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Government Subsidies for Industrial Symbiosis: Is It Always Worth It? Assessing Effectiveness and Efficiency Through Agent-Based Modeling

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ABSTRACT

Policy intervention can be a driver for industrial symbiosis (IS). However, given the wide variety of policy instruments available, policymakers should be guided in the policy design process to ensure that their intervention is effective and efficient. In this paper, we propose an agent-based (AB) model intended to assess the effectiveness and efficiency of different subsidy programs for IS. The model depicts the development of an ISN where the government can provide two types of subsidies, that is, (1) subsidies for IS investments and (2) subsidies for the waste exchange. Results suggest that policy effectiveness is primarily related to design and that the most effective design depends on the specific industrial context targeted. Specifically, increasing financial support is not necessarily the most effective solution. Moreover, effectiveness and efficiency are not directly related. Therefore, efficiency should only be considered to choose between policies with comparable levels of effectiveness. This study enhances the current state of the art by proposing a novel methodological approach to address the problem of policy effectiveness in the field of IS, offering a systemic and dynamic perspective.

1 | Introduction

The concept of circular economy (CE) proposes an alternative path to the dominant "take-make-use-dispose" economic development model by means of a variety of new business opportunities for companies, including several recycling, reuse and recovery options (Ghisellini et al. 2016; Pearce and Turner 1989). Among them, industrial symbiosis (IS) is recognized as one of the most promising CE strategic tools (D'Amato et al. 2019). IS entails the replacement of raw material inputs required by a given company with by-products and wastes produced by another. This practice enables involved companies to simultaneously reduce costs and achieve environmental benefits (Chertow 2000; Gertler 1995). Indeed, the reduction in waste disposal and in the use of virgin raw materials translates into lower disposal costs for waste producers and lower input purchasing costs for waste users (Martin et al. 2015; Wolf and Karlsson 2008). Despite these advantages, additional costs (both economic and environmental) may arise when engaging in IS, for example, to treat the waste and to transport it from the waste producer to the waste user (Fraccascia et al. 2019; Fraccascia et al. 2017a). In addition, new infrastructures or machinery investments may be required as a precondition to start an IS relationship (ISR). Therefore, both economic and environmental benefits for companies depend on the trade-off between ceasing and additional costs of IS (Jacobsen 2006). IS can either be restricted to the cooperation between two firms (i.e., a waste producer and a waste user) or evolve into more complex and interrelated structures, where several companies benefit from sharing resources and exchanging wastes and by-products within IS networks (ISNs) (Chertow 2007) or eco-industrial parks (EIPs) (Shi et al. 2010).

Despite the theoretical potential, IS is still scantly adopted by companies due to technical, financial, operational, and social barriers (Lombardi 2017; Golev et al. 2015). In particular, it is widely recognized that the main driver for companies to engage in IS is the expected economic benefit (Neves et al. 2019; Mortensen and Kørnøv 2019). In this regard, policymakers could intervene by increasing the profitability of the waste market, for example, by introducing taxes to discourage waste disposal or subsidizing waste exchanges (Dong et al. 2024; Sinayi and Rasti-Barzoki 2018). Nevertheless, such *market-based* incentives may be not enough if an upfront investment is required to start a symbiotic synergy (Golev et al. 2015; Neves et al. 2019). Therefore, governments may need to grant subsidies for companies to invest in technologies, machinery, or infrastructures, too (J.-Y. Chen et al. 2019). In a context where limited funds are available to support companies in the transition, how should the government commit its financial resources? Indeed, if different requirements and setbacks are embedded in different industrial contexts, how can the government decide which tool may be the most effective? As stated by Van Beers et al. (2007), there is no "one-size-fits-all" approach. Although policy intervention has been argued to be a driver for IS (Neves et al. 2019), policies can also be ineffective or limiting depending on the context (Lybæk et al. 2021). As a result, it is particularly challenging for policymakers to design an appropriate policy.

Several studies in the literature of IS tried to assess the effectiveness of government intervention in the development of IS. Such studies aimed to evaluate the impact of policies both qualitatively, through the analysis of case studies (Lehtoranta et al. 2011; Lybæk et al. 2021; Costa et al. 2010), and quantitatively, through theoretical models (Meng et al. 2023; Zhao et al. 2020; Dong et al. 2024). On the one hand, the former stream of the literature evaluates the policy by looking at the outcome. However, analyzing case studies does not allow for comparison with the counterfactual: It is not possible to assess what would have happened with a different policy or in the total absence of government intervention. On the other hand, theoretical models mainly focus on a single ISR in a static framework. Therefore, they lack both systemic and dynamic perspectives, which, according to Jiao and Boons (2014), are essential to properly analyze the effects of policy on the development of IS. We argue that agent-based modeling (ABM) may be the appropriate methodological approach to overcome these limitations. Indeed, ABM is particularly suited to capture the dynamics of IS (Demartini et al. 2022; Lange et al. 2021). ISNs are complex adaptive systems (CASs), that is, systems made of heterogeneous and independent agents interacting with each other and shaping their behavior according to the environment and past experience. Because agent-based (AB) models are adequate tools to depict the evolution of complex systems, they have been extensively used in the literature of IS (Albino et al. 2016; Fraccascia and Yazan 2018; Ghali et al. 2017; Saghafi and Roshandel 2024). With reference to policy measures, to the best of our knowledge, only Fraccascia et al. (2017a) proposed an AB model that investigates the effectiveness of government intervention in the development of an ISN. However, this paper presents several limitations. First, the analysis considered only *market-based* incentives, that is, a landfill tax and a subsidy for waste exchange, neglecting any required financial support for upfront investments. Second, the authors did not impose limits to government expenditures, that is, the budget is assumed to be unlimited, which is not consistent with real-world dynamics.

In this paper, we propose an AB model that assesses the effectiveness and efficiency of different subsidy programs comprising both financial support for IS-related investments and a *market-based* incentive to support IS operations. Specifically, a *subsidy program* is defined as the set and combination of policy instruments introduced by the government to foster IS. The model depicts the development of an ISN in which waste producers must invest as a precondition for engaging in IS. This latter assumption hampers the economic feasibility of IS, thus justifying government intervention. The government is assumed to have a limited budget that can be allocated between (1) investment subsidies for waste producers and (2) waste-purchasing subsidies for waste users.[1] The AB simulation is run using a case study depicting an ISN between the steel industry (i.e., waste producers) and the cement industry (waste users). The effectiveness of the subsidy program is evaluated with respect to the economic and environmental performances of the overall system. Conversely, the efficiency of the subsidy program is related to the government total expenditure. For the aim of our study, a subsidy program is considered to be *effective* if it can significantly shape the behavior of the system according to the specific policy purpose, that is, if the system behavior *when the subsidy program is in force* determines the outcome intended by the government action. Specifically, not only the outcome of the system should be aligned with the policy purpose, but such outcome should not be achieved *without* the subsidy program. The *economic efficiency* of a subsidy program, instead, is related to the government expenditure required to achieve a given performance level.

This paper aims to answer the following research questions:

RQ1: Which type of subsidy program is most effective in achieving the government's objectives within a given industrial context?

RQ2: Given a limited budget, how can the government design the program most efficiently from the economic perspective?

The novelty of this paper is threefold. First, the use of ABM allows assessing the effectiveness of different subsidy programs by explicitly comparing policy scenarios with a counterfactual baseline (i.e., the system behavior in the absence of government intervention), thus enhancing the robustness of the results. Second, this is the first study that simultaneously considers investment subsidies, waste-purchasing subsidies, and budget constraints. Finally, it contributes to the policy literature for IS adopting a dynamic and systemic perspective.

The remainder of this paper is structured as follows. Section 2 provides the theoretical background. The AB model is presented in Section 3. The results and discussion are provided in

Sections 4 and 5, respectively. Finally, conclusions are drawn in Section 6.

2 | Literature Review: Policy Measures for IS

The facilitating role that policy intervention may play in the development of IS has been recognized since the earliest studies in the literature of IS (Chertow 2007; Gibbs and Deutz 2007). Soon, this awareness led to the flourishing of a rich policy-related literature in the field of IS. The most established stream of this literature is based on the analysis of case studies. By interviewing various stakeholders from the industry within the Macheon Industrial Park in South Korea, Kim (2007) found out that the lack of proper economic incentives was a key barrier in the development of symbiotic synergies. Conversely, Van Berkel et al. (2009) argued how the legislative framework for a recycling-oriented society and the availability of government subsidies through the Eco-Town program has contributed to fostering IS in the Japanese city of Kawasaki. Costa et al. (2010) analyzed how waste management policies from supranational to sub-national levels affected the outgrowth of IS in Denmark, the United Kingdom, Portugal and Switzerland. The authors concluded that policy and legislation can positively influence IS development through a balanced mix of strong economic/regulatory instruments and flexible regulations at sub-national level. In their study, Salmi et al. (2012) discovered that the emergence of ISRs in the Gulf of Bothnia, between Finland and Sweden, is hampered by regulatory bottlenecks: The authors suggested a common pool resource-based governance system to exploit the technological and economic potential for IS in the region. Drawing from the Ulsan case study, Behera et al. (2012) proposed an "out of experience" guideline for the development of EIP, that highlighted the importance of policy instruments such as national programs, facilitators, and frameworks.

According to Jiao and Boons (2014), policy-related research in the field of IS is divided into four main streams: (1) overviews of policy programs, (2) policies as mechanisms for stimulating IS, (3) evaluation of policy programs, and (4) lessons learned from policies. In its renowned literature review, Jiao and Boons (2014) proposes a research agenda to investigate the mechanisms with which policy intervention and facilitation can affect IS from a dynamic perspective. According to the authors, understanding policies' influence on IS requires analyzing the dynamic translation of policy concepts into local practices, considering institutional contexts and causal mechanisms. In recent years, a similar classification has been proposed by Lybæk et al. (2021). After reviewing the relevant policy-related literature on IS and discussing some policies and framework conditions provided by the EU, the UN, and the OECD, the authors focused on the key role of indirect policies in supporting IS development. In their opinion, indirect policies and flexible framework conditions (e.g., feed-in tariffs, funding schemes, and institutional support) are often more effective in fostering IS than direct regulatory approaches. Similar conclusions were already drawn by Lehtoranta et al. (2011). Indeed, by analyzing the Kymi forest IS, they highlighted how indirect policy instruments can effectively foster symbiotic practices when aligned with local conditions. A different perspective is offered by Tao et al. (2019), who examined the issue through a firm-level lens. The authors argue that policy effectiveness depends on the alignment between (1) policy type, (2) firms' implementation stage, and (3) the fostering model adopted, suggesting a tailored combination of direct and indirect policy measures.

Recently, the effectiveness of policies in fostering IS has been studied through theoretical models, too. Zhao et al. (2020) developed an evolutionary game to prove how the proper combination of environmental incentives and external financing is critical to ensure the emergence and the stability of ISRs. Meng et al. (2023) proposed a game-theoretical model to analyze how different subsidy programs can enhance IS operations and contribute to social welfare within different supply chain scenarios Dong et al. (2024). explored the implementation of IS under environmental tax policy, showing its effectiveness in fostering IS and reducing environmental pollution. Finally, with respect to simulation studies, only Fraccascia et al. (2017a) proposed an AB model simulating the emergence of an ISN under the introduction of a landfill tax and an economic subsidy by the government. The authors showed that the effects of the investigated policy measures on the emergence and persistence of ISRs depends on market conditions.

3 | The AB Model

3.1 | System Description

Let us consider two industries: Industry A, consisting of n firms, and Industry B, consisting of m firms. Industries A and B serve two distinct markets, that is, Market A demanding Product A and Market B demanding Product B, respectively. Let us assume that each firm, regardless of the industry to which it belongs, requires one primary input to produce one main output. Moreover, it generates one waste as a result of its production process (Fraccascia et al. 2017; Fraccascia 2019). The output demand for each firm belonging to Industry A (B) is stochastic over time and follows a normal distribution of mean μ_A (μ_B) and standard deviation σ_A (σ_B). Conversely, the amount of input required and waste generated depends on the output demand according to an enterprise input–output (EIO) approach (Lin and Polenske 1998; Fraccascia et al. 2017).[2]

In the following, we will describe the material, economic, and environmental flows of the above-mentioned industrial system (1) as is, that is, without IS, and (2) in the case IS is implemented. Finally, we will introduce the government and explain the tools that it can provide to incentivize the outgrowth of IS. For clarity, we will narrow the scope of the analysis to include only the flows relevant to our model, that is, waste flows related to Industry A and input flows related to Industry B.

3.1.1 | The System Without IS

Let us consider company i belonging to Industry A and company j belonging to Industry B, along with their output demand at time t, that is, $d_i(t)$ and $d_j(t)$, respectively. To meet the demand, company i generates an amount of waste $w_i(t)$, while company j requires an amount of primary input $r_j(t)$. These quantities are computed according to Equation (1).

$$
\begin{aligned}
w_i(t) &= W_A \cdot d_i(t) \\
r_j(t) &= R_B \cdot d_j(t)
\end{aligned} \tag{1}
$$

W_A and R_B are technical coefficients of substitution, that is, they represent the amount of waste generated and the amount of primary input required by i and j to produce one unit of Products A and B, respectively. We assume that firms within the same industry share the same production technology. Thus, the technical coefficient W_A (R_B) is common to all firms in Industry A (B) (Fraccascia et al. 2017; Albino et al. 2016).

