ means full exploration. That is to say, the optimisation choice function *f(x)* is given by:

$$f(x) = \begin{cases} max\ k_t, & with\ p = 1 - \varepsilon \\ k_t \sim U([1, k]), & with\ p = \varepsilon \end{cases}$$

where $max\ k_t$ is the optimal action according to the observed data at time t, and $k_t \sim U([1, k])$ is a uniform random choice that takes values in $K = [1, \ldots, k]$.

Resource domains:

The proposed mathematical model comprises three sequential resource domains, each representing a distinct resource and its corresponding dynamics. *Resource Domain 1* pertains to Primary Energy (PE) and is quantified in terms of the existing resource stock denoted as gross available energy, measured in abstract units that can be mapped into physical units (e.g. in kilowatt-hour, kWh), and the mean consumption level denoted as the overall primary energy consumption. *Resource Domain 2* represents target good 2, a natural resource that is initially consumed due to the indirect rebound effect of the first domain, and is quantified in abstract numerical units. Finally, *Resource Domain 3* captures the consumption dynamics of target good 3, which starts to be utilized following an improvement in consumption efficiency of target good 2, and is also quantified in abstract numerical units. These resource domains enable the modelling of the interdependencies and feedback mechanisms between the resources and their impact on the overall system, irrespective of the specific physical units used. The distinct representation of each resource domain facilitates the assessment of the cascading effects of changes in one domain on the other domains, which is a crucial feature for policy formulation and scenario analysis.

Resource consumption:

At each time step, the resources consumed from the primary resource domain by a typical agent with efficiency E_a are computed as the baseline per capita consumption plus the difference between the aggregate consumption due to the direct rebound effect and the unrealised consumption due to efficiency gains.

$$C_1 = \beta_1 + c_1 E_a D_1 - (1 - D_1) c_1 E_a$$

And simplifying the equation we have:

$$C_1 = \beta_1 + E_1 D_1 - (1 - R_1) E_1$$

where β_1 stands for the baseline per capita consumption in resource units, $E_1 = c_1 E_a$ stands for agent's real efficiency, D_1 is the marginal direct rebound level measured as additional number of resource units consumed for each unit of efficiency gain. This means that when the rebound D_1 is less than 0.5, efficiency gains compensate for the rebound effect (i.e. sustainable scenario). When D_1 is greater than 0.5, efficiency gains cannot compensate for the rebound effect (i.e. Jevons paradox scenario). When D_1 is 0.5, we have a neutral model, where the actual resource savings are equal to the increase in usage (according to some classical measures this corresponds to scenarios where the rebound effect (r) is at 100%).

Indirect rebound effects at the consumer level occur when potential savings (e.g. lower greenhouse gas emissions due to less consumption of fossil resources) resulting from the use of more efficient technologies or more responsible consumption in one consumption domain are partially or fully offset by adverse consumption in other domains. We model indirect rebound effects as the additional resource consumption in a subsequent domain due to a shift of resource consumption away from the primary domain as a consequence of efficiency gains (e.g. efficiency gains associated with a fall in the relative price of secondary domain resource consumption). We assume that for each discrete jump by one unit in efficiency in *E*, agents are able to start consuming resources from a subsequent domain. The consumption function is governed by the following expression.

$$
f(C) = \begin{cases} if\ E < e_1 \begin{cases} C_1 = \beta_1 + E\,D_1\ - (1 - D_1\,)E \\ C_2 = \beta_2 \\ \dots \\ C_k = \beta_k \end{cases} \\ else\ if\ e_1 < E \le e_2 \begin{cases} C_1 = \beta_1 + E\,D_1\,(1 - I_1) - (1 - D_1\,)E \\ C_2 = \beta_2 + E\,D_2\,I_1 - (1 - D_2\,)E \\ \dots \\ C_k = \beta_k \end{cases} \\ \dots \\ else\ if\ e_{k-1}\ < E \le e_k \begin{cases} C_1 = \beta_1 + E\,D_1\,(1 - I_1) - (1 - D_1\,)E \\ C_2 = \beta_2 + E\,D\,I_1\,(1 - I_2) - (1 - D_2\,)E \\ \dots \\ C_n = \beta_n E\,D_n\,I_1 I_2 \dots I_{n-1} \end{cases} \end{cases},
$$

