Limiting Rebound Effect in Streaming Services: a Simulation Study

Gabriel Andy Szalkowski and Jan Arild Audestad

Abstract— Rebound effects are gaining attention in the sustainability and ICT literature. Although several studies have addressed possible measures for reducing rebound effects, the literature on modelling and simulating the mechanisms of those measures remains scarce, especially in the context of ICT. This study develops a simulation model—based on compartmental methods—examining two taxation strategies to reduce rebound effects in subscription-based streaming services. In addition to a more conventional environmental impact tax (e.g., carbon tax), a Rebound tax that 'confiscates' part of the efficiency gains is implemented. Results suggest that, compared with the Environmental tax, applying a Rebound tax would be more beneficial for companies. In the two studied scenarios, the final revenues are higher for similar environmental impacts when only applying the Rebound tax. Implementing both taxes simultaneously time offers the greatest benefits in terms of impact reduction, but it can also result in excessive financial pressure on the company.

Keywords— Compartmental Modelling, Digital Technologies, Rebound Effects, Rebound Tax, Sustainable Technologies

I. Introduction

Efficiency improvements do not always result in reduced resource usage. In the words of Hilty [1], "Efficiency improvements due to optimization can also be partially compensated or even over-compensated for by changes in use patterns". This concept, commonly known as the rebound effect [1], is far from new; relevant studies on it date back to the late 1970s and early 1980s [2], [3]. Nonetheless, it has garnered significant attention [4] since the definition of the 17 Sustainable Development Goals (SDGs) of the General Assembly of the United Nations[1]. This growth in interest has been present, especially in the Information and Communication Technologies (ICT) sector [5], [6], where numerous works underscore the importance of additional research [7]–[10].

Digital technologies are often described as a double-edged sword, offering the potential for both reducing our environmental impact and increasing the risks of exacerbating it [11]. The rebound effect is one mechanism[2] that increases those risks which have already been observed in areas where ICT has led to improved efficiency [12]. To work with a comprehensive yet practical definition, in the context of this paper, we define *rebound effects* as any added environmental impact resulting from increasing efficiency, which may reduce the benefits of such improvements, or result in a higher impact than before the efficiency increase had taken place. Refer to Sec. II-C for a more in-depth discussion of environmental impacts.

While the main focus of rebound effect studies is usually on the extent and magnitude of these effects [13], it does not come as a surprise that some authors ask to mitigate, or at least reduce these rebound effects. Some of these authors (e.g., [6]) focus on proposing concrete measures and policies for this purpose. However, there have been few studies that discuss quantitatively the effect of proposed anti-rebound measures, as pointed out in [14]. This shortage is even more pronounced for papers that employ mathematical models to explore possible solutions to the rebound effect.

Despite the wide range of simulation and empirical studies addressing the mechanisms behind the rebound effect [14]–[19], only a few instances have been found where the mechanisms of anti-rebound measures were modelled (e.g., [20]–[27]). This scarcity, remarked in [27], [28], is identified as a research gap. The method used for the simulations in [20]–[26] was system dynamics.

A comprehensive literature search suggests that the main focus of the authors tends to be interventions and policies for reducing CO_2 and energy use. These approaches have been particularly well studied in the transportation sector [21]–[25]. Additionally, as depicted in [29], we can also find examples related to heating, refrigeration, industrial processes and lighting. Another area of application was packaging design [20]. The authors of [20] identify a possible rebound effect arising from *eco-design* policies and propose a *packing tax* as a countermeasure. An instance of a study with a different environmental focus is [26], where the implementation of interventions to reduce air pollution in general (not only CO_2 emissions) was analyzed using system dynamics, broadening the perspective of which environmental policies are used to reduce impact due to rebound effects.

Regarding other methods of simulation, some studies apply Computable General Equilibrium (CGE) models to analyse the impact of diverse climate policies. For instance, the authors of [27] assess five policy approaches for community-wide rebound effect mitigation. An application of this methodology to assess the necessary tax level for offsetting rebound on a country level can be found in [28]. There are also studies that use agent-based modelling to study rebound effects, such as the

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[1] https://www.un.org/sustainable-development-goals

[2] In fact, it is a set of mechanisms. The rebound effect is an umbrella term that includes several mechanisms [4].

ones described in [30]. However, it is notable that literature specifically devoted to modelling anti-rebound measures using this technique is currently lacking.

Literature search has revealed that:

1) Much of the literature on modelling the effects of anti-rebound measures focuses on transportation, industrial processes, and temperature regulation. There is a research gap when it comes to developing these types of studies for ICT products.
2) While there has been recent research into diverse policy instruments [27], [31], the most common ways of addressing reduction in rebound effects in the literature are taxes on emissions (e.g., Carbon Taxes), and strategies involving increasing energy prices. Although there is growing interest in said approaches, which have proven to be effective [32], [33], there are other solutions worth analysing and more research is needed.

This paper proposes a different approach based on a rebound tax (see definition below). The dynamics of the system are described using compartmental modelling and system dynamics [34]. Compartmental modelling is novel for this field of research but is one of the key methodologies in epidemiology and several other sciences [35], [36].

To address these issues, we focus on one specific sub-sector of ICT: video-on-demand subscription-based streaming services, such as video-streaming platforms like Netflix or HBO Max. In this study, two different anti-rebound strategies are compared. Before detailing the strategies, however, let us discuss how rebound effects emerge in these services. Using the classification framework presented in [4], we identify the following mechanisms:

- Consumer side, indirect rebound effects (Income Effects). “Consuming more of other goods due to savings on good 0.” If one service becomes cheaper, people may join other services at the same time.
- Consumer side, indirect rebound effects (Behavioral Effects). “Indirect rebounds not caused by [energy efficiency] improvement, but by changes in consumption behaviours.” Better quality streaming services (improved attributes) can lead to more usage, and thus a higher chance of substituting lower impact activities (e.g., going for a walk) with using the service.
- Producer side, indirect rebound effects (Output effects). “Free expenditure (savings) to use more of other inputs due to cost reduction resulting in increased production.” Saving in production costs increases the budget for developing new features and creating more content.

In addition to the framework presented in [4], one can identify supplementary rebound mechanisms that could apply to the industry at study in [29]. For instance, any purchase of devices with increased efficiency generates indirect effects on energy use. Another example would be the changes in efficiency and effective price of energy due to international trade and relocation costs. The presence of these effects underscores the need for strategies to prevent rebound effects, further motivated by the policies outlined in [29].