From an economic perspective, disposing of the waste in the landfill requires company i to pay a disposal cost. Likewise, carrying out the production activities with the traditional primary input has a production cost for company j. Let udc_A^{eco} be the unit disposal cost of the waste generated by producing Product A and upc_B^{eco} the unit purchasing cost of the primary input required to produce Product B. The economic disposal cost for company i ($DC_i^{eco}(t)$) and the production cost for company j ($PC_j^{eco}(t)$), respectively, can be computed according to Equation (2).

$$
\begin{aligned}
DC_i^{eco}(t) &= (udc_A^{eco} + utrac^{eco} \cdot dist_{i\to L}) \cdot w_i(t) \\
PC_j^{eco}(t) &= upc_B^{eco} \cdot r_j(t)
\end{aligned} \tag{2}
$$

$utrac^{eco}$ is the unit transportation cost and $dist_{i\to L}$ is the distance (in km) from company i to the landfill. We assume that firms, in addition to disposal costs, independently bear the cost of transporting the waste to the landfill. Conversely, assuming a freight-absorption pricing strategy[3] adopted by the primary input supplier (Lederer and Hurter 1986), we can consider the purchasing cost as the only significant component of production costs[4] for company j.

From an environmental perspective, the impact of production and waste disposal can be measured in terms of CO_2 equivalents emitted. Specifically, for each unit of waste $w_i(t)$ disposed of in the landfill at time t by company i the environmental disposal cost ($DC_i^{env}(t)$) can be computed as reported in Equation (3). Likewise, for each unit of primary input $r_j(t)$ used by company j, Equation (3) defines the environmental production cost ($PC_j^{env}(t)$), too.

$$
\begin{aligned}
DC_i^{env}(t) &= (udc_A^{env} + utrac^{env} \cdot dist_{i\to L}) \cdot w_i(t) \\
PC_j^{env}(t) &= (upc_B^{env} + utrac^{env} \cdot dist_{S_B\to j}) \cdot r_j(t)
\end{aligned} \tag{3}
$$

udc_A^{env} is the unit environmental disposal cost, upc_B^{env} denotes the unit environmental cost of production, and $utrac^{env}$ the unit environmental cost of transportation.[5] To avoid unnecessary model complexity, we assume that all firms belonging to Industry B purchase the primary input from the same supplier, that is, Supplier B (S_B). Accordingly, $dist_{S_B\to j}$ represents the distance (in km) between company j and Supplier B (S_B).

3.1.2 | The System With IS

Let us assume that the waste generated from firms belonging to Industry A can replace the primary input required by firms belonging to Industry B, after undergoing a treatment process, whose efficiency $\eta \in [0,1]$, depends on the technology adopted. The efficiency η represents the share of waste that can substitute the primary input after treatment, and it is always lower than 1: When treating an amount w of waste, only $w^* \le w$ can be used (Equation 4), while the remaining must be disposed of.

$$
w^* = \eta \cdot w \tag{4}
$$

Let ξ the technical coefficient of substitution of the primary input with the waste (representing how many units of waste are required to substitute one unit of the primary input), w^* units of waste can replace r units of primary input, according to Equation (5).

$$
r = \xi \cdot w^* \tag{5}
$$

ISRs may arise between firms belonging to Industries A and B. Assume that company i has incurred an investment I in new machinery and technology required to perform the treatment process. Once the investment is completed, company i can search for a symbiotic partner. Let company i and company j be two potential symbiotic partners. If they decide to establish a symbiotic relationship at time t, they can exchange an amount $e_{i\to j}^{IS}(t)$ of waste at time t. Such an amount is the minimum between the waste produced and successfully treated by i and the amount required by j (Equation 6)[6]:

$$
e_{i\to j}^{IS}(t) = \min\left\{ W_A \cdot d_i(t) \cdot \eta \ , \ R_B \cdot d_j(t) \cdot \frac{1}{\xi} \right\} \tag{6}
$$

If the waste is exchanged, company i saves disposal costs ($SAV_{i\to j}^{eco}(t)$) and company j saves input purchasing costs ($SAV_{j\to i}^{eco}(t)$) (Equation 7):

$$
\begin{aligned}
SAV_{i\to j}^{eco}(t) &= (udc_A^{eco} + utrac^{eco} \cdot dist_{i\to L}) \cdot e_{i\to j}^{IS}(t) \\
SAV_{j\to i}^{eco}(t) &= upc_B^{eco} \cdot e_{i\to j}^{IS}(t) \cdot \xi
\end{aligned} \tag{7}
$$

However, additional operating costs arise: specifically, treatment costs ($utreac_w^{eco}$) and transportation costs of the waste from i to j (Equation 8) (Fraccascia et al. 2019; Albino et al. 2016).

$$
AOC_{i\to j}^{eco}(t) = \left(\frac{utreac_w^{eco}}{\eta} + utrac^{eco} \cdot dist_{i\to j} \right) \cdot e_{i\to j}^{IS}(t) \tag{8}
$$

If the sum of savings is higher than the additional costs of IS, that is, if $SAV_{i\to j}^{eco}(t) + SAV_{j\to i}^{eco}(t) > AOC_{i\to j}^{eco}(t)$, the waste exchange is convenient from the economic perspective. However, benefits must be properly shared between the two companies.

Let us assume that the treatment of waste is in charge of company i (which has invested in new machinery and technology), as well as the transportation costs. For its part, company j purchases the treated waste from i at a price p_{w^*}. Introducing p_{w^*} allows us to model how i and j share the additional operating costs of IS. In the literature, typically the sharing of additional costs is negotiated. A parameter α is introduced to represent the share of additional operating costs ($AOC^{eco}_{i\to j}(t)$) paid by company i (Albino et al. 2016). Correspondingly, the share of additional costs paid by company j is $1-\alpha$. If $\alpha_{ij} \in [0,1]$, $AOC^{eco}_{i\to j}(t)$ is shared between i and j; if $\alpha_{ij} > 1$, company i sustains the overall $AOC^{eco}_{i\to j}(t)$ and further pays company j to dispose of the waste; if $\alpha_{ij} < 0$, company j sustains the overall $AOC^{eco}_{i\to j}$ and further pays company i to buy the waste (Fraccascia et al. 2020). We can relate the price of the treated waste p_{w^*} to the parameter α, without loss of generality, according to Equation (9):

$$p_{w^*} = (1-\alpha)\cdot\frac{AOC^{eco}_{i\to j}(t)}{e^{IS}_{i\to j}(t)} = (1-\alpha)\cdot\left(\frac{utreac^{eco}_{w}}{\eta} + utrac^{eco}\cdot dist_{i\to j}\right) \tag{9}$$

In addition to the operating costs, the establishment and management of the ISR determine transaction costs to be paid (Hobbs 1996; Williamson 1981). According to the literature, transaction costs can be modeled as the sum of three components (Equation 10), that is, search costs (sc), negotiation costs (nc), and enforcement costs (ec).

$$\begin{aligned} TC_i &= sc_i + nc_i + ec_i \\ TC_j &= sc_j + nc_j + ec_j \end{aligned} \tag{10}$$

Transaction costs are company specific and, to ensure a thorough analysis of the net economic benefits achieved by each company, they have to be considered, too.

From the environmental perspective, let us assume that the replacement of the primary input with waste determines lower environmental costs, that is, the environmental cost of production is reduced:

$$upc^{env}_{w^*}\cdot e^{IS}_{i\to j}(t) < \left(udc^{env}_{A} + upc^{env}_{B}\cdot\frac{1}{\xi}\right)\cdot e^{IS}_{i\to j}(t) \tag{11}$$

where upc^{env}_{w*} is the unit environmental cost of production when replacing r with w^*. Therefore, the exchange of an amount $e^{IS}_{i\to j}(t)$ of waste determines savings in environmental costs (Equation 12).

$$\begin{aligned} SAV^{env}_{i\to j}(t) &= (udc^{env}_{A} + utrac^{env}\cdot dist_{i\to L})\cdot e^{IS}_{i\to j}(t) \\ SAV^{env}_{j\to i}(t) &= (upc^{env}_{B} + utrac^{env}\cdot dist_{S_B\to j})\cdot e^{IS}_{i\to j}(t)\cdot\xi \end{aligned} \tag{12}$$

However, environmental additional costs arise, too (Equation 13).

$$AOC^{env}_{i\to j}(t) = \left(\frac{utreac^{env}_{w}}{\eta} + upc^{env}_{w^*} + utrac^{env}\cdot dist_{i\to j}\right)\cdot e^{IS}_{i\to j}(t) \tag{13}$$

If the sum of savings is higher than the additional costs of IS, that is, if $SAV^{env}_{i\to j}(t) + SAV^{env}_{j\to i}(t) > AOC^{env}_{i\to j}(t)$, the waste exchange is environmentally convenient.

3.1.3 | The Role of the Government

Let us assume that the government decides to encourage firms belonging to Industries A (hereafter waste producers) and B (hereafter waste users) to engage in IS, aiming at enhancing the economic and environmental performance of the system. The government has a limited budget to be allocated between two policy tools. Specifically, the government can use the budget to

1. *subsidize the investments for firms belonging to Industry A*, that is, sustaining a percentage β of the investment I for those waste producers that decide to invest;
2. *subsidize the purchasing of treated waste for firms belonging to Industry B*, that is, providing a rebate on the purchasing price of the treated waste p_{w^*}, which is equivalent to sustaining a percentage s of the purchasing costs of the waste.[7]

The budget is defined a priori,[8] which is in line with real-world dynamics, where funds are usually accorded ex ante by policymakers. The budget can be used to grant subsidies of type β and/or s, until the funds are exhausted, according to a specific policy design. The policy design determines (1) how the budget is allocated between the two policy tools and (2) the tools' maximum per-unit extent.

In the following, according to the definition proposed in Section 1, we will refer to any specific set of policy tools and design introduced by the government with the term *subsidy program*, and we will indicate it by letter Ψ.

3.2 | Agents' Behavioral Rules and Model Dynamics

The proposed AB model enables the interaction of waste users and waste producers, that is, the agents of the model. The government is not included among the agents: The subsidy program Ψ is defined at time $t=0$ and does not change over time. The dynamic evolution of the system is determined by two main decision-making processes: (1) the investment decision of waste producers and (2) the cooperation decision between waste producers (that have made the investment) and waste users.

In the following, we will describe the behavioral rules of the agents (Section 3.2.1). Subsequently, we will provide a brief description of the dynamics of the model (Section 3.2.2).

3.2.1 | Agents' Behavioral Rules

In the literature of ABM, the decisions undertaken by agents are typically modeled through fitness functions (Budinis et al. 2020; Albino et al. 2016). Specifically, any agent undergoing a decision-making process evaluates a fitness function (associated with a set of behavioral rules), and decides what to do according to whether the fitness function is higher than a predefined threshold. In our model, agents can take two main decisions: (1) whether to invest or not to invest in new machinery and technology for the treatment of the waste (this decision is limited to companies belonging to Industry A, who are entitled to invest) and (2) whether to cooperate or not to cooperate with a potential symbiotic partner. These decisions are described in detail below.

3.2.1.1 | The Investment Decision.

To engage in symbiotic relationships waste producers are required to invest in new machinery and technology for the treatment of the waste. Accordingly, the investment decision of waste producer i is driven by the *willingness to invest* function (WTI_i). The WTI function has been built as a simplified version of the investment net present value (NPV) (Equation 14), where the potential future benefits achievable through IS are compared with the actual cash outflow (Brealey et al. 2014): If $WTI_i > 0$, company i decides to invest; otherwise, it does not.

$$WTI_i = \sum_{t=1}^{U} \frac{p_i \cdot \mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]}{(1+r)^t} - (1-\beta)\cdot I \tag{14}$$

This modeling approach is grounded in the existing theory of ABM. Indeed, similar investment decision rules have been adopted in ABM studies analyzing technology adoption and infrastructure investments under uncertainty (Budinis et al. 2020; Sachs et al. 2019). Here, firms evaluate irreversible investments by comparing expected discounted benefits with upfront costs. In Equation (14), $\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]$ accounts for the mean discounted economic benefit per unit of time that i expects to achieve from IS, while p_i is the expected probability of achieving such benefit. For the sake of simplicity, both p_i and $\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]$ are assumed to be fixed in time and company specific. Specifically, the parameter p_i is randomly chosen between 0 and 1 for each firm. The stochastic assignment of p_i is aimed to represent population-level heterogeneity in trust and awareness,[9] which is empirically observed in IS contexts (Gibbs 2003; Doménech and Davies 2011): The higher the value of p_i, the higher the expected probability that company i will invest in IS, ceteris paribus. Concerning $\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]$, when making the investment decision, firms do not know *if* and *with whom* they will cooperate, nor the amount of waste that will be exchanged over time. Therefore, future benefits achievable through IS are highly uncertain. To reflect this uncertainty, the expected discounted economic benefit per time ($\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]$) is calculated for each firm according to Equation (15):

$$\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)] = SAV^{eco}_{i\to x}\big|_{e^{IS}_{i\to x}(\cdot)} - \alpha\cdot(1-s)\cdot AOC^{eco}_{i\to x}\big|_{e^{IS}_{i\to x}(\cdot),\ d_{i\to x}} \tag{15}$$

Basically, $\mathbb{E}[EcoB_i(\cdot) \,\|\, e^{IS}_{i\to x}(\cdot)]$ represents the economic benefit that company i expects to obtain at any time t by exchanging an amount of waste $e^{IS}_{i\to x}(\cdot)$ with a generic partner x at distance $d_{i\to x} = \overline{dist}_{A\to B}$.[10] It is calculated as the difference between expected economic savings from disposal and expected operating costs of IS. Both costs and benefits are calculated considering an amount $e^{IS}_{i\to x}(\cdot) = W\cdot \overline{d_i}\cdot \eta$, that is, the mean expected supply of waste successfully treated per unit of time,[11] while the parameter α (see Equation 9) is randomly chosen between 0 and 1.[12] Finally, the parameter r is the discount rate,[13] while U is the useful life of the investment.[14]

3.2.1.2 | The Cooperation Decision.

