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Simulating Innovation Systems and STI Policy: An Agent-Based Perspective

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Abstract

This paper develops an Agent-Based Model (ABM) to study the impact of Science, Technology, and Innovation (STI) policies on innovation systems. The model, which we call the Adaptive Innovation System Model (AdaptISM), simulates the technological innovation capabilities required for knowledge and technology generation, diffusion, and utilisation, integrating decision rules that capture the emergent behaviours of agents interacting with innovation opportunities. The model is empirically validated using data from the coffee and avocado agricultural production chains (APCs) in Antioquia, Colombia, which are two sectors of regional economic and local importance. The validation process allows the evaluation of individual and combined STI policy modes, identifying which policy strategies most effectively enhance innovation performance and economic outcomes. By enabling the exploration of "what-if" scenarios, the ABM provides a tool to assess STI policy contributions systematically and offers practical insights into resource allocation in local innovation systems. This approach addresses a critical challenge in innovation policy design: understanding how STI policies influence system performance. The findings highlight the utility of combining policy approaches to improve innovation and economic growth, offering a replicable framework for policymakers and researchers seeking to optimise the performance of innovation systems.

Keywords: STI policy, innovation systems, agricultural production chains, Agent-based modelling

JEL: O32, C63, Q16

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1. Introduction

Over the last decades, Science, Technology and Innovation (STI) policymakers have experimented with different policy combinations to improve the performance of innovation systems. As noted by Crespi and Dutrénit (2014), these combinations have been shaped by different policy paradigms, innovation models and modes, each reflecting specific historical contexts. Three main policies are identified: *technology push* approaches targeting mode I policies for *STI* with a science-based orientation; *market pull* models focusing on innovation mode II; and the systemic approach, which targets mode III, characterised by innovation through learning by *Doing, Using and Interacting* (DUI) (Jensen et al, 2007; Crespi & Dutrénit, 2014).

Empirical research examining the impact of STI policies and innovation modes on the economic performance of innovation systems highlights the benefits of combining different innovation approaches. Studies conducted in various countries – Denmark (Jensen et al., 2007); Norway (Isaksen & Karlsen, 2010, 2013; Aslesen et al., 2011; Fitjar & Rodríguez-Pose, 2013); China (Chen et al., 2011); Portugal (Nunes et al., 2013); Belarus (Apanasovich et al., 2016); and Spain (Parrilli & Alcalde, 2016)—generally find that combining approaches yields better results than relying on individual policies. However, these findings also show that outcomes vary by country, influenced by local politics, culture, and historical patterns of economic and technological development (Malaver & Vargas, 2013).

In some cases, evidence contradicts the preference for combining policies. Parrilli and Elola (2012) found that in Spain, - showed that, the STI mode with a science-based approach led to better economic and innovation performance in small and medium-sized businesses (SMBs) than the DUI approach. Similarly, Malaver and Vargas (2013) in Colombia reported that the *STI* innovation mode with a science-based approach was more efficient than the DUI mode and that combining the two approaches did not provide additional benefits. These findings underscore the role of local contexts, including institutional structures that support the innovation system.

These findings emphasise that better results are obtained, in terms of the system's economic and innovation performance, when different types of STI policies, STI innovation mode with a science approach and DUI mode are combined. Nevertheless, as we have seen, there is evidence that, in some cases, this is not true. Even more problematic, in practice, sometimes available resources are insufficient to combine all STI policies if each policy instrument requires a budget allocation. This increases the complexity of formulating STI policies, as trade-offs exist between the different policy instruments in each innovation mode.

Uncertainty regarding the effect each policy will have on the system's economic and innovation performance is aggravated by the fact that combinations of STI policies are typically put into place, which makes evidence-based decision-making even more difficult. To complete this picture of uncertainty, we must consider that innovation systems never reach a state of equilibrium (Brunet & Mara, 2016). Thus, policies must be adapted to the system's evolution to guarantee long-term performance, sometimes strengthening one innovation approach rather than another. This suggests the impossibility of a general formula and the need to attend to each case individually. What is addressed from qualitative or deterministic methodologies would represent extensive, unattainable efforts.

This research proposes a simulation model to represent real-world innovation systems to overcome the challenge of attributing innovation system performance to specific STI policy instruments. Simulations permit researchers to formulate *what-if* questions and test different scenarios to better understand the impact of policies on system performance. We developed an agent-based model (ABM) to simulate the capabilities required for the core functions of innovation systems: generating, diffusing, and utilising knowledge and technology. The model incorporates decision rules to analyse emergent behaviours and identify leverage points, particularly the impacts of STI policies on system performance.

This approach fills a gap in the literature by providing a dynamic tool to evaluate the effects of STI policies across various scenarios, complementing existing empirical and theoretical studies. Our ABM builds on frameworks such as those by Jensen et al. (2007) and Crespi and Dutrénit (2014). The model supports policy experimentation by capturing how heterogeneous agents and innovation opportunities interact under different policy configurations to foster more equitable innovation outcomes.

The model was validated in the coffee and avocado agricultural production chains (APCs) in the Antioquia region of Colombia, chosen for their economic importance and development level. It demonstrated its utility in assessing the impacts of STI policies on innovation and economic performance within real-world contexts. **The formal complete specification of the model is provided in the annexe**, offering transparency and a methodological foundation for exploring performance and resource-efficient innovation systems.

After this introduction, Section 2 reviews the key theoretical frameworks and empirical evidence that inform the model, including the conceptual foundations of STI policies and innovation systems. Section 3 introduces the AdaptISM framework, detailing its structure, assumptions, and methodological approach, including the ODD (Overview, Design concepts, and Details) protocol. Section 4 describes the application and validation of the model in the coffee and avocado agricultural production chains (APCs) in Antioquia, Colombia, focusing on their innovation capabilities and the calibration of the simulation parameters. Section 5 analyses the results of the STI policy scenarios simulated using the model, offering insights into their economic and innovation impacts across different contexts. Finally, Section 6 discusses the broader implications of these findings for STI policymaking and concludes with recommendations for enhancing innovation system performance through tailored policy interventions. This structure aims to comprehensively understand the model's capabilities and contributions to innovation policy research.

2. Approaches to STI policy

We present the key approaches to STI policymaking, drawing on the categorisation proposed by Crespi and Dutrénit (2014):

a. *Mode I: The market-pull or technology-push approach, or STI innovation mode with a scientific approach.*

According to Rothwell's typology of innovation generation models (Rothwell 1994), the technology push was developed towards the end of the Second World War. At that time, science and technology were recognised to provide a key market advantage, something that the war had previously evidenced. In that context, the innovation process was understood as a simple linear sequential process, going from knowledge production to market exploitation through a series of stages: basic research, design and engineering, production, marketing, and the final stage of sales. From this point of view, STI policies are geared towards the "production and use of codified scientific and technical knowledge" (Jensen et al., 2007), which is achieved through formal learning (higher education and research) and the commercial exchange of explicit knowledge. The aim of this policy approach as to "increase the R&D capacity of the actors in the system and increase cooperation between firms and R&D organisations" (Isaksen & Nilsson, 2013, p. 1923), promoting top-down, unidirectional learning processes and research elites (Brunet & Mara, 2016). Nowadays, its efficiency is considered a measure of R&D costs, employment of science and technology postgraduates, cooperation with industries (Jensen et al., 2007) and radical innovation (Asheim B., 2012).

b. *Mode II: Focusing on demand or the market-pull approach.*

The second-generation innovation models emerged in the mid-60s when countercultural movements led by a generation of baby boomers challenged the established values and structures (Menéndez, 2017, p. 162). This caused significant changes in consumption, which affected product-oriented businesses that were applying the technology push innovation model in what has been called marketing myopia (Levitt, 1960). For this reason, the market gained great relevance, which became reflected in second-generation innovation models. Although still linear, such models were activated by specific market needs to continue onto the development, production and marketing stages.

c. *Mode III: The systemic approach, interactive learning mode (DUI).*

Rothwell considered Mode III a 5th-generation innovation model (Rothwell, 1994). It stresses the association between actors with complementary innovation abilities and those capable of learning in different ways within the innovation process. This approach appears in the context of the development of mass information and communication technologies, which hugely facilitate interaction. It also coincides with the emergence of innovation systems proposals, which argue, based on the analysis of specific countries, that innovation is a product not only of businesses' capacities but that it also occurs in the framework of a system of knowledge and technology generation, diffusion and use, through the interaction of heterogeneous agents who learn through doing, using and interacting (Freeman (1982; 1987), Lundvall (1985; 1988; 1992), Nelson (1993) and Edquist (1997)).

For Jensen, "the Doing, Using and Interacting (DUI) mode relies on informal processes of learning and experience-based know-how" (Jensen et al., 2007, p. 680). DUI is thus related to *know-how* and *who-know*, informal learning (interactive, practical and involving the participation of many agents), open access and knowledge spillovers. The main aim of the DUI mode is "to foster organizational and inter-organizational learning and increase cooperation between the particular producers and users" (Isaksen & Nilsson, 2013, p. 1923). Its function promotes bottom-up, informal, multidirectional learning processes that generate knowledge diffusion and dissemination (Brunet & Mara, 2016). The assessment of its contribution normally involves measures such as the number of interdisciplinary workgroups, the formation of quality circles, systems for collecting proposals, autonomous groups, integration of functions, softened demarcations, and cooperation with customers and providers (cf. Jensen et al 2007) and incremental innovation (Asheim B., 2012).

3. Theoretical and empirical foundation of AdaptISM

Initially, our proposed model understands the relationship between resources, capabilities, core competencies and learning from a resource-based view of the firm (Penrose, 1959). According to Grant (1991), resources encompass any asset, tangible or intangible, physical, intellectual or cultural, that a firm can access or acquire to achieve its corporate goals. Capabilities are "the ability to use resources to perform some task or activity" (Hafeez et al., 2002, p. 40). Another critical element is core competencies, which Hafeez et al. (2002, p. 41) describe as "organizational routines manifested in business activities and processes that bring assets together and enable them to be deployed advantageously." For capabilities to be regarded as core competencies, they must be valuable, rare, and difficult to imitate or substitute (Barney, 1991).

Technological learning refers to the dynamic process of accumulating capabilities and core competencies within a firm (Robledo, 2016). Representing learning as the accumulation of capabilities highlights its critical role in developing and evolving innovation systems, where it enhances interactivity and connectivity (Archibugi et al., 1999). Interactive learning is particularly vital for the economic performance of firms, regions and nations, as their success depends on their learning capacity (Lundvall, 2007). In this context, the ability and speed of accumulating (learning) and losing (unlearning) capabilities are key to understanding the performance of innovation systems (Quintero, 2016). Relevant theoretical contributions also include Ernst et al. (1998), Teece et al. (1997), and Helfat (1997).

Our approach to innovation systems draws on Freeman (1987, p.1), who defines such systems as "the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies". It also builds on Edquist's (1997) system of innovation framework, which integrates analytic approaches (national, regional, sector-based, and technological). Expands Edquist's framework by incorporating considerations of location and geographical proximity, as emphasized by Lundvall and Johnson (1994) and Asheim and Gertler (2004). Additional theoretical references include Carlsson et al. (2002), and Lundvall et al. (2002).

Given the complexity of studying social processes such as innovation, we draw on the Adaptive Complex Systems (ACS) literature. ACSs evolve through initial conditions, multiple interactions, long-term tendencies, and random variations among agents and their interactions (Ekboir et al., 2006). AdaptISM is an ACS - a system of agents that interact according to rules that change over time through the accumulation of experience (Holland, 2004). These adaptive processes result in evolving systems and flows, introducing complexity that motivates the use of computational models. As Holland (2004) noted, such models enable the exploration of governing patterns in ways that real systems cannot. Additional support for this approach comes from the work of Gilbert et al. (2001).

