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Original article

Absorptive capacity in a two-sector neo-Schumpeterian model: a new role for innovation policy

Isabel Almudi,[1] Francisco Fatas-Villafranca,[2] Carlos M. Fernández-Márquez,[3] Jason Potts,[4,*] and Francisco J. Vazquez[5]

[1]University of Zaragoza. e-mail: ialmudi@unizar.es, [2]University of Zaragoza. e-mail: ffatas@unizar.es, [3]Universidad Autónoma de Madrid. e-mail: carlosm.fernandez@uam.es, [4]RMIT University. e-mail: jason.potts@rmit.edu.au and [5]Universidad Autónoma de Madrid. e-mail: franciscojose.vazquez@uam.es

*Main author for correspondence.

Abstract

We propose a new *co-evolutionary* computational *two-sector approach* to the design of national innovation policy that recognizes the importance of intersectoral *absorptive capacity* constraints in innovation linkages between sectors in an economy. We show how the innovative capacity of an upstream producer sector can be constrained by the absorptive capacity of the downstream-user sector. This suggests that the low productivity performance of modern innovation policy might in part be understood as a consequence of sectorally unbalanced knowledge evolution, where the problem lies in underinvestment in innovative capabilities in the downstream sector. Our computational two-sector model suggests an important role for innovation policy to create a balanced, sectorally targeted approach.

JEL classification: B52, C63, O31

1. Introduction

Modern *innovation policy* is built on two foundational support pillars: one, economic theory of the production of new information under uncertainty (Nelson, 1959; Arrow, 1962a); and two, the evolutionary economic model of innovation diffusion (Schumpeter, 1939; Nelson and Winter, 1982). The product is a policy suite of institutional solutions to market failure to support innovating firms to adopt new technologies and to develop new markets and industries (Martin and Scott, 2000). It is generally regarded as incidental, or at least analytically expedient, that this entire logic is formulated within a representative market and representative industry context. Market failure occurs in a sector. Innovation diffusion occurs across a sector. Specifically, consideration of how other sectors affect innovation in a target sector is generally treated as a potentially interesting but fundamentally second-order effect—an additional complexity, as it were—in what is essentially a monosectoral analysis.

The absence of a multisectoral approach in modern innovation policy is striking when compared to its centrality in the modern *innovation strategy* literature, which builds on the same evolutionary economic foundations—namely Schumpeter's model of an industrial trajectory and Penrose's model of firm capabilities—but instead follows Coase's transaction cost line of analysis to consider how innovation creates value in firms by assembling capabilities within organizational boundaries. A multisectoral approach is fundamental to strategic analysis of innovation because value creation in complex technological systems is an interdependent process across multiple firms. Such analysis of the balance of knowledge thereby requires understanding how firm capabilities are arrayed across value chains and within industry architectures, and how these in turn give rise to business ecosystems (Rosenberg, 1969; Teece *et al.*, 1997; Jacobides *et al.*, 2006; Adner and Kapoor, 2010). Being highly attuned to modular structure, complementarities, interdependencies, and bottlenecks in the innovation process (Adner and Kapoor, 2016; Baldwin, 2018), the innovation strategy literature is foundationally multisectoral.

Yet, nothing in the innovation policy mandate actually requires a multisectoral approach, nor implies that specific concern with the intersectoral balance of knowledge is the fundamental problem to be solved. Indeed, modern innovation policy has always had a singular direction of intersectoral attention, namely that all problems originate upstream with weak market incentives to basic science and technology development. Innovation policy has of course developed a long way from the linear model (Bush, 1945). However, the basic analytic formulation of technology creation in firms and diffusion in markets has made innovation policy largely self-contained within an industry, as per the framework of industrial dynamics. Equivalently, this perspective is commonly applied to an entire economy, in which innovation is "upstream" of consumer markets, and in which innovation policy seeks to furnish the institutions of an innovation system (Nelson, 1993). While economists and policy-makers have long observed that constrained downstream factors, such as sophisticated demand, can block upstream development of innovation (Saviotti and Pyka, 2013), or that technological innovation can overshoot a market (Earl and Potts, 2013, 2016), modern innovation policy still lacks a well-developed analytic framework through which to study the effects of intersectoral structure and coordination, as for instance through bottlenecks such as the balance of capabilities, technological overshooting, and absorptive capacities.

This article will develop a new analytic framework to study how innovation policy works in a multisectoral economy. We propose a new class of co-evolutionary computational model that is designed to explore multisectoral innovation interdependence (although we simplify this to a two-sector upstream/downstream model for analytic convenience). Our model uses properties of the Beta distribution (specifically its skew) to model institutional scenarios in which certain parameters correspond to alternative innovation policy settings. We develop a model that builds on Nelson and Winter (1982), Almudi *et al.* (2013), and Dosi *et al.* (2013) that consists of a two-sector neo-Schumpeterian economy with an "upstream" capital goods producer sector, and a "downstream" user sector. It provides a general framework for analyzing how the innovation properties of one sector can affect innovation properties of another, providing an agent-based computational model of the co-evolution of an innovation ecosystem. An implication of our model is to show how knowledge coordination failures can cause intersectoral innovation bottlenecks in the form of absorptive capacity constraints that backpropagate between firms, and can thus become a new target for innovation policy.

Innovation strategy scholars have long emphasized the importance of dynamic competence, bottlenecks, and industry architectures to an understanding of how innovation creates value in complex technology systems. Our core contribution is to propose a new class of analytic model to translate these insights from firm strategy into implications for policy analysis. We do this by representing the strategies and capabilities of innovating firms as outcomes from statistical distributions operating in a complex model, as a result of these firms learning by doing and adaptation. We characterize bottlenecks arising from overshooting and absorptive capacity constraints in our multisector model as knowledge coordination problems by representing these with the simulated probability of collapse of intersectoral trading. Our stochastic computational model can show how different policy settings that affect the institutional properties of one sector of an economy—over parameters such as a firm's absorptive capacity for a sectoral technology (what we will call the "understanding radius")—are dynamically interdependent with innovation properties of firms in other sectors. With these new theoretical concepts and analytic techniques, we are able to propose a multisectoral economic model to guide innovation policy.

We proceed as follows. In Section 2, we present the theoretical background. Section 3 explains the model in a descriptive manner. This explanation can be completed with the corresponding formal structure, with technical details presented in Appendices A and B (provided online). Section 4 presents the computational analysis of the model and results. We pay special attention to the novelties regarding the role of absorptive capacity in intersectoral co-evolution and innovation. To show the relevance of our results, we relate our findings to two specific examples: The puzzle of commercial supersonic aviation failed technology and the challenges posed by advanced robotics to be successfully implemented in the factory of the future. Finally, the implications of our co-evolutionary model for innovation theory and policy are offered in conclusion, along with lines for future empirical and theoretical research.

2. Theoretical background

The neo-Schumpeterian economics that underpins modern innovation policy largely focuses on fostering innovation through design of supporting institutions complementary to entrepreneurial knowledge-creating innovating firms. The most developed bodies of theoretical work that support innovation policy in this stream are those around the concepts of National Innovation Systems (Freeman, 1987; Lundvall, 1988, 1992; Nelson, 1993) and Sectoral Systems of Innovation (Malerba, 2005), both derived from the industrial dynamics literature. These policy supporting literatures explore the roles of specific institutions that facilitate the sharing of knowledge, skills, and resources that are necessary for technological change to occur. It is nevertheless remarkable that both the contributions on national systems of innovation and on sectoral systems of innovation dismiss the detailed study of multisectoral interactions. This analytic propension has been corrected to a certain extent by those evolutionary economists dealing at the meso-to-macro levels with structural change and the emergence of economic growth (Dosi *et al.*, 2013; Saviotti and Pyka, 2013).