Two strategies for reducing the impact of rebound effects are compared: an Environmental tax (that could take the form of a Pigouvian tax on CO_2 emissions, energy use, etc.) as described by [37], and a *Rebound tax*, based on the idea of directly confiscating a fraction of the savings derived from efficiency gains [38]. It is worth noting that this *rebound tax* is not a tax on the negative externalities arising from the rebound effect; it is a tax on efficiency designed to prevent those externalities in the first place, without the need to quantify or assess the extent of the rebound effect. The implementation of this tax is based on the idea that efficiency gains can be treated as “value added”, and thus it would be possible to reduce investment in technology by means of a tax on efficiency [38]. No other study has been identified that implements a *rebound tax* in the same way as in this paper in the context of ICT. Discussing the details of how this tax would be implemented in practice (e.g., the type of surveillance or incentives that would be necessary) is out of the scope of this paper.

The objective of this study is to demonstrate the effectiveness of a rebound tax formulated in this manner. This is done by demonstrating that it outperforms a Pigouvian tax approach in terms of profitability, despite both taxes achieving similar environmental benefits. The effects of the two taxes are explored using a simulation model based on compartmental methods, a novel procedure for this kind of applications[3]. These results may prove valuable for policymakers, as they advocate for an alternative taxation scheme that could be beneficial for both businesses and the environment.

This study is structured as follows. In section II, the model used for simulating the evolution of a subscription streaming service and the effect of the anti-rebound strategies is described, in conjunction with the theoretical background behind it. Section III presents the results of the simulations in several scenarios. We present the final remarks in section IV.

II. Theoretical Basis of the Simulation Model

This section addresses the theoretical basis of the simulation model used for this study. The model aims to depict in comprehensive terms the dynamics of a subscription-based streaming service (i.e., a platform that grants you online access to multimedia content in exchange for a monthly fee), using compartmental modelling techniques. To maintain the model’s simplicity, we made the following assumptions:

- The only source of income for the service is the monthly subscription fees paid by the customers.
- The type of subscription is unique, in the sense that there are no “tiers” or premium access levels where customers can pay more for having better features or content. This can also be understood as if the price used is a weighted average of the prices of all tiers accounting for all users in each tier.
- Each month, the income is first used to pay for taxes (see Sec. II-C) and to cover the costs of running the service (Sec. II-B).

[3] We have been unable to find literature applying Compartmental Modeling for solving this problem.

- The remaining revenue after covering the costs is fully re-invested in the service as described in Sec. II-E.
- The system is isolated from complex dynamics like stock market fluctuations, and it is assumed that the effect of inflation is negligible since it does not add any additional explanatory value to the model.

Following the idea of the famous quote by the British statistician George E. P. Box ("All models are wrong, but some are useful"), we are aware that our model is a simplification of reality but, as we will explain in the following sections, it shares some important aspects with real systems.

As this model has several parts, each of them should be explained separately.

A. *Evolution of the Userbase*

The users of the service are the only source of income it has. It is therefore crucial to comprehend how the userbase evolves in order to understand the evolution of the service itself. We assume that the population of people who may be interested in the service N remains constant during the analyzed timeframe. The population N can be divided into two groups or compartments: users (subscribers) and non-users (people without a subscription). Non-users can join the service and become users, and users can leave it, becoming non-users. The flow of users between these two compartments is described by a differential equation based on the Bass diffusion model [39], where users can join the service spontaneously (because of the intrinsic value the service offers, being then called innovators) or because other users have joined it before (accounting for same-side network effects [40], being then called imitators). For a comprehensive description of these types of models, see Chapter 18 of [40]. Some examples of studies modelling userbase dynamics this way are [41]–[43] and in particular [44], where these methods were applied to video streaming services. It is important to note that, although the fee is paid once a month, users can join or leave the service at any point in time, so time is considered a continuous variable. If a user leaves, the fee they paid for the month of subscription is not refunded and the users can keep using the service for the rest of the month[4].

To describe the flow between the two compartments, presented graphically in Figure 1 (non-users and users), a differential equation is used. Following the Bass model, we assume that there are innovators and imitators joining the service, and the probability of a person joining the service is proportional to the number of non-users. We also assume that the network effects for people leaving the service are very small (people leave the service because of individual motives; the total count of nonusers has no influence on the decision). Taking into account that the total population is fixed, the fraction of the population that owns a subscription $U \in [0,1]$ evolves then as

$$\frac{dU}{dt} = (r + sU)(1 - U) - \varepsilon U \,, \qquad (1)$$

where r is the innovation coefficient (moderating the flow of innovators), s is the imitation coefficient (moderating the flow of imitators) and ε accounts for the rate at which people leave the service.

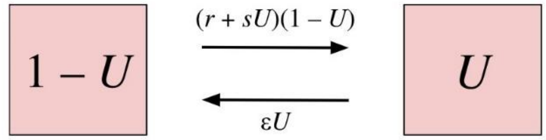

Fig. 1 Compartmental diagram of the non-user and user compartments and the flows between them.

The parameters r, s, ε are functions of time and several other values, such as the price of the subscription ($p(t)$, lower values are preferable), the perceived value attributed by customers to the service ($v(t)$, influenced by factors including content quality, quantity, and functionality) and the popularity or visibility of the service ($\mathrm{pop}(t)$ considering factors such as the company's public outreach, media presence, and advertising campaigns). Mathematically, these parameters are defined as follows:

$$r(t) = \mathrm{pop}(t) \cdot v(t) \cdot f\big(p(t)\big) \,, \qquad (2)$$

$$s(t) = s_0 \cdot \mathrm{pop}(t) \,, \qquad (3)$$

$$\varepsilon(t) = \varepsilon_0 \frac{p(t)}{v(t)} \,, \qquad (4)$$

with s_0 and ε_0 constant values that will depend on the model. The functions $v(t)$ and $f(p(t))$ require further elaboration. The value function $v(t)$ accounts for the subjective value that the customers perceive the streaming service offers, and it diminishes over time (TV shows become dated, new shows are introduced, etc.) so if a company ceases investment in providing value to their customers, the userbase starts to shrink. One can account for this loss of value over time by using an exponential function,

$$v(t) = v_0 e^{-kt} \,, \qquad (5)$$

with v_0 and k constant parameters representing, respectively, the initial value delivered and the rate at which people lose interest leading to value loss.

The other function, $f(p(t))$, is a function that accounts for the fact that lower prices are more attractive to the customers and lowering the price in relation to the initial one is a positive thing in terms of attracting new customers. To make it such that when the price is equal to the original one, the output of the function is 1 (leaving $r(t)$ unchanged), and to be able to modify the importance that customers give to changes in price, this function is defined as

$$f\big(p(t)\big) = \left[\frac{p(0)}{p(t)}\right]^{\nu} \,, \qquad (6)$$

where $p(0)$ is the initial price, $p(t)$ is the price at time t and ν is the parameter that modifies the importance that users give to the price of the subscription. By definition, prices can never reach 0€ per subscription because the subscriptions are the only source of income for the company.