Trust is a key factor in the relationships between competing agents who associate to exploit innovation opportunities, impacting both costs and profits. On the one hand, cooperation between successful competing agents lowers transaction costs associated with partner search and activity coordination (Ruiz et al., 2016). On the other hand, a satisfactory working partner makes it easier to find new knowledge components and increases economic performance (Beckenbanch et al., 2009).

Agents with strong diffusion and association capacities play a critical role in trust-building by fostering shared norms of transparency and reciprocity. This enhances organisational learning and reduces transaction costs for knowledge and technology diffusion (Dyer & Singh, 1998). Trust, therefore, is both a cause and an outcome within innovation systems (Beckenbach et al., 2009). Furthermore, interactive learning is deeply embedded in social contexts. The success of learning processes depends on social factors like trust, authority, and recognition, emphasising the need to consider social and economic contexts when analysing relationships within innovation systems (Lundvall & Christensen, 2007).

The design of the model's interactions between heterogeneous agents for knowledge and technology diffusion is based on four key proposals. First, the Simulating Knowledge Dynamics in Innovation Networks (SKIN) model by Gilbert et al. (2001), which was refined and expanded in subsequent works (e.g., Ahrweiler et al., 2004, 2011; Pyka & Scholz, 2008; Pyka et al., 2009; and Triulzi et al., 2011). Second, the hyper-cycle and catalytic models, introduced by Eigen and Schuster (1979) and Kauffman (1996, 2000), respectively, and later adapted by Padgett (1997) and further developed by Padgett et al. (2003), Padgett et al. (2009), and Watts & Binder (2012). Third, the SSRIS model proposed by Ponsiglione, Quinto, and Zollo (2014) integrates elements of the SKIN and hyper-cycle models. Finally, the innovation system, capabilities, and learning/unlearning model developed by Ruiz et al. (2016) and extended by Quintero et al. (2017). These references collectively informed the design assumptions of the model, particularly in defining agents, values and scales, the motivation for agent associations, and the functions of innovation systems.

4. Explanation of the Adaptive Innovation Systems Model (AdaptISM)

The Adaptive Innovation Systems Model (AdaptISM) we propose provides a dynamic framework for analysing how Science, Technology, and Innovation (STI) policies influence the performance of innovation systems. Central to the model are agents—entities such as firms, organisations, or individuals—whose capabilities must align with the attributes of emerging innovation opportunities within a competitive environment. The model explores the interplay between agents, their capabilities, and innovation opportunities, offering a comprehensive tool for assessing STI policies. Annex 1 details the mathematical specification of the model, including its formal rules, processes, and parameters.

Innovation opportunities are classified into two distinct types: market opportunities (MO) and technological opportunities (TO). MOs represent market-pull dynamics, emerging unpredictably from market demands, while TOs reflect technology-push mechanisms, often originating from agents with advanced research capabilities. This dual classification enables a nuanced exploration of how different innovation drivers affect system performance.

The model represents an innovation system comprising two types of entities: **competing agents** and **innovation opportunities**. Competing agents are defined by their innovation capabilities, which enable them to fulfil the core functions of innovation systems: knowledge and technology generation, diffusion, and utilization. Table 1 outlines the relationship between these functions and their corresponding innovation capabilities.

Table 1. Correlation between the functions and innovation capabilities of innovation systems

Function	**Capability**	**Application**
Knowledge and technology generation	Research	Produce and adapt knowledge and technology
	Development	Experiment with and develop new products and processes.
Knowledge and technology diffusion	Diffusion	Collect and spread R&D results and technologies.
	Association	Build trust-based relationships to exploit complementary capabilities through joint R&D and innovation projects.
Knowledge and technology usage	Appropriation for production	Efficiently operate and maintain productive infrastructure while adapting and improving production technologies.
	Innovation marketing	Identify market needs, dissemination of new products and processes, establish distribution channels, and promote innovations.

Source: Ruiz, Quintero & Robledo (2016)

Competing agents are classified into three broad categories based on their capabilities:

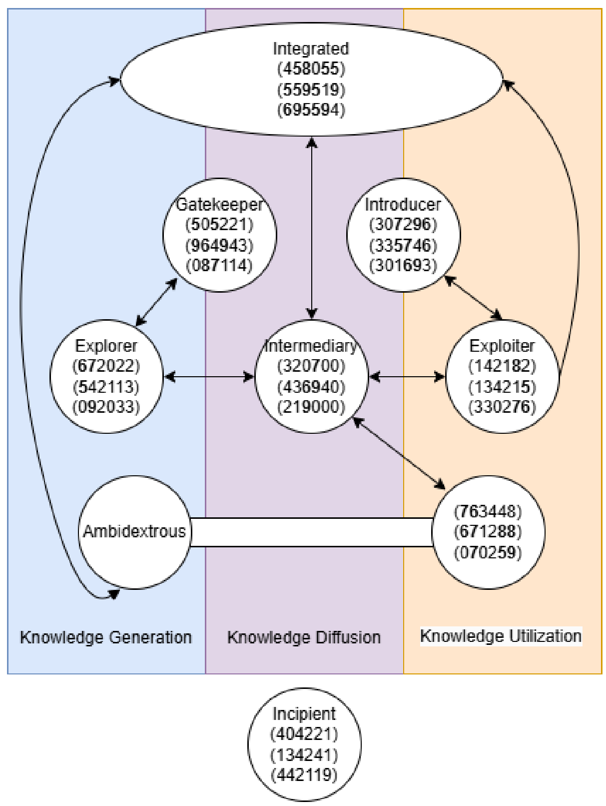
- Exploiter agents (e.g. firms), with capabilities in appropriation for production and/or innovation marketing.
- Intermediary agents (e.g., technology parks, incubators) with association and/or diffusion capabilities.
- Explorator agents (e.g., universities, research centres) with research and/or development capabilities.

Recognising the complexity of real-world systems, AdaptISM allows agents to possess multiple capabilities, enabling them to play diverse roles within the innovation system. This flexibility leads to nuanced classifications of agents, including:

- **Gatekeepers**: Firms that engage in technology watch, foresight, road mapping, benchmarking, and experimental development. These agents possess both exploitation and intermediation capabilities.

- **Introducer agents**: Universities with science and technology transfer departments, business incubators, or entities that combine exploration and intermediation capacities.
- **Integrated agents**: Companies with R&D departments and open innovation strategies that simultaneously explore, intermediate, and exploit innovation results.
- **Ambidextrous agents**: Companies with R&D capabilities that can explore and exploit results but engage in limited interaction with other actors in the system.
- **Incipient agents**: Latecomers or enterprises with underdeveloped innovation capabilities. These agents cannot perform any of the innovation system's functions (See Figure 1.)

Figure 1. AdaptISM Agent Typology



Source: Adapted from Ruiz et al. 2016.

Figure 1. Positioning and relationship between competing agents in an innovation system.

Innovation opportunities are represented as six-dimensional **Attribute Vectors (AV)**, defining the capabilities required for exploitation. Each dimension corresponds to one of the six innovation capabilities (research, development, diffusion, association, appropriation for production, and marketing). The values range from 0 (no capability required) to 9 (state-of-the-art capability required), reflecting the complexity and demands of the opportunity.

Competing agents possess corresponding **Capability Vectors (CV)**, representing their ability to meet and supply the demands of an opportunity. CV values evolve through learning (accumulation) or unlearning (decay), shaped by interactions with opportunities and other agents. Matching between AVs and CVs occurs through a sequential process:

1. **For Market Opportunities (MOs)**: Matching starts with marketing capabilities and progresses toward research, reflecting a demand-driven process. Agents unable to meet all requirements individually may form associations with others possessing complementary capabilities.

2. **For Technological Opportunities (TOs)**: Matching begins with research and proceeds toward marketing, reflecting a technology-push approach. Associations are similarly formed to address gaps in capabilities.

The maximum coalition size is six agents, each contributing one capability dimension. Once all attributes of an opportunity are satisfied, benefits are distributed among the participating agents.

Competing agents participate in innovation dynamics when their capabilities align with the requirements of innovation opportunities within a competitive environment. Innovation opportunities are classified as market opportunities (MO) or technological opportunities (TO). MOs emerge from the demands of a competitive environment, representing market-pull mechanisms. TOs, on the other hand, emerge from agents with strong research capabilities and embody a technology-push dynamic. Competing agents exploit these opportunities by matching their innovation capabilities to the attributes of the opportunities.

Attributes are represented by six-dimensional vectors, each corresponding to a specific innovation capability. An individual agent can satisfy these attributes or associate with other agents that possess complementary capabilities.

Attribute Vector (AV)

Each innovation opportunity is characterized by an Attribute Vector ($AV = [a_1, a_2, a_3, a_4, a_5, a_6]$), which consists of six dimensions: research capability (a_1), development capability (a_2), diffusion capability (a_3), association capability (a_4), appropriation for production capability (a_5), and marketing capability (a_6). These dimensions collectively define the attributes required to exploit the opportunity effectively within the competitive environment.

The values for these dimensions range from 0 (no capability required) to 9 (state-of-the-art capability required). The volatility of innovation opportunities determines how long they remain in the system before disappearing if unexploited. Opportunities also follow a lifecycle, modelled as a Gaussian distribution, dictating the benefits they generate over time, as inspired by Rogers' (2003) diffusion curves.

In short, competing agents aim to exploit innovation opportunities in a competitive environment, either through their own innovation capabilities or through association with other competing agents with complementary innovation capabilities.

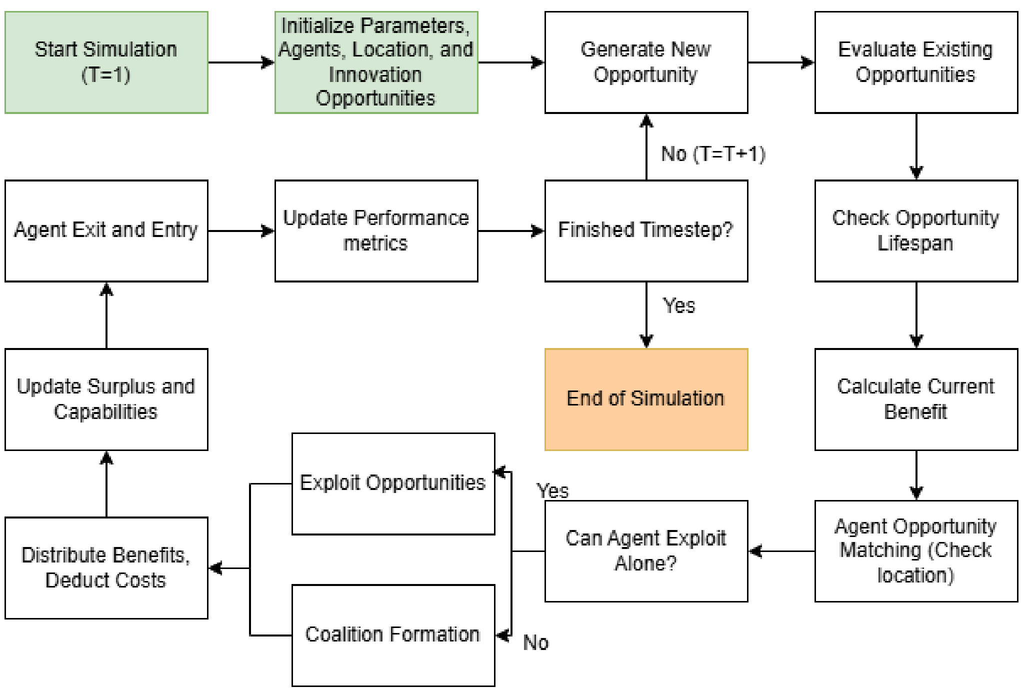
Capability Vectors (CV)

Agent's capabilities are represented through Capability Vectors (CV), which comprise six dimensions ($CV = [c_1, c_2, c_3, c_4, c_5, c_6]$). The value and scale associated with the competing agents' innovation capabilities are null (value 0), basic (1-3), average (4-6) and advanced (7-9). The current level of one capability is the result of the different learning and accumulation stages (Dodgson, 1993; Kim, 1997; Hobday, 1997; Ernst, Mytelka, & Ganiatsos, 1998; Lundvall, 2007; Lundvall & Vinding, 2007; Lund, 2007; Helfat et al., 2007). Innovation capability is "the ability to use resources to perform some task or activity" (Hafeez et al., 2002, p. 40). From this perspective, we understand that maintaining innovation capabilities has a cost, which depends on the agent's current innovation capabilities. The agent's surplus meets this cost.