The cooperation decision between the waste producer i and the waste user j at time t is modeled through the *willingness to cooperate* function ($WTC^{IS}_{i\to j}(t)$). According to the literature (Albino et al. 2016; Fraccascia et al. 2019; Fraccascia and Yazan 2018), the willingness of agents to cooperate in ISRs depends on two main factors: (1) the economic benefits stemming from cooperation and (2) the path dependence phenomenon, that is, past experience of cooperation exerts an influence on the current cooperation decision. Accordingly, the $WTC^{IS}_{i\to j}(t)$ and $WTC^{IS}_{j\to i}(t)$ functions are modeled as reported in Equations (16) and (17), respectively.

$$\begin{aligned} WTC^{IS}_{i\to j}(t) &= \frac{1}{L_{ij}(t)+1}\cdot \frac{SAV^{eco}_{i\to j}(t) - AOC^{eco}_{i\to j}(t) + p_{w^*}\cdot e^{IS}_{i\to j}(t)}{DC^{eco}_{j}(t)} \\ &\quad + \left[1 - \frac{1}{L_{ij}(t)+1}\right]\cdot WTC^{IS}_{i\to j}(t-1) \end{aligned} \tag{16}$$

$$\begin{aligned} WTC^{IS}_{j\to i}(t) &= \frac{1}{L_{ij}(t)+1}\cdot \frac{SAV^{eco}_{j\to i}(t) - p_{w^*}\cdot e^{IS}_{i\to j}(t)\cdot(1-s)}{PC^{eco}_{j}(t)} \\ &\quad + \left[1 - \frac{1}{L_{ij}(t)+1}\right]\cdot WTC^{IS}_{j\to i}(t-1) \end{aligned} \tag{17}$$

$L_{ij}(t)$ is the number of consecutive periods in which agent i and agent j have been cooperating until time t. $SAV^{eco}_{i\to j}(t)$ and $SAV^{eco}_{j\to i}(t)$ are the economic savings in disposal and purchasing costs, respectively (see Equation 7), while $AOC^{eco}_{i\to j}(t)$ denotes the additional operating cost of IS (see Equation 8). Finally, p_{w^*} is the negotiated waste exchanged price. The price negotiation is modeled as an iterative process that starts with a random price proposal made by i[15] and take turns between the parties until an agreement is found, or the negotiation (hence the symbiotic relationship) is abandoned. Note that this representation of the waste exchange price negotiation between potential symbiotic partners is well established in the ABM literature on IS (Mollica et al. 2025; Fraccascia and Yazan 2018). Here, the aim is not to reproduce detailed negotiation strategies but to evaluate whether mutually acceptable exchange conditions can emerge given agents' cost structures and policy incentives. Accordingly, results are not driven by the specific negotiation mechanism, but by cost–benefit trade-offs. To decide whether to cooperate, the willingness to cooperate is compared with an agent-specific threshold ($Thre_x$): i and j cooperate at time t only if both $WTC^{IS}_{i\to j}(t) \geq Thre_i$ and $WTC^{IS}_{j\to i}(t) \geq Thre_j$.

3.2.2 | Model Dynamics

At time $t = 0$, the government introduces a subsidy program $\Psi^* = \{\beta^*, s^*\}$ for which a limited budget is agreed. The information about the subsidy program and the budget is publicly available and complete information is assumed during the whole simulation time, that is, firms are aware of the subsidies' extent and of the remaining funds when taking decisions. At the beginning of the simulation ($t = 1$), all waste producers evaluate whether to invest: only waste producers that decide to invest can establish ISRs. If company i has decided to invest, it searches for a partner; otherwise, it takes no action. Note that a potential partner j is eligible for i only if it is not yet engaged in other ISRs, that is, only one-to-one ISRs are allowed.[16] When a potential partner j is found, i and j evaluate whether to establish an ISR and negotiate the waste exchange price p_{w^*}.

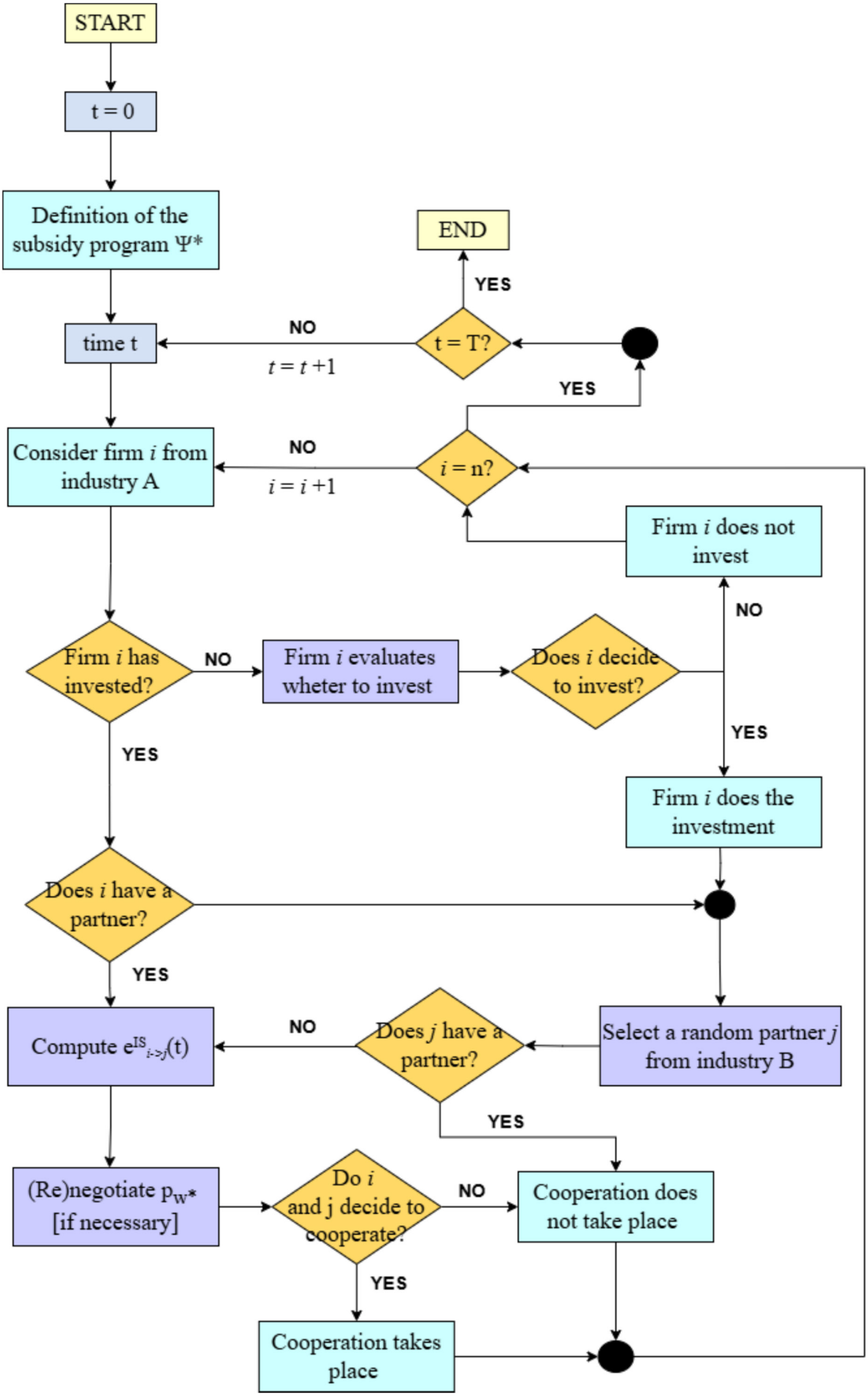


FIGURE 1 | Model dynamics flowchart.

At the generic time t, waste producers that have not invested yet re-evaluate the investment. Then, among waste producers that have made the investment, those still without a partner try to establish an ISR; those already engaged in IS re-evaluate their cooperation. Finally, waste users not engaged in IS search for a potential partner among waste producers.

To ease the reader comprehension, the dynamics of the model are resumed in the flowchart reported in Figure 1.

3.3 | The Simulation

In this section, we will describe how the model has been implemented and used to answer research questions RQ1 and RQ2. After briefly introducing the case study used as the simulation setting, we will provide the input dataset used to run simulations and explain which variables have been selected to derive insights from the model. Finally, we will explain the methodological approach used to analyze the simulations' results.

3.3.1 | Case Study

There are several examples of symbiotic relationships that align with our model's main assumptions—specifically, the need for the waste to be treated before replacing the primary input (the literature refers to this phenomenon with the term *imperfect* IS) and, accordingly, for waste producers to make investments as a prerequisite for IS. A well-documented and widely studied case of imperfect symbiosis can happen between the steel-iron industry and the cement industry (H. Wang et al. 2016; Martins et al. 2021). Blast furnace slag (BFS) (a by-product of iron and steel production) can be rapidly quenched to obtain a glassy material and subsequently dried and finely ground to produce ground granulated BFS (GGBFS). GGBFS can then be used as a supplementary cementitious material to partially replace clinker in Portland cement production. This practice is technologically mature and well established in the European industrial context. Indeed, its use is explicitly regulated in Europe under EN 197-1, which defines CEM III cements with GGBFS contents ranging from 36% to 95% (European Committee for Standardization 2011). Clinker production is extremely polluting, and replacing clinker with GGBFS can cut CO_2 emissions by 50%–80% per ton of cement (Ammenberg et al. 2015). Given the high environmental benefits derived from this symbiotic exchange, an extensive literature is available on this topic (C. Chen et al. 2010) and several real industrial applications exist, for example, Ecocem (Thompson et al. 2016), Tata Steel IJmuiden, and Heidelberg Materials (Xavier and Oliveira 2021). For these reasons, in our model, we considered a hypothetical case based on this real underlying application. Nevertheless, beyond the steel-cement case, similar structural features characterize other potential symbiotic exchanges: for instance, within the agri-food and plastic industries, where potato or starch processing plants may invest in building facilities for microbial fermentation to convert organic waste into lactic acid. This latter can be sold to bioplastic manufacturers to produce PLA (Mose and Maranga 2011; Agustin et al. 2014). Another example may be the production of biofuels from algae cultivation (Borowitzka and Moheimani 2013), which again requires high investment in building the required facilities and technologies to engage in IS. These cases highlight that the proposed model is not sector specific but can be adapted to different industrial contexts.

3.3.2 | Simulation Setting

The model has been implemented in Python 3.13.3 using the *Mesa* library. The input dataset used for the simulations is reported in Table 1.[17] We have run simulations of the model with different policy settings, corresponding to different designs of the subsidy program Ψ, and compared them with a baseline scenario, where no subsidies are granted. Specifically, let $\varphi \in [0,1]$ be the percentage of the overall budget allocated to subsidies of type β (accordingly, the percentage allocated to subsidies of type s will be $1-\varphi$). Five different allocations of the budget (i.e., φ) between the two

TABLE 1 | Parameters used in the simulation.

Model structure parameters	
Number of waste producers (N)	50
Number of waste users (M)	50
Simulation time (T)	80 (trimesters)
Average demand for Product A (μ_A)	4500 (t/trimester)
Average demand for Product B (μ_B)	2450 (t/trimester)
Spatial dimension X	100 (km)
Spatial dimension Y	100 (km)
Technical substitution coefficient of the waste (W_A)	$0.3\left(\frac{t\ BFS}{t\ steel}\right)$
Technical substitution coefficient of the input (R_B)	$1.35\left(\frac{t\ clinker}{t\ cement}\right)$
Technical substitution coefficient of IS (ξ)	$1\left(\frac{t\ GGBFS}{t\ BFS}\right)$
Economic parameters	
Unit input purchasing cost (upc_B^{eco})	$66\left(\frac{eur}{t\ clinker}\right)$
Unit waste disposal cost (udc_A^{eco})	$6\left(\frac{eur}{t\ BFS}\right)$
Unit waste treatment cost ($utreac^{eco}$)	$112\left(\frac{eur}{t\ BFS}\right)$
Unit transportation cost ($utrac^{eco}$)	$2.5\left(\frac{eur}{t \cdot \mathrm{km}}\right)$
Investment useful life (U)	80 (trimesters)
Discount rate (r)	0.05
Budget	$3 \cdot 10^8$ (eur)
Environmental parameters	
Unit production emission cost (upc_B^{env})	$850\left(\frac{CO_2eq}{t\ clinker}\right)$
Unit disposal emission cost (udc_A^{env})	$255\left(\frac{CO_2eq}{t\ BFS}\right)$
Unit treatment emission cost ($utreac^{env}$)	$170\left(\frac{CO_2eq}{t\ BFS}\right)$
Unit transportation emission cost ($utrac^{env}$)	$0.062\left(\frac{CO_2eq}{t \cdot \mathrm{km}}\right)$

available tools have been considered, as well as two levels for each type of subsidy (i.e., β and s). Each setting is the result of combining the levels of φ ($\varphi \in \{0, 0.25, 0.5, 0.75, 1\}$) with the levels of each type of subsidy (i.e., $\beta \in \{0.4,\ 0.8\}$ and $s \in \{0.4,\ 0.8\}$). For each level of φ, four possible combinations of β and s are possible, except when $\varphi = 0$ or $\varphi = 1$. In these cases, only two settings out of four (deriving from combining β and s) have been considered. In summary, a total number of 16 policy settings (plus the *baseline* scenario) has been simulated. Additionally, to understand the impact of the same subsidy program within different market contexts, simulations have been performed with three levels of market dynamicity (i.e., $CV \in \{0.1, 0.3, 0.5\}$). In conclusion, 48 scenarios have been simulated. To ensure statistical significance of the results, 550 replications of each scenario have been performed.