Combining all these definitions, one can write the equation that models the evolution of the userbase as

[4] This is a prevalent policy observed in platforms where users keep using the service until the next billing period starts (see https://help.netflix.com/en/node/407?ba=SwiftypeResultClick&q=quit%20account)

$$\frac{dU}{dt} = \mathrm{pop}(t)\left\{v_0\left[\frac{p(0)}{p(t)}\right]^{\nu} e^{-kt} + s_0 U\right\}(1-U) - \varepsilon_0 \frac{p(t)}{v(t)} U\,. \quad (7)$$

This equation of evolution could be further developed including more complex interactions, different user categories or by differentiating between people who never used the service and people who have discontinued their use (as done in [41]). Delving into those options is an added layer of complexity that is deemed premature at this point and is left for future studies.

B. Cost Structure

This section describes how the expenses of running a streaming service are accounted for in our model. These expenses exclude considerations about taxes. In this model, we assume that these expenses may be categorized into labour costs and infrastructure costs. Personnel expenditures, referred to as labor costs C_{lab} are the costs of paying the salaries of the employees. We define C_{lab} as

$$C_{\text{lab}} = a_s n_w h_w\,, \quad (8)$$

where a_s denotes the average hourly wage of an employee, n_w is the number of workers that the company has and h_w is the average number of hours that an employee works in a month.

The infrastructure costs C_{inf}, conversely, are formulated according to three assumptions:

- Firstly, there is a fixed minimum cost of running the service. Even in the absence of users, the company must cover expenses such as electricity, rentals, maintaining equipment, etc. As a result, the service becomes profitable when the number of users, and therefore the revenue, exceeds a certain value threshold U_{min}.
- Secondly, the infrastructure for servicing a small number of users requires less expenditure than an infrastructure that serves a big number of users. In essence, the costs of running the service rise with the number of users.
- Lastly, the increase of the infrastructure costs with the number of users is sub-linear. This means that the additional cost per new user diminishes as the user base expands. Adding 100 users to a system that offers a service for 100 users is not the same as adding 100 users if it already hosts 1 million users.

To take these conditions into account, the infrastructure cost is defined as:

$$C_{\text{inf}}(U) = \begin{cases} \delta_0 & \text{for } U < U_{\text{min}} \\ a + bU^x & \text{for } U \geq U_{\text{min}} \end{cases} \quad (9)$$

The constant parameters δ_0, a and b are determined by definition once the other system parameters, such as the price of the subscription, costs of labour, U_{min}, and the maximum costs of the infrastructure (costs when $U = 1$) are specified. The parameter x takes is responsible for the decreasing costs per user when the number of users increases, so $x < 1$. The choice of value that will be used is $x = \frac{1}{2}$.

The infrastructure costs are modelled as a simplified value encompassing all costs associated with service maintenance and delivery, excluding labour costs. For a service like Netflix, those costs would include licensing and producing content, data centres, cloud storage, etc. [45].

C. Taxes

To better portray the essential effects studied in this paper, we separate between income tax, environmental tax and rebound tax. Any other taxes that may appear in real scenarios are not included here because they would not add explanatory value to our model and would make it more complicated.

The income tax T_{inc} is designed with the aim of simplicity and transparency, setting it as a fixed percentage of the income: $T_{\text{inc}} = \gamma \cdot (\textit{Gross Income}) = \gamma p(t) N U(t)$, where γ is a number between 0 and 1.

This study revolves around two types of taxes: an *environmental* tax and a *rebound* tax. Here, we understand the environmental tax as a payment proportional to the environmental impact of a company. Although the concrete measurement used for calculating this impact is outside the scope of this paper, this tax could come in the form of a Pigouvian tax [46], or a combination of Pigouvian taxes, on CO_2 emissions, energy use, or other impacts such as e-waste. We assume that, in the same fashion as with the costs, running the facilities necessary for providing the service has a fixed impact E_{i0}, which can be reduced by improving the efficiency of the company's processes. The impact resulting from the usage of the service is twofold. First, there is a proportionality between the total number of users and the environmental impact. Second, the more time the average user spends using the service, the greater the impact. We assume that the better the service is (the more value it provides or seems to provide to its users), the more the customers tend to use the service. Thus, this impact due to the users, E_{iu}, can be defined as

$$E_{iu} \propto v(t) \cdot U(t)\,.$$

The total environmental impact of a company is then $E_{it} = E_{i0} + E_{iu}$. Finally, we define the environmental tax as proportional to this impact: $T_{\text{env}} \propto E_{it}$.

The rebound tax is essentially distinct from the environmental tax: it is proportional to the efficiency improvements that the company makes to reduce both costs and (to a certain extent) the environmental impact of their activities. This tax is implemented by calculating the difference between the infrastructure expenses that the company would have if it had not implemented efficiency improvements and the actual expenses after the improvements. The magnitude of the rebound tax is proportional to this difference:

$$T_{\text{reb}} \propto C_{\text{inf}}(\text{no improvements}) - C_{\text{inf}}(\text{with improvements})\,.$$

For the purpose of this study, we intentionally set this tax to confiscate 60% of all reductions in costs due to efficiency gains. A combination of the *environmental* tax and the *rebound* tax can determine to a certain extent the fate of the service on which they are imposed, but they also have the potential to greatly reduce their environmental impact, as presented in sec. III.

D. General Overview of the Model

The model developed for this paper can be understood as a combination of two interacting subsystems: a *userbase* system (in Fig. 2 presented in blue) and a *money* system (presented in red in Fig. 2). At each point in time, users may leave or join the service, and the evolution of the userbase is determined by the dynamics described by (7). In this *userbase* system, time is a continuous variable.

At the end of each month, the number of users at that point is sampled. This number multiplied by the price of the subscription is the gross income of the company running the streaming service. This money represents the input of the *money* system and is used for paying taxes, labour costs and infrastructure costs. The remaining money is invested into the company performing one or more of four actions, inspired by the literature on the factors that users find important for adopting a streaming service [47]. We define the following investment options:

- Improving the service, by increasing $v(t)$: Delivering a better product (more value) to the customer. This represents a unified concept encompassing both quality and content, as value perceived by the users, and can be increased through actions like developing new functionalities or adding new content to the platform. This makes the service more appealing to new customers and makes it less likely that people leave the service. It also increases the environmental impact of each user, as the better a product is, the more people use it. This also accounts for the importance of innovation in streaming services [47]. This generalised concept is employed for simplicity. Separating between content and delivery would introduce additional complexity to the model, and it would not result in many valuable insights at this stage. In other words, we operate under the assumption that if the content is good but the video quality or user experience is suboptimal, or vice versa, the service is perceived as less valuable.
- Lowering the price of the subscription, reducing $p(t)$. This makes the service more appealing to new customers and makes it less likely that people leave the service, but it also diminishes future revenue per user. Unlike, for example, streaming in higher quality which directly leads to a greater amount of information transmitted, reducing the price has an indirect effect on the environmental impact of the company. Although it does not change the impact of the operations of the company in the short term, reducing prices leads to an increase in users, which in turn leads to a greater environmental impact.
- Increasing the popularity (or visibility) of the service, increasing pop(t). In this context, this refers to advertising and public outreach, wherein the more popular the service is, the more users will know about it. This increases the probability of new users joining but has no direct environmental consequences or any effect on users leaving the service. The impact is indirect, in the same fashion as for lowering the price of the subscription.
- Increasing the efficiency of delivering the service by reducing some fixed costs by, for example, using more efficient technologies. This results in cost reduction and, to a certain extent, of the environmental impact of the company [5]. We implement this by including a multiplicative factor called the *efficiency factor*, ψ_{eff}. For the purpose of this study, we impose a limit on the maximum efficiency that a company can reach: 90% more efficient than in the beginning (in other words, $\psi_{\text{eff}} \in [1,0.1)$). Moreover, each successive improvement is smaller than the previous one. Although this limit is artificial, it is meant to represent the physical limits to efficiency (i.e., it is not possible to transmit bits of data without consuming energy). The value of 90% is a reference value that is kept constant for all scenarios so that every scenario happens under the same conditions and we can compare the different results. Introducing the ψ_{eff} factor, we describe the infrastructure costs after improvement as C_{inf}(with improvements) = $\psi_{\text{eff}} C_{\text{inf}}$(no improvements).

Given that these actions modify the parameters within the equation that governs the movement of users (7), they influence future revenue too. Consequently, this leads to more investment provided that the costs do not exceed the income. The relation between the two subsystems is illustrated in Figure 2.

In Fig. 2 one can observe that individuals of a population can jump between being users and non-users, and the transitions are influenced by the price, the visibility (or popularity) and the perceived value of the service. The members of the “Users” compartment pay the price of the monthly subscription, and these funds are directed into the “money” subsystem (indicated in red). The money that comprises the Revenue is allocated toward paying for taxes, and labor and infrastructure costs. The rest is invested in increasing efficiency (which reduces infrastructure costs), reducing price, and increasing visibility and value. As mentioned in Sec. II, the definition of the model implies that the priority of the business is covering its costs, including both operational expenses and taxes, and only the remaining money after all costs have been covered can be invested in developing the service. Thus, for example, if an investment in efficiency is made at the end of a month, the money is sourced from the net revenue of the company for that month, and the effect of that investment is reflected in lower costs of running the service in subsequent months.

[5] Companies may choose to improve efficiency not only to reduce their costs motivated by the need to outperform competing services, but also to reduce their environmental footprint

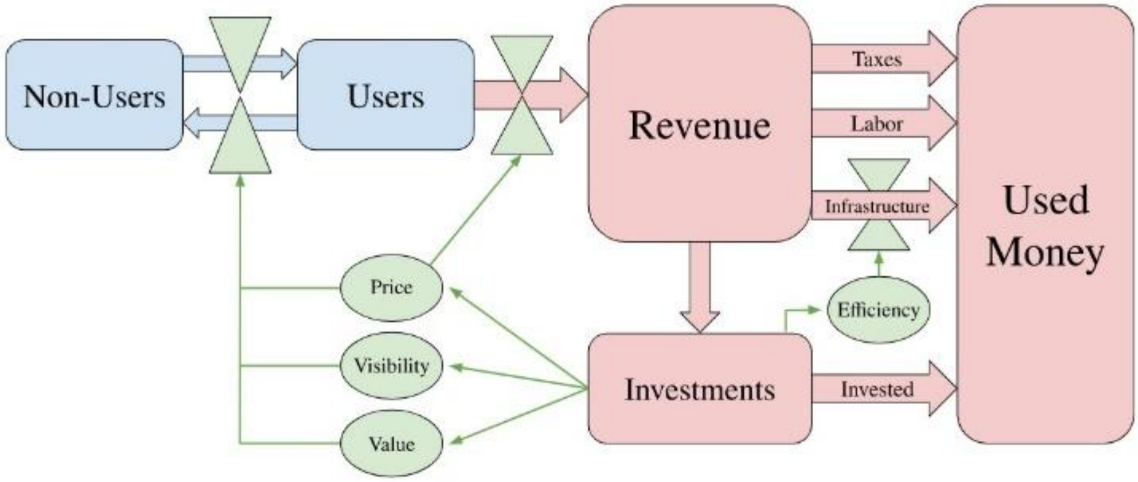

Fig. 2. Diagram of the two subsystems (*money*, in red and *userbase*, in blue) that form the dynamic model used for representing a streaming service. The valve symbols (the two green triangles) represent a modulation of the flow, in the sense that, for example, efficiency affects infrastructure costs or visibility modifies the number of users joining the service. The compartment "Used Money", which is added with the purpose of bookkeeping, is where all the money spent by the company ends up. We use the word "Used" to emphasize that, as a resource, the company's money that ends in that compartment has been spent and cannot be retrieved.

The investment options in Fig. 2 should be interpreted as direct links. The flow of users joining or leaving the service is affected by the parameters of *popularity*, *value* and *price*. Changes in price also affect the income that the service makes from the subscriptions. Changes in *efficiency* reduce the infrastructure costs of the service. There are also indirect links and feedback mechanisms that appear as a consequence of the definition of the model (although not presented in Fig. 2 as direct arrows). For example, increasing efficiency can leave more money to invest in value or popularity in the following months, thus moderating indirectly the flow of users. Furthermore, reduced costs from increasing efficiency may enable price reductions, also linked to increased user flow.

From the definition of the model, one can identify the mechanisms that account for the rebound effects described in Sec. I. Following the behavioural change assumption that the better the product offered (higher value $v(t)$), the more time people spend using it, we identify Consumer side, indirect rebound effects (Behavioral Effects), that contribute to higher environmental impact. Furthermore, as services become more efficient, the costs are reduced and investments in other areas can be made. These investments can lead then to higher environmental impact, evidencing Producer side, indirect rebound effects (Output effects). Finally, as the environmental impact grows both with the number of users and the usage of the service, one can implicitly identify in the construction of the model the presence of Consumer side, indirect rebound effects (Income Effects).

E. Choice of Investment Strategy

This section explains how the subscription-based streaming company grows, by describing the strategy followed for investing their revenue.

The multitude of different possibilities for investing the company's revenue renders it impractical to explore them all simultaneously. For the purposes of this study, we need to choose a strategy that is simple enough to be understandable, yet complex enough to be a reasonable strategy. Over-simplified strategies have many drawbacks too: investing only in value may increase greatly the environmental impacts; investing only in popularity is not enough to attract users, as they won't buy a product that they find valueless regardless of how much it is advertised to them; investing in efficiency may result profitable in the beginning, but this choice is subject to diminishing returns with every additional investment, as there is a limit to how much the efficiency can be improved; only lowering the price is not a sustainable strategy due to loss of value over time and low visibility of the service.