where I_n represents the share of resource consumption due to rebound effects that are consumed in the subsequent domain n+1 as a consequence of the indirect rebound effect. For each resource domain, an indicative sustainability index i can be computed at each time step by $i = \beta_n/C_n$, reflecting baseline needs at t_0 met for each unit of resources consumed. When $i = 1$, it means that for each unit of resources consumed, we maintain the needs of one individual. When $i < 1$, it means that more resources are consumed than the population would need to meet its basic needs. When $i > 1$, it means that fewer resources are consumed than the population would need to cover their basic needs.

Existing resources:

We compute existing resources X in each resource domain n at each time step t as the existing resources minus the resources consumed times the replenishment rate of the remaining resources:

$$X_{nt} = (X_{n(t-1)} - C_{nt}) + (X_{n(t-1)} - C_{nt})\alpha_n$$

Which can be grouped as:

$$X_{nt} = (X_{n(t-1)} - C_{nt})(1 + \alpha_n\,)$$

where α_n stands for resource units replenished per unit of existing resources at each time step.

We ran 1000 simulations for each of the parameter combinations shown in table 1.

Results

We first consider outputs from the standard model without indirect rebound effects. We then simulate scenarios with indirect rebound effects across three consecutive resource domains. Finally, we analyse scenarios with partial indirect rebound effects subject to low replenishment rate conditions.

Direct rebound effect

We first consider the effects of exploration-exploitation strategies on efficiency, consumption and sustainability, assuming only direct rebound effects. Here we show simulation results for the parameter values indicated in Fig. 1.

When the marginal direct rebound level D is less than 0.5 (Fig. 1A), there is no resource depletion. In our model, this corresponds to a situation where the actual resource savings are higher than the expected savings. Efficiency gains offset the rebound effect. In this scenario, as efficiency increases, average consumption in the primary resource domain goes down and sustainability index grows over time. The sustainability index grows faster in the scenarios with optimal efficiency strategies (i.e. ε=0.1, strategies with relatively high exploration levels, but not too high to prevent exploitation). This scenario is equivalent to a scenario where the consumption of fossil resources decreases over time, leading to a reduction in relative emissions, but not necessarily to an absolute reduction in the concentration of greenhouse gases in the atmosphere.

When D = 0.5 (Fig. 1B), this corresponds to a situation where the actual resource savings are equal to the expected savings due to efficiency gains. In this scenario there is no resource depletion, there is constant average consumption (assuming a constant population) and the sustainability index remains constant at 1. This model corresponds to a neutral model. This corresponds to a 100% direct rebound effect (r) according to the classical measurement, i.e. $r = 1 - (E - D) = 1$.

When 0.5 < D ≤ 1 (e.g. Fig. 1B), the actual resource savings are less than expected savings. In this scenario, optimal efficiency strategies increase the probability of resource depletion when the replenishment rate is not high enough. Paradoxically, there is no resource depletion in scenarios with lower efficiency (ε = 0), because the rebound effect does not overtake the resource replenishment rate. The higher the efficiency, the faster resources are depleted. Consumption increases over time in most scenarios. The sustainability index decreases over time. In general, in this scenario, backfire depends on the amount of available resources, the rate of resource replenishment and population size

When D = 1 (Fig. 1D), in this scenario there is no real saving of resources because all the efficiency gain is transformed into rebound effect. This situation captures the Jevons paradox for all possible exploration-exploitation strategies. The higher the efficiency, the faster the probability of resource depletion. Consumption goes up over time and the sustainability index decreases over time.