3.3.3 | Performance Measures

To evaluate which subsidy program Ψ^* is the most *effective*[18] within a given industrial context (i.e., to answer RQ1), a measure of effectiveness is required. We decided to assess the effectiveness of a subsidy program with respect to the economic and environmental performance of the system. Indeed, among the most common policy objectives there is the maximization of the economic and/or environmental benefits. Specifically, we considered the following metrics:

1. *Economic performance*: Total economic benefits achieved by the system, net of investment costs:

$$EcoB_{Tot}^{Net} = \sum_{t=1}^{T}\left[\sum_{i\in N}(SAV_{i\to j}^{eco}(t) - AOC_{i\to j}^{eco}(t)) + \sum_{j\in M} SAV_{j\to i}^{eco}(t)\right] - N_{inv}\cdot I + Budget\_Used \tag{18}$$

2. *Environmental performance*:
   a. Total amount of CO_2 emissions saved by the system:

$$CO_2E_{saved} = \sum_{t=1}^{T}\left[\sum_{i\in N}(SAV_{i\to j}^{env}(t) - AOC_{i\to j}^{env}(t)) + \sum_{j\in M} SAV_{j\to i}^{env}(t)\right] \tag{19}$$

   b. Total amount of waste exchanged within the system:

$$W_{Tot}^{Exch} = \sum_{t=1}^{T}\sum_{i\in N} e_{i\to j}^{IS}(t) \tag{20}$$

For each metric $\mathscr{M}$ and each scenario, the effectiveness of the policy $\Psi^* = \{\beta^*, s^*\}$ is assessed according to the following criterion:

$$\Psi^* \text{ is effective} \Leftrightarrow \mathbb{E}[\mathscr{M}|\Psi^*] > \mathbb{E}[\mathscr{M}|\Psi_{base}] \wedge \textit{the difference is statistically significant at 5\%} \tag{21}$$

In Equation (21), the expected value is computed as the arithmetic mean of the values of $\mathscr{M}$ observed across n_{rep} replications of the considered scenario. To assess statistical significance, we performed a one-tailed t-test at the 5% level. Once the effectiveness of a given subsidy program is ascertained, the magnitude of such effectiveness is evaluated by computing the Cohen's d[19] ($d_{\mathscr{M}}^{\text{Cohen}}$) and the percentage difference between the means $\overline{\mathscr{M}}_{\Psi^*}$ and $\overline{\mathscr{M}}_{\Psi_{base}}$ ($\Delta_{\mathscr{M}}^{\%}$):

$$d_{\mathscr{M}}^{\text{Cohen}} = \frac{\overline{\mathscr{M}}_{\Psi^*} - \overline{\mathscr{M}}_{\Psi_{base}}}{S_{\text{pooled}}}. \tag{22}$$

$$\Delta_{\mathscr{M}}^{\%} = \frac{\overline{\mathscr{M}}_{\Psi^*} - \overline{\mathscr{M}}_{\Psi_{base}}}{\overline{\mathscr{M}}_{\Psi_{base}}}\cdot 100 \tag{23}$$

The higher the Cohen's d (and the percentage difference between the means), the more the policy Ψ^* is effective, ceteris paribus. With respect to efficiency, which is required to answer RQ2, we defined the marginal cost (MC) of the subsidy program Ψ^* ($MC_{\Psi^*}^{\mathscr{M}}$). $MC_{\Psi^*}^{\mathscr{M}}$ is computed as the ratio between the total government expenditure and the observed increase in the metric $\mathscr{M}$ compared with the baseline (Equation 24).

$$MC_{\Psi^*}^{\mathscr{M}} = \frac{Budget\_Used}{\overline{\mathscr{M}}_{\Psi^*} - \overline{\mathscr{M}}_{\Psi_{base}}} \tag{24}$$

This measure represents the cost incurred by the government to determine a unitary increase in the metric $\mathscr{M}$ under policy Ψ^*: The lower the MC of the subsidy program Ψ^*, the higher the efficiency of the program in relation to the objective measured by the metric $\mathscr{M}$ will be.[20]

4 | Results

In this section, we will show and analyze the results of the performed simulations. First, results will be used to detect some expected behaviors of the system, thus ascertaining the consistency of the model (Section 4.1). Second, the main insights on the dynamics of the model will be explained and discussed. Finally, the analysis of the results will be deepened, following the methodological approach proposed in Section 3.3.3, and research questions RQ1 and RQ2 will be answered (Section 4.2).

4.1 | The Impact of Variables on the System Behavior

Results from the 550 replications of the model for each scenario have been analyzed to understand the impact of the key variables on the system behavior. Different market scenarios characterized by three levels of market dynamicity (represented by the demand coefficient of variation, i.e., *CV*) have been considered. The effect of market dynamicity on the system performances is expected to be negative from both the economic and environmental perspectives, as suggested by the literature (Fichtner et al. 2005; Fraccascia and Yazan 2018; Leferink and Chertow 2025). Figures 2 and 3 illustrate how the expected negative impact of *CV* on the system's economic and environmental performance is confirmed by our model. Specifically, the total economic benefit achieved

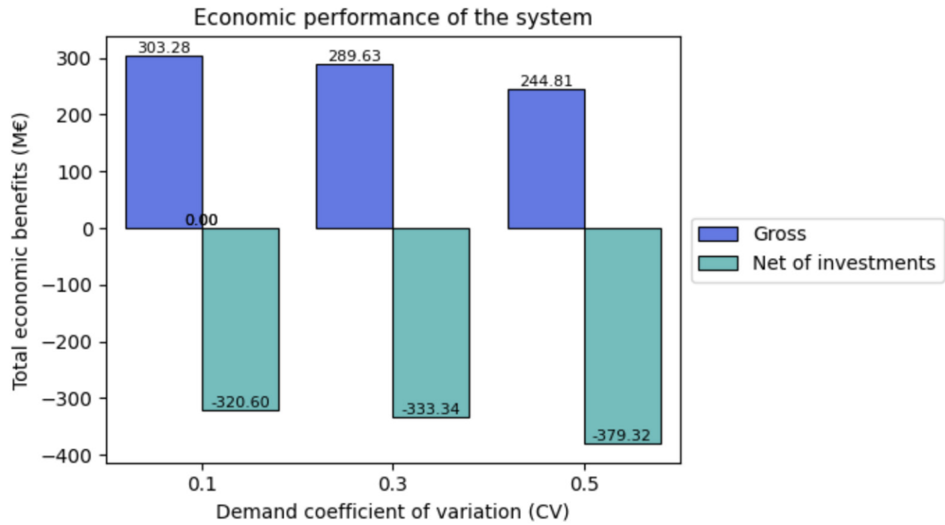
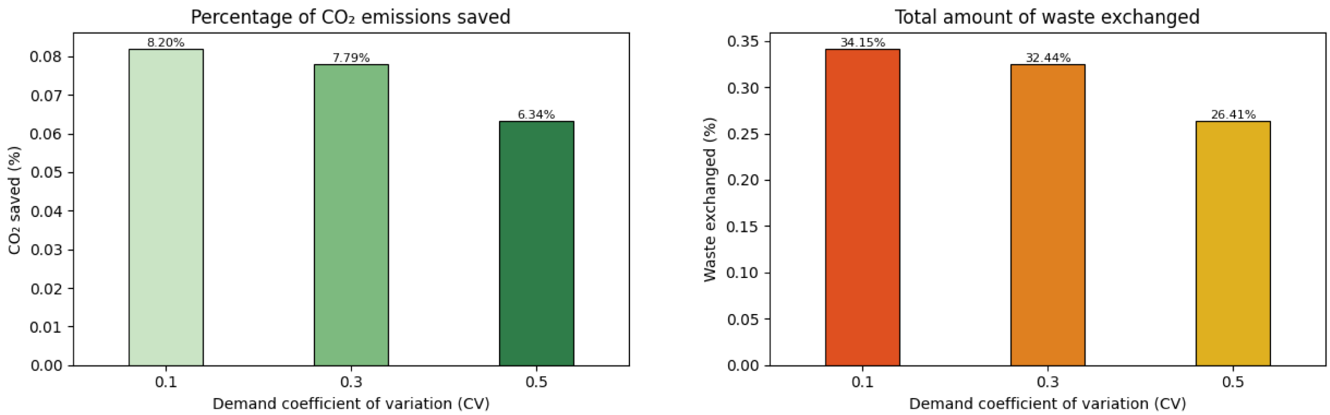


FIGURE 2 | Economic performance of the system by CV.



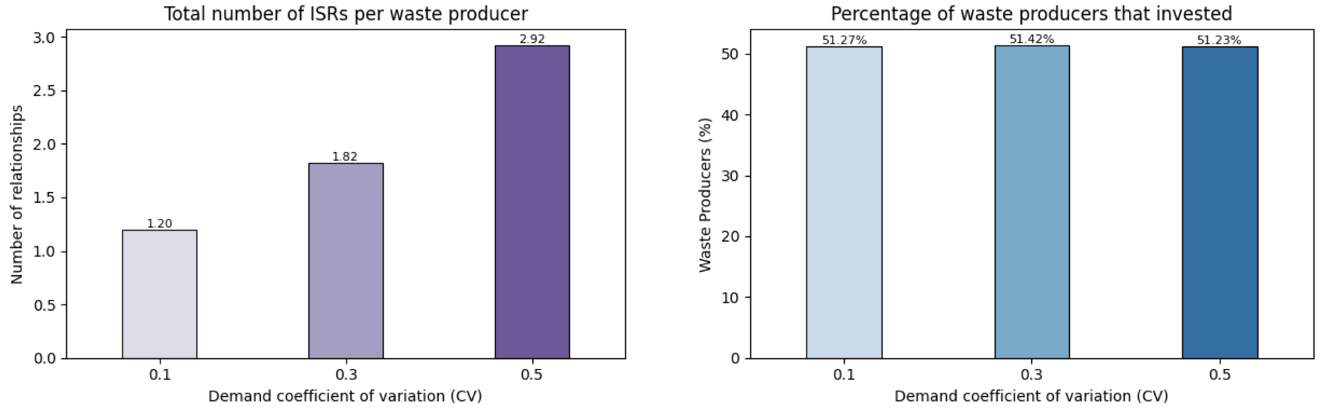
(a) Percentage of CO_2 saved per CV.

(b) Percentage of waste exchanged per CV.

FIGURE 3 | Environmental performance of the system by CV.

by the system is reduced by 19% when increasing CV from 0.1 to 0.5. The same happens in terms of environmental performance: The percentage reduction in CO_2 emissions decreases from 8.20% to 6.34%, while the percentage of waste exchanged from 34.15% to 26.41%, ceteris paribus. Additionally, we can observe that variations in market dynamicity exert no significant effect on the investment decisions of waste producers (Figure 4). Indeed, even if the investment choice is dependent on the expected economic benefits achievable through potential future symbiotic relationships (which are dependent on CV, as we have mentioned before), having a more stable market is not enough to increase the willingness of a waste producer to invest: a stronger economic incentive is required. Market dynamicity hampers the stability of established symbiotic relationships (Fraccascia et al. 2017b; Fraccascia 2019). As we can see in Figure 4a, the average number of symbiotic partners with which each waste producer cooperates during the overall simulation time increases when CV increases, keeping fixed all the other variables. When the market is stable ($CV = 0.1$), on average, waste producers have only one partner. This suggests that established ISRs are unlikely to break down. Conversely, when the market is more dynamic ($CV = 0.5$), on average, waste producers cooperate with three partners. This is in line with the literature, where it is renowned that mismatches in waste demand and supply (worsened by market fluctuations) act as major barriers to IS (Golev et al. 2015; Neves et al. 2019), not seldom leading to the interruption of symbiotic relationships: Having detected this mechanism within our results is a further proof of consistency of the dynamics of the model.

Moving to the effects of the subsidy program design, Figure 5 shows government expenditure per type of subsidy with respect to φ. We recall that φ is the percentage of the available budget allocated to subsidies of type β. Indeed, holding all other factors constant, government expenditure for subsidies of type β increases when φ increases—which is in line with the expectations. Conversely, the effect of φ on the expenditure for granting subsidies of type s is less predictable: At first, the expenditure increases with φ; then, it decreases. This is because subsidies of type s are granted only when waste is exchanged: If there are fewer ISRs, less waste is exchanged. Accordingly,



(a) Average number of waste producers' symbiotic relationships per CV.

(b) Number of waste producers that made the investment per CV.

FIGURE 4 | Waste producers' decisions by CV.

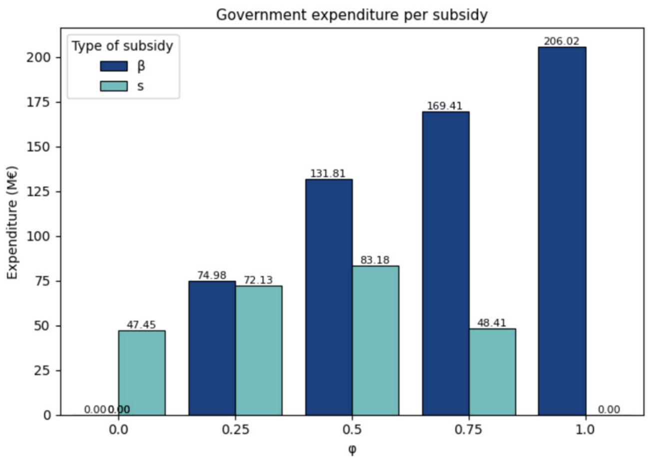


FIGURE 5 | Average expenditure of the government by φ.

the amount of budget allocated to subsidies of type s remains mostly unspent. From the results, we can notice that when the budget is entirely allocated to subsidies of type s (i.e., $\varphi = 0$), the overall government expenditure is of 47.45 out of 300 million euros: Almost 85% of the budget is unspent. Conversely, when the budget is entirely allocated to subsidies of type β (i.e., $\varphi = 1$), the percentage of budget unspent is reduced to 31%, ceteris paribus. The best allocation of the budget occurs when $\varphi = 0.75$: On average, 72% of the budget is granted to firms, under otherwise identical conditions. The main explanation for such significant differences in government expenditures lays in the fact that the subsidy program design has a strong effect on the investment decisions of waste producers, as we can see from Figures 6 and 7. Indeed, the percentage of waste producers that decide to invest is higher than in the baseline scenario, *whatever the subsidy program design*. However, isolating the effect of φ, its increase has always a positive effect on waste producers' investment decisions, and investments are (almost) always accompanied by government disbursement. Moreover, if the number of investments is higher, it is more likely that a higher amount of waste will be exchanged, and government will grant more subsidies of type s, too.