In this research, only two strategic scenarios (see Fig. 3 and 4) are explored, with the purpose of contrasting the results in different cases. These strategies represent simplified modes of operation of a streaming services company, while, at the same time, clearly showcasing the variation of the parameters that control the model. Beyond the two chosen strategies, other strategic scenarios were tested obtaining similar results in every case. The rationale behind our choice here resides in presenting how two different decision-making paradigms, with clearly distinct levels of complexity and adaptability, lead to similar results. Developing more complex strategies is left for future research. The first strategy (Investment Strategy 1, IS1, Fig. 3) is intentionally basic and rudimentary:

1) On odd months (1, 3, 5, ...), invest all remaining revenue in improving the efficiency of the service.
2) On even months (2, 4, 6, ...), invest a third of the revenue in each of the three remaining options: value, popularity and reducing the price. If the price reaches half the initial value, stop reducing it and distribute the remaining revenue between value and popularity.

The second strategy (Investment Strategy 2, IS2, Fig. 4) is more adaptable, as it responds to some degree to the conditions of the market:

1) Given the importance of innovation and the decreasing nature of the value perceived by the users with time, prioritize investing in value. If the value falls below a

threshold of 0.5 (in the scale of our model), invest in value.

2) If the perceived value is above the threshold, invest in efficiency until it reaches the threshold value of 75%.
3) If the previous values are above their respective thresholds, invest in popularity until it reaches 1.5 in the scale of the model.
4) When the previous values are above their respective thresholds, reduce the price until it reaches half of its initial value.
5) If the price has reached its threshold (half of the initial price), stop reducing it, and update the thresholds for value (from 0.5 to 1), efficiency (from 75% to 85%) and eliminate the threshold for popularity.

In Sec. III, we explore how the service evolves with both strategies and under the influence of the taxes described in Sec. II-C. To perform the simulations, we have developed a code using the Python programming language. The program solves numerically the equations of evolution of the *userbase* subsystem for one month. Based on the final number of users, the revenue and the expenses for the month are calculated. Then, investments are made according to the investment strategy chosen, and the process begins anew for the next month. A summary of the parameters presented in the text is shown in Table I. The values of these parameters can be scaled to represent different timescales, producing faster or slower adoption, changing the currency, or representing the absolute number of customers of the company. The only constraint applied to these parameters is that the value of cumulative environmental impact of the case with only environmental tax and the case with only rebound tax should be similar at the end of the study period, for purposes of further comparison.

III. Results and Discussion

The results of this study describe the time evolution of a streaming service under four different tax scenarios: No Tax, Environmental Tax, Rebound Tax, and Both Taxes applied at the same time. Said evolution is analyzed by studying the evolution of the parameters and magnitudes of the model used to simulate the streaming service. The results for a service

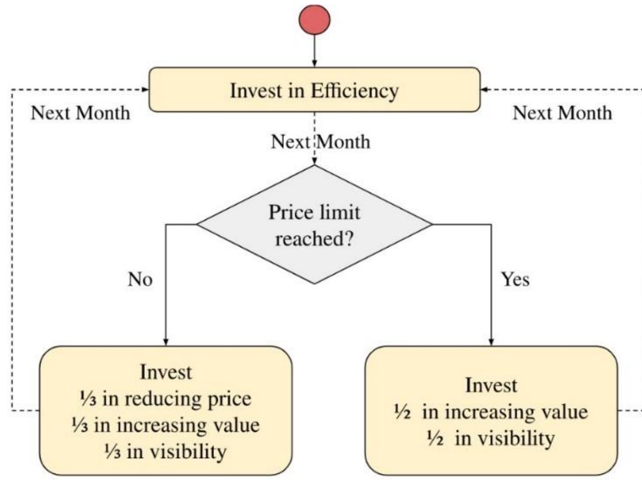

Fig. 3. Diagram of the Investment Strategy 1.

that evolves following the investment strategy IS1 are presented in Fig. 5, and for a service that follows IS2 the results are presented in Fig. 6. Different timescales are used for IS1 and IS2 to better portray qualitative differences in the long term.
In each of the sub-figures, the four lines represent the evolution of a magnitude under the four tax scenarios for the purpose of comparison. Regarding the different magnitudes, although their

TABLE I: Summary of the parameters of the simulation model and their values for both investment strategies, IS1 and IS2.

Name	Definition	Value IS1	Value IS2
N	Size of the population.	10^8	10^8
U(t)	Fraction of the population in the "Users" compartment.	Variable, U(0) = 0.1	Variable, U(0) = 0.1
p(t)	Price of the subscription.	Variable, p(0) = 15	Variable, p(0) = 15
v(t)	Perceived value of the product by the customer. See (5).	Variable, v(0) = 1	Variable, v(0) = 1
k	Parameter of loss of interest.	0.25	0.25
pop(t)	Popularity or visibility of the product (ads, etc.)	Variable, pop(0) = 1	Variable, pop(0) = 1
r(t)	Intensity of the flow of innovators. See (2).	Variable	Variable
s(t)	Intensity of the flow of imitators. See (3).	Variable	Variable
ε(t)	Intensity of the flow of people leaving the service. See (4).	Variable	Variable
f(p(t))	Function for the importance given to the price. See (6).	Variable	Variable
ν (nu)	Parameter of the importance of the price for f(p(t)).	2	2
C_lab	Monthly costs of labour. See (8).	6.4×10^6	6.4×10^6
C_inf	Monthly costs of infrastructure. See (9).	Variable	Variable
δ_0	Fixed cost of running the service (profitable when U(t) > 0.05).	9.1×10^7	9.1×10^7
x	Parameter for decreasing costs per user, increasing in absolute value. See (9).	0.5	0.5
γ (gamma)	Income tax (fixed percentage of income).	25%	25%
C_inf	Monthly costs of labour. See (9).	Variable	Variable
ψ_eff	Multiplicative efficiency factor.	Variable, ψ_eff(0) = 1	Variable, ψ_eff(0) = 1

absolute values (y-axis) can be re-scaled to represent different units (different currencies, units of environmental impact, etc.), the relative differences between the tax scenarios are scale-independent. As the results of this study rely on relative comparisons, we do not artificially impose any units on the y-axis.