Indirect rebound effect

To expand our model, we now consider the effects of exploration-exploitation strategies when efficiency gains (e.g. more efficient technologies) are partially offset by adverse consumer behavioural responses in other resource domains. This aims to capture scenarios where potential savings in one domain (e.g. lower greenhouse emissions due to decreased consumption of fossil resources) leads to a corresponding increase in the consumption of resources in other domains. We assume that for each discrete jump by one unit in efficiency, agents can start consuming resources from a subsequent domain.

Backfire indirect rebound effects, capturing the Jevons paradox at the systemic level, can be observed in simulations with $D > 0.5$ (r > 100%). For illustrative reasons we show simulations for $D = 0.75$ and I = 0.75 in Fig. 2. Three resource domains representing three different types of resources are consumed consecutively with each efficiency leap. Agents start by consuming from resource domain 1, but as they become more efficient they start consuming from resource domain 2, and similarly, as they reach the next efficiency threshold, they start consuming from resource domain 3.

Indirect rebound effects, by shifting consumption from the primary domain to subsequent domains, allow the exploitation pressure to be reduced in the primary domains. Fig. 2 shows how in domain 1, and especially in domain 2, the average consumption increases and then decreases, while the sustainability index decreases and then increases. However, assuming the same level of resource replenishment, this only shifts the unsustainable exploitation pattern to downstream domains. For optimally efficiency strategies, the simulations show resource exhaustion in domain 3, which is where the transferred backfire effects are observed. Again, this captures the Jevons paradox at a systemic level.

Partial rebounds (0 < D < 0.5, i.e. 0 < r < 100%) can also be the cause of resource depletion when the replenishment level is not high enough. We present simulations for partial rebound scenarios where the actual resource savings are lower than expected due to 50% direct rebound effects (D = 0.25) and 25% indirect rebound effects across domains (I = 0.25). We analyse scenarios where resources are scarcely renewable; replenishment rate is set at 0.0001 (see Fig. 3).

In this scenario of partial indirect rebound effects, the exploration-exploitation strategies that best maximise efficiency can compensate for the increase in consumption due to the rebound effect in the primary and secondary domains. Although there is an initial drop in the level of existing resources due to low initial efficiency and low replenishment rate, these strategies eventually allow the ecosystem to revert to the original resource levels. However, the indirect rebound effect transmits the level of consumption to subsequent levels, so extremely low replenishment rates always result in system collapse in the last resource extraction domain.

Discussion

In this study we aimed to investigate the effects of exploration-exploitation strategies on efficiency, consumption, and sustainability, taking into account different levels of direct and indirect rebound effects. Our model successfully formalizes the Jevons' paradox at a systemic level, demonstrating how efficiency-driven decision-making strategies can lead to unsustainable development patterns. Our results provide a comprehensive understanding of the behavioural mechanisms driving rebound effects and the quantification of the consequences of these mechanisms in terms of resource consumption and sustainability. Furthermore, it highlights the importance of considering both efficiency improvements and demand-side solutions for achieving sustainable development goals. While improving efficiency is crucial in reducing relative resource consumption and emissions, it may not be enough on its own to achieve absolute reduction. As proposed in a large number of previous studies, it is also essential to address demand-side factors by reducing aggregate resource use, energy demand and emissions, and implementing redistribution policies, cap-and-trade schemes or carbon taxes (Creutzig, 2021; Mundaca, 2019; Bajželj, 2014; Lenzen, 2022). This approach ensures that sustainable development goals can be met in a comprehensive and holistic manner.

Concrete results of rebounds – estimation of exploration-exploitation parameters and connexion with case studies mention which implies in each case.