Summary of the process, rules and sequential logic of the model:

The processes in the innovation system take place in the following order: First, as mentioned earlier, the appearance of an innovation opportunity within the competitive environment triggers a sequence of events. Such an innovation opportunity may be either a market opportunity or a technological opportunity. The following steps depend on the nature of the innovation opportunity (see Figure 2).

Figure 2. Model Flow Chart



Exploitation of Market and Technological Opportunities

Market opportunities emerge randomly within the competitive environment, reflecting the inherent unpredictability of market demands. This triggers a search for a competing agent capable of meeting the opportunity's attributes. The opportunity's attributes and the agent's location are assigned randomly to account for the uncertainty typical of innovation markets.

This process exemplifies a **market pull dynamic**, where a competing agent must meet demand from an actor in the innovation system (e.g., consumer, company, or public entity). The agent's ability to address the opportunity depends on its capacity to fulfil the attributes specified in the **Attribute Vector (AV)**. For instance, a consumer seeking clothing may prioritize a well-known brand, demonstrating the brand's capability to market innovations effectively.

The search for a suitable competing agent begins locally, focusing on agents' marketing capacities. If no local agent can satisfy the opportunity, the search expands geographically. Once a qualified agent is identified, a link is established between the agent and the market opportunity.

Technological opportunities, by contrast, originate from agents with advanced research capabilities, aligning with a **technology-push dynamic**. These opportunities are initially linked to the originating agent. Validation ensures that all other required attributes are satisfied as defined in the AV.

Validation of Attributes

For market opportunities, attributes are validated in the following sequence: Appropriation for production capability, Association capability, Diffusion capability, Development capability, Research capability. If the selected agent cannot fulfil all required attributes, it searches for other agents with complementary capabilities to form associations. This iterative process continues until the opportunity's requirements are fully met. A maximum of six agents can collaborate, each contributing a specific capability.

For technological opportunities, the sequence of validation is reversed, starting with development and progressing through diffusion, association, appropriation for production, and marketing. The formation of associations follows the same collaborative logic.

Once all attributes of an innovation opportunity are satisfied—either by a single agent or through associations—the opportunity begins generating benefits. These benefits depend on the opportunity's lifecycle, modelled as a Gaussian distribution, and the value associated with each fulfilled attribute.

Projects involving agent collaboration to exploit opportunities also produce **learning (or unlearning)** outcomes. This dynamic reflects **learning by doing** or **unlearning by non-doing**, where specific capabilities' use (or neglect) influences their accumulation (or decay). The rate of learning or unlearning is governed by a factor that considers the system's competitive environment and the agent's existing capability levels.

Renewal and Evolution

Market opportunities themselves evolve through a learning process driven by the competitive environment. When an opportunity's lifecycle concludes, it is replaced by a new one with attributes shaped by the learning dynamics of the previous cycle.

At the end of each simulation period:

I. Competing agents update their surplus stocks by adding profits from exploited opportunities and deducting costs associated with maintaining capabilities and transaction costs from collaborative associations.

II. Agents with a negative surplus are removed from the system.

As the new period begins, the system is updated:

- New competing agents enter the environment, with capabilities assigned stochastically based on prior system dynamics.
- Expired market and technology opportunities are replaced.
- New innovation opportunities (MO and TO) born in the competitive environment
- Agents with advanced research capabilities may generate new technological opportunities.

5. Application, data collection, and validation of the model

The proposed model was empirically applied and validated in Colombia's coffee and avocado agricultural production chains (APCs), specifically in the Antioquia department. These APCs were selected due to their economic significance for the country and region, as well as their differing levels of maturity, enabling a comparative analysis to deepen the understanding of the phenomenon under study. Validation followed the operational technique outlined by Sargent (2013), which compares the occurrence of events in the simulation model with those observed in the real system to assess their similarity. We conducted a field study of the coffee and avocado APCs in Antioquia, Colombia, which involved collecting data through interviews with various stakeholders.

The tool we developed is based on Nadler and Tushman's organisational congruence model (1997), which identifies four key dimensions of organisational management:

- Formal organisation: The structured hierarchy and processes that define roles and guide individuals in executing their tasks.
- Informal organisation: The unwritten cultural framework encompassing past and present practices, management style, organisational culture, interpersonal and interdepartmental relationships, informal work arrangements, and social norms.
- The technological dimension refers to the organization's core work, including process technology, machinery, tools, and methods for transforming input into output. Building on Nadler and Tushman's focus on tasks, we adopt the University of Michigan's perspective, emphasising the technological nature of tasks and redefining them as technology.
- Human resources: The organisation's members, encompassing their knowledge, skills, experience, needs, preferences, and expectations for recognition and incentives.

Innovation capabilities (research, development, diffusion, association, appropriation for production, and innovation marketing) comprise the formal, informal, technological, and human elements. The interview questions targeted these elements for each capability to estimate each actor's approximate capability level. Given the linear nature of the simulation model, it was essential to assess the current state of these elements and their progression over time. To achieve this, each question addressed three points in time: 10 years ago, 5 years ago, and the present. Interviews were conducted in 2018.

The data collected enabled us to estimate how innovation capabilities accumulated or decumulated within each APC. This allowed us to evaluate whether the simulation model mirrored this behaviour, providing a basis for operational validation.

We began by systematising data for each APC, measuring the innovation capabilities of the actors interviewed at the three defined time points. Using these measures, we calculated the average capacity for each innovation capability over time, yielding the results summarised in Table 2.

Table 2. Average innovation capability for APCs over time

	APC Coffee			**APC Avocado**		
Average Innovation Capacity	**2008**	**2013**	**2018**	**2008**	**2013**	**2018**
Research	0.15	0.16	0.19	1.45	1.14	0.83
Development	0.16	0.15	0.16	1.29	1	0.77
Diffusion	1.00	1.06	1.19	2.97	3.11	2.8
Association	1.31	1.41	1.58	3.74	4.47	4.25
Appropriation	0.99	1.19	1.52	2.72	3.07	2.75
Marketing	0.18	0.26	0.42	1.98	2.05	1.59

Source: Data obtained by the authors through field study

For the study to be significant, we interviewed 256 agents in the coffee APC and 74 in the avocado APC. To introduce such agents in the model, we normalised data for 100 agents and calibrated the parameters, adjusting them to the real system. The goal was that after simulating for 10 periods, the simulated APCs showed similar behaviour to that of real APCs regarding the accumulation of innovation capabilities. The model's parametrisation is found in Annex 2.

a. *Selection, results and analysis of STI policy scenarios*

Plausible scenarios are projections of future behaviour designed to address policymakers' challenges. STI policy scenarios help anticipate the potential impact of one or more events by projecting future outcomes (Quintero & Giraldo, 2018). Systematic variations in uncertain or unknown parameters within the model generate multiple trajectories, some of which are selected to represent distinct scenarios that characterise different behaviours. These parameters, which describe an APC's economic and innovation performance, are critical for scenario analysis. The scenarios considered in this study are as follows:

1. Mode I Policy Scenario: Represents APCs that benefit from doing-using learning and accumulating research and development capabilities. This behaviour is shaped by routines acquired through agents' past experiences (Nelson & Winter, 1982).
2. Mode II Policy Scenario: This scenario focuses on innovative marketing programs and tools that enhance the detection, interpretation, and prediction of market trends. This includes funding, methodologies, and techniques for market exploration, benefiting agents in the productive chains.
3. Mode III Policy Scenario: Aims to foster interaction and overcome collective learning barriers (Fritsch & Slavtchev, 2007; Ponsiglione, Quinto, & Zollo, 2014; Albino, Carbonara, & Giannoccaro, 2006). This scenario reflects APCs that rely on doing-using-interacting (DUI) learning approaches.
4. Mode IV (Combined Mode): This mode integrates features of multiple modes, combining Mode I, II, and systemic STI policies. It reduces the costs of imported capital assets, promotes technological modernisation, and improves production infrastructure. Additionally, it supports research and development projects, human resource training, and the appropriation and transformation of technologies through enhanced interactions among actors in the chain.

Analysis of STI policy scenarios based on simulations:

Avocado APC

Significant differences are observed in the avocado APC in the following variables: surviving agents, market capacity, and exploited market opportunities. Figure 3 reflects the number of surviving agents in the APC. Mode IV and III policy scenarios reveal a better performance regarding agents' survival. Although the economic performance of all policy scenarios is similar, and surplus stock shows no statistically significant difference, scenarios IV and II ensure more agents remain active in the APC's innovation dynamics. Thus, many agents benefit from innovation dynamics, the opposite of scenarios I and II, where few agents benefit from and remain active in the innovation system. This implies that both the combination of policies and the systemic policy ensures better performance in the participation of more agents in the innovation dynamics.

Given that a scarcity of resources forbids the possibility of investing in all policy types and that the aim is to have a greater participation of actors in innovation dynamics without any negative impact on economic performance, the best recommendation based on the simulations would be to adopt mode III policy. This policy mode supports actors that perform knowledge and technology diffusion functions and build trust for associations to be made. Such actors promote the use of knowledge and technology among other actors in the APC, who, in turn, become involved in innovation dynamics. This would also allow for a more significant number of actors to benefit from their participation in such dynamics.

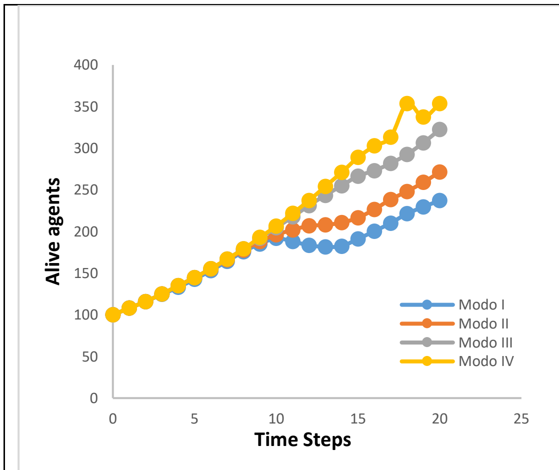


Figure 3. Alive agents in the System

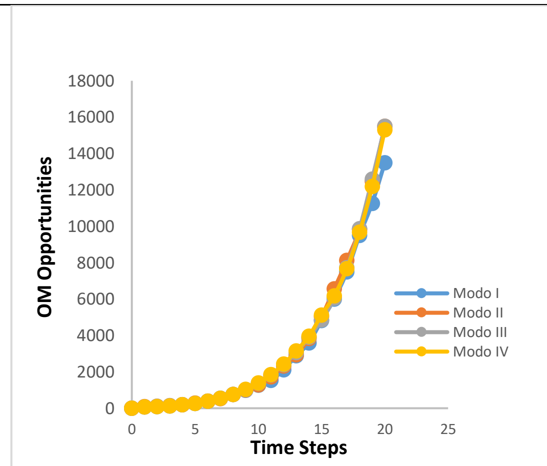


Figure 4. Agents benefiting from Market Opportunities

Figures 3 and 4 show that the mode I policy scenario results in 49.07% fewer active agents and 14.90% fewer exploited market opportunities than other scenarios. This suggests that policies focused on fostering R&D have a limited impact on the innovation performance of the APCs, whereas mode II and III policies yield more balanced outcomes. During resource-constrained periods, implementing mode II or III policies appears more effective for enhancing diffusion, association, appropriation for production, and marketing capabilities within the Avocado APC.