The lack of a multisectoral approach from the knowledge coordination perspective is surprising, since the idea of *technological imbalances* has long been recognized as central to understand the direction of technological change. According to Rosenberg (1969) technological imbalances (or bottlenecks) arise when complex technologies explore forward and backward linkages creating complex and interlinked technological trajectories. Technological change can be seen as a set of exploratory activities that stimulate change in complementary processes. Therefore, knowledge coordination problems caused by technological imbalances or bottlenecks may arise in any direction of the search space, blocking further developments of interconnected technologies. To unblock specific technological trajectories requires effective design of institutional frameworks with engagement and participation by a range of organizational players involved in technological change.

Unlike the innovation policy approach, the multisectoral approach to innovation is well developed in the organizational strategy literature. Management scholars have focused on innovation strategy, that is, the strategic dimensions through which the innovating firm creates and captures value. This literature is centered about the concepts of capabilities, industry architectures, and ecosystems (Baldwin and Clark, 2000; Jacobides, 2008; Adner and Kapoor, 2010; Jacobides *et al.*, 2018,). Sectors are seen as complex architectures with clear complementarities in knowledge and complex vertical and horizontal interconnected links among organizations (Jacobides *et al.*, 2016; Kapoor, 2018). Value chain dynamics and change is explained because of the mutual influence of interconnected knowledge and links among organizations (Teece *et al.*, 1997; Jacobides *et al.*, 2006). In this sense, the importance of understanding vertical adjoining segments and the circumstances under which bottlecknecks can emerge have been explicitly recognized in this context (Adner, 2012, 2017; Jacobides *et al.*, 2014; Jacobides and Tae, 2015; Baldwin, 2018).

There is a lack of theoretical work in economics focused on potential multisectoral knowledge coordination problems and the policy implications that follow. We have developed a two-sector model in which technological unbalances and bottlenecks can arise intersectorially in which *technological overshooting* occurs because of a lack of *intersectoral absorptive capacity*. We develop a model in which different parametric setting can be posed, representing different institutional frameworks, as mechanisms of innovation policy control. The following sections discuss our assumptions and results in terms of the existing literature.

2.1 A multisectoral approach to innovation policy

Sectoral knowledge capacities are interconnected. Absorptive capacity (i.e. bottleneck) constraints in a sector limit the value of innovation that is complementary to that sector. Conversely, innovation developments in one sector can overshoot adoption and use capabilities in another sector. This has important implications for innovation policy.

In the multisectoral approach, the innovation prospects and capabilities in one sector affect the innovation prospects of another. Moreover, these relationships flow forward and backward; underinvestment in an upstream sector can limit the prospects of a downstream sector, just as the capabilities of a downstream sector can constrain an upstream sector. New theory and evidence now consistently emphasizes the reality and consequence of unbalanced sectoral knowledge and the multisectoral complexity of market linkages, technological interdependencies, industrial architectures, and innovation ecosystems (Pitelis, 2012; Adner, 2017; Jacobides *et al.*, 2018). A growing finding in modern innovation economics is that evolutionary technical change is widely characterized by extreme interfield unevenness and, moreover, that technological progress emerges from the co-evolution of practice and understanding in coupled multisector domains (Dosi and Grazzi, 2010; Dosi and Nelson, 2010; Nelson, 2012). The upshot of the incipient "multisectoral revolution" in innovation theory is a growing awareness that innovation policy may also require fundamental reconsideration.

A core component of this growing recognition is the prospect that innovation policy might work differently in a multisectoral economy compared to a single sector economy. To show how this can be, we develop a new class of computational model (an agent-based co-evolutionary model) built around two key mechanisms in the multisectoral revolution: *aborptive capacity* (Cohen and Levinthal 1990; Zahra and George, 2002) and *innovation overshooting* (Earl and Potts, 2013, 2016; Almudi *et al.*, 2018). Absorptive capacity is an ability to adopt, understand and make use of a technology or capability originating in another sector. We suppose that innovation in each sector is characterized by Schumpeterian competition in which heterogeneous firms develop and co-evolve within spaces of performance and price determined by R&D spending and technological learning. Overshooting occurs where the technological capabilities developed in one sector exceed the absorptive capacity constraints of the other sector owing to unbalanced knowledge development incentives. Our model of unbalanced sectoral knowledge in a multisector context can help to explain the low productivity performance of modern innovation policy as a consequence of downstream bottlenecks and suggests a new role and rationale for innovation policy. For instance, advanced technology procurement by the public sector can be effective as demand-side innovation policy.

2.2 The multisectoral approach in economics

Our model, which builds on Nelson and Winter (1982), Almudi *et al.* (2013), and Dosi *et al.* (2013), consists of a two-sector neo-Schumpeterian economy with an "upstream" capital goods producer sector, and a "downstream" user sector in which capital goods are acquired and used to produce consumption goods for final consumers. Absorptive capacity limitations in the downstream sector constrain innovation in the upstream sector. Innovation overshooting is due to unbalanced Schumpeterian competition between different sectors. We identify in unbalanced intersectoral knowledge a general coordination failure problem in innovation, and not just a bilateral problem in capital and consumer goods sectors.

The multisectoral modeling tradition in economics originates in Leontief-type input-output (IO) models that connect sectors of an economy through flows of commodities and payments. IO-type models have long been a workhorse of macroeconomic planning and policy (Chenery, 1960). By integrating prices and microfoundations, general equilibrium models (e.g. CGE, DSGE) developed in the 1980s have subsumed the IO approach. Both IO and GE models are designed to represent industrial market economies where the main constraints between sectoral flows are factor supply and demand for commodities expressed in income and prices. These models have been optimized to macroindustrial planning (IO models for *industry policy*) and macrodynamic forecasting (GE models for *competition policy*, Aghion and Griffith 2005). However, less attention has been afforded to a related but different problem in a Schumpeterian economy, namely unbalanced intersectoral knowledge and the innovation constraints this causes. Consequently, the multisectoral approach has proven less useful in the context of *innovation policy*, which has instead used an institution-centered innovation systems approach (Nelson, 1993; Etzkowitz and Leydesdorff, 2000; Foray *et al.*, 2009; Edler and Fagerberg, 2017).

This matters, because IO and GE approaches struggle to explain low aggregate productivity measures on public sector R&D and innovation policy widely reported across OECD nations (Jaumotte and Pain, 2005). In the "basic-science technology-push" model, the practical innovation policy prescription is to target the source of market failure (Nelson, 1959; Arrow, 1962a; Martin and Scott, 2000; Trajtenberg, 2012). This is equivalent to a single sector innovation target in our multisectoral approach. However, if absorptive capacity between sectors is a more general constraining factor, as we argue here, then market failure targeting may lead to overshooting. This will manifest in misallocation of innovation spending and low absorptive capacity. Alternatively, our multisectoral approach predicts that an unbalanced distribution of innovation policy may produce multisectoral innovation blockages and bottlenecks, leading to a slow-down of productivity growth or to sectorally bounded search and innovation processes. Such outcomes are easily misdiagnosed as demand-side failures, or adoption–diffusion constraints rather than their true cause, according to our model, in unbalanced sectoral knowledge. As we will show, if we analyze innovation as resulting from the co-evolution of interlinked sectors, subject to the possibility of knowledge coordination problems, then new arguments for current vivid debates on the innovativeness of modern economies emerge (Gordon, 2012; Mokyr, 2017).