The United Nations' Sustainable Development Goals (UN, 2015) include the aim to implement energy efficiency improvements to promote sustainable development. However, as previous studies have shown, the effort to achieve these goals through technical innovations (Binswanger, 2001; Azevedo et al. ,2014; and Santarius and Soland, 2018) or consumer behaviours (Druckman et al., 2011; Buhl and Acosta, 2016) is often thwarted by rebound effects. Our research builds upon this literature by focusing on how the micro level behaviour of individuals affect resource consumption on a macro level, and provides a mathematical model that captures the complexity of these phenomena. Our model confirms the findings of previous research that rebound effects can occur when an increase in resource and energy efficiency is offset by adverse behavioural responses.

Behavioural responses in this context are expected to vary across resource domains and income levels (Sorrell, 2007; Guerra and Sancho, 2010; Chitnis et al., 2013; Thomas and Azevedo 2013a, 2013b; Santarius and Soland, 2018; Reimers et al., 2021). Our results indicate that the optimal exploration-exploitation strategies for increasing efficiency can lead to different outcomes depending on the level of rebound effect. Specifically, we found that when R is above 0.5 (i.e. efficiency gains cannot compensate for the rebound effect), optimally efficiency strategies can lead to increased consumption and ultimately resource depletion, whereas when R is below 0.5 (i.e. efficiency gains compensate for the rebound effect), optimally efficiency strategies lead to decreased consumption. This is in line with previous studies, such as Chitnis (2014), which found that rebound effects can vary depending on the type of measure being implemented and the household income level, highlighting the importance of addressing adverse behavioural responses and rebound effects while protecting low income groups.

A key feature of our study is to highlight the importance of decision-making strategies as a potential driver of rebound effects. Research in this field, such as the studies by Catlin and Wang (2013) and Noblet and McCoy (2018), have shown that consumers may acquire a moral license in one product or consumption domain, which liberates them to act less environmentally conscious in the same or another domain. This is consistent with the findings of our model, where agents may be motivated by a sense of virtuousness to pursue exploration strategies, leading to an increase in resource consumption. However, previous research on rebound effects and individual decision-making has limitations, such as the scarcity of studies that examine the relationship between psychological processes and environmental consequences (Reimers et al., 2021). Studies on rebound effects tend to focus on either within-domain (Catlin and Wang, 2013; Ma et al., 2019) or cross-domain effects (e.g. Truelove et al., 2016), but not both (e.g. Seebauer, 2018; Tiefenbeck et al., 2013). Furthermore, there is a lack of research that formalises, models and quantifies the negative impact of behavioural responses on resource consumption. Our study aims to fill these gaps by providing a comprehensive understanding of the exploration-exploitation mechanisms that drive indirect rebound effects within and across domains, and by quantifying the consequences of these mechanisms in terms of resource consumption and sustainability.

In the literature, the study of partial rebound effects under low replenishment rate conditions is not well established. However, it is important to consider that if the extraction rate of a resource exceeds the replacement rate, the resource will become finite and eventually depleted (e.g. Höök et al., 2010). Therefore, it is crucial to explore behavioural strategies that improve efficiency while mitigating the consumption increase resulting from rebound effects in the primary domains. We show that while initial resource levels may decrease due to low efficiency and replenishment rates, optimal exploration-exploitation strategies for increasing efficiency have the potential to restore the primary resource domain to its original resource levels. However, it should be noted that indirect rebound effects can propagate the consumption level to downstream domains. For instance, in cases where replenishment rates are extremely low, collapse of the system in the final resource extraction domain may be inevitable if resource demand is not limited, constrained or restrained.

Tables

Table 1. Parameters and state variables.