The mode I policy scenario fails to adequately integrate exploratory agents such as research centres, universities, and technological hubs into the APC. This shortcoming reflects the APC's structural reliance on numerous small growers, limiting the appropriation and adaptation of new knowledge and technologies. As a result, the APC struggles to meet the demands of an increasingly competitive and dynamic market.

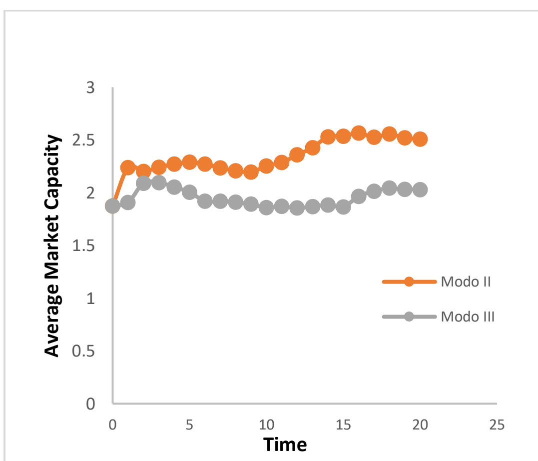


Figure 5. Market capacity

Figure 5 shows a greater accumulation of marketing capacity in the APC under the mode II policy scenario compared to the mode III scenario. Furthermore, the mode II scenario presents a lower number of actors involved in innovation dynamics than modes III and IV. This feature shows a more significant appropriation and exploitation of market opportunities by fewer competing agents. Their knowledge base has allowed them to accumulate and thereby learn these capacities, developing processes that allow for the perception and satisfaction of market opportunities. This translates into greater profits that sustain the capacity costs and produce surpluses. Considering the foregoing, we can infer that it is important to opt for policies that are not only market-based but also policies that strengthen the connections between every link in the chain to improve innovative processes and thus allow for more efficient exploitation of the market opportunities and better economic performance.

To conclude, the mode III STI policy scenario shows a lower proportional difference (9.61%) in the number of living agents compared to the combined mode policy scenario. This indicates that systemic policies help APCs stabilise, improving connections between actors, which allows them to satisfy demands in the competitive environment and its market opportunities, which has a greater impact on the different performance levels of the chain compared to STI policies modes I and II.

Coffee APC

Figure 6 indicates that the different policy scenarios have very similar behaviour in the APC´s surplus stock until year 15; however, modes I and II show superior performance from then on. Figure 5 indicates a similar economic performance to that of year 15 for policy scenarios with significant differences; their performance can be observed in the APC's surplus stock. It shows a growth curve where modes I and II show superior performance. Growth in economic performance contrasts with the number of living agents in the system (see Figure 7), indicating that such policies provide stability for some agents in the system but not for most of them. The agents benefited from the policy, considering their previous accumulation capability, and were able, thanks to greater connectivity, to respond better to market opportunities and exploit them.

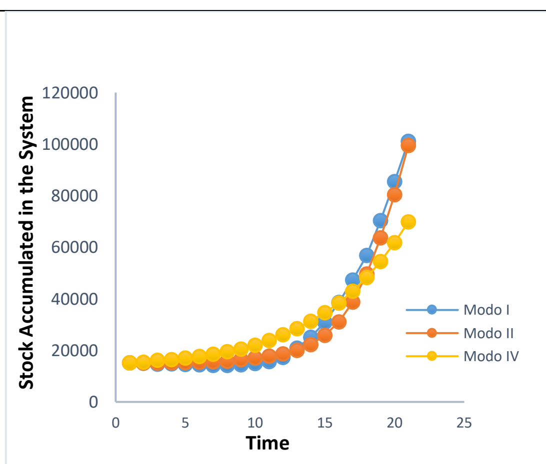


Figure 6. Surplus Stock Accumulation

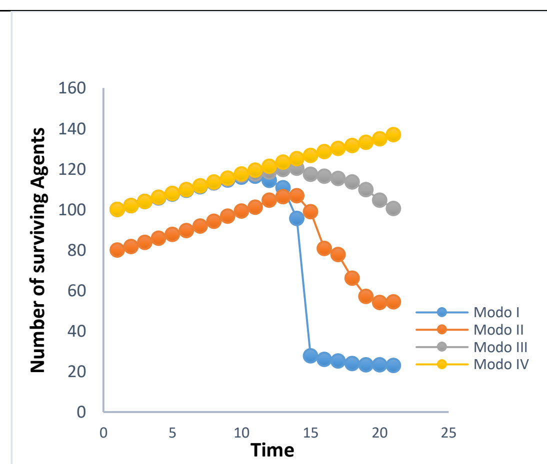


Figure 7. Survival Agents in the System

Source: Prepared by authors Prepared by authors

Regarding market opportunities exploited, we observe a statistically significant difference between modes I and III (see Figure 8). Compared to earlier behaviour, this evidences the importance of STI policies involving a greater number of actors. Although mode I *STI* innovation mode (technology push) increased economic performance, which was reflected in a greater surplus stock (shown in Figure 5), this policy mode dismisses small producers and lower innovation capability actors, forcing them out of interactions and impeding access to the market opportunities that the APC's competitive environment demands.

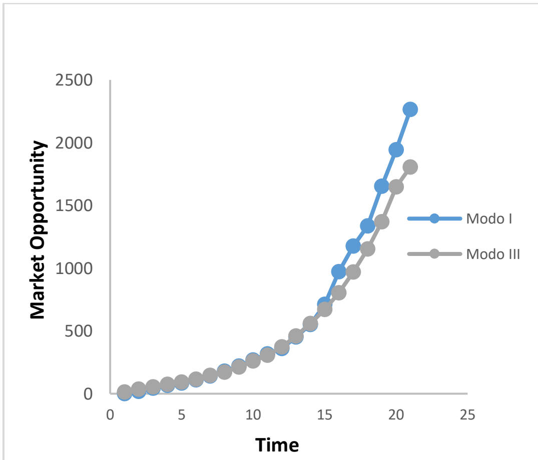


Figure 8. Agents Benefiting from Market Opportunities

The foregoing contrasts with the reality of the coffee APC in the region, as it involves insufficient agents with advanced capabilities. Most agents in the APC are engaged in grain production. They are not aiming towards giving their product added value or advancing and appropriating new technologies for their transformation and marketing. It is worth stressing that the exploitation of market opportunities does not imply that all agents in the system reach a specific market. This may be directly linked to the connection between agents in the APC. Small producers forge a marketing process when they sell their coffee grain, and then a dealer or buyer continues the transactional process until an existing market opportunity is met.

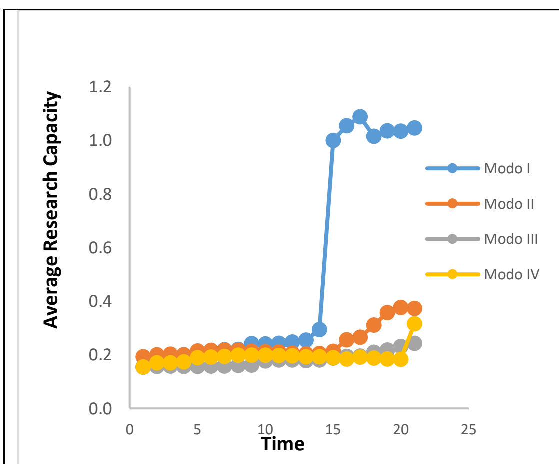


Figure 9. Research capability

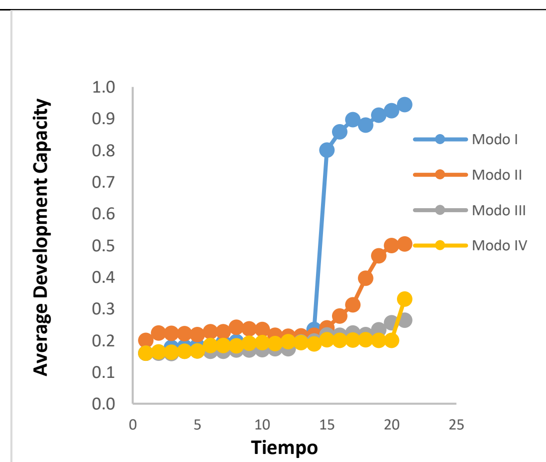


Figure 10. Development capability

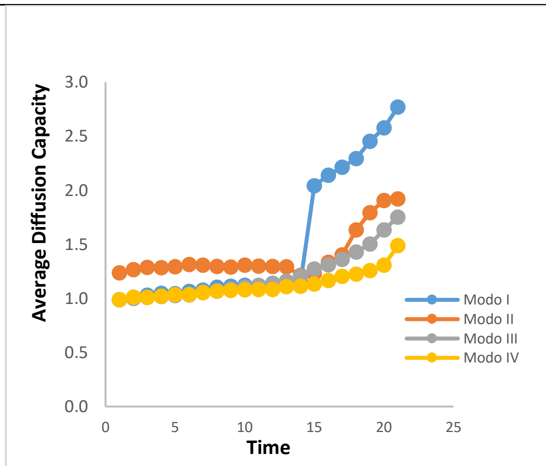


Figure 11. Diffusion capability

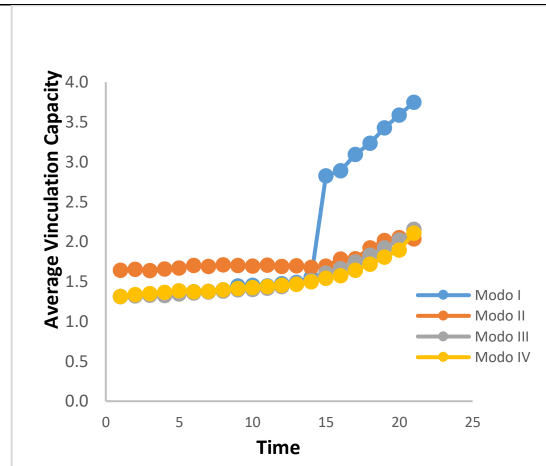


Figure 12. Association capability

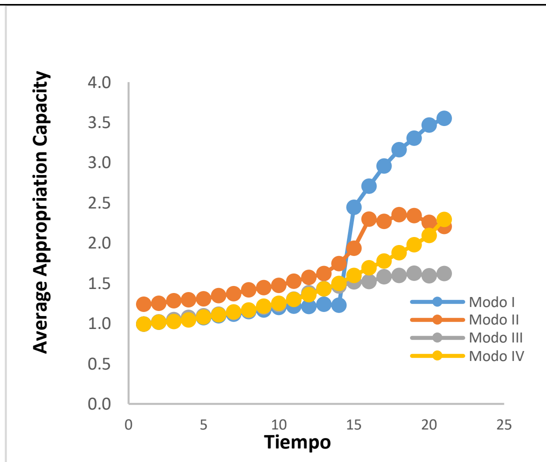


Figure 13. Appropriation capability

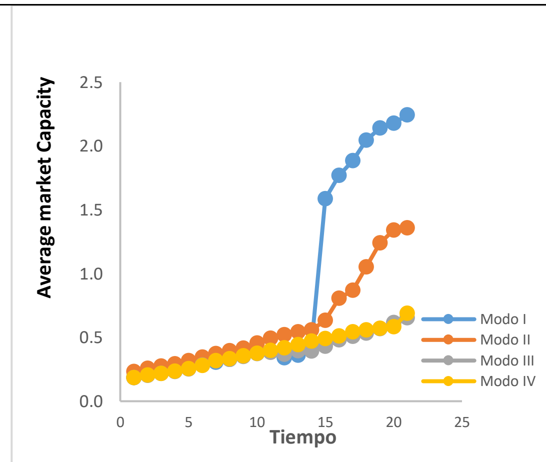


Figure 14. Market capacity

As regards the differences between innovation capabilities, we observe that research (see Figure 9), development (Figure 10), diffusion (Figure 11), association (Figure 12), appropriation (Figure 13) and market innovation (Figure 14) capabilities showed similar behaviours, where mode I policy scenario presented statistically significant differences with the other scenarios. This STI innovation mode with a science approach reduced research and development capacity costs, fostering and strengthening only some agents with advanced capabilities. These pulled the average value for the whole system, which became reflected in a proportional increase of all capabilities in the scenario under evaluation.