The results presented here are of interest at multiple levels. An initial observation is that the two strategies (both on their own and in conjunction) are effective in reducing the environmental impact of the simulated company (see Env. Imp. Cumulative in Figs. 5 and 6). We have set the parameters so that the reduction in environmental impact of the two strategies when applied separately is roughly the same. The rationale behind this decision is that it enables a comprehensive comparison of the financial outcomes of the business in the different cases. For instance, because a consequence of the reduction of environmental impact

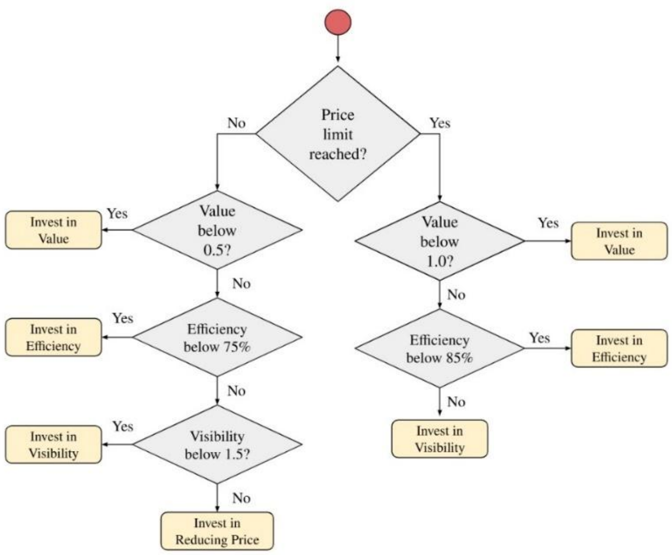

Fig. 4. Diagram of the Investment Strategy 2. The process is evaluated once each month from the beginning.

is a decrease in revenue (as opposed to the scenario with no other taxes than an income tax, labelled as “No Taxes”), the strategy that sustains the higher revenue will be the preferable one.

In both figures (5 and 6)) one may discern an unexpected outcome: the novel rebound tax, which confiscates 60% of the economic benefits of increased efficiency, performs better than the well-established environmental tax. In the two strategic scenarios, it is manifest that with the Rebound tax, the service captures the market notably faster than with the Environmental tax, as portrayed by the sub-figure Users (end month). That is, the service is able to achieve a state where all, or most, of the potential customers have become customers. There, the orange line (Rebound tax) appears above the blue line (Environmental tax). In Fig. 5, the value delivered by the company is also higher with the Rebound tax, although this fact becomes a little more complicated in the case of Fig. 6. The oscillations in value are a direct consequence of the strategies depicted in Sec. II-E: value diminishes with time but the service is updated and improved either periodically (IS1) or when the value falls below a certain limit (IS2), which results in a series of ups and downs in Value Perceived.

As the Rebound tax case is more efficient in capturing users quickly, the monthly revenue grows faster in the beginning, increasing the profitability of the service in comparison to the Environmental tax. This allows more investment in popularity (or visibility, advertising, etc.), which attracts more users and finally leads to more revenue. One can note that using Strategy IS1 (Fig.5), the Rebound tax provides a stable solution for the Monthly Revenue, which appears as a roughly constant line in the graph. Conversely, to have the same reduction in environmental impact, the environmental tax becomes so high that the service follows a tendency towards negative revenues (i.e., the costs are so high that the company is unable to pay for everything, resulting in net losses). This does not happen when using the more adaptable strategy IS2 (see Monthly Revenue in Fig. 6). Both taxes offer stable solutions, but the Rebound tax results in a higher return.

One key result of this study is obtained by analysing the Total Revenue, the amount of money that the service has received in total during the studied period. This is an indicator of the long-term profitability of the service. In both strategic scenarios, the total revenue achieved with the Rebound tax is higher than the one obtained with the Environmental tax. Moreover, the tendency of the total revenue in both cases indicates that it will achieve faster growth in the future with the Rebound tax.

Considering the costs, a Rebound tax on efficiency improvements is more effective in keeping the initial costs low, close to the scenario with no anti-rebound taxes. This fosters the growth of the business in its initial phases but hinders it considerably when it captures a significant portion of the market. A fact worth noting is that, despite the lower costs, the environmental impact in the end is the same for both cases. In Fig. 6 (Monthly Costs) one can notice that the initial and the long-term costs are lower with the Rebound tax. There is however an intermediate moment where the costs become higher than in the rest of the cases, which corresponds to the point of faster growth of the userbase of the service and faster increase in efficiency. In the end, we note that efficiency improvements reduce the costs once again.

In general, regardless of the chosen strategy, the efficiency factor ends up being lower (more efficient) with the Rebound tax, although this tax is explicitly dependent on the improvements in efficiency. Thus, it is unsurprising that after a substantial initial improvement in efficiency (big reduction in the efficiency factor) in Fig. 6, there is an increase in monthly costs which prevents the efficiency factor from going lower for some period. Once that period is over (because the costs are covered and the service has grown), further improvements are possible.

One can also observe that the price reduction happens faster with the Rebound tax than with the environmental tax, although in both cases they reach the limit in price reduction set in the beginning.