Parameter	Symbol	Number of levels	Value(s)
Time, time steps	T, t	10000	0 to 10000 in steps of 1
Population size	A	2	100, 1000
typical agent	a		
actions	$K = \{1, \dots, k\}$	4	
strategies	Exploration and exploitation	2	
probability of choosing to explore	ε	5	0, 0.01, 0.05, 0.1, 0.5
efficiency distributions	$E = \{e_1, \dots, e_k\}$	4	0 to 3 in steps of 1
real efficiency of agent a with action k at time t *(normalised)*	$\hat{E}_{akt} = e/\max(e)$		0 to 1
expected efficiency of agent a with action k at time t	$E(E_{akt})$		
rewards	$M = \mu_1, \dots, \mu_k$	4	0 to 3 in steps of 1
baseline consumption	β	1	0.1
total consumption	C		
existing resources	X		
replenishment rate	α	2	0.01, 0.001
direct rebound level	D	11	0 to 1 in steps of 1

rebound effect	r	11	0 to 2 in steps of 2
indirect rebound level	*I*	11	0 to 1 in steps of 1
correction factor	*c*	1	10
resource domain	*n*	3	

Figures

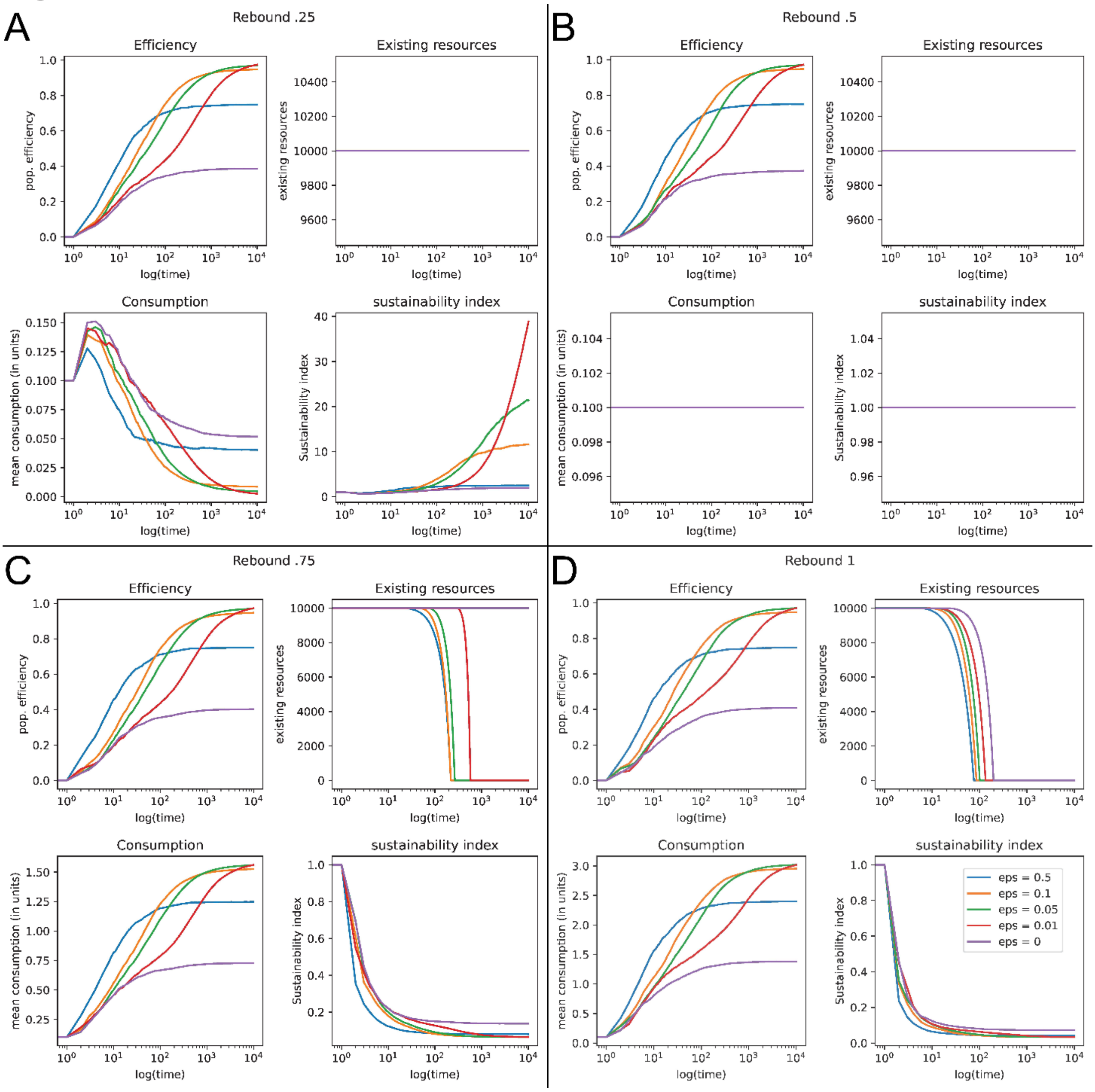

Figure 1. Direct rebound effect analysis. Trajectories for efficiency, existing stock of Primary Energy (PE) resources denoted as gross available energy, and average primary energy consumption for different levels of direct rebound effect and probability of exploration (eps). We use abstract numerical units that can be mapped into physical units (e.g. gross available energy and mean primary energy consumption expressed in kilowatt-hour, kWh). Simulations using the following parameter values: N=100; t = 10000; ε *= [0, 0.01, 0.05, 0.1, 0.5];* β_1*=0.1;* $X_{1(t=0)}$*=10000;* α_1 *= 0.01;* D_1 *= [0.25, 0.5, 0.75, 1];* I_1 *= 0; M = [0, 1, 2, 3].*