We must clarify something that could lead to erroneous interpretations. According to the average results of the system's capabilities, we could assume that the mode I STI policy is the most successful in improving the system's performance. Nevertheless, the number of competing agents that enter the innovation dynamics in this scenario amounts to less than a fifth compared to scenario III and six times less in scenario IV, both of which involve STI policies that facilitate knowledge and technology diffusion, as well as trust among agents to form the associations needed in the process of forming the innovation system. In the mode I policy scenario, the capacity of appropriation for production (see

Figure 12) increased from its basic value to its average value, which shows evidence of a direct relationship between the value of such capability in the system and the economic and innovation performance of the chain. This is reflected in the increase in competitiveness that helps satisfy a greater number of market opportunities. Nevertheless, in mode I, only a few agents play a role in and benefit from the innovation dynamics. This, in turn, generates greater gaps in the APC, which already presents this imbalance.

Mode II STI policy scenario (market pull) behaved similarly to mode I, showing fewer agents entering the innovation dynamics at the end of the simulation. Nevertheless, this scenario lacked a significant increase in the value of the capabilities compared with the mode I policy scenario. Research and development basic capacity is probably a factor that hinders the accumulation of capabilities in the coffee APC.

Regarding policy scenarios III and IV, there was no evidence of a significant increase in innovation capabilities nor an increase of surplus stocks in the system. These scenarios, nevertheless, present a larger number of alive agents at the end of the simulation period, with a 496% increase in the number of agents (between modes III-IV policy scenarios), in comparison to mode I and II STI policy scenarios. The coffee APC in Antioquia comprises 79,000 actors, of which approximately 97% are small producers with basic innovation capabilities. Diffusion processes are required to bridge the gap between the actor's innovation capabilities and market opportunities, allowing for their inclusion and permanence in a competitive environment.

To conclude, given the different challenges the coffee sector faces, there is a need to formulate policies that aim to lessen the innovation capabilities gap between APC actors. Such policies should also consider the importance of this productive activity for Colombian rural development, which is realised through the economic and social impact on many agents, including small producers. For this reason, policies that do not consider different actors in the land could hurt their position in the competitive environment, creating a system that relegates some of the actors in the APC. For these reasons, mode III and IV policies, despite failing to show a better economic and innovation performance or a larger capacity for accumulation, allow for a larger number of participating actors in the innovation process, resulting in a system with a greater distribution of market opportunities. Furthermore, the (moderately fast) accumulation of innovation capabilities by a more significant number of agents in the APC helps close the gap and help a greater inclusion of actors in the innovation dynamics. This is fundamental for an APC of such high prominence in the region and the country.

6. Implications for STI policy and conclusion

The model underscores how each APC's unique circumstances, such as its agents' baseline innovation capacities, shape the effectiveness of STI policies, leading to outcomes that vary significantly across contexts. This variability reflects real-world scenarios where regions and countries often achieve divergent results despite implementing similar policies.

Crucially, the model demonstrates the importance of tailoring STI policies to the specific dynamics of the system under study. The results reveal that outcomes are not always intuitive, as illustrated by the divergent impacts observed across the different policy modes and APCs. The validation of the model using data from the coffee and avocado APCs in Antioquia, Colombia, confirms its ability to approximate real-world conditions, providing robust insights into the interaction between policy interventions and system dynamics.

Notably, the systemic mode (Mode III) emerged as a key policy approach, fostering knowledge and technology diffusion, enhancing connectivity among agents, and narrowing capability gaps within the system. In contrast, its direct economic and innovation outcomes may not surpass other policy modes; its capacity to integrate more agents into the innovation dynamics positions it as an essential strategy for inclusive and sustainable development. By bridging disparities among agents and promoting widespread participation, Mode III exemplifies the potential of systemic policies to generate long-term benefits for innovation ecosystems.

Building on the findings of this study, the following steps involve refining and extending the model to enhance its applicability and analytical depth. One immediate avenue for development is to incorporate additional sectors and regional contexts, allowing for a comparative analysis of STI policy impacts across diverse economic and institutional settings. This expansion will enable the model to capture the dynamics of innovation systems in varying levels of maturity and development, broadening its relevance for global policymaking. Furthermore, incorporating cross-sectoral linkages and international trade dynamics could offer deeper insights into how global value chains and transnational interactions influence local innovation systems. Another priority is improving the representation of learning and unlearning processes by adopting more sophisticated functions, such as S-curves, to better reflect real-world capability accumulation patterns. Future iterations of the model could also integrate dynamic policy adjustments, enabling the simulation of adaptive STI strategies that respond to evolving system conditions. Finally, collaboration with policymakers and stakeholders in live case studies could further validate the model and provide actionable recommendations, ensuring that its insights directly apply to real-world decision-making processes.

7. References

Ahrweiler, P., Pyka, A., & Gilbert, N. (2004). Simulating knowledge dynamics in innovation networks (SKIN). In Industry and labor dynamics: The agent-based computational economics approach (pp. 284-296).

Ahrweiler, P., Pyka, A., & Gilbert, N. (2011). A new model for university-industry links in knowledge-based economies. *Journal of Product Innovation Management, 27*(2), 218-235.

Albino, V., Carbonara, C., & Giannoccaro, I. (2006). Innovation in industrial districts: An agent-based simulation model. *International Journal of Production Economics, 104*, 30-45.

Apanasovich, N., Alcalde, H., & Parrilli, M. D. (2016). The impact of business innovation modes on SME innovation performance in post-soviet transition economies: The case of Belarus. *Technovation, 57-58*, 30-40.

Archibugi, D., Howells, J., & Michie, J. (1999). *Innovation systems and policy in a global economy.* Cambridge University press.

Asheim, B. (2012). The Changing Role of Learning Regions in the Globalizing Knowledge Economy: A Theoretical Re-examination. *Regional Studies, 46*(8), 993-1004.

Asheim, B. T., & Gertler, M. S. (2004). The geography of innovation: regional innovation systems. In J. Fagerberg, D. C. Mowery, & R. R. Nelson, *The Oxford Handbook of Innovation* (p. 291-317). Oxford: Oxford University Press.

Aslesen, Isaksen, A., & Karlsen, J. (2011). Modes of innovation and differentiated responses to globalization. *J. Knowl. Econ, 2*.

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management, 17*, 99-120.

Beckenbanch, F., Briegel, R., & Daskalakis, M. (2009). Evolution and Dynamics of Networks in 'Regional Innovation Systems' (RIS). In *Innovation Networks. New Approaches in Modelling and Analyzing* (p. 58-100). Berlin: Springer-Verlag Berlin Heidelberg.

Brunet, I., & Mara, L. C. (2016). Formación profesional y procesos de innovación a nivel regional. *Revista Venezolana de Gerencia, 21*(74), 257-271.

Carlsson, B., Jacobsson, S., Holmén, M., & Rickne, A. (2002). Innovation systems: analytical and methodological issues. *Research Policy, 31*, 233-245.

Chen, J., Chen, Y., & Venhaverbeke, W. (2011). The influence of scope, depth and orientation of external technology sources on the innovative performance of Chinese firms. *Technovation, 31*, 362-373.

Cohen, W., & Levinthal, D. (1990). Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly Special Issue: Technology, Organizations, and Innovation, 35*(1), 128-152.

Crespi, G., & Dutrénit, G. (2014). Introduction to science, technology and innovation policies for development: The Latin American experience. In *Science, Technology and Innovation Policies for Development: The Latin American Experience* (pp. 1-14). Cham: Springer International Publishing.

Dodgson, M. (1993). Organizational Learning: A review of some literatures. *Organization Studies, 14*, 375-394.

Dyer, J., & Singh, H. (1998). The relational view: cooperative strategy and sources of interorganizational competitive advantage. *The Academy of Management Review, 23*, 660-679.

Edquist, C. (1997). *Systems of Innovation: Technologies, Institutions and Organisations.* (C. Edquist, Ed.) London: Pinter/Cassell.

Eigen, M., & Schuster, P. (1979). *The Hypercycle: A principle of Natural Self-Organization.* New York: Springer-Verlag.

Ekboir, J. M., Dutrénit, G., Martínez, G., Torres, A., & Vera-Cruz, A. (2006). *Las Fundaciones Produce a diez años de su creación: pensando en el futuro.* Washington: International Food Policy Research Institute.

Ernst, D., Mytelka, L., & Ganiatsos, Y. (1998). Technological capabilities in the context of export-led growth. A conceptual framework. In D. Ernst, Y. Ganiatsos, & L. Mytelka, *Technological Capabilities and Export Success in Asia* (p. 5-45). London, New York: Routledge.

Fitjar, R., & Rodríguez-Pose, A. (2013). Firm collaboration and modes of innovation in Norway. *Research Policy, 42*, 128-138.

Freeman, C. (2008). Technological infrastructure and international competitiveness. *Systems of Innovation*, 6-37.

Freeman, C. (1987). *Technology Policy and Economic Performance: Lessons from Japan.* London: Pinter.

Fritsch, M., & Slavtchev, V. (2007). Industry Specialization, Diversity and the Efficiency of Regional Innovation Systems. *Jena Economic Research Papers*, 1-27.

Gilbert, N., Pyka, A., & Ahrweiler, P. (2001). Innovation Networks - A Simulation Approach. *Journal of Artificial Societies and Social Simulation, 4*(3).

Grant, R. M. (1991). The resource-based theory of competitive advantage: Implications for strategy formulation. *California Management Review*, 114-135.

Hafeez, K., Zhang, Y., & Malak, N. (2002). Determining key capabilities of a firm using analytic hierarchy process. *International Journal of Production Economics, 76*, 39-51.

Helfat, C. E. (1997). Know-how and Asset Complementary and Dynamic Capability Accumulation: The Case of R&D. *Strategic Management Journal, 18*(5), 339-360.

Helfat, C. E., Finkelstein, S., Mitchell, W., Peteraf, M., Singh, H., Teece, D., & Winter, S. G. (2009). Dynamic capabilities: Understanding strategic change in organizations. John Wiley & Sons.

Hobday, M. (1997). *Innovation in East Asia. The Challenge to Japan.* Cheltenham and Lyme: Edward Elgar.

Holland, J. H. (2004). *El Orden Oculto: De cómo la adaptación crea la complejidad.* (E. Torres-Alexander, Trad.) México, D.F., México: Fondo de Cultura Económica.

Isaksen, A., & Karlsen, J. (2010). Different modes of innovation and the challenge of connecting universities and industry: Case studies of two Regional Industries in Norway. *European Planning Studies, 18*(12), 1193-2010.

Isaksen, A., & Nilsson, M. (2013). Combined Innovation Policy: Linking Scientific and Practical Knowledge in Innovation Systems. *European Planning Studies, 21*(12), 1919-1936.