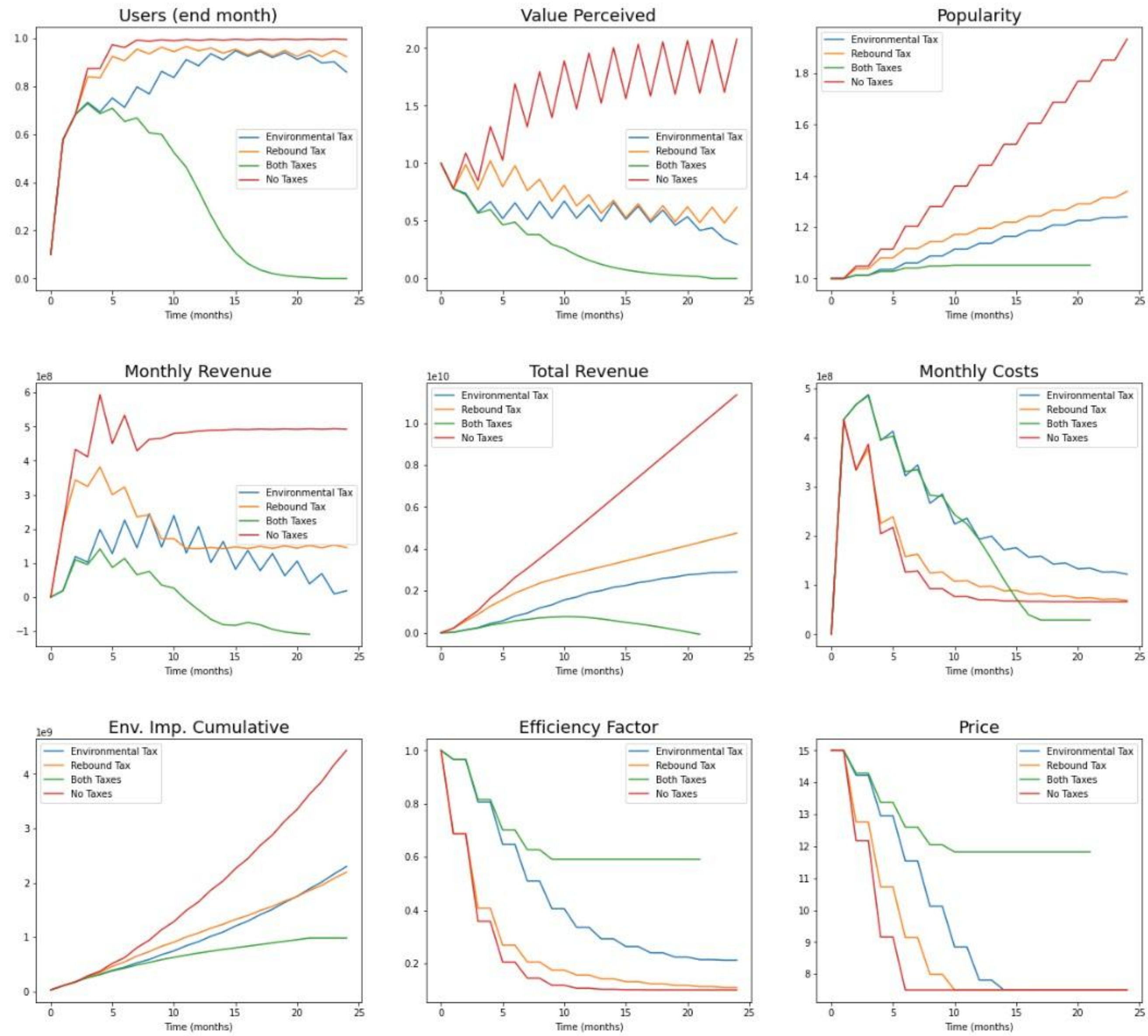

Fig. 5. Results for Investment Strategy 1 from sec. II-E. The evolution of several variables is represented. Users (end month) is the number of users (fraction of the total market) at the end of each month; Monthly Revenue is the net revenue of the company after taxes and costs; Total Revenue is the cumulative sum of the monthly revenue. Monthly Costs are the sum of costs described in sec. II-B; Env. Imp. Cumulative is the total cumulative environmental impact of the service. The other graphs represent parameters described throughout sec. II.

One additional interesting comparison to make is the total amount of taxes (excluding income tax) paid in the contexts of IS1 and IS2. Using IS1, (Fig. 7) the amount paid because of the Rebound tax is lower than the Environmental tax in the beginning, which explains the faster initial growth. Then, when the service gets bigger, the tax increases. In the case of IS2 (8), the amount paid in Rebound tax is always lower than the Environmental tax for the same reduction in Environmental impact. The implication of this is that there is less money flowing into public funds with the Rebound tax, and more money ends up invested in the service.

Finally, one should discuss what happens when both taxes are implemented at the same time. Depending on the strategy, one can observe distinct results for the service at study. Figure 5 demonstrates that Strategy 1 is not capable of supporting the implementation of both taxes. After an initial (relatively small) surge in Monthly Revenue, the curve falls and the company loses money until it goes bankrupt[6]. The userbase falls quickly, the popularity remains low and very few improvements are possible.

[6] We set a total maximum for losses of $5 \cdot 10^8$. When the total revenue reaches that point, the service is discontinued.

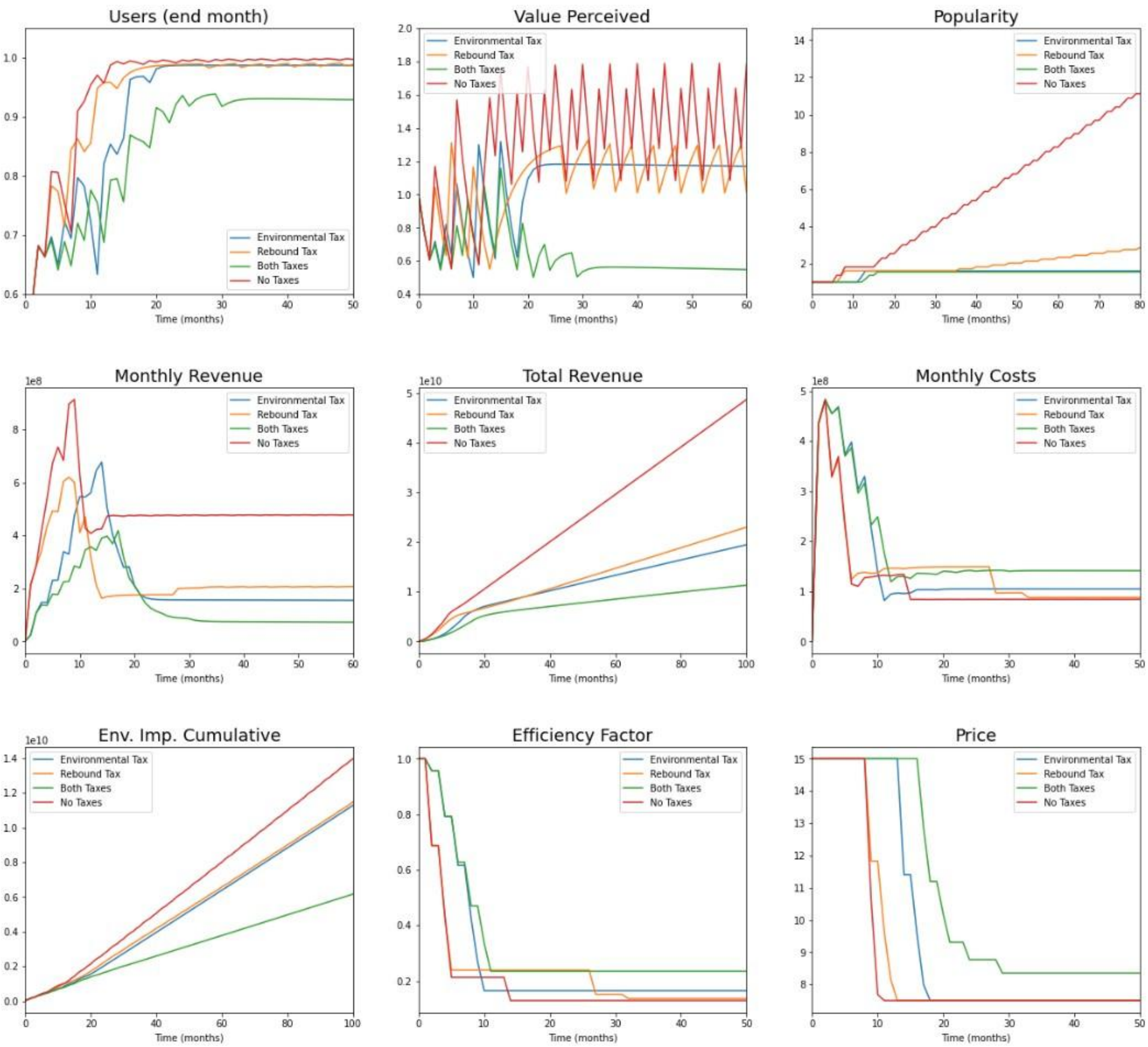

Fig. 6. Results for Investment Strategy 2 from sec. II-E. The evolution of several variables is represented. Users (end month) is the number of users (fraction of the total market) at the end of each month; Monthly Revenue is the net revenue of the company after taxes and costs; Total Revenue is the cumulative sum of the monthly revenue. Monthly Costs are the sum of costs described in sec. II-B; Env. Imp. Cumulative is the total cumulative environmental impact of the service. The other graphs represent parameters described throughout sec. II.