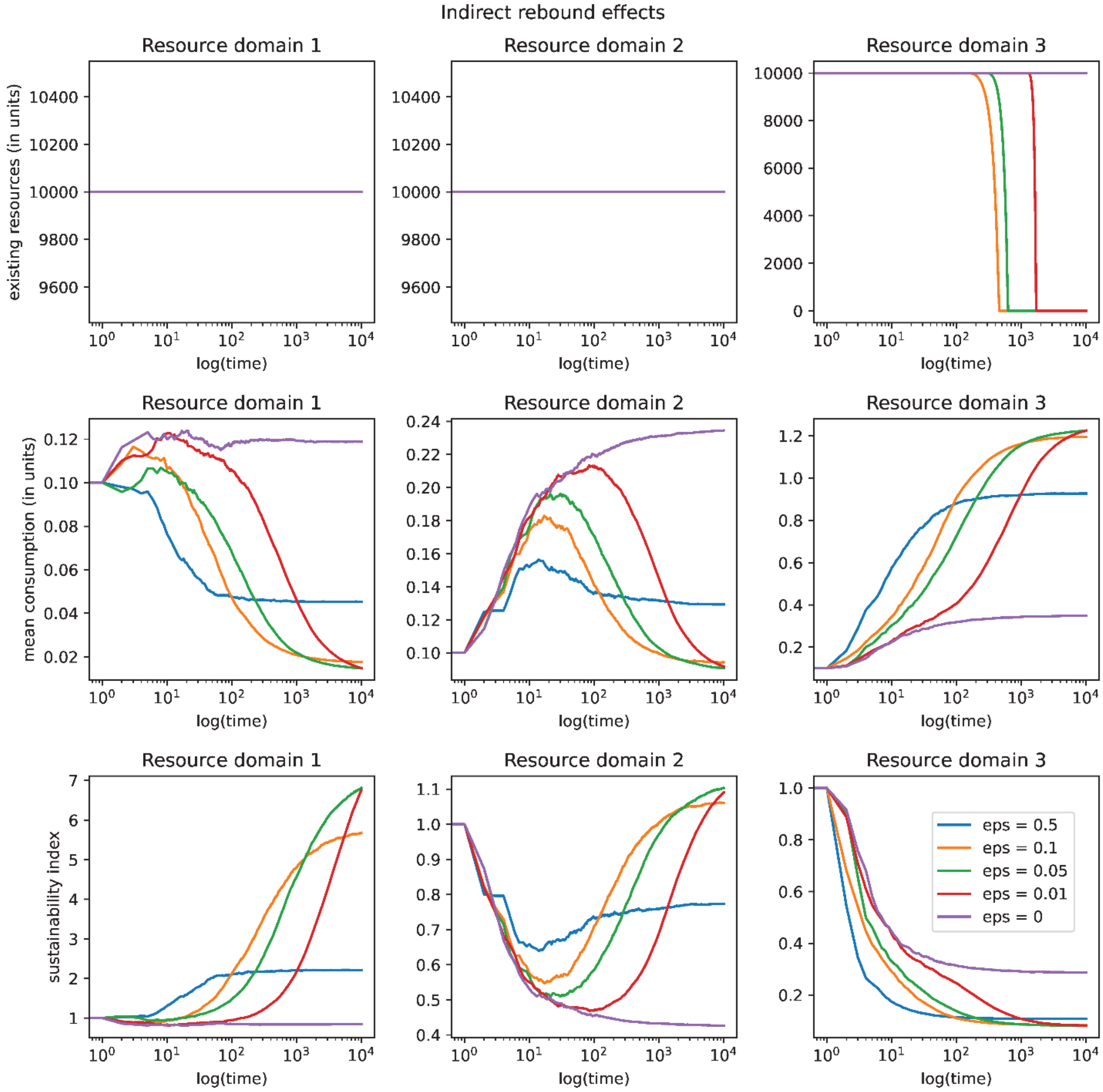

Figure 2. Indirect rebound effect analysis. Trajectories for efficiency, existing resources and consumption across three sequential resource domains. Resource Domain 1 pertains to Primary Energy (PE) and is quantified in terms of the existing resource stock denoted as gross available energy, measured in abstract units that can be mapped into physical units (e.g. in kilowatt-hour, kWh), and the mean consumption level denoted as the primary energy consumption. Resource Domain 2 represents target good 2, a natural resource that is initially consumed due to the indirect rebound effect of the first domain, and is quantified in abstract numerical units. Resource Domain 3 captures the consumption dynamics of target good 3, which starts to be utilized following an improvement in consumption efficiency of target good 2, and is also quantified in abstract numerical units. Simulations using the following parameter values: $N=100$; $t = 10000$; $\varepsilon = [0, 0.01, 0.05, 0.1, 0.5]$; $\beta_1 = \beta_2 = \beta_3 = 0.1$; $X_{1(t=0)} = X_{2(t=0)} = X_{3(t=0)} = 10000$; $\alpha_1 = \alpha_2 = \alpha_3 = 0.01$; $D_1 = D_2 = D_3 = 0.75$; $I_1 = I_2 = I_3 = 0.75$; $M = [0, 1, 2, 3]$.