Jensen, M. B., Johnson, B., Lorenz, E., & Lundvall, B. A. (2007). Forms of Knowledge and Modes of Innovation. *Research Policy, 36*, 680-693.

Kauffman, S. (1996). *At home in the universe.* London: Penguin.

Kauffman, S. (2000). *Investigations.* Oxford: Oxford University Press.

Kim, L. (1997). *Imitation to Innovation. The Dynamics of Korea's Technological Learning.* Massachusetts: Harvard Business School Press.

Levitt, T. (1960). Marketing Myopia. *Harvard Business Review*, 45-56.

Lund, R. (2007). The Organization of Actors' Learning in Connection with New Product Development. In J. L. Christensen, & B.-Å. Lundvall (Edits.), *Product Innovation, Interactive Learning and Economic Performance* (p. 129-153). Bingley: Emerald.

Lundvall. (2007). National Innovation Systems-Analytical Concept and Development Tool. *Industry and Innovation, 14*(1), 95-119.

Lundvall, B., & Christensen, J. (2007). *Product Innovation, Interactive Learning and Economic Performance.* Bingley: Emerald.

Lundvall, B., & Vinding, A. (2007). Product Innovation and Economic Theory -User- Producer Interaction in the Learning Economy. In J. Christensen, & B. Lundvall, *Product Innovation, Interactive Learning and Economic Performance* (Vol. 8, p. 101-128). Bingley, UK: Emerald.

Lundvall, B., Johnson, B., Anderson, E., & Dalum, B. (2002). National systems of production, innovation and competence building. *Research Policy*, 213-231.

Lundvall, B.-Å. (1985). *Product Innovation and User-Producer Interaction.* Aalborg: Aalborg University Press.

Lundvall, B.-Å. (1988). Innovation as an interactive process: from user-producer interaction to the national innovation system. In G. Dosi, C. Freeman, R. R. Nelson, G. Silverberg, & L. Soete, *Technical Change and Economic Theory.* London: Pinter.

Lundvall, B.-Å. (1992). *National System of Innovation. Towards a Theory of Innovation and Interactive Learning.* (B.-Å. Lundvall, Ed.) London: Pinter.

Lundvall, B.-Å., & Johnson, B. (1994). The Learning Economy. *Journal of Industry Studies, 1*(2), 23-42.

Malaver, F., & Vargas, M. (2013). Formas de innovar y sus implicaciones de política: lecciones de una experiencia. *Cuadernos de Economía, 60*, 537-570.

Martin de Holan, P., & Phillips, N. (2004). Organizational forgetting as strategy. *Strategic Organization, 2*, 412–430.

Menéndez, G. (2017). La revolución de la longevidad: Cambio tecnológico, envejecimiento poblacional y transformación cultural. *Revista de Ciencias Sociales, 30*(41), 159-178.

Nadler, D., & Tushman, M. (1997). The Power of Organization Architecture. *Oxford University Press*.

Nelson, R. R. (1993). *National Innovation System. A Comparative Analysis.* (R. R. Nelson, Ed.) New York: Oxford University Press.

Nelson, R., & Winter, S. (1982). *An Evolutionary Theory of Economic Change.* Boston, MA: The Belknap Press of Harvard University Press.

Nunes, S., López, R., & Días, J. (2013). Innovation modes and firm performance: the case of Portugal. *ERSA Conference.* Palermo.

Padgett, J. F. (1997). The emergence of simple ecologies of skill: a hypercycle approach to economic organization. In W. B. Arthur, S. N. Durlauf, & D. A. Lane (Edits.), *The Economy as an Evolving Complex System II.* Addison-Wesley: Reading MA.

Padgett, J. F., Lee, D., & Collier, N. (2003). Economic Production as Chemistry. *Industrial and Corporate Change, 12*, 843-877.

Padgett, J. F., McMahan, P., & Zhong, X. (2009). Economic Production as Chemistry II. *Working Papers*. Paper 10.

Parrilli, M. D., & Alcalde, H. (2016). STI and DUI innovation modes: Scientific-technological and context-specific nuances. *Research Policy, 45*, 747-756.

Parrilli, M. D., & Elola, A. (2012). The strength of science and technology drivers in SME innovation. *Small Bus. Econ., 39*, 897-907.

Penrose, E. T. (1959). *The Theory of the Growth of the Firm.* New York: John Wiley.

Ponsiglione, C., Quinto, I., & Zollo, G. (2014). Bridging the SKIN model to the debate on territorial innovation systems: the proposal of an agent-based model of self-sustaining regional innovation systems. *SKIN 3 Workshop Joining Complexity Science and Social Simulation for Policy.* Budapest: Eötvös Lorán University.

Pyka, A., & Scholz, R. (2008). A Narrative Description of the Agent Based NEMO-Model. *NEMO-Working paper*.

Pyka, A., Gilbert, N., & Ahrweiler, P. (2009). Agent-Based Modelling of Innovation Networks: The Fairytale of Spillover. In A. Pyka, & A. Scharnhorst (Edits.), *Innovation Networks. New Approaches in Modelling and Analyzing* (p. 101-126). Berlin: Springer-Verlag Berlin Heidelberg.

Quintero, S. (2016). Aprendizaje en los sistemas regionales de innovación: Un modelo basado en agentes. Medellín: Universidad Nacional de Colombia.

Quintero, S., & Giraldo, D. (2018). *El aprendizaje en los sistemas regionales de innovación desde la perspectiva de la modelación basado en agentes.* Medellín: Universidad Pontificia Bolivariana.

Quintero, S., Ruiz, W., & Robledo, J. (2017). Learning in the Regional Innovation System, An Agent Based Model. *Cuadernos de Administración, 33*(57), 7-20.

Robledo, J. (2016). *Introducción a la gestión de la tecnología y la innovación.* Medellín: Universidad Nacional de Colombia.

Rogers , E. (2003). *Diffusion of innovations.* New York: Free Press.

Rothwell, R. (1994). Towards the Fifth-generation Innovation Process. *International Marketing Review, 11*(1), 7-31.

Ruiz, W., Quintero, S., & Robledo, J. (2016). Impacto de los Intermediarios en los Sistemas de Innovación. *Journal of Technology Management & Innovation, 11*(2), 130-138. From https://www.jotmi.org/index.php/GT/article/view/2073/1030

Ruiz, W., Quintero, S., & Robledo, J. (2016). Impacto de los Intermediarios en los Sistemas de Innovación. *Journal of Technology Management and Innovation, 11*(2), 130-138.

Sargent, R. G. (2013). Verification and Validation of Simulation Models. (M. E. Kuhl, N. M. Steiger, F. B. Armstrong, & J. A. Joines, Edits.) *Journal of Simulation, 7*(1), 12-24.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal, 18*(7), 509-533.

Triulzi, G., Scholz, R., & Pyka, A. (2011). *R&D and knowledge dynamics in university-industry relationships in biotech and pharmaceuticals: An agent-based model.* FZID discussion papers.

Villalba, M. L., Ruiz, W., & Robledo, J. (2023). Configuration of inclusive innovation systems: Function, agents, and capabilities. *Research Policy*, 52 (7). https://doi.org/10.1016/j.respol.2023.104796.

Watts, C., & Binder, C. R. (2012). Simulating Shocks with the Hypercycles Model of Economic Production. In R. Seppelt, A. A. Voinov, S. Lange, & D. Bankamp (Ed.), *International Environmental Modelling and Software Society (iEMSs) 2012 International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet.* Leipzig: Sixth Biennial Meeting.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting.* New York: The Free Press A Division of Macmillan, Inc.

Annex 1. Mathematical Appendix: Formalization of the Adaptive Innovation Systems Model (AdaptISM)

A1.1. Formal model

This section provides a detailed explanation of the mathematics behind the Adaptive Innovation Systems Model (AdaptISM), the Agent-Based Model (ABM) we developed to delineate and analyse the dynamics of innovation systems under various Science, Technology, and Innovation (STI) policy scenarios. The model simulates interactions between agents (firms, universities, and intermediary organisations) and innovation opportunities (market and technological opportunities). Its purpose is to evaluate the effects of different policies on innovation performance, economic outcomes, and collaboration patterns within the system.

Definitions and Variables

a. **Innovation System** $\mathcal{S}$: A system define**d** $\mathcal{S} = (\mathcal{A}, \mathcal{O}, \mathcal{R}, \mathcal{P})$ where:

- $\mathcal{A}$: Set of agents.
- $\mathcal{O}$: Set of innovation opportunities.
- $\mathcal{R}$: Set of rules governing agent behaviour.
- $\mathcal{P}$: Policy environment.

b. **Agents** $\mathcal{A}$**:** agents $a_i \in \mathcal{A}$ are heterogeneous and defined by the following attributes:

- **Location (x_i):** Agents are situated in a spatial or abstract d-dimensional space ($\mathbb{R}^d$). This location can represent geographic proximity or network relationships, influencing how agents interact with opportunities and other agents.
- **Capability Vector ($\boldsymbol{CV_i}$):**

$$CV_i = [c_{i,1}, c_{i,2}, \dots, c_{i,6}], \qquad c_{i,j} \in [0,9] \tag{1}$$

where each element corresponds to a specific innovation capability: Research ($c_{i,1}$), Development ($c_{i,2}$), Diffusion ($c_{i,3}$), Association ($c_{i,4}$), Appropriation for Production ($c_{i,5}$), and Marketing Capacilities ($c_{i,6}$).

- **Surplus stock:** Each agent maintains a surplus ($S_i \in \mathcal{R}$), representing its available resources. Surplus evolves dynamically based on the agent's actions and interactions:

$$S_i(t+1) = S_i(t) + \Delta S_i(t) \tag{2}$$

Agents with insufficient surplus ($S_i(t) < 0$) exit the system.

c. **Innovation Opportunities** $\mathcal{O}$**:** Each opportunity $o_k \in \mathcal{O}$ is characterized by:

- An attribute vector $AV_k = [a_{k,1}, a_{k,2}, \dots, a_{k,6}], a_{k,j} \in [0,9]$, where j denotes an attribute (e.g., brand).

$$AV_k = [a_{k,1}, a_{k,2}, \dots, a_{k,6}], a_k, j \in [0,9] \tag{3}$$

- A volatility v_k, representing its lifespan in the system. Opportunities have a finite lifespan, modeled as volatility

$$v_k \sim U(v_{min}, v_{max}) \tag{4}$$

- A lifecycle ($L_k(t)$) that governs the temporal distribution of benefits delivered to agents. These benefits follow a Gaussian diffusion curve, characteristic of innovation diffusion patterns, ensuring that the opportunity delivers most of its benefits during the peak period while tapering off before and after this peak.

$$L_k(t) = \frac{1}{\varsigma_k \sqrt{2\pi}} e^{-\frac{(t-\omega_k)^2}{2\varsigma_k^2}} \tag{5}$$

where: ω_k is the time at which the opportunity's benefit peaks. And ς_k is the standard deviation representing the spread of the lifecycle curve.

When an opportunity is exploited, it distributes benefits to the agents (or coalitions) that fulfilled its attributes. The allocation is based on the **Attribute Contribution (**Benefits are proportional to the specific attribute fulfilled by the agent, weighted by the magnitude of the attribute and the associated capability involved) and the Lifecycle **Influence (**Benefits are distributed over the opportunity's lifecycle, following the Gaussian curve).