2.3 Balanced economic change in knowledge and innovation

Systemic innovation requires balanced sectoral knowledge, which requires solving a meso–macro coordination problem. The consequences of unbalanced sectoral knowledge are wasted resources and capabilities, but also frustrated advance or even sectoral collapse. Examples can be contemporaneously observed in green energy technologies, where retail and consumer adoption constraints are limiting upstream deployments of more advanced technologies. Further examples are in distributed ledger technologies where downstream regulatory barriers and consumer learning barriers constrain adoption of cryptocurrency payments and smart contracts into mainstream financial services, causing investment overshooting of blockchain infrastructure (Davidson *et al.*, 2018). Similar claims can reasonably be made with respect to genetic engineering and artificial intelligence technologies, where the relevant innovation constraint does not necessarily lie with the fundamental science and translational engineering, but with the absorptive capacities in downstream consumer-facing health, agricultural and financial sectors.

In a perfectly *balanced innovation economy*, every sector can absorb and adopt technologies from every other sector. In such an economy, sectoral innovation constraints are purely a consequence of variation in resources, prices and income, as in IO and GE models. Note that the standard absorptive capacity literature focuses on intrasectoral constraints, not intersectoral constraints. However, in an *unbalanced innovation economy*, absorptive capacity constraints (i.e. bottlenecks) in a sector—because of prior experiential learning (Dosi *et al.*, 2005; Arrow, 1962b) or because of weak user-firm dynamic capabilities—limit its ability to adopt technologies from another sector, which in turn reduces the demand for technological advances. In this way, the innovation choices of firms in different sectors interlink. Constrained R&D in a downstream sector can limit innovation in the upstream sector through absorptive capacity constraints. We characterize this as an intersectoral knowledge coordination problem, with excess innovation spending in one sector and too little absorptive capacity in a connected sector. The consequence of an *unbalanced innovation economy* is the inefficient waste of private and public innovation effort because benefits fail to diffuse, owing to absorptive capacity constraints.

3. The model

This section describes our agent-based computational neo-Schumpeterian model of a multisectoral economy (Metcalfe *et al.*, 2006; Dosi *et al.*, 2013; Saviotti and Pyka, 2013). The model description can be completed with the equations, technical details, and the pseudocode in Appendices A and B. To simplify, we constrain the model to just two sectors, each containing a population of heterogeneous firms, and with each firm operating over several dimensions. In Sector 1 different and gradually improved varieties of a capital-good (machines) are produced and sold to Sector 2. In Sector 2, different varieties of a final good are produced by firms and sold to consumers. Firms in downstream Sector 2 buy different varieties of machines from the upstream Sector 1 and produce specific varieties of the consumption good for final consumers.

Firms producing and offering machines in Sector 1 compete in price and quality (i.e. machine-performance). They fix prices according to a modified-pricing rule (Winter, 1984; Vives, 2001; Bloch and Metcalfe, 2018) with a markup that evolves according to each firm's changing market power, and according to each firm's estimates of its close competitor's market power. This is a simple and novel way to incorporate (intrasectoral) strategic interactions in an evolutionary model. Each firm then charges an endogenously changing margin on expected unit cost. Unit cost includes a unit production cost, which is common and constant across firms, and a unit R&D-cost (*ex ante* to fix prices, and realized *ex post* to calculate real *ex post* profits once the market has operated). R&D intensity in a firm is a firm-specific behavioral trait, as a lagged proportion of profits. Likewise, we model firm performance in Sector 1 as a relative and normalized specific dimension that evolves through innovation. Each firm in Sector 1 produces machines up to the demand point of users from Sector 2. The demand captured by each firm in Sector 1 probabilistically depends on both the offerings over price and quality dimensions of its machines. Each firm in Sector 2 buys at most one machine per period of time. Machines fully depreciate and disappear in one period. At any time period only profitable firms remain, and new firms enter continuously the upstream sector, although many will fail.

On the other side, Sector 2 consists of a changing number of firms due to entry and exit that produce and sell different varieties of a consumption good. Sector 2 firms use one machine (bought from Sector 1) each to produce their variety of the consumption good, with each quality (variety) of the consumption good dependent on the firm's production technology (i.e. the quality of the corresponding machine). Sector 2 firms have a specific knowledge endowment that evolves with experience, and they observe and assess different parts of the distribution of machines supplied by Sector 1. They combine price and machine performance from a range of (cogntitively understandable) options under consideration and choose probabilistically. Once downstream firms buy machines, they set prices and qualities and compete over price and performance to capture final consumers. There is an ongoing process of firm entry in the downstream sector too, although as with the upstream sector, many entrants will fail.

We assume that firms in Sector 2 update their knowledge endowments according to the performance of their most recent machines. Likewise, each firm in Sector 2 has, as a specific behavioral trait, what we call a cognitive *radius* when scanning the supply of machines supplied by Sector 1: the higher the radius, the wider the scope of innovative search. Thus, Sector 2 firms have differential absorptive capacity (Cohen and Levinthal, 1990) as an ability to understand and adopt innovation from Sector 1. Clearly, this absorptive capacity in reality may be constructed over several distinct cumulative mechanisms. The first dimension we can mention is the cognitive capacity of each firm and the implications of bounded rationality for organizational learning (Simon, 1955, 1957, 1991). A second dimension is related to what Kremer (1993) called O-Ring theory, where the absorptive capacity is constrained by the worst performing members of the organizational team. Third, absorptive capacity in Sector 2 may be determined and constrained by the social technologies and institutions needed for training technical people (Nelson and Sampat, 2001). As we explain in the formal presentation of the model in the Appendices, the process described generates co-evolutionay dynamics linking Sectors 1 and 2 from which emergent properties arise. We present in a very detailed way the model equations in Appendix A, and the computational implementation in Appendix B (provided online). We devote the following Section 4 to obtain results on the role of absorptive capacity in this co-evolution model. As we will see, interesting policy implications follow.

4. Computational analysis of the model

Our model is suitable for addressing many different research questions that require modeling multisectoral industrial dynamics and innovation. Indeed, we propose it as a general framework for complementary research lines dealing with the determinants of industrial dynamics, open issues related to economic development as a learning process, industrial ecologies and sectoral ecosystems, price dynamics and firm theory as it relates to the sources of innovation, economic growth, and innovation policy. Nevertheless, in this current initial work we only seek to analyze the following specific questions: can knowledge-coordination problems be responsible of systemic failures in multisector innovative economies? Which is the specific role of absorptive capacity in these processes? And, from a policy perspective, what should we do to deal with these knowledge coordination problems? We respond to these questions through the computational analysis of the model (see below). We then illustrate how our theoretical findings can explain two pertinent examples: (i) the puzzle of the failed commercial supersonic aviation technology; and (ii) the challenges posed by advanced robotics to design successful factories in the future. These two cases exemplify the sense in which our results are useful to interpret innovation dynamics in terms of intersectoral knowledge coordination problems, and how our theory can help orientate innovation policy toward solving them.

Our model is implemented in JAVA and the statistical analysis is carried out with R-Project (see the formal structure of the model in Appendices A and B). The model dynamics reach limit states in approximately 5000 periods, which is the time-span to stationary situations that we have obtained through several methods, including the Kolmogorov-Smirnoff (K-S) test (see a detailed discussion in Fernández-Márquez *et al.*, 2017a,b). Because of stochasticity, we run the model 100 times and average the data for each setting of parametric values.