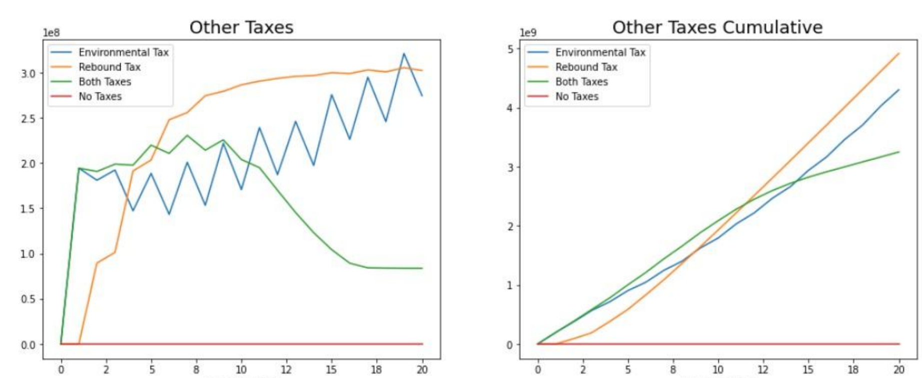

Fig. 7. Results for the amount of taxes, excluding income tax, paid by the company using Strategy IS1 from sec. II-E. The cumulative value represents the sum over time of the total amount of taxes paid, excluding income tax. The values presented are in units of money and may be scaled to represent different currencies.

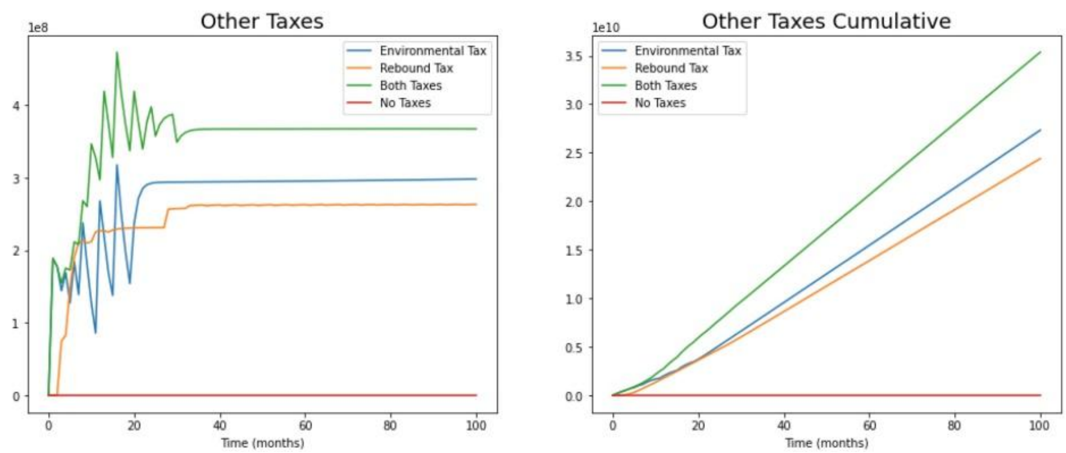

Fig. 8. Results for the amount of taxes, excluding income tax, paid by the company using Strategy IS2 from sec. II-E. The cumulative value represents the sum over time of the total amount of taxes paid, excluding income tax. The values presented are in units of money and may be scaled to represent different currencies.

In contrast, Strategy IS2 suggests that it is possible to apply both taxes to the same extent as in Strategy IS1 and still obtain a profitable and economically sustainable business. This is manifested in Fig. 6, where the monthly revenue reaches a stable solution greater than 0. This means that the service is earning money at a rate that is sufficient to maintain its activity in the long run. This is an encouraging result, as it is in line with the idea that several simultaneous policies may be needed to effectively offset environmental impacts from rebound effects [27], [48]. This result suggests the viability of implementing both an environmental tax and a rebound tax to greatly reduce the environmental impact (much more than with any of the measures on their own) without significantly compromising the future development of the business.

IV. Conclusion

This study demonstrates the effectiveness of two taxation schemes − an Environmental tax, and a Rebound tax based on confiscating economic gains from efficiency improvements − for mitigating the environmental impact of subscription-based streaming services due to rebound effects. The compartmental model reveals that, for similar environmental benefits, the proposed Rebound tax proves more advantageous for companies. This was evidenced by higher and more rapid revenue growth at the end of the study period with the Rebound tax in place. Applying both taxes simultaneously yields the highest environmental impact reduction, accompanied by the heaviest strain on the company, leading to bankruptcy in some cases. However, in certain scenarios, the company is able to persevere despite the taxes, which is beneficial given the need to combine several policies to counteract rebound effects [27], [48].

Addressing the scarcity of evidence for counter-rebound measures [27], [28], a novel concept of Rebound tax is defined in this work. This concept may seem rather unorthodox at first sight when compared with measures such as carbon taxes or increasing energy prices. However, the analysis shows that the concept is viable and should be considered by policymakers and regulators as a possible alternative to more conventional solutions.

Another important result of this study is that it demonstrates the strength of applying compartmental models to study the dynamic evolution of economic systems. The model consists of two interacting sub-models, one describing the evolution of users and non-users, and the other showing the flow of money from revenue to spending. The model developed in this paper, which represents another key contribution, can be expanded to more complex cases and other settings, consisting of several interacting sub-models and applied to areas other than environmental problems. This may include more complex user dynamics such as the BPQ model [43], multisided platforms, customer lock-in, and competition between services and churning of users between providers [49]). Future studies could also explore other measures and new contexts using our framework, like a Robot tax [6], increasing employees' salaries or reducing working hours.

Further research (both theoretical models and simulations, and empirical studies) on the implications of the Rebound tax as defined in this paper is needed. Preferably, this should be multidisciplinary research (digital economics, behavioural economics, psychology, law, business...) with the objective of developing more advanced, comprehensive, and holistic models. This tax could be applied and studied in conjunction with other policies, such as the ones depicted in [27], [31].
Finally, one limitation of this study is the fact that the presented results are based on simulations. Thus, to assess further the validity of the model, it should be applied to a scenario where empirical data on anti-rebound policies is available, and the results of the model should be contrasted with real-world scenarios. This would make the model more robust and more suitable for making predictions about future policy implementations.

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