- A benefit function $B_k(t)$, Distributed across attributes and calculated using a Gaussian function:

$$B_k(t) = \sum_{j=1}^{6} \left(a_{k,j} \cdot \ income_j \cdot \frac{1}{\sigma_k \sqrt{2\pi}} e^{-\frac{(t-\mu_k)^2}{2\sigma}} \right) \tag{6}$$

where $income_j$ is the calibrated income per attribute.

a. **Policy Environment** ($\mathcal{P}$)**:** Policy modes $P_m \in \mathcal{P}$ modifies agent behaviour and opportunity dynamics through:

- **Capability Adjustment Rates ($\boldsymbol{\alpha_j}, \boldsymbol{\beta_j}$):** Policies influence how quickly agents learn (α_j) or unlearn (β_j) capabilities.
- **Opportunity Generation Rates (p_{MO}, p_{TO}):** Policies affect the probabilities of generating market (MO) and technological opportunities (TO): $p_{MO} \sim \lambda_k^{MO}, \ p_{TO} \sim \lambda_k^{TO}$
- **Capability Maintenance Costs ($\boldsymbol{C_j}$)**: Policies affect costs based on the emphasized capabilities:
    - **Mode I:** Prioritizes research and development capabilities. $\alpha_{R,D} = high, \alpha_{M,A,D,A} = low$

- **Mode II:** Enhances marketing and production capabilities. $\alpha_{M,P} = high, \alpha_{R,D,A} = low$
- **Mode III:** Encourages diffusion and collaboration. $\alpha_{D,A} = high, \alpha_{R,M,P} = moderate$
- **Mode IV (Combined):** A weighted combination of all policies.

Dynamics of the System

a. **Innovation Opportunity Generation:** Opportunities appear probabilistically at each timestep. The policy environment influences market and technological opportunities. Opportunities o_k appear at time t with probabilities:

- Market Opportunities (MO): Triggered by market demand, activating agents from exploitation to exploration (right to left in CV_i).

$$p_{MO} = f(P_m, t) = f(M_{policy}, Demand) \tag{7}$$

- Technological Opportunities (TO): Generated by agents with advanced research capabilities, activating agents from exploration to exploitation (left to right in CV_i). Geographically, TOs emerge at the location of the generating agent—typically one with high research capabilities. This spatial linkage underscores the localized nature of technological innovation.

$$p_{TO} = g(P_m, t) = g(T_{policy}, Capability_{R,D}) \tag{8}$$

Functions f and g depend on the policy environment.

b. **Capability Matching:** Agents match their capabilities (CV_i) with opportunity attributes (AV_k):

$$M(a_i, o_k) = \prod_{j=1}^{6} \mathbb{I}(c_{i,j} \geq a_{k,j}) \tag{9}$$

where $\mathbb{I}$ is an indicator function. If no single agent can match, a coalition (C) is formed based on proximity and complementary capabilities to pool capabilities: If $M(a_i, o_k) = 0$, agents form a coalition C such that:

$$CV_C = \sum_{a_n \in C} CV_n \, , with \ \mid C \mid \leq 6 \tag{10}$$

and:

$$\sum_{a_n \in C} c_{n,j} \geq a_{k,j}, \forall j \tag{11}$$

c. **Capability Evolution:** Capabilities $c_{i,j}$ evolve based on linkage, exploitation, learning and unlearning. Agents' capabilities evolve based on learning by doing:

$$c_{i,j}(t+1) = \begin{cases} c_{i,j}(t) + \alpha_j \cdot f_{learn}(t) - \beta_j \cdot \mathbb{I}_{unused}(j), & if\ Si(t) > 0 \\ 0, & if\ Si(t) \leq 0 \end{cases} \tag{12}$$

where:

$$f_{learn}(t) = \frac{1}{1 + e^{-k(t-\tau)}} \tag{13}$$

And

$$\mathbb{I}_{unused}(j) = \begin{cases} 1, & if\ c_{i,j}\ \ was\ not\ used \\ 0, & if\ c_{i,j}\ was\ used. \end{cases} \tag{14}$$

where $f_{learn}(t)$ and $\mathbb{I}_{unused}(j)$, are indicator functions, and α, β are learning/unlearning rates.

d. **Surplus Dynamics:** Surplus stock S_i is updated based on benefits from exploited opportunities, minus maintenance and transaction costs:

$$S_i(t+1) = S_i(t) + \sum_{o_k} \left[Bk(t) \cdot \mathbb{I}_{exploited}(o_k) - Cost_{cap}(a_i) - Cost_{trans}(C) \right] \tag{15}$$

- **Capability Maintenance Costs:**

$$Cost_{cap}(a_i) = \sum_{j=1}^{6} \gamma_j \cdot c_{i,j}(t) \tag{16}$$

- **Transaction Costs (Based on coalition structure):**

$$Cost_{trans}(C) = \frac{\kappa}{|C|} \tag{17}$$

e. **Agent Survival:** Agents with negative surplus ($S_i(t) < 0$) exit the system:

$$\mathcal{A}(t+1) = \mathcal{A}(t) \setminus \{a_i \mid S_i(t) < 0\} \tag{18}$$

f. **New Agent Entry:** New agents a_n enter the system with stochastically assigned CV_n:

$$CV_n \sim \mathcal{N}(\tau_{CV}, \xi_{CV}) \tag{19}$$

where τ_{CV} and ξ_{CV} are derived from empirical calibration according to the entrepreneurial dynamics of the context under study. The entry process can be fully random, with location and capability magnitudes determined arbitrarily, or stochastic, shaped by the composition of the simulated environment. A hybrid approach is also viable, where attributes are randomly generated within predefined ranges.

1) Performance Metrics

a. **Innovation Performance** (I):

$$I = \frac{1}{|\mathcal{A}|} \sum_{a_i \in \mathcal{A}} \sum_{j=1}^{6} c_{i,j} \tag{20}$$

Innovation performance is measured as the number of innovation opportunities exploited, which requires the capabilities of the participating agents or coalitions to fulfill all attributes of the opportunity.

b. **Economic Performance** (E):

$$E = \sum_{a_i \in \mathcal{A}} S_i(t) \tag{21}$$

c. **Survival Rate** (η):

$$\eta = \frac{|\mathcal{A}_{alive}(t)|}{|\mathcal{A}(t)|} \tag{22}$$

d. **Collaboration Intensity (ϕ):**

$$\phi = \frac{\sum_{C \in \mathcal{C}} |\ C\ |}{\mathcal{A}} \tag{23}$$

2) Policy Dynamics

Policies influence:

i. **Learning and unlearning rates** (α_j, β_j).

ii. **Opportunity generation rates** (p_{MO}, p_{TO}).

iii. **Collaboration incentives** (κ).

iv. **Capability Maintenance Costs** ($Cost_{cap}(a_i)$)

Simulation and Analysis

- Simulate $\mathcal{S}$ over T periods for each policy scenario.

- Compare metrics I, E, η across scenarios to determine optimal policy interventions.

A1.2. Agent Typologies and Capability Classification in AISM

Capability Vector (CV)	Classification Criteria	Agent Type	Description	Transaction Cost
High $c_{i,1}$ (Research) and $c_{i,2}$ (Development)	$c_{i,1}, c_{i,2} \geq 4.5$, $Rest < 4.5$	Explorer	Focused on exploration activities, such as research and development.	Low when paired with another Explorer or Diffuser or Gatekeeper; High when paired with a Latecomer or Exploiter; Medium with Introductor and Integrated
High $c_{i,3}$ (Diffusion) and $c_{i,4}$ (Association)	$c_{i,3}, c_{i,4} \geq 4.5$, $Rest < 4.5$	Diffuser	Specializes in connecting and disseminating knowledge and technologies.	Low when paired with another Diffuser, Explorer, Exploiter, Gatekeeper, Integrated, Ambidextrous, or Introductor; Medium with Latecomer.
High $c_{i,5}$ (Appropriation) and $c_{i,6}$ (Marketing)	$c_{i,5}, c_{i,6} \geq 4.5$, $Rest < 4.5$	Exploiter	Focused on exploiting existing knowledge, production, and market outreach.	Low with Intermediary or Introductor; High with Latecomer.
High $c_{i,3}$ (Diffusion) and $c_{i,5}$ (Exploitation)	$c_{i,3}, c_{i,4} \geq 4.5, c_{i,5}, c_{i,6} \geq 4.5, Rest < 4.5$	Introductor	Combines strong intermediation and exploitation capabilities to integrate Research results into practical applications.	Low when paired with Diffuser or another Introductor or Exploiter; medium with Explorer or Gatekeeper or Integrated or Ambidextrous; high with Latecomer.
High $c_{i,1}$ (Research) and/or $c_{i,2} \geq$ (Development), and high $c_{i,3}$ (Diffusion) and/or $c_{i,4}$ (Association)	$c_{i,1}, c_{i,2} \geq 4.5, c_{i,3}, c_{i,4} \geq 4.5, Rest < 4.5$	Gatekeeper	Facilitates collaboration and technology foresight between agents but lacks strong exploitation capabilities.	Low with Explorer or Diffuser or another Gatekeeper; Medium with Ambidextrous or introductor or Integrated or Exploited agents; High with Latecomer.
High $c_{i,1}$ (Research) and/or $c_{i,2} \geq$ (Development), and high $c_{i,5}$ (Appropriation) and/or $c_{i,6}$ (Marketing)	$c_{i,1}, c_{i,2} \geq 4.5, c_{i,5}, c_{i,6} \geq 4.5, rest < 4.5$	Ambidextrous Agent	Balances exploration and exploitation but lacks strong intermediation.	Low with another Ambidextrous or Diffuser or Integrated; Medium with Explorer or Exploiter or Introductor or Gatekeeper agents; High with Latecomer.
High $c_{i,1}$ (Research) and/or $c_{i,2}$ (Development), $c_{i,3}$ (Diffusion) and/or $c_{i,4}$ (Association), $c_{i,5}$ (Appropriation) and/or $c_{i,6}$ (Marketing)	$c_{i,1}, c_{i,2} \geq 4.5, c_{i,3}, c_{i,4} \geq 4.5, c_{i,5}, c_{i,6} \geq 4.5$	Integrated Agent	Combines exploration, diffusion, and exploitation functions effectively.	Low when paired with another Integrated agent; High with a Latecomer.
Low $c_{i,j}$ across all dimensions	$c_{i,j} < 4.5$ for all j	Latecomer	Lacks specialized capabilities, representing latecomers or nascent entities.	High with most agent types except Medium with Diffuser, as limited capacities increase transaction costs.

A1.3. Timeline of Events

(1) Start Simulation: Initialize the model with parameters and prepare for the first timestep.
(2) Initialize Simulation Parameters: Randomly assign Agents (Capability vectors, surplus, and locations) and Opportunities (Attribute vectors, locations, volatility, product lifecycle and benefits)

- Set the total number of timesteps T.
- Define policy parameters: Learning rates α_j ; Unlearning rates β_j. Maintenance cost coefficients γ_j .
- Transaction cost coefficient κ, which depend on agent typologies in coalitions.
- Initialize performance metrics.

(3) Initialize Agents:

- Create a set of agents $\mathcal{A}$.
- For each agent a_i:
  - Assign location x_i.
  - Initialize capability vector $CV_i = [ci, 1, ci, 2, \dots, ci, 6]$
  - Set initial surplus S_i.

(4) **Initialize Innovation Opportunities**

- Create an initial set of opportunities $\mathcal{O}$.
- For each opportunity o_k:
  - Assign attribute vector $AV_k = [a_{k,1}, a_{k,2}, \dots, a_{k,6}]$.
  - Set volatility ν_k.
  - Set Lifecycle $L_k(t)$.
  - Define the benefit function $B_k(t)$ for each attribute.

(5) Loop Over Timesteps ($t = 1$ to T): Iterate through a defined number of timesteps.

a. Generate New Opportunities –

Differentiate between Market Opportunities (MO) and Technological Opportunities (TO):

- Market Opportunities (MO):
  - Driven by market needs (demand-pull).
  - Activation follows a market pull mechanism, completing attributes right-to-left (exploitation to exploration).
- Technological Opportunities (TO):

- Generated by agents with high research capabilities (supply-driven).
- The Research attribute equals the generating agent's capability, while other attributes are randomly assigned.
- Activation follows a technology push mechanism, completing attributes left-to-right (exploration to exploitation).