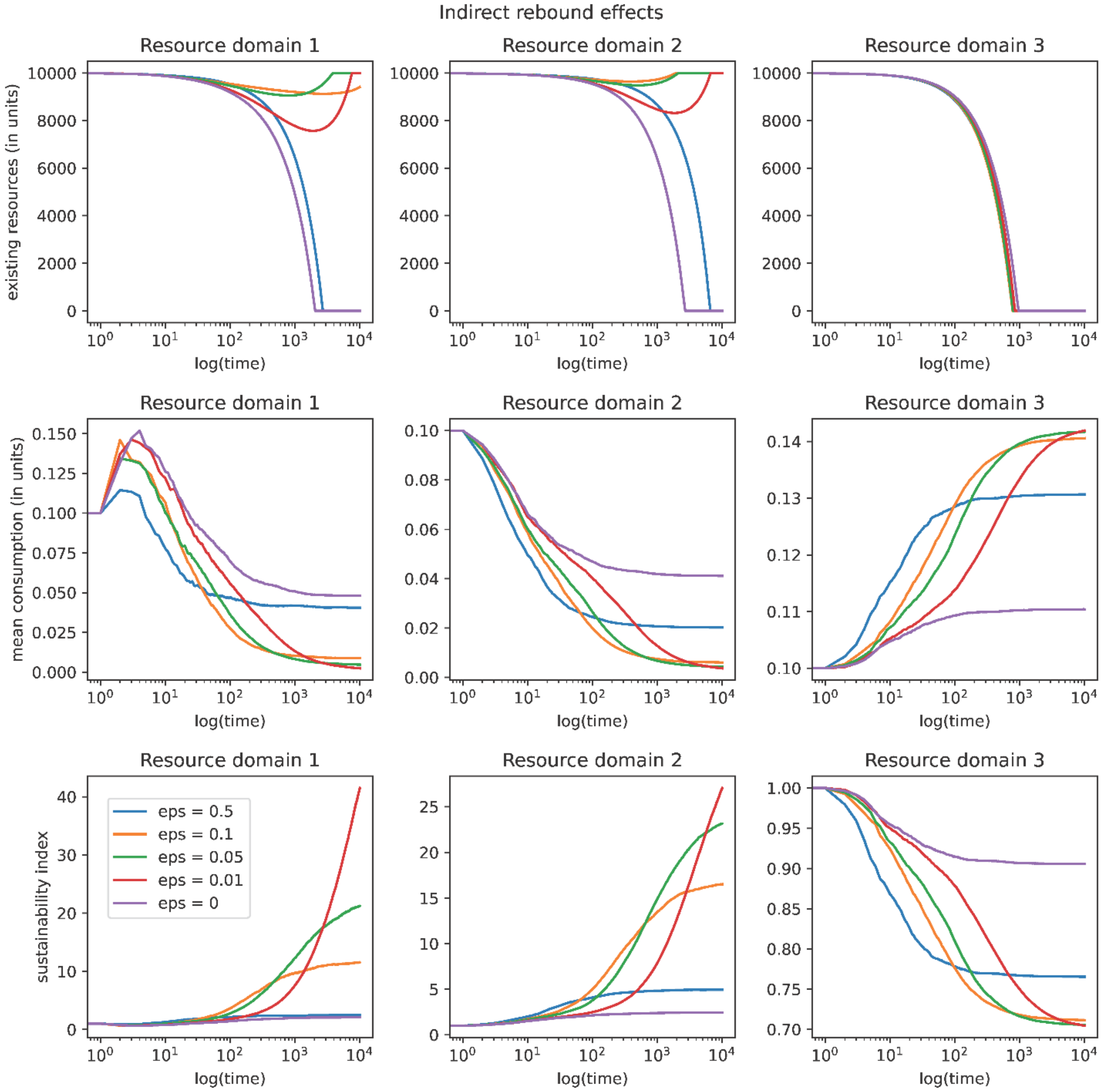

Figure 3. Simulations using the following parameter values: N=100; t = 10000; ε *= [0, 0.01, 0.05, 0.1, 0.5];* $\beta_1 = \beta_2 = \beta_3 = 0.1$*;* $X_{1(t=0)} = X_{2(t=0)} = X_{3(t=0)} = 10000$*;* $\alpha_1 = \alpha_2 = \alpha_3 = 0.0001$*;* $D_1 = D_2 = D_3 = 0.25$*;* $I_1 = I_2 = I_3 = 0.25$*; M = [0, 1, 2, 3].*

Data accessibility

For reasons of reproducibility the code and supplementary materials will all be made freely accessible at the following link: https://github.com/School-of-Collective-Intelligence/Jevons-Paradox-and-Cultural-Evolution
The simulator can be accessed via the following link: https://jsegoviamartin.pythonanywhere.com/

Ethics

We ensure the credibility, truth, authenticity, and scientific honesty of our work.
All code and supplementary materials are freely accessible.

Competing interests

We have no competing interests.

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