Concerning the effect of the β-type subsidy level on waste producers' investment decisions, it changes with φ, as well. For instance, when $\varphi = 0.25$ and $\beta = 0.4$, the percentage of waste producers investing is 43.7%, and it decreases to 40.6% when $\beta = 0.8$, ceteris paribus. Conversely, when $\varphi = 0.75$, if $\beta = 0.4$, on average, 57% of waste producers decide to invest, while if $\beta = 0.8$, the percentage shifts to 64.7%. This phenomenon is driven by the faster depletion of the budget available for investment subsidies when φ is low. Indeed, the decrease in the total number of investments when increasing β suggests that some waste producers, that would have settled with less, reap more benefits than necessary, leaving other waste producers with no more fundings available. This determines an inefficient market outcome, that does not happen when $\beta = 0.4$: In this case, the percentage of budget allocated to subsidies of type β is not exhausted, meaning that all waste producers willing to invest with the lower level of subsidy can invest. After this point, to reach a higher percentage of waste producers, a higher investment subsidy should be granted by the government.

Finally, our results highlight that the level of s-type subsidies on waste producers' investment decisions is always positive. This is related to the expected higher price that waste producers may arrange with waste users to exchange the waste. Indeed, as the government subsidizes the purchasing of waste through subsidies of type s, it is reasonable to expect that the higher the percentage of the purchasing price of the waste covered by the subsidy, the more waste users will be willing to pay waste producers a higher price. Accordingly, expected revenues from selling the waste increase, too. This behavior is confirmed when analyzing the effect of s on the average exchange price of the waste: whatever φ, the average waste exchange price increases with the level of s (Figure 8).

4.2 | Effectiveness and Efficiency of Subsidy Programs

To answer research questions RQ1 and RQ2, we followed the methodological approach proposed in Section 3.3.3. The main

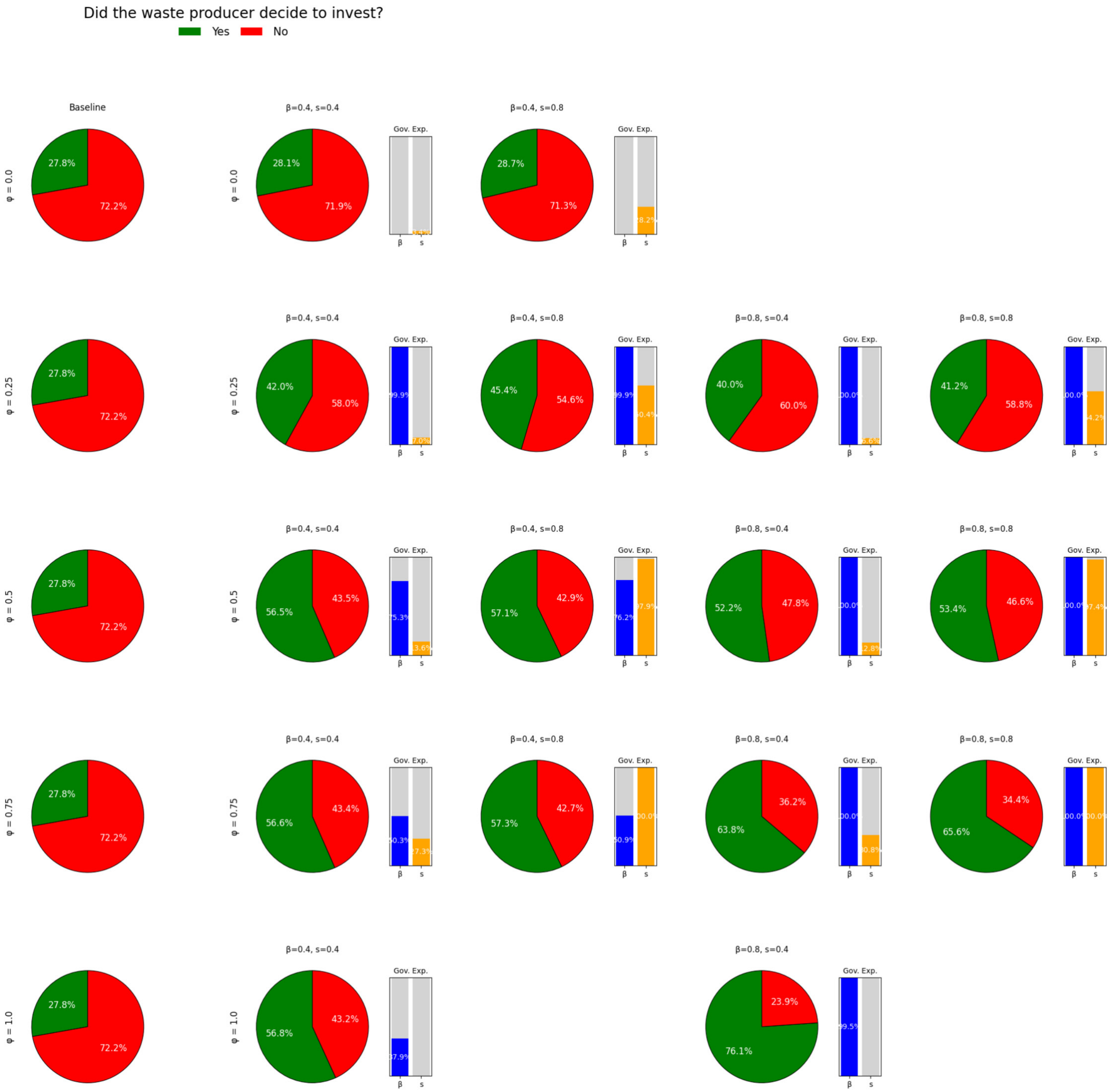


FIGURE 6 | Investment decisions and government expenditure under different subsidy programs.

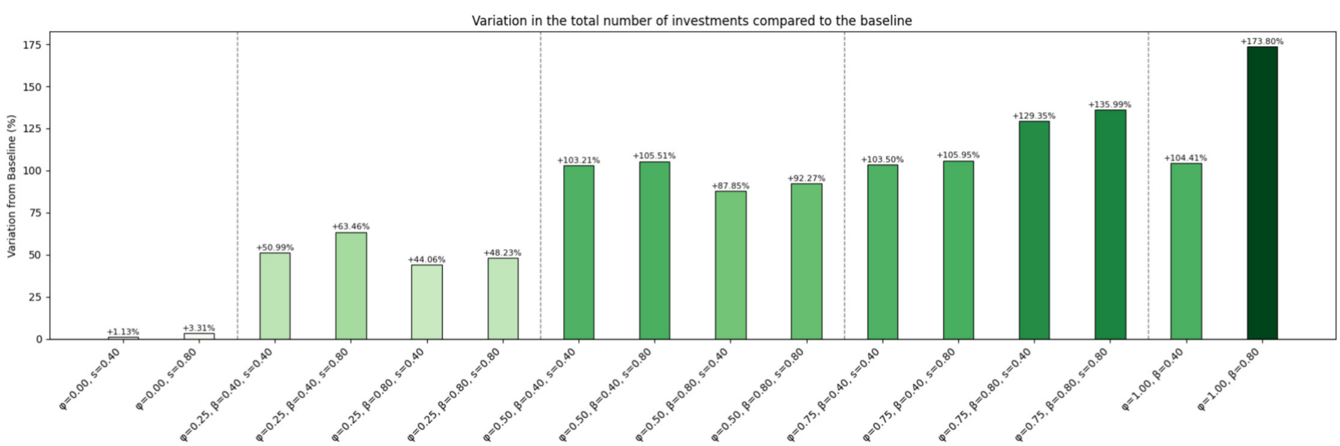


FIGURE 7 | Variation in waste producers' investment decisions under different subsidy programs.

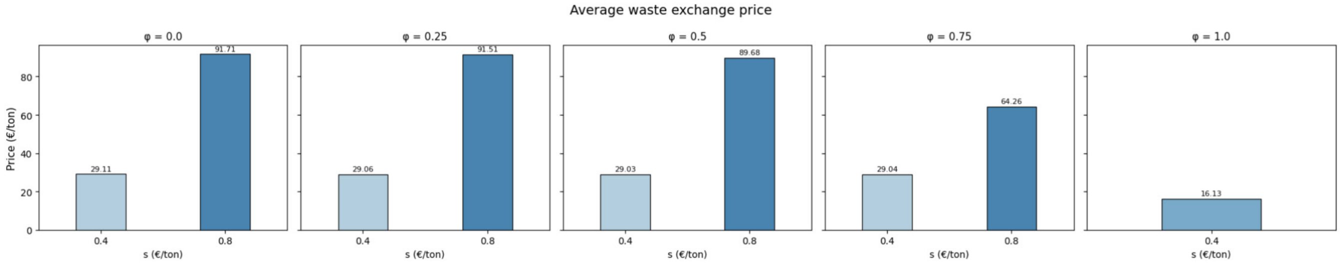
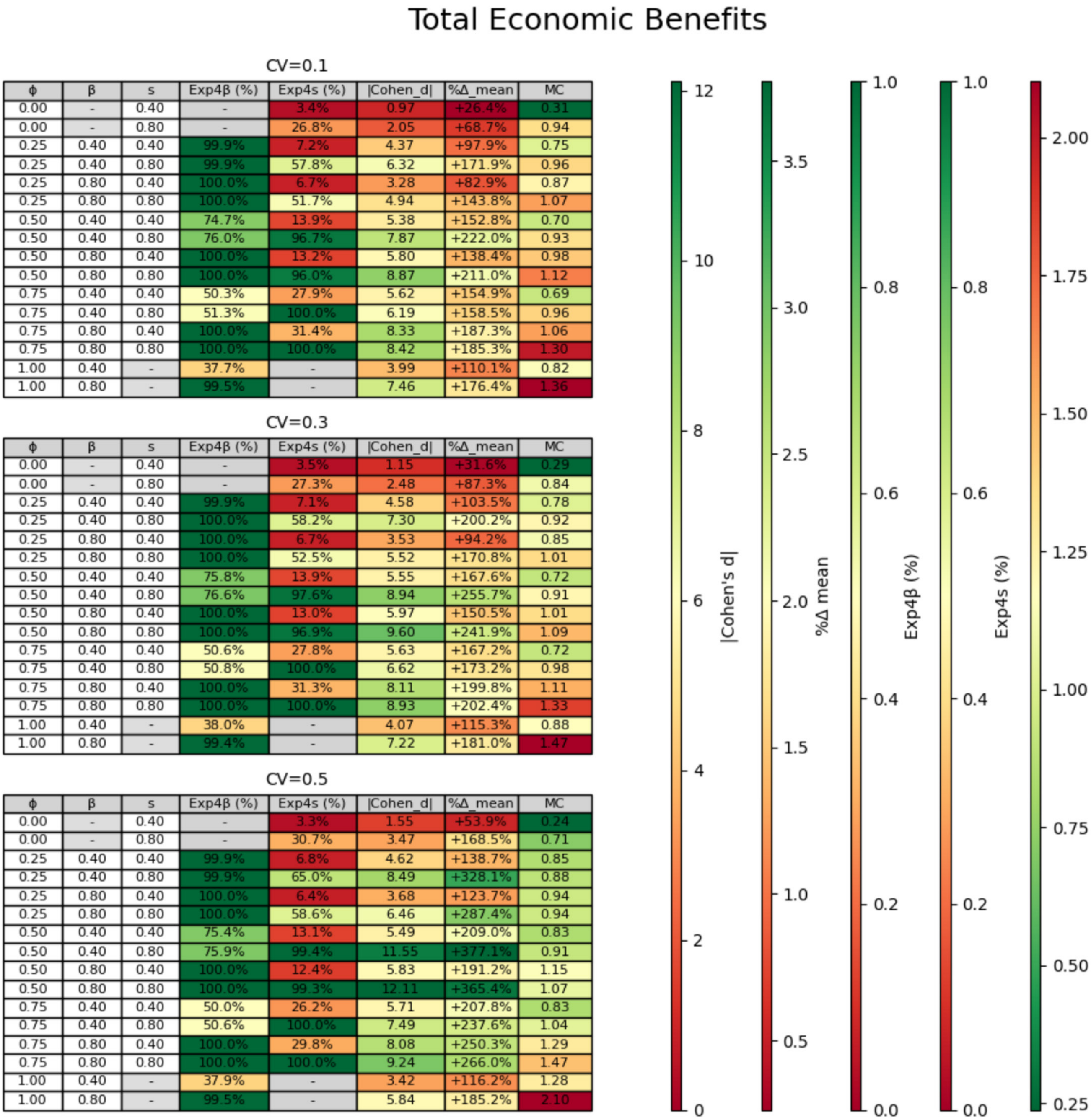


FIGURE 8 | Average waste exchange price by φ.