- Localization in Opportunity Generation:
  - Local proximity plays a significant role in link generation and coalition formation, acknowledging regional innovation systems literature.

b. Evaluate Existing Opportunities - For each opportunity o_k in $\mathcal{O}$: - **Check Opportunity Lifespan** - If $\nu_k \leq 0$, remove o_k from $\mathcal{O}$. - Else, decrement ν_k by 1. - **Calculate Current Benefit** - Compute $B_k(t)$ for each fulfilled attribute j, reflecting its magnitude and the agent's contribution.

c. Agent-Opportunity Matching - For each agent a_i in $\mathcal{A}$: - **Capability Matching**:

- Agents assess their proximity to opportunities and compare capabilities to attributes.
- Matching proceeds sequentially based on MO or TO dynamics (right-to-left for MO, left-to-right for TO).
- If the agent's capabilities meet or exceed the attribute requirements, the agent engages directly.
  - Otherwise, proceed to coalition formation.

d. Coalition Formation - Form Potential Coalitions - Identify groups of agents whose combined capabilities meet AV_k. Consider proximity and complementary capabilities. Limit coalition size to a maximum of 6 agents. - Evaluate Coalitions - For each potential coalition C: - Check if $\sum a_n \in C\ c_{n,j} \geq a_{k,j}$ for all j. - If true, coalition can exploit o_k.

e. Exploit Opportunities - Distribute Benefits:

- Benefits are allocated based on attribute contributions:
  - Agents contributing more to fulfilling a specific attribute j receive a larger share of $B_{k,j}(t)$.
- Benefit distribution reflects attribute magnitudes and the agent's role.

- Deduct Costs - Capability Maintenance Costs - For each agent a_i: $Cost_{cap}(a_i) = \sum_{j=1}^{6} \gamma_j \cdot c_{i,j}(t)$

- Transaction Costs - For each coalition C: $Cost_{trans}\ (C) = \frac{|C|}{\kappa}$.- Shared among coalition members based on their link-specific costs. - Update Surplus - For each agent a_i: $S_i(t+1) = S_i(t) + Benefit_i - Cost_{cap}(a_i) - Cost_{trans}(a_i)$. - Update Capabilities - Learning (Used Capabilities) - Increase capabilities used in exploiting opportunities: $c_{i,j}(t+1) = c_{i,j}(t) + \alpha_j \cdot f_{learn}(t)$, where $f_{learn}(t)$ is the learning function. - Unlearning

(Unused Capabilities) - Decrease capabilities not used: $c_{i,j}(t+1) = c_{i,j}(t) - \beta_j \cdot \mathbb{I}_{unused}(j)$.

f. Agent Exit and Entry - Agent Survival Check - If $S_i(t+1) \ < \ 0$, agent a_i exits the system. - Introduce New Agents - With a certain probability, new agents enter the system with initial capabilities and surplus.

g. Update Performance Metrics - Innovation Performance, Economic Performance, Survival Rate and Collaboration **Intensity**.

(6) End of Simulation
(7) Analyse Results: Compare performance metrics across different policy scenarios and interpret how policies impacted innovation capabilities, economic outcomes, and collaboration.

A1.4. Variables of the AdaptISM model and Descriptions

Symbol	**Name**	**Meaning**
$\mathcal{S}$	Innovation System	The set of agents, opportunities, rules, and policies defining the system.
$\mathcal{A}$	Set of Agents	The collection of all agents (firms, universities, intermediaries, etc.).
$\mathcal{O}$	Set of Opportunities	The collection of market and technological opportunities.
$\mathcal{R}$	Rules	Behavioral rules governing how agents interact and evolve.
$\mathcal{P}$	Policy Environment	External factors (policies) influencing the system's dynamics.
a_i	Individual Agent	A single agent within the system, characterized by its capabilities.
o_k	Individual Opportunity	A single innovation opportunity within the system.
x_i	Location of Agent	The spatial or abstract location of agent a_i.
x_k	Location of Opportunity	The spatial or abstract location of opportunity o_k.
CV_i	Capability Vector	A 6-dimensional vector representing the capabilities of agent aia_iai.
$c_{i,j}$	Individual Capability	The jjj-th capability of agent aia_iai, where $j \in \{1, \ldots, 6\}$
AV_k	Attribute Vector	A 6-dimensional vector defining the requirements of opportunity o_k.
$a_{k,j}$	Individual Attribute	The j-th attribute of opportunity o_k, where $j \in \{1, \ldots, 6\}$
S_i	Surplus Stock	The economic resources available to agent a_i.
ν_k	Volatility	The lifespan of opportunity o_k.
λ_k	Opportunity Generation Rates	Probability of generating market (MO) or technological (TO) opportunities.
$L_k(t)$	Lifecycle	Temporal distribution of benefits for opportunity o_k, typically Gaussian in form
ω_k	Peak Benefit Lifecycle Time	Time at which the lifecycle benefit peaks.
ς_k	Standard Deviation of Lifecycle Benefit	Standard deviation representing the spread of the lifecycle curve
$B_k(t)$	Benefit Function	The time-dependent benefit of exploiting opportunity o_k.
μ_k	Peak Benefit Time	The timestep when the benefit of o_k is maximized.
σ_k	Standard Deviation of Benefit	Controls the spread of the benefit function for o_k.
α_j	Learning Rate	Rate at which agents improve capability j.
β_j	Unlearning Rate	Rate at which unused capabilities decay.
γ_j	Maintenance Cost Coefficient	Cost to maintain one unit of capability j.
κ	Transaction Cost Coefficient	Cost associated with forming and maintaining coalitions.
p_{MO}	Market Opportunity Probability	Probability of generating a new market opportunity.
p_{TO}	Technological Opportunity Probability	Probability of generating a new technological opportunity.

$\mathbb{I}$	Indicator Function	Evaluates whether a condition is met (1 if true, 0 otherwise).
$M(a_i, o_k)$	Matching Function	Determines if agent a_i can exploit opportunity o_k.
C	Coalition of Agents	A group of agents pooling their capabilities to exploit an opportunity.
$\mathcal{C}$	Set of Coalitions	The collection of all coalitions formed in the system.
$f_{learn}(t)$	Learning Function	A sigmoid function defining how quickly agents learn from experience.
$I(t)$	Innovation Performance	Percentage of innovation opportunities exploited.
$E(t)$	Economic Performance	Total surplus of all agents at time t.
$\eta(t)$	Survival Rate	Proportion of agents that remain in the system at time t.
$\phi(t)$	Collaboration Intensity	Average size of coalitions relative to the number of agents.

Annex 2. Calibrating the AdaptISM Model: Insights from Antioquia's Agricultural Production Chains

The calibration of the model was grounded in empirical data and qualitative insights gathered through interviews with stakeholders in the Antioquia agricultural production chains (APCs), including farmers, cooperative managers, R&D professionals, and policymakers. These data informed the characterisation of agents, represented by six-dimensional capability vectors normalised to reflect observed capacities, as well as the distribution and complexity of technological opportunities. The spatial configuration of agents and opportunities was aligned with the geographically dispersed and heterogeneous innovation landscape described by stakeholders. Interview data were also instrumental in defining the dynamics of the system, such as opportunity emergence rates, learning and unlearning processes, and transaction costs, ensuring consistency with the reported behaviours and interactions within the APCs. For example, the coffee APC's high barriers to entry and limited R&D capacity led to slower entry rates and fewer opportunities, while the avocado APC, characterised by stronger exploratory agents and emerging market demand, displayed more frequent entry and higher innovation capacity. These calibrations allowed the model to reflect the structural and behavioural diversity inherent in the Antioquia APCs.

Systems initial conditions:

Table A2.1 shows the initial parameters used to calibrate and validate the model for each APC.

Table A2.1. Coffee and Avocado APC parametrisation

Parameter	APC Coffee	APC Avocado	Technical Note
Initial n. of market opportunities	100	100	Interview results for both APCs were normalised for scenario comparability.
Initial no. of firms	100	100	Both markets show a high global demand for innovations.
Market opportunity appearance rate	15%	20%	Both markets exhibit dynamic opportunities, especially in the avocado market.
Entrepreneurial rate	2%	8%	The avocado APC shows greater entrepreneurial activity due to market growth and pricing.
Learning factor	0.4	0.3	Coffee APC agents require higher learning rates due to intense competition.
Unlearning factor	0.1	0.4	Tradition in Antioquia APCs slows unlearning by adhering to established routines.
Market opportunities learning factor	0.4	0.5	Avocado properties drive market learning and increase demand.
Random volatility	Yes	Yes	Both markets are highly volatile due to high innovation intensity.
Initial surplus stock	800	3000	The avocado APC requires more significant initial investment for market entry.
Life-cycle time	10	10	Both APCs are dynamic in terms of new product offerings and demand.

Maximum volatility	5	5	Given the existence of an extensive range worldwide, volatility is accelerated.
Low transaction cost	0.1	1	Given its traditional component, trust in the coffee APC is higher.
Medium transaction cost	0.5	1.25	Given its traditional component, trust in the coffee APC is higher.
High transaction cost	1	1.5	Given its traditional component, trust in the coffee APC is higher.
Income per attribute	10 (per unit)	10 (per unit)	Innovation is profitable in both APCs but less so for coffee commodities.
Capability Maintenance cost	1 (per unit)	1 (per unit)	Public STI policies are similar in both APCs but mostly generic.
Technological opportunity generation threshold	4.5	7	Speciality coffee behaviours highlight the stronger impact of STI policies in the coffee APC.

Table A2.2 shows the average results after a series of simulations with the model parameters set as described.

Table A2.2. Average innovation capability for each APC over time obtained through the simulation model

	APC Coffee			APC Avocado		
Average Innovation Capacity	**2008**	**2013**	**2018**	**2008**	**2013**	**2018**
Research	0.15	0.20	0.22	1.47	1.35	1.20
Development	0.16	0.21	0.22	1.31	1.32	1.17
Diffusion	0.99	1.07	1.12	2.91	2.97	2.80
Association	1.31	1.41	1.50	3.69	3.89	3.64
Appropriation	0.99	1.14	1.40	2.62	2.73	2.54
Marketing	0.19	0.32	0.48	1.87	2.05	1.90

The comparison between the simulation model and the real system is shown in Table 5.

Table A2.3. Difference between capabilities in the real system and the model in absolute terms

	APC Coffee			APC Avocado		
Average Innovation Capacity	**2008**	**2013**	**2018**	**2008**	**2013**	**2018**
Research	0.00	0.04	0.03	0.00	0.21	0.34
Development	0.00	0.06	0.06	0.00	0.32	0.38

Diffusion	0.01	0.01	0.07	0.00	0.11	0.00
Association	0.00	0.00	0.08	0.00	0.58	0.60
Appropriation	0.00	0.05	0.12	0.00	0.36	0.14
Marketing	0.00	0.06	0.06	0.00	0.00	0.31

The analysis demonstrates that the model accurately replicates the real behaviour of the APCs, particularly the coffee APC, where the largest deviation from the real value occurs in the appropriation capability, with an error of only 1.33%. As a newer and more emergent system, the avocado APC presents greater challenges for precise representation. Even so, the results are highly satisfactory, with the association capability showing the largest deviation at 6.67%, while deviations for other capabilities are approximately half this value.

Based on these findings, we conclude that the model has been successfully validated. This validation allows us to proceed to the next phase, conducting experiments to gain deeper insights into the effects of STI policies on innovation systems, specifically in the coffee and avocado APCs considered innovation systems.