We focus computational analysis on the role played by *absorptive capacity* in the downstream machine-using Sector 2 as a key driver of intersectoral co-evolution and innovation. Specifically, we consider how the generative stochastic structure *Beta (a, b) distribution* (from which machine-user firms emerge) affects multisector co-evolution. The shape of the Beta distributions varies depending on parameters (*a, b*) (see Figure 1). We can relate these frames to the role of national Universities, different training and regulatory frameworks, R&D programs, and professional associations leading to more or less absorptive firms and permeable industrial ecologies. More precisely, we analyze the influence of the skewness of the Beta (*a, b*) distribution on the probability of technological overshooting (Earl and Potts, 2013, 2016). We denote this effect in the model as the probability of collapse in the dynamics. We

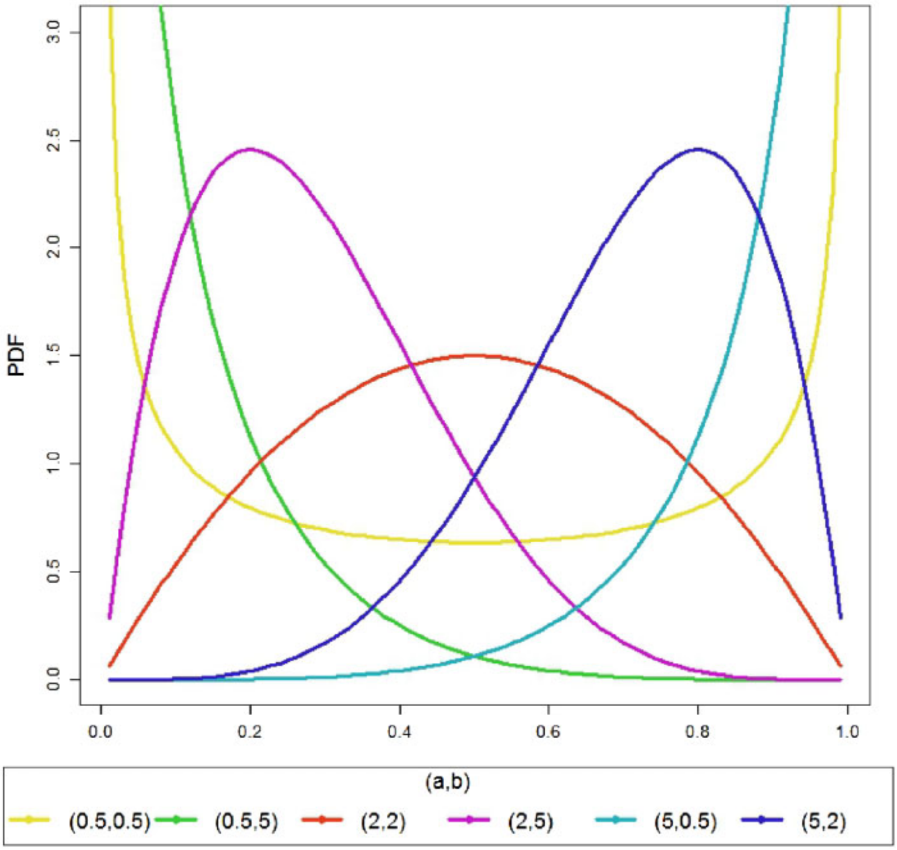

Figure 1. Density functions for the Beta (*a*, *b*) distribution.

consider that technological overshooting occurs in the model when the rate of innovation in Sector 1 does not fit with the absorptive capacity of firm-users in Sector 2. In these situations trade collapses. We measure the (average) *probability of collapse* for each setting, as the average number of times in which either Sector 1 or Sector 2 vanish during the 100 initial steps of the average run. The probability of collapse for each parametric setting enables us to obtain a base of simulated data. From these data we can study the relation between absorptive capacity in the downstream sector and innovation overshooting from the upstream sector.

A temporary collapse of intersectoral trading in our model is a consequence of knowledge coordination problems that block the co-evolutionary process (Almudi *et al*., 2018). When we study the precise origin of these coordination problems, we obtain below a statistical relation linking technological overshooting (as represented by the *probability of collapse*), and the *skewness* of the generative distribution *Beta (a, b)* in Sector 2. Once we have analyzed the precise relations between probability of collapse and the skew of the Beta distribution, we wonder whether the overall innovativeness of our system may be related also with the shape of the *Beta (a, b)* in Sector 2. We obtain that the skew of the Beta distribution arises also as a crucial factor which indirectly guides the overall pattern of R&D innovation in the model. The emergent average level of (upstream) sectoral R&D intensity is clearly related to absorptive capacity in the downstream sector. The analysis will lead us to propose a new type of innovation policy that is focused on eliminating intersectoral cognitive-coordination problems.

4.1 Relations between absorptive capacity in Sector 2 and the probability of collapse

Is it possible that a lack of absorptive capacity in the machine-using sector back-propogate to a collapse of activity in the upstream innovative sector? If these paths emerge, we say that our two sector economy is experiencing *technological overshooting*. There is a knowledge coordination problem: Sector 1 has overshot Sector 2 caused by the lack of absorptive capacity in the downstream sector, and this failure also leads the upstream sector to collapse. Regarding this question, we find a strong statistical relation in the model explaining the *probability of collapse* in our two-sector economy in terms of specific *skewness* patterns of the *Beta (a, b)* in Sector 2. As we stated in Section 3 and in Appendix A, this distribution is the generator of the firm's *understanding radius* $\rho_j \in (0, 1)$.

It is a well-known general statistical result that the *Beta (a, b)* distribution can be assimilated to different distributions (uniform, power law, truncated normal, and negative exponential) depending on the *(a, b)* parameters. To recall this fact, we show in Figure 1 alternative shapes for the *Beta-probability density function* (PDF) with different values for *(a, b)*. This versatility in representing different generative structures for machine user-firms is the reason why we chose the Beta distribution. If we consider the role and place of this distribution in the model, it can be easily related to the institutional structure (ecology of training centers, Universities, supporting organizational sources of entrepreneurial initiatives) from which Sector 2 firms with higher or lower absorptive capabilities [as measured by the firm's *understanding* $\rho_j \in (0, 1)$ *radius* emerge (see Appendices A and B].

Our first analysis consists of trying to relate the *probability of collapse* in the model, to specific shapes (i.e. specific values for the (*a, b*) parameters underlying alternative shapes in Figure 1) of the *Beta (a, b)* in Sector 2. Thus, we run the model for different initial conditions and parametric values. Specifically, we depart from what we call in the Appendix B the *base-setting* and we run the model for 6241 (79×79) different parametric combinations (we run the model 100 times for each possibility, since the model is stochastic).

Figure 2 shows the *probability of collapse* related to the specific values of the (*a*, *b)* parameters. We can clearly see in the heat-graph that the *probability of collapse* is higher for high values of *b*, and for low values of the parameter *a* (notice red-orange-yellow to dark blue colors).