CV=0.1

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.4%	0.97	+26.4%	0.31
0.00	-	0.80	-	26.8%	2.05	+68.7%	0.94
0.25	0.40	0.40	99.9%	7.2%	4.37	+97.9%	0.75
0.25	0.40	0.80	99.9%	57.8%	6.32	+171.9%	0.96
0.25	0.80	0.40	100.0%	6.7%	3.28	+82.9%	0.87
0.25	0.80	0.80	100.0%	51.7%	4.94	+143.8%	1.07
0.50	0.40	0.40	74.7%	13.9%	5.38	+152.8%	0.70
0.50	0.40	0.80	76.0%	96.7%	7.87	+222.0%	0.93
0.50	0.80	0.40	100.0%	13.2%	5.80	+138.4%	0.98
0.50	0.80	0.80	100.0%	96.0%	8.87	+211.0%	1.12
0.75	0.40	0.40	50.3%	27.9%	5.62	+154.9%	0.69
0.75	0.40	0.80	51.3%	100.0%	6.19	+158.5%	0.96
0.75	0.80	0.40	100.0%	31.4%	8.33	+187.3%	1.06
0.75	0.80	0.80	100.0%	100.0%	8.42	+185.3%	1.30
1.00	0.40	-	37.7%	-	3.99	+110.1%	0.82
1.00	0.80	-	99.5%	-	7.46	+176.4%	1.36

CV=0.3

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.5%	1.15	+31.6%	0.29
0.00	-	0.80	-	27.3%	2.48	+87.3%	0.84
0.25	0.40	0.40	99.9%	7.1%	4.58	+103.5%	0.78
0.25	0.40	0.80	100.0%	58.2%	7.30	+200.2%	0.92
0.25	0.80	0.40	100.0%	6.7%	3.53	+94.2%	0.85
0.25	0.80	0.80	100.0%	52.5%	5.52	+170.8%	1.01
0.50	0.40	0.40	75.8%	13.9%	5.55	+167.6%	0.72
0.50	0.40	0.80	76.6%	97.6%	8.94	+255.7%	0.91
0.50	0.80	0.40	100.0%	13.0%	5.97	+150.5%	1.01
0.50	0.80	0.80	100.0%	96.9%	9.60	+241.9%	1.09
0.75	0.40	0.40	50.6%	27.8%	5.63	+167.2%	0.72
0.75	0.40	0.80	50.8%	100.0%	6.62	+173.2%	0.98
0.75	0.80	0.40	100.0%	31.3%	8.11	+199.8%	1.11
0.75	0.80	0.80	100.0%	100.0%	8.93	+202.4%	1.33
1.00	0.40	-	38.0%	-	4.07	+115.3%	0.88
1.00	0.80	-	99.4%	-	7.22	+181.0%	1.47

CV=0.5

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.3%	1.55	+53.9%	0.24
0.00	-	0.80	-	30.7%	3.47	+168.5%	0.71
0.25	0.40	0.40	99.9%	6.8%	4.62	+138.7%	0.85
0.25	0.40	0.80	99.9%	65.0%	8.49	+328.1%	0.88
0.25	0.80	0.40	100.0%	6.4%	3.68	+123.7%	0.94
0.25	0.80	0.80	100.0%	58.6%	6.46	+287.4%	0.94
0.50	0.40	0.40	75.4%	13.1%	5.49	+209.0%	0.83
0.50	0.40	0.80	75.9%	99.4%	11.55	+377.1%	0.91
0.50	0.80	0.40	100.0%	12.4%	5.83	+191.2%	1.15
0.50	0.80	0.80	100.0%	99.3%	12.11	+365.4%	1.07
0.75	0.40	0.40	50.0%	26.2%	5.71	+207.8%	0.83
0.75	0.40	0.80	50.6%	100.0%	7.49	+237.6%	1.04
0.75	0.80	0.40	100.0%	29.8%	8.08	+250.3%	1.29
0.75	0.80	0.80	100.0%	100.0%	9.24	+266.0%	1.47
1.00	0.40	-	37.9%	-	3.42	+116.2%	1.28
1.00	0.80	-	99.5%	-	5.84	+185.2%	2.10

FIGURE 9 | Detailed results: total economic benefits.

results of the analysis are reported in Figures 9–11. For each metric of interest—that is, total economic benefits achieved by the system (Equation 18), total amount of CO_2 emissions saved (Equation 19), and total amount of waste exchanged (Equation 20)—three heatmaps per level of market dynamicity ($CV = 0.1, 0.3, 0.5$) show (1) the percentage of budget allocated

CO_2 Emissions Saved

CV=0.1

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.4%	0.92	+24.7%	0.09
0.00	-	0.80	-	26.8%	1.66	+51.1%	0.35
0.25	0.40	0.40	99.9%	7.2%	4.34	+95.6%	0.21
0.25	0.40	0.80	99.9%	57.8%	5.78	+144.2%	0.32
0.25	0.80	0.40	100.0%	6.7%	3.24	+80.9%	0.25
0.25	0.80	0.80	100.0%	51.7%	4.41	+118.9%	0.36
0.50	0.40	0.40	74.7%	13.9%	5.37	+150.1%	0.20
0.50	0.40	0.80	76.0%	96.7%	6.94	+195.7%	0.29
0.50	0.80	0.40	100.0%	13.2%	5.80	+135.9%	0.28
0.50	0.80	0.80	100.0%	96.0%	7.81	+182.3%	0.36
0.75	0.40	0.40	50.3%	27.9%	5.58	+152.1%	0.20
0.75	0.40	0.80	51.3%	100.0%	5.96	+150.4%	0.28
0.75	0.80	0.40	100.0%	31.4%	8.29	+184.0%	0.30
0.75	0.80	0.80	100.0%	100.0%	8.24	+177.0%	0.38
1.00	0.40	-	37.7%	-	4.01	+110.0%	0.23
1.00	0.80	-	99.5%	-	7.51	+176.6%	0.37

CV=0.3

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.5%	1.11	+30.1%	0.09
0.00	-	0.80	-	27.3%	2.07	+65.4%	0.31
0.25	0.40	0.40	99.9%	7.1%	4.59	+101.2%	0.22
0.25	0.40	0.80	100.0%	58.2%	6.61	+164.7%	0.31
0.25	0.80	0.40	100.0%	6.7%	3.49	+91.8%	0.24
0.25	0.80	0.80	100.0%	52.5%	5.01	+139.7%	0.34
0.50	0.40	0.40	75.8%	13.9%	5.55	+164.7%	0.20
0.50	0.40	0.80	76.6%	97.6%	7.72	+223.7%	0.29
0.50	0.80	0.40	100.0%	13.0%	5.97	+147.7%	0.28
0.50	0.80	0.80	100.0%	96.9%	8.31	+207.7%	0.35
0.75	0.40	0.40	50.6%	27.8%	5.67	+164.2%	0.20
0.75	0.40	0.80	50.8%	100.0%	6.34	+164.1%	0.29
0.75	0.80	0.40	100.0%	31.3%	8.17	+196.6%	0.31
0.75	0.80	0.80	100.0%	100.0%	8.78	+193.2%	0.38
1.00	0.40	-	38.0%	-	4.11	+115.8%	0.24
1.00	0.80	-	99.4%	-	7.37	+181.5%	0.41

CV=0.5

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.3%	1.49	+50.5%	0.07
0.00	-	0.80	-	30.7%	3.00	+124.4%	0.27
0.25	0.40	0.40	99.9%	6.8%	4.61	+133.5%	0.24
0.25	0.40	0.80	99.9%	65.0%	7.72	+257.8%	0.31
0.25	0.80	0.40	100.0%	6.4%	3.65	+118.6%	0.27
0.25	0.80	0.80	100.0%	58.6%	5.85	+223.2%	0.33
0.50	0.40	0.40	75.4%	13.1%	5.51	+202.2%	0.24
0.50	0.40	0.80	75.9%	99.4%	9.87	+317.3%	0.30
0.50	0.80	0.40	100.0%	12.4%	5.86	+184.7%	0.33
0.50	0.80	0.80	100.0%	99.3%	10.41	+301.9%	0.36
0.75	0.40	0.40	50.0%	26.2%	5.70	+201.0%	0.24
0.75	0.40	0.80	50.6%	100.0%	6.96	+214.8%	0.32
0.75	0.80	0.40	100.0%	29.8%	8.19	+242.8%	0.37
0.75	0.80	0.80	100.0%	100.0%	8.81	+243.7%	0.44
1.00	0.40	-	37.9%	-	3.50	+116.2%	0.35
1.00	0.80	-	99.5%	-	6.02	+185.0%	0.58

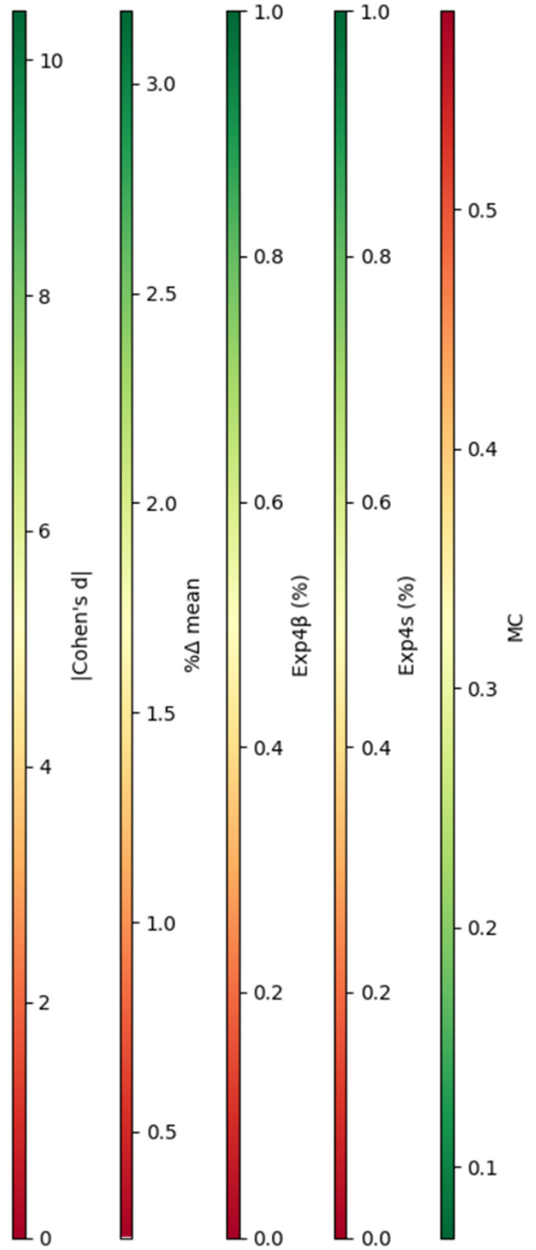


FIGURE 10 | Detailed results: CO_2 emissions saved.

to β and to s spent by the government during the simulation period (indicated with "Exp4β" and "Exp4s," respectively); (2) the metrics selected to measure the efficiency of the subsidy program, that is, the Cohen's d ($d^{\text{Cohen}}_{\mathscr{M}}$) and the percentage difference between the means ($\Delta^{\%}_{\mathscr{M}}$) (Equations 22 and 23); and (3) the MC of each subsidy program analyzed (Equation 24).

From the economic perspective, results highlight that different subsidy programs lead to significantly different levels of effectiveness. The effectiveness of the investigated subsidy programs on the economic performance of the system ranges from a minimum of 0.97 to a maximum of 12.11, if measured in terms of $d^{\text{Cohen}}_{\mathscr{M}}$, and from a minimum $+26.4\%$ to a maximum $+377.1\%$ in terms of $\Delta^{\%}_{\mathscr{M}}$ (Figure 9). Looking at the color scales, it is possible to notice that the two metrics selected to measure effectiveness are consistent with each other.[21] Therefore, in the following discussion, we will consider only $d^{\text{Cohen}}_{\mathscr{M}}$. Indeed, while $\Delta^{\%}_{\mathscr{M}}$ has a more intuitive physical interpretation and facilitates a practical reading of the results, $d^{\text{Cohen}}_{\mathscr{M}}$ accounts for the variability inside the data, thus providing a more robust measure of the policy effect. Results clearly show that the ranking of the investigated subsidy programs in terms of effectiveness remains basically unchanged with market dynamicity. Interestingly, the effectiveness of the same subsidy program is higher if market dynamicity increases, under otherwise identical conditions. This is true for each subsidy program, suggesting that government intervention is more effective when markets are subject to worst conditions. The most effective subsidy program is the one where

Total Amount of Waste Exchanged

CV=0.1

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.4%	0.92	+24.8%	52.63
0.00	-	0.80	-	26.8%	1.67	+51.4%	197.71
0.25	0.40	0.40	99.9%	7.2%	4.34	+95.7%	120.67
0.25	0.40	0.80	99.9%	57.8%	5.79	+144.7%	179.25
0.25	0.80	0.40	100.0%	6.7%	3.24	+81.0%	140.81
0.25	0.80	0.80	100.0%	51.7%	4.42	+119.4%	202.69
0.50	0.40	0.40	74.7%	13.9%	5.37	+150.1%	112.06
0.50	0.40	0.80	76.0%	96.7%	6.96	+196.3%	166.96
0.50	0.80	0.40	100.0%	13.2%	5.81	+136.0%	157.93
0.50	0.80	0.80	100.0%	96.0%	7.83	+182.9%	203.45
0.75	0.40	0.40	50.3%	27.9%	5.58	+152.2%	111.46
0.75	0.40	0.80	51.3%	100.0%	5.98	+150.7%	159.76
0.75	0.80	0.40	100.0%	31.4%	8.30	+184.1%	170.85
0.75	0.80	0.80	100.0%	100.0%	8.26	+177.4%	213.97
1.00	0.40	-	37.7%	-	4.01	+110.0%	130.16
1.00	0.80	-	99.5%	-	7.51	+176.6%	213.82