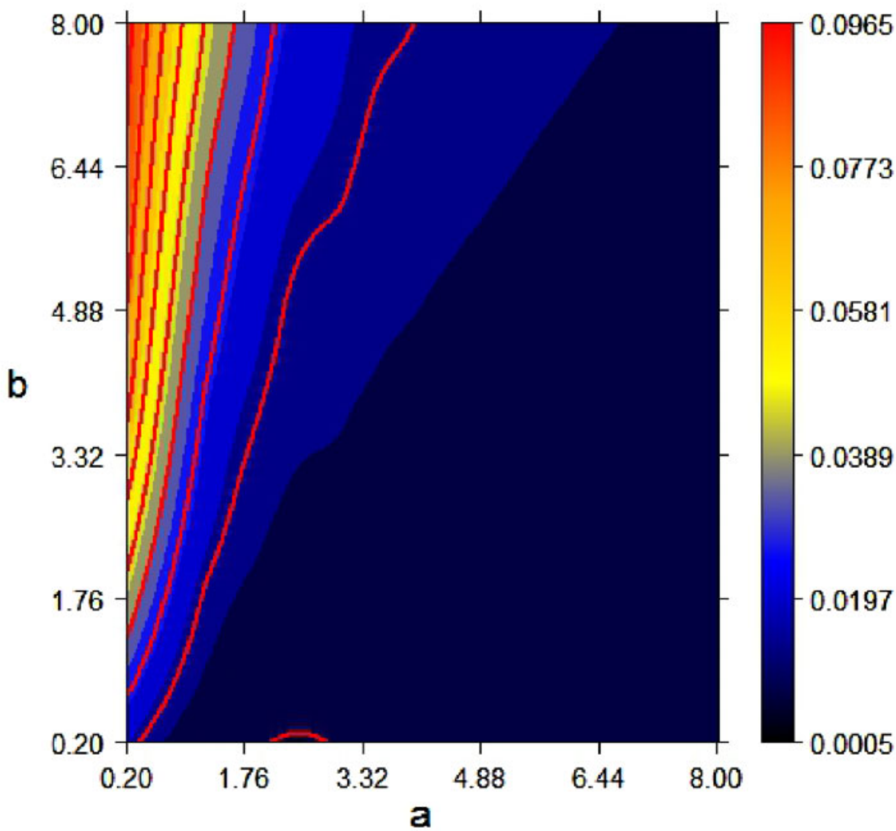

Figure 2. Probability of collapse related with the Beta (*a*, *b*) parameters.

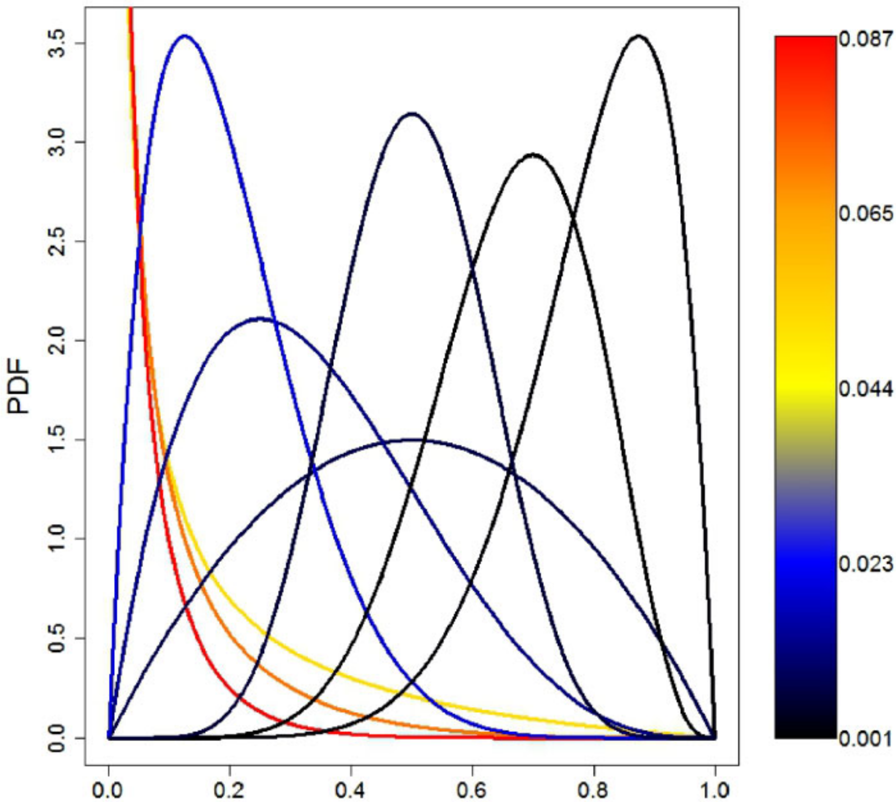

Figure 3. Beta distributions and probability of collapse.

If we relate Figure 2 with the Probability Density Functions for Beta distributions showed in Figure 1, we have a first indicator suggesting how the Beta distribution's shape may be crucial in driving the model results. We see in Figure 1 that higher values of "*a*" tend to generate higher levels of average radius in Sector 2, and higher absorptive capacity. This effect leads—according to Figure 2—to lower probabilities of collapse. The opposite effect occurs for parameter "*b*".

To sharpen this intuition, and given that parameters (*a, b*) determine the shape of the Beta distribution, we show in Figure 3 *alternative specific shapes of the Beta (a, b)* density function, and we have *colored each shape* depending on the corresponding *probability of collapse* when running the model. In Figure 3, the *probability of collapse* is higher (red-orange-yellow, i.e. the hot colors) when the Beta-PDF is convex-shaped and the distribution is closer to the ordinate axis. These shapes correspond to intensely right-tailed distributions. Likewise, when the Beta-density function presents a maximum, it is less likely that collapse emerges (blue and black). In principle, as shown in Figure 3, the probability of collapse is lower the more left-tailed-shape we have in the Beta-distribution. This profile corresponds to generative structures tending to create firms with high absorptive capacity in Sector 2.

Thus, hot-colored (right-tailed) Beta distributions in Figure 3 generate high probability of multisectoral collapse. We have pointed out that right-tailed Beta distributions can represent in the model institutional aspects and framing conditions tending to generate user-firms with low-absorptive capacity (small understanding radius). Figure 3 clearly shows that, when institutional frames with this characteristics are in place, they may lead not only to low innovativeness in their domain-related industries, but also to back-propagating slow-downs and multisectoral blockages.

To formalize the graphical results in Figures 2 and 3, we can analyze from an statistical perspective the explicative power of the parameters (a, b), and also the explanatory significance of the skewness of the Beta distribution, as regressors for the probability of collapse by technological overshooting. As we will see, the best fits we find in both cases correspond with polynomial regressions. For a detailed explanation of the econometric methodology for

Table 1. Polynomial regressions for *(a, b)*

Collapse = $P(a, b)$			
Degree	**Coe.**	**Fit-estimates**	***P*-value**
1	a^0b^0	0.01789939±0.000576302	0.0000000000000002
	a^1b^0	−0.00391692±0.000092497	0.0000000000000002
	a^0b^1	0.00206380±0.000092498	0.0000000000000002
	$R_{adjusted}$=0.4983		
	P−value= 0.00000000000000022		
2	a^0b^0	0.02059867±0.000748923	0.0000000000000002
	a^1b^0	−0.01215065±0.0002691396	0.0000000000000002
	a^2b^0	0.00140464±0.00002921586	0.0000000000000002
	a^0b^1	0.00544907±0.0002691324	0.0000000000000002
	a^1b^1	−0.00080105±0.00002613197	0.0000000000000002
	a^0b^2	−0.00001231± 0.00002921566	0.488
	$R_{adjusted}$=0.7918		
	P−value= 0.00000000000000022		
3*	a^0b^0	0.021010944±0.000824935	0.0000000000000002
	a^1b^0	−0.022615002±0.0005055976	0.0000000000000002
	a^2b^0	0.006149604±0.0001197051	0.0000000000000002
	a^3b^0	−0.000465648±0.000009228442	0.0000000000000002
	a^0b^1	0.009887639±0.0005055976	0.0000000000000002
	a^1b^1	−0.003192800±0.00009537797	0.0000000000000002
	a^2b^1	0.000239635±0.000008100738	0.0000000000000002
	a^0b^2	−0.000197762±0.000119705	0.00659
	a^1b^2	0.000052042±0.000008100326	0.0000000000000002
	a^0b^3	−0.000002270±0.000009228393	0.68572
	$R_{adjusted}$=0.9168		
	P−value= 0.00000000000000022		

polynomial regressions, the use of P-values as indicators of statistical significance, and the nonlinear regression methodology we use below see Montgomery *et al.* (2006: chapters 7 and 13) and Stachurski (2016).

In Table 1, we show the statistical fit when we regress the model generated data for the *probability of collapse* to alternative settings in terms of *parameters (a, b)*. In Table 1, we show (in columns), first, the polynomial degree in each fit, second the summand which appears in the polynomial $P(x, y) = a_0x^0y^0 + a_1x^1y^0 + \ldots + a_nx^0y^n$. In the third column, we present the estimated coefficient value with confidence interval (5% and 95%) and the P-value (H0: a null coefficient). As we see, the $R_{adjusted}$ becomes acceptable (>0.9) for a three-polynomial degree.

To present very clearly this result, note in Table 1 that *the best estimation* (3*) we get from the model, linking the probability of collapse as a polynomial function of (a, b), is given by the *cubic polynomial* which we can be approximately expressed as:

$$P(a, b) = 0.021 - 0.02a + 0.00614a^2 - 0.000465a^3 + 0.0098b - 0.00319ab + 0.000239a^2b - 0.00019b^2 \\ + 0.000052ab^2 - 0.00000227b^3$$

In Table 1 we show the confidence intervals for the fit-estimates, and the very low values we obtain for the P-values-which indicate the high statistical significance of the regressors. Likewise, regarding the quality of the statistical estimation, notice that in Table 1 the confidence intervals are narrow, and the indicator $R_{adjusted} = 0.9168$ is very high for the cubic polynomial. Thus, we have a very good fit and a significant statistical relation linking *probability of collapse*—through a cubic polynomial—with *(a, b) parameters of the Beta distribution* in the model. The results in Table 1 support statistically the findings in Figure 2, and they suggest the need to dig deeper along these lines.

Therefore, and to sharpen our results, we recall now what we depicted in Figure 3 showing that the *skewness of the Beta distribution* is a good candidate to explain (in a more compact and understandable manner), the *probability of collapse* in the model. To check and formalize this possibility we have analyzed the statistical relationship between the Beta-skew in alternative settings, and the corresponding probabilities of collapse arising from the simulations. We present the results in Table 2 and Figure 4.

As we show in Table 2 and Figure 4, the best fit for this *emergent property* of our model is a polynomial regressions with "skew" of the Beta-distribution as the *unique explanatory variable* for the *probability of collapse*. Now the interpretation of the coefficients is simpler and more informative. Table 2 reports that a second-degree polynomial notably increases the quality of adjustment $R_{adjusted}$ (>0.9), while increasing the degree adds little to the quality of the adjustment. Therefore, we choose a two-degree polynomial as the best fit to explain the probability of collapse in the model in terms of the Beta-skew. From Table 2, we can see that the specific polynomial with the best fit (2*), in which the *probability of collapse* emerges in the model as a quadratic function of *skew*, is given by the expression (confidence intervals in Table 2):

$$P(skew) = 0.0066425 + 0.01192869(skew) + 0.00402343(skew)^2.$$

Table 2. Polinomial regressions for skew

Collapse = *P*(skew)			
Degree	**Coef.**	**Fit-estimates**	***P*-value**
1	$skew^0$	0.0103665±0.00018184	0.0000000000000002
	$skew^1$	0.0119287±0.00018898	0.0000000000000002
	$R_{adjusted}$=0.6365		
	P−value= 0.00000000000000022		
2*	$skew^0$	0.00664250±0.000086206	0.0000000000000002
	$skew^1$	0.01192869±0.00008093	0.0000000000000002
	$skew^2$	0.00402343±0.000039975	0.0000000000000002
	$R_{adjusted}$=0.9334		
	P−value= 0.00000000000000022		
3	$skew^0$	0.00664250±0.000085733	0.0000000000000002
	$skew^1$	0.01141738±0.000129326	0.0000000000000002
	$skew^2$	0.00402343±0.0000397563	0.0000000000000002
	$skew^3$	0.00010179±0.0000201477	0.0000000000000002
	$R_{adjusted}$=0.9341		
	P−value= 0.00000000000000022		

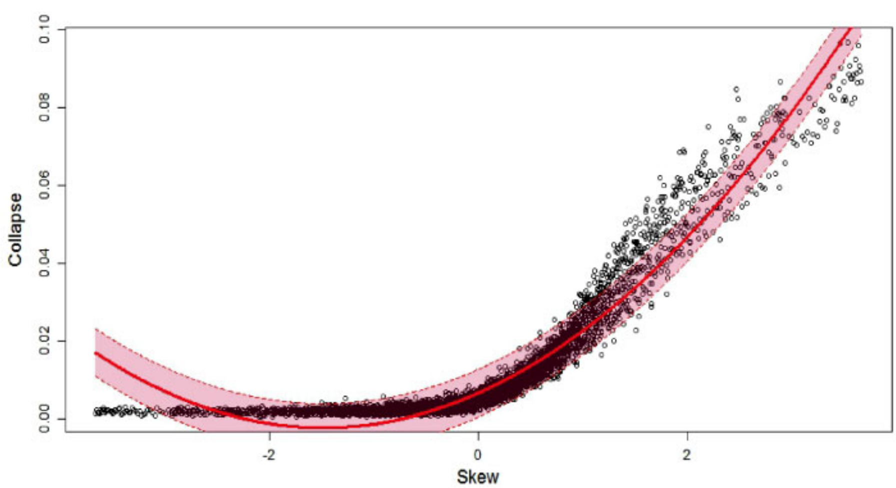

Figure 4. Second-order polynomial fit (collapse/skew).

This statistical result is represented graphically in Figure 4, where we show the fit for the second-order polynomial (2*) with Beta distribution *skew* as the explanatory variable. We depict *with the continuous thick-line* the representation of the estimated polynomial, and with *shaded bands* the confidence set (Stachurski, 2016: chapter 10). Notice in Table 2 and in Figure 4 that the effect of skew is statistically significant (very low P-values), and that the quality of the estimation is good.

Figure 4 and Table 2 show that a higher skew (a more right-tailed Beta-distribution) produces a higher probability of collapse. In economic terms, the outcomes of the model simulations reveal a fast-increasing probability of multisectoral collapse for institutional settings with low capacity for creating absorptive machine user-firms. As right-tailed distributions tend to generate user-firms with low understanding radius, and this feature induces in the model back-propagating effects, we obtain blocked co-evolution because of knowledge coordination problems. The lack of absorptive capacity by user-firms can block overall industrial change. Therefore, the model reveals as an emergent property the existence of mesolevel coordination failures for specific institutional conditions (i.e. deficient institutional and socio-economic frames unable to engender high numbers of absorptive user-firms: right-tailed Beta distributions).