CV=0.3

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.5%	1.11	+30.2%	48.62
0.00	-	0.80	-	27.3%	2.08	+65.8%	175.53
0.25	0.40	0.40	99.9%	7.1%	4.59	+101.3%	126.55
0.25	0.40	0.80	100.0%	58.2%	6.62	+165.3%	175.93
0.25	0.80	0.40	100.0%	6.7%	3.49	+91.9%	138.39
0.25	0.80	0.80	100.0%	52.5%	5.02	+140.3%	194.41
0.50	0.40	0.40	75.8%	13.9%	5.55	+164.8%	115.19
0.50	0.40	0.80	76.6%	97.6%	7.74	+224.4%	164.36
0.50	0.80	0.40	100.0%	13.0%	5.98	+147.8%	161.83
0.50	0.80	0.80	100.0%	96.9%	8.33	+208.4%	200.10
0.75	0.40	0.40	50.6%	27.8%	5.68	+164.3%	115.71
0.75	0.40	0.80	50.8%	100.0%	6.36	+164.5%	162.54
0.75	0.80	0.40	100.0%	31.3%	8.18	+196.7%	178.26
0.75	0.80	0.80	100.0%	100.0%	8.80	+193.6%	218.77
1.00	0.40	-	38.0%	-	4.12	+115.8%	139.11
1.00	0.80	-	99.4%	-	7.38	+181.5%	231.98

CV=0.5

ϕ	β	s	Exp4β (%)	Exp4s (%)	|Cohen_d|	%Δ_mean	MC
0.00	-	0.40	-	3.3%	1.49	+50.5%	40.18
0.00	-	0.80	-	30.7%	3.01	+124.9%	151.92
0.25	0.40	0.40	99.9%	6.8%	4.62	+133.6%	139.19
0.25	0.40	0.80	99.9%	65.0%	7.74	+258.7%	176.32
0.25	0.80	0.40	100.0%	6.4%	3.65	+118.7%	155.09
0.25	0.80	0.80	100.0%	58.6%	5.86	+224.0%	190.30
0.50	0.40	0.40	75.4%	13.1%	5.51	+202.3%	135.34
0.50	0.40	0.80	75.9%	99.4%	9.89	+318.3%	170.32
0.50	0.80	0.40	100.0%	12.4%	5.86	+184.8%	188.03
0.50	0.80	0.80	100.0%	99.3%	10.44	+302.8%	203.50
0.75	0.40	0.40	50.0%	26.2%	5.70	+201.1%	135.38
0.75	0.40	0.80	50.6%	100.0%	6.97	+215.3%	180.70
0.75	0.80	0.40	100.0%	29.8%	8.20	+242.9%	209.89
0.75	0.80	0.80	100.0%	100.0%	8.83	+244.2%	253.23
1.00	0.40	-	37.9%	-	3.50	+116.2%	201.59
1.00	0.80	-	99.5%	-	6.02	+185.0%	332.54

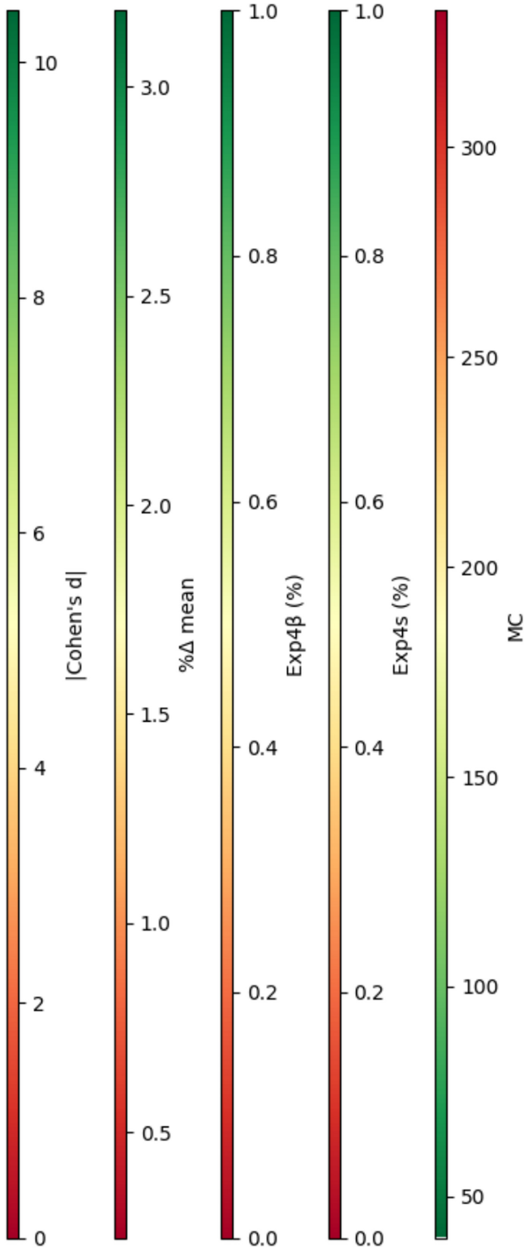


FIGURE 11 | Detailed results: amount of waste exchanged.

$\varphi = 0.5$, $\beta = 0.8$, and $s = 0.8$,[22] *whatever CV*. In this scenario, the total economic benefit achieved by the system increases by 211% when $CV = 0.1$, by 241.9% when $CV = 0.3$, and by 365.4% when $CV = 0.5$, as a result of government intervention. Analyzing government expenditure per subsidy, it is possible to notice that the budget is efficiently used in this scenario. Indeed, the whole budget available for subsidies of type β is exhausted and the budget allocated to s is almost entirely consumed, too (up to 96.0%, 96.9%, and 99.3%, respectively, when increasing CV). It is clear from results that higher levels of effectiveness are related to more efficient allocations of the budget between the two subsidy types. Indeed, the poorest performances in terms of economic effectiveness of the subsidy programs are achieved when much of the budget remains unspent. This happens (1) when φ is too low, (2) when β is too high with respect to φ, and (3) when β is too low with respect to the needs of waste producers. In all these cases, the budget allocated to s remains largely unspent because too few waste producers can establish symbiotic relationships, and, as a result, lower amounts of waste are exchanged.

Moving to the economic efficiency, again efficiency rankings do not depend on market dynamicity. In some cases, the efficiency of a subsidy program is higher when market dynamicity increases. For instance, the MC of the subsidy program with $\varphi = 0.25$, $\beta = 0.4$, and $s = 0.8$ decreases from 0.96 to 0.92 to 0.88 with CV. However, it is not always the case. For instance, when $\varphi = 0.75$, $\beta = 0.4$, and $s = 0.8$, the MC of the subsidy program is 0.98 when $CV = 0.3$ and it rises to 1.04 when $CV = 0.5$. Note that higher levels of efficiency do not always correspond to higher levels of effectiveness. By construction, the MC of the subsidy program decreases when there is a higher positive difference in the performances of the system *with* and *without* the subsidy program, holding all other factors constant (see Equation 24). However, the lower the budget used by the government, the lower the MC of the subsidy program will be, too. When a large part of the budget remains unspent, the subsidy program is typically ineffective. Therefore, the assessment of efficiency becomes secondary to the evaluation of effectiveness. Indeed, efficiency should only be considered when comparing subsidy programs with similar levels of effectiveness.

From the environmental perspective, results are aligned with the economic performance both in terms of effectiveness and efficiency (Figures 10 and 11). These results were expected as they are due by construction. Indeed, in our model, we have assumed that exchanging waste determines both economic and environmental benefits *whatever* the amount exchanged (see Equation 11). Nevertheless, this result cannot be generalized: it may be possible that economic and environmental effectiveness (efficiency) do not match. In such cases, governments should find trade-offs or win–win solutions (if available) to ensure both economic and environmental effectiveness/efficiency.

In summary, we can answer RQ1 by suggesting that the most effective subsidy program lies in the right combination of policy tools for the specific industrial context. On the one hand, a key issue is the level of readiness of the industry to implement IS in terms of infrastructure and technology: If little (or null) investments are required (compared with the financial resources of companies or the level of perceived risk), the investments should be accompanied by subsamples to reach a higher number of companies. Conversely, if the financial burden that investments represent for the industry is high, a strong financial support is required. Concerning *market-based* incentives, supporting IS operations, they are fundamental to help developing and keeping ISRs alive. Nevertheless, they are useless if there is no room for them to be granted. Therefore, finding the right mix between tools is crucial for the policy to be effective.

With regard to RQ2, efficiency proves to be a challenging criterion to choose between different subsidy programs. Indeed, efficiency should be the highest when the government expenditure is mirrored by as much economic (or environmental) benefits. However, our results show that high levels of efficiency can be trivially related to little expenditures, not leading to significant benefits. Lower expenses are typically the reflection of lower effectiveness. Conversely, high expenditures typically lead to improved system performance, but the associated increase in benefits is not linear. Beyond a certain threshold, the increase in economic (or environmental) benefits is not enough to justify additional spending. Although it is important for governments to keep the expenses under control, the effectiveness of the policy should be the priority. In conclusion, efficiency should be used only to assess which policy to adopt in those cases where the effectiveness is comparable.

5 | Discussion

The proposed AB model allows us to derive relevant insights for policymakers. The main takeaway is that a proper policy design is key to achieving the intended outcomes. Specifically, before implementing any kind of measure, governments should prioritize a thorough understanding of the surrounding industrial and social context. As stated by L. Wang et al. (2022, 970): "the government needs to consider factors such as the quantity mismatch of waste supply and demand, and the level of industrial development, in order to put forward a policy that can maximize the possibility of IS relationships arising, rather than emphasizing financial revenue/expenditure." Sometimes governments mistakenly believe that providing grants and financial support may be enough. However, very often this solution is just the easiest, not the most effective. Underrating the relevance of the context may lead the government to sustain significant expenses without achieving the expected benefits. Indeed, implementing one-size-fits-all policies, while ignoring the real needs of companies, is ineffective (H. Wang et al. 2021). Many variables should be taken into account to design an effective policy to support the development of IS: level of awareness and readiness of firms, extent of the investment required, financial support required to carry out operations, major barriers to the actual implementation of the waste exchange, and type and extent of the competitive advantage that may be gained. Accordingly, deeply analyzing the context should be a primary concern to be taken over by experts. Similar considerations had been already made in the broader context of green technologies. For instance, Georgia Perakis, a professor at MIT, stated that "policy makers cannot develop effective subsidy programs for green technologies without a clear understanding of what drives consumers to adopt the technologies and companies to invest in them" (Stauffer 2013). We argue that this insight extends to the case of IS: Policymakers should understand what makes both waste users and waste producers willing to cooperate to properly incentivize them.

Given that government financial resources are limited, the benefits generated by the budget allocated to policies aimed at stimulating IS should be enough to justify the expenditure. Not always financial help is required: targeting an industrial context where the incentives intrinsically provided by the market are already enough to push companies toward IS may be a common mistake. Sometimes, implementing IS may be so beneficial for companies that (if they are aware of such benefits) they will establish ISRs without any further financial support. Indeed, the literature reports many cases of ISRs arising spontaneously from bottom-up (Chertow and Ehrenfeld 2012; Jacobsen 2006). In these cases, as observed by L. Wang et al. (2023), providing subsidies is unlikely to effectively further stimulate the development of IS. Nevertheless, companies will generally accept financial aid and seek to leverage it to maximize their benefits. This generates inefficient outcomes: Granting subsidies in these contexts means misallocating resources that may be destined more effectively to alternative needs. Indeed, not only the needs of companies should be taken into account but also the expected outcomes on society and the environment. Our results highlighted a correspondence between economic and environmental benefits. However, as already noticed, this is specific to our case study. A detailed analysis of the environmental benefits of IS should be conducted. Outcomes such as rebound effects, additional environmental costs of IS activities (especially when investments in new plants or infrastructures are required), emissions due to new logistic paths, and—more broadly—the social impact of reshaping a given industrial context should be kept under control. Similar conclusions have been drawn also by Li et al. (2020) and Meng et al. (2023): Through their theoretical models, they found out that there exist cases in which the optimal solution in terms of social welfare may also be not to subsidize at all. Specifically, according to Li et al. (2020), it is not useful to give any subsidy to support green innovation when the environmental impact of such innovation is low, neither if the cost of innovation is low, nor if both the cost of the innovation and the cost of operations are very high. Accordingly, explicitly referring to subsidies for IS, Meng et al. (2023) noticed that when companies voluntarily engage in IS, introducing subsidies can negatively impact the behavior of the system and generate distortions. In these cases, nonfinancial type of support should be preferred. For instance, a well-known and useful example of nonfinancial support offered by the government is the promotion of matchmaking platforms and the diffusion of best practices during ad hoc events for companies (Laybourn and Lombardi 2012; Fraccascia and Yazan 2018), especially in the initial stages of IS development. In these regards, we support the suggestion of L. Wang et al. (2022) that the policymaker should design the policy through fine-tuning. Indeed, evidence from real case studies indicates that IS policies must evolve over time to remain effective. For instance, in the Danish Maabjerg case, early progress was enabled by strong incentives and political support. However, the project ultimately collapsed when the policy environment was no longer able to provide the stability and the market conditions required for large-scale bioenergy investments (Lybæk et al. 2021). To enhance policy effectiveness, a staged implementation approach may be required, whereby an initial limited allocation of public funds is directed toward a restricted set of firms. Subsequent funding rounds can then be progressively expanded to achieve broader industrial coverage, based on observed responses. This approach allows policymakers to assess firms' actual financial needs and to mitigate the risk of oversubsidization. Comparable policy designs have also characterized the Japanese Eco-Town Program, which relied on pilot projects and incremental funding adjustments to foster viable symbiotic configurations (Van Beers et al. 2007). Note that even after a careful analysis, it is not possible to fully foresee the system's response to a given policy. Time is key in this regard: As ISNs are CASs, the dynamics of the system may lead to unexpected behaviors. Moreover, we support the idea that policy effectiveness depends on the implementation stage of IS (L. Wang et al. 2023): For instance, subsidies or tax reliefs are effective tools to stimulate the first stage development of IS; however, supervisory policies are fundamental for IS to survive (Santos and Rembalski 2021; L. Wang et al. 2023). For instance, the long-term development of the Kymi Forest symbiosis in Finland demonstrates that different phases of the system require different policy tools: Initial growth emerged under weak regulation, while later consolidation depended on increasingly stringent environmental standards and integrated permitting (Lehtoranta et al. 2011). Accordingly, we can further emphasize the need for a dynamic adjustment of the policy design, which is in line with the idea of Jiao and Boons (2014). With respect to the type of policy instrument that may be more useful to support the development of IS, our results suggest to find the right mix. This is in line with several observations in the literature (H. Wang et al. 2021; J.-Y. Chen et al. 2019; Li et al. 2020). Many policy instruments can be used to achieve the same results. The findings indicate that *market-based* incentives are ineffective if there is not enough room for the waste exchange to take place, that is, if there is a lack of infrastructures or technologies. Accordingly, when IS requires the enhancement of existing infrastructures or their building ex novo, providing financial support to the upfront investment is the priority. In contrast, granting funds for these kinds of investment may be useless if IS operations are hampered by economic or logistic barriers.

Last but not least, our results highlight that it is important to consider the efficiency of policies only after considering their effectiveness. Efficiency and effectiveness are not clearly related. Incurring low expenditures is typically associated with achieving nonsignificant results in terms of effectiveness. In contrast, under otherwise identical conditions, higher expenditures are not always related to higher benefits. As noticed by L. Wang et al. (2023), often policies exhibit decreasing marginal utility. Therefore, it is important to understand up to what point to spend public money: It is unrealistic to expect the whole system to embrace the transition immediately. This process requires time, and policy intervention may just be the initial push.

6 | Conclusions

In this paper, we propose an AB model to investigate the effectiveness and efficiency of different subsidy programs to support the development of IS. Each subsidy program consists of a combination of two types of subsidies, that is, (1) a subsidy for the upfront investment that waste producers are required to make before engaging in IS and (2) a subsidy for each unit of waste purchased by waste users (which is a *market-based* kind of incentive). The government is assumed to have a limited budget to allocate to each type of subsidy. The budget extent, the allocation of the budget between the subsidies, and the per-unit subsidy level are defined ex ante. The effectiveness of each subsidy program is measured in terms of the economic and environmental performance achieved by the system with respect to a baseline scenario, where there is no government intervention. Efficiency is measured as the ratio between the total government expenditure and the difference between the economic (environmental) performance of the system. Results highlight how the effectiveness of a subsidy program for IS primarily depends on its design. Subsidies are more effective in more dynamic markets. However, according to our results, the subsidy program ranking of effectiveness remains unchanged across market conditions, suggesting that the most effective design depends primarily on the characteristics of the targeted industrial context. Specifically, from the results, we can derive that if high upfront investments are required to engage in IS, the role of the government in providing financial support to the investment is key. However, the level of the financial support should be commensurate with the available budget and with firms' actual financing needs: if there are few funds available, it is better to subsidize more companies with less, than doing the opposite. With respect to *market-based* incentives, results highlight that they can be very useful, but only if there is enough room for waste exchange. Finally, according to our results, efficiency is not directly related to effectiveness: ineffective subsidy programs may show high levels of efficiency, due to the lower government expenditure.

This study has several *policy implications*. Firstly, governments should prioritize the design of the subsidy program over generosity: increasing financial support is not necessarily the most effective solution. In contrast, sometimes financial support can be unnecessary or even harm the system. Secondly, policymakers should carefully analyze the industrial context, the needs of companies, and the barriers to the development and implementation of IS. Thirdly, a dynamic fine-tuning of the policy can be useful to take into account the unpredictability of companies' behavior, changes in the industrial context, and the different needs of companies across IS development stages. Lastly, although it is important to maintain the control of government expenditures, effectiveness should be always preferred over efficiency.

As to the *theoretical implications*, this paper proposes a novel methodological approach to assess the effectiveness and efficiency of government intervention on IS development, that is, ABM. Differently from the existing literature, such methodological approach allows to take into account the counterfactual, thus enhancing the reliability of results. In addition, this paper contributes to the state of the art by adopting a dynamic and systemic perspective, which has been recognized as a major limitation in the policy-related IS literature to date. Moreover, it is the first study in the context of IS to simultaneously consider investment subsidies, waste-purchasing subsidies, and budget constraints. It is worth noting that, although the model is applied to a specific industrial case (i.e., steel-cement IS), many other symbiotic exchanges share similar structural features. Consequently, the results are not case dependent but can be extended to a wide range of industrial, national, and policy contexts.

Certainly, this study has several limitations. From the modeling perspective, we considered a simplified ISN, where only one-to-one ISRs are allowed. This assumption is in line with several AB models for IS in the literature (Fraccascia and Yazan 2018; Fraccascia 2019; Albino et al. 2016). However, future developments of the work may consider more complex network structures. With respect to the policy tools investigated, we limited the analysis to two simple instruments, that is, an investment subsidy and a subsidy on the waste exchange price. Nevertheless, many other policy instruments may be considered, even more complex, for example, binding regulations, cap-and-trade systems, taxes on disposal, and emission taxes (Meng et al. 2023; Dong et al. 2024; Fraccascia et al. 2017a). Subsidies are granted following a FIFO logic: The first waste producer/user asking for the subsidy is granted the money. Furthermore, subsidies' extent does not depend on the agent to which it is granted. More complex rules to decide (1) to whom, (2) when, and (3) to which extent to grant subsidies (e.g., according to agent-specific characteristics and availability of the funds) may be considered in future developments of the work. Moreover, in our model, the budget allocated to the subsidy program is fixed, as well as the subsidy program design: the policymaker cannot take action during the simulation time. Future studies may consider the policymaker as one of the agents of the model and enable it to take decisions, too. This would allow a deeper investigation of the effectiveness and efficiency of staged policies, advancing the understanding of how IS policies evolve dynamically and shape system outcomes. We suggest the above-mentioned limitations as the starting point for future research avenues.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] We have chosen these two policy tools as they are the most commonly used and studied in the literature and employed in case studies (Jiao and Boons 2014; Lybæk et al. 2021).

[2] These assumptions are widely used in the literature when modeling firms within the EIO framework, as a means of keeping the model analytically and computationally tractable (Lin and Polenske 1998; Albino et al. 2016).

[3] Transportation costs are sustained by the supplier of primary input or, equivalently, the cost of transportation is included in the unit purchasing cost.

[4] This choice is in line with several other AB models in the literature of IS (Albino et al. 2016; Fraccascia and Yazan 2018).

[5] These unit costs are all measured in CO_2eq.

[6] This assumption is in line with the literature (Albino et al. 2016; Fraccascia et al. 2017; Fraccascia et al. 2019).

[7] This tool enables waste users to purchase the waste at higher prices, thus making the ISR potentially more profitable.

[8] Before the government knows the choices of firms.

[9] Refer to Appendix A.3 to see the model's results in more optimistic, neutral, or pessimistic scenarios.

[10] $\overline{dist}_{A \to B}$ is the average distance between firms of Industry A and firms of Industry B.

[11] Given that the probability p_i already smooths expected benefits, we do not consider the possible mismatch between demand and supply.

[12] This parameter is also uncertain, as it is the result of a negotiation with a partner which is unknown at this stage.

[13] Higher level of r reflects higher aversion to risk.

[14] We are assuming that during the useful life of the machinery, the technology does not change and the machinery do not break nor require significative maintenance costs to be sustained.

[15] The initial price proposal is always such that $WTC^{IS}_{j \to i}(t) \geq Thre_i$.

[16] This assumption is consistent with other models in the literature (Fraccascia and Yazan 2018; Albino et al. 2016).

[17] Model validation is described in Appendix A.1. Appendix A.2 provides details on the sources of the input data. Appendix A.3 reports the sensitivity analysis.

[18] The definition of *effective* for the aim of this study is provided in Section 1.

[19] Cohen's *d* is a standardized measure of effect size that expresses the difference between two means in terms of standard deviation units (Diener 2010).

[20] The proposed metric is in line with the literature. A complementary measure of efficiency has been proposed by Li et al. (2020), who defined the efficiency of the subsidy as the ratio between the reduction in pollution emissions and the total subsidy expenditure (i.e., $SE = \frac{pollution\ emission\ reduction}{subsidy\ expenditure}$).

[21] Only minor ranking discrepancies can be found.

[22] If we consider $\Delta^{\%}_{\mathcal{M}}$ as the metric for effectiveness, this subsidy program is the second most effective only after the one with $\varphi = 0.5,\ \beta = 0.4,$ and $s = 0.8$.

[23] Results are available in the Supporting Information.

[24] Results are available in the Supporting Information.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. Governement_Subsidies_for_IS_Supplementary_Materials.pdf.

Appendix A

A.1 | Model Validation

AB models are widely used to explore the dynamics of CASs and to derive generalizable insights into the underlying mechanisms (Axelrod 1997). Accordingly, the model validation is typically performed through a well-established methodological approach consisting of a four-step process: (1) microface validation, (2) macroface validation, (3) input validation, and (4) output validation (Bianchi et al. 2008; Manson 2003; Giannoccaro and Carbone 2017; Albino et al. 2016; Fraccascia and Yazan 2018). This paper has been fully validated according to the aforementioned methodology, as described below.

Concerning the microface validation, the validation's criteria are satisfied because the behavioral rules followed by the agents are consistent with the literature. Specifically, the willingness to cooperate depends on the economic benefits achievable through IS and on path dependence (Albino et al. 2016; Fraccascia and Yazan 2018). Likewise, the investment decisions of waste producers depend on the trade-off between the expected economic benefits from investing and the actual payout required (Brealey et al. 2014).

Concerning the macroface validation, the validation's criteria are satisfied because the dynamics of the model are consistent with the real-world dynamics. Specifically, agents decide to cooperate only if the benefits they will achieve are higher than the minimum benefit they expect (i.e., decisions are based on individual thresholds). Similarly, waste producers decide to invest only if the investment NPV is higher than zero, which aligns with the conventional financial appraisal method employed in practical investment contexts. Moreover, the budget depletion process is modeled such that available funds are gradually reduced until they are fully exhausted. To further test the consistency of the model's dynamics, we performed a sensitivity analysis (see Appendix A.3) to investigate the response of the model when waste producers are either pessimistic, neutral, or optimistic with respect to IS. We observed that the more positive is the attitude of waste producers toward IS, the higher is the number of investments undertaken, both with and without the introduction of subsidies. This aligns with real-world dynamics, providing an additional proof of consistency of the model.

Concerning the input validation, the validation's criteria are satisfied because part of the input dataset has been borrowed by Fraccascia and Yazan (2018), and the remaining has been derived from reliable sources (see Appendix A.2).

Concerning the output validation, the validation's criteria are satisfied because results are consistent with the expectations. Indeed, both the economic and environmental benefits achieved by the system decrease with market dynamicity (Fraccascia and Yazan 2018; Fraccascia et al. 2020). Furthermore, the stability of ISRs is reduced when there are higher supply–demand fluctuations (Fraccascia 2019; Madsen et al. 2015). Finally, the higher the amount of funds granted to subsidize the investments, the higher the number of investments, ceteris paribus.

A.2 | Details on the Input Dataset Sources

The input data for the model were collected from a combination of scientific literature, specialized databases, and official institutional sources. In particular, economic and operational parameters regarding demand levels, production coefficients, and cost factors were taken from Fraccascia and Yazan (2018), while environmental impact data were derived by comparing multiple sources. For instance, data retrieved from the International Energy Agency report that cement production is a major source of CO_2 emissions, with approximately 0.6 tons of CO_2 emitted per ton of pure cement produced (International Energy Agency 2023), which corresponds to about 0.85 tons per ton of clinker. For industrial waste disposal and transport, emission factors were derived from the Climatiq database (Climatiq 2025). Accordingly, we found out that BFS disposal (excluding transport) is associated with about 255 kg $CO_2\boldsymbol{eq}$ per ton, while average transportation generates 0.062 kg $CO_2\boldsymbol{eq}$ per ton-km. Additional context on low-organic-content waste landfilling was obtained from Manfredi et al. (2009), confirming that inorganic residues, for example, BFS, produce relatively low landfill emissions (between 85.3 and 228.2 kg per ton depending on landfill operational conditions). Note that institutional sources such as the European Cement Association (Cembureau 2025) were consulted, as well, to ensure further consistency of the data retrieved.

A.3 | Sensitivity Analysis

To enhance the reliability of results a sensitivity analysis has been performed. Specifically, we considered a higher and a lower value for two key parameters of the model: the government budget and the unit waste transportation cost ($utrac^{eco}$). We ran 100 replications of the simulation per each new setting and results remained consistent with those provided in the main of the paper, confirming their robustness to plausible changes in the underlying assumptions.[23]

Additionally, we have tested the sensitivity of the results to the attitude of waste producers toward IS, that is, p_i. In the main of the paper, we assumed heterogeneous levels of awareness and trust in IS among waste producers (i.e., $p_i \in [0, 1]$ randomly distributed). Therefore, we investigated the cases of pessimism ($p_i = 0.25$), neutrality ($p_i = 0.5$), and optimism ($p_i = 0.75$) of waste producers toward IS. We ran 100 replications of the simulation per each new setting, and the main results confirmed the consistency of the model.[24]