We have related the shape or skew of the *Beta-distribution* with the characteristics of the institutional framework that generates downstream absorptive capacity, or what we called high values for the “firm-specific understanding radius” (see Section 3 and Appendices A and B). This framework involves supporting institutions for the provision of specific skills by training (Universities and technical institutes), but also domain-specific schools for users or professional associations, or even new linking institutions.

The model results point out that innovation policy should not only target increasing knowledge where producer-innovation takes place, but also at the level of the user-sector, and this may imply institution-building policies. This is a new perspective different from taxing, giving subsidies, applying neo-classical market-failure corrections or picking winners. This need to promote absorptive capacity at the Sector 2 (the downstream level) to reduce blockchages upstream (Sector 1) is however not usually a key target for innovation policy. This implication becomes even reinforced from the new results we will show below in subsection 4.2.

4.2 Absorptive capacity, R&D intensity, and innovation

Consider another set of results. In our co-evolutionary model, firm specific R&D to profit ratios are the key behavioral variables to explain innovation and technological change in the upstream sector. Notice that the distribution of these firm-specific ratios r_i at any time, and the average R&D ratio $\overline{r_t} = \sum_i s_{i,t} r_i$ in Sector 1 at t, are dynamic emergent properties dependent on the overall functioning of the model. The next step is to consider whether we might detect regularities in the computational results by connecting R&D intensity (given by $\overline{r_t} = \sum_i s_{i,t} r_i$) in the upstream innovative sector, and the Beta (a, b) generative distribution in the downstream sector. The skewness of the Beta (a, b) distribution is a good target to explain the limit-stationary value of $\overline{r_t} = \sum_i s_{i,t} r_i$.

Figure 5 shows a surprising result that we call *the slump effect* in the model. This effect admits an interesting economic interpretation and suggests a new implication for innovation policy. Specifically Figure 5 illustrates a sigmoidal fit for the

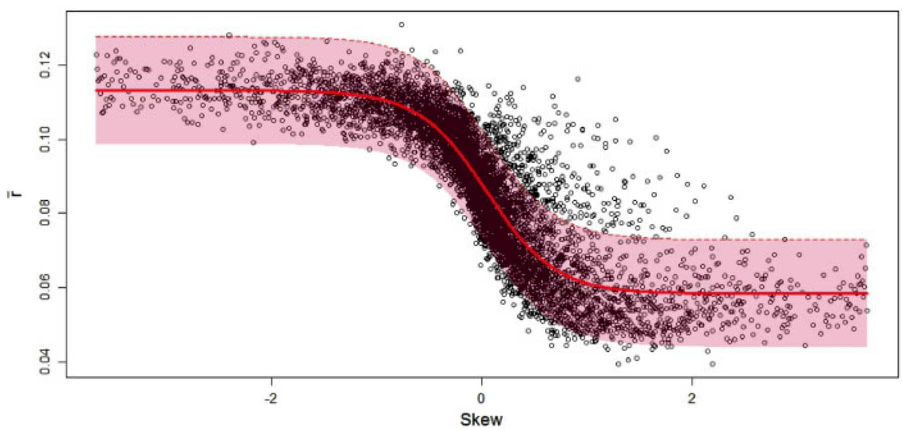

Figure 5. Sigmoidal fit (Average R&D to profits ratio/skew).

Table 3. Sigmoidal fit for the result in Figure 5

$\bar{r} = F(\text{skew})$			
Function	**Coef.**	**Fit**	***P*-value**
Sigmoidal	C_1	0.0546695±0.00091479	0.0000000000000002
	C_2	3.0831232±0.11519132	0.0000000000000002
	C_3	−0.1610722±0.03749395	0.00000000000282
	C_4	0.0584723±0.00061389	0.0000000000000002
	Residual Standard Error=0.008813		

limit-stationary data $\overline{r_t} = \sum_i s_{i,t} r_i$ emerging from our runs in Sector 1 as we change the skew of the Beta (a, b) distribution. The model reaches stationary in 5000 steps.

We can see in Figure 5 how departing from negative skew (highly left-tailed) distributions in Sector 2 (in horizontal axis), we obtain in correspondence high average R&D to profits ratios in Sector 1 in the stationary limit of the dynamics. High levels of $\overline{r_t} = \sum_i s_{i,t} r_i$ in the innovative Sector 1 spontaneously emerge. Note that this emergent change happens not because of subsidies or favorable tax reductions in Sector 1, but because of a left-tailed pattern in the Beta (a, b) in Sector 2. That is to say, suitable generative structures in the user-sector, from which new firms with high absorptive capabilities (cognitive radius) stochastically are drawn and selected in coevolution, spontaneously induce high R&D investment upstream. Institutional structures that are dense in probability around relatively high absorptive capacity (i.e. cognitive radius) in the downstream sector drive innovative efforts in the upstream sector. As a policy model this means that to increase the return to R&D in Sector 1, we need to boost absorptive capacity in Sector 2.

The decreasing relationship explaining lower values for $\overline{r_t} = \sum_i s_{i,t} r_i$ in Sector 1 in terms of increasing Beta (a, b) skew is clear in Figure 5. Notice that the range of change in the emergent values for $\overline{r_t} = \sum_i s_{i,t} r_i$ is wide: from around 13% of net profits devoted to R&D (on average in Sector 1 as a stationary value) in the best cases, to 2% of profits to R&D on average in Sector 1 under less innovative conditions.

In Table 3 the numerical results of the sigmoidal estimation for Figure 5, show a very good statistical fit to the model-generated data when we use the inverted sigmoidal. The specific functional form that we have estimated for the stationary results of $\bar{r}$ and skew is: $\bar{r} = \frac{C_1}{1+e^{C_2 \cdot Skew + C_3}} + C_4$ where C_1, C_2, C_3, C_4 are the coefficients to be estimated. It is a highly nonlinear regression, so that we paint (in shaded bands in Figure 5; 90% confidence interval) the confidence set around the fitted curve in Figure 5 and we can observe that the estimation is a good fit. Table 3 shows the numerical results for coefficients, intervals and very low *P*-values (high statistical significance of the explanatory variable).

The best-fit (sigmoidal) that can be seen in Table 3 is given by:

$$\bar{r} = \frac{0.0546695}{1 + e^{3.0831232 \cdot Skew - 0.1610722}} + 0.0584723.$$

What is relevant in this result (Figure 5 and Table 3) is the nonlinear collapse, or what we call the "slump effect" of R&D intensity. In economic terms, a nonlinear relationship explains R&D intensity in the innovative upstream sector with absorptive capacity in the downstream sector (*skew*) as the regressor. Moreover, the inverted sigmoidal shape in Figure 5 indicates that, as the generative structure in the downstream sector becomes less generative of absorptive capacity (Beta (a, b) becomes more right-tailed), then we obtain initially slight reductions in $\overline{r_t} = \sum_i s_{i,t} r_i$. Eventually, we reach a point of skew from which $\overline{r_t} = \sum_i s_{i,t} r_i$ decreases sharply: from emergent values of about 11% of profits to R&D in Figure 5, we quickly fall to values of 5% along the vertical axis. This is the slump effect. As we see in Figure 5, in our model, absorptive capacity in the user-sector influences in a highly nonlinear manner the R&D-to-profits emergent ratio in the innovative upstream sector.

From an economic point of view, constructive institutional policies targeting the Beta (a, b) generative structure in the downstream sector have a significant effect in increasing R&D intensity and technological change in the upstream sector. Thus, the model suggests that the user-firm's capability to understand and assimilate innovations is crucial in generating spontaneous and voluntary increases in R&D upstream. This is an important result that poses additional arguments in favor of procurement policies capable of unchaining technological progress with no need to rely on taxes, picking winners, subsidies and other traditional policies.

Interestingly, our model formally supports previous results in the innovation strategy literature which empirically and theoretically show how coordination failures within industry ecosystems may block innovation adoption and technological change (e.g. Adner and Kapoor, 2010; Adner, 2017; Jacobides *et al.*, 2018). Nevertheless, our model adds something important to these results, namely, the possibility that the mechanisms underlying innovation slowdowns may be highly nonlinear (i.e. our *slump effect*). In these cases, silent and even moderate deteriorations of the socio-economic and institutional frames engendering user-firms are predicted to have only minor effects (at first!) in the innovation rates; but unexpectedly and quickly a slightly higher deterioration of the generative structure near the inflection zone (see Figure 5) can produce an intense decrease in innovativeness (in an inverse sigmoidal way). This is a possibility that adds a new perspective to recent debates on possible innovation slowdowns in modern economies (e.g. the Gordon vs. Mokyr controversy).

4.3 Illustrative examples

Consider two specific examples of these effects: first, the puzzle of commercial supersonic aviation and second, the challenges posed by advanced robotics in the future of manufacturing across a range of sectors. Both cases highlight: (i) the need of knowledge coordination between vertical adjoin segments in complex industrial architectures; (ii) the need of proper supporting institutions to coordinate technological knowledge at the intersectoral level; and (iii) the potential speed-up of feedback between the absorptive capacities of downstream sectors and the innovation performance of upstream sectors. These mechanisms can be related to what we have called in the model the *slump effect*.

4.3.1 The puzzle of commercial supersonic aviation

Aviation technology was born at the beginning of the 20th century. Just a few decades later, in 1926, technological developments made possible commercial aviation, and in 1947, a manned aircraft broke the sound barrier, and so arrived supersonic technology. During the 1950s the technology was developed for military applications, with engineers focused on aircraft safety and control. But during the 1960s supersonic technology came to be seen as promising technology for commercial aviation. During that decade, research teams at competing airframers in USA, USSR, and Europe worked to make possible supersonic commercial flights, resulting in the first supersonic prototypes: the soviet Tupolev TU-144 prototype appeared in 1968, and the British–French *Concorde* was next, in 1969. In the USA, Boeing and General Electric tried but failed to deliver a viable commercial aircraft. At that time, it was widely believed that the future of commercial aviation would be supersonic. But subsequent decades would show that, after some flights, mainly intercontinental and operated in a very discontinuous manner, supersonic technology would fail to subsequently develop, and would eventually collapse at the beginning of the 21st Century.

The reasons behind the interruption of the commercial supersonic technology remain intriguing. As a nonmature technology, it suffered significant shortcomings as noise pollution, excessive fuel consumption and safety concerns. There are also abundant studies questioning the long-term profitability of supersonic commercial flights owing to demand-side factors (Bale and Sharp, 2013). But, as in any other nonmature technology, all these shortcomings could have been overcome by technological investments in better airframe and engine performance upstream, while, commercial exploitation downstream could have led to a more profitable business model. What seems clear is that commercial supersonic flight operated both under a strict monitoring regulatory control on design and development of the technology upstream, and in a discontinuous manner for airlines and consumers. Therefore, during the time at which commercial supersonic flights were in place, airframers, airlines and consumers were not able to align their needs around technological improvements. Technology was developed up-bottom without putting attention to the vertical inter-links (between airframers, airlines and final customers). Under these conditions, it seems difficult for a technology to achieve the proper innovation and development needed to consolidate a market position. In terms of our models results, the failure of commercial supersonic technology is a consequence of a knowledge coordination problem. Technological developments upstream overshot in some directions the implement ability of supersonic commercial aircraft. Indeed, commercial flights are nowadays slower than they were in the 1970s. On the other side, safety and noise-related technological shortcomings remained unsolved because upstream and downstream firms were unable to coordinate needs and efforts. Finally, if we look at the potential developments that are currently perceived for the re-opening of this industry, for example, the American *Boom Supersonic* airframer together with *Japan*

Airlines announced a re-start of the supersonic commercial flights at some point in the mid-2020, if can be predicted that a possible speed-up of this trajectory once vertically linked efforts may be carried out.

4.3.2 The challenges posed by advanced robotics to design the factory of the future

Advanced robotics is seen as one of the main potential driving forces to dynamize the factory of the future. According to Krüper *et al.* (2019), this will require: (i) significant reductions in price for future acquisitions of advanced robotics machinery (expected due to process innovation in advanced robotic sectors); (ii) better interconnections between the needs of factories and the performance developments of advanced robotics (expected due to product innovation in advance robotic sectors); and (3) development of managerial capabilities in downstream firms. Therefore, if we analyze these requirements through the lense of our model, the effective implementation of advanced robotics will require intersectoral knowledge coordination between advanced robotics producers upstream and specific manufacturing sectors involved downstream (e.g. in transportation and logistic firms, consumer technology producers and automotive companies). Otherwise, our model predicts a potential technological overshooting upstream that can be propagated downstream frustrating the expected promising productivity gains in factories. In other words, further intersectoral absorptive capacities are needed downstream to avoid the *slump effect* occurring upstream. Since advanced robotics is a technology with many potential developments in downstream sectors (e.g. transport, automotive, engineeiring, healthcare, etc.), the development of intersectoral supporting institutions would be also very important for economic development and growth. This knowledge coordination role to facilitate the development of downstream absorptive capacity would be the function of a new innovation policy.

Examples of the kind of institutional support required to achieve this policy outcome include the *Manufacturing Advisory Services* of the UK Department for Business, Innovation and Skills, the *Manufacturing Extension Partnership* funding from the US National Institute of Standards and Technolog, and the *Industrial Research Assistance Program* sponsored by Canada's National Research Council (Shapira and Youtie, 2016). However, these organizations are marginal compared to the R&D driven supply side measures, and are not specifically focused on the intersectoral connections. The same argument applies to skill enhancement policies already in place. Therefore, a new rationale can be inferred from our model in which the key focus of innovation policy is with intersectoral interdependencies.

5. Conclusion

This article has proposed a specific (two-sector) model of a general analytic concept of multisector innovation interdependence. In our computational two-sector model (following Dosi *et al.*, 2013) Sector 1 is an innovative sector that produces and sells machines, and Sector 2 is a user innovative sector that buys machines from Sector 1, produces consumption goods and supplies goods to final consumers. The key point of our model is that the cognitive alignment of knowledge creation and absorption capabilities among the innovation trajectories of Sector 1 and Sector 2 is complex, setting up a knowledge coordination problem that we argue innovation policy should target. This problem arises because absorptive capacity constraints in the downstream sector can backpropagate to cause innovation overshooting in the upstream sector. We are able to show that this has important implications for the role and design of innovation policy, which requires a multisectoral focus in order to address this knowledge coordination problem.

We have therefore developed a new class of computational model of a general knowledge coordination problem as a multisectoral process. In our model, firms producing machines in Sector 1 compete in price and machine-type (quality) performance to capture users. They fix prices following a mark-up pricing rule and spend on R&D-innovation a lagged proportion of profits. Firm performance in Sector 1 evolves by innovation. Downstream in Sector 2, firms buy machines, fix prices, and produce varieties of a consumer good. Both sectors have entry and exit mechanisms. A new feature of our model is that firms in Sector 2 have a specific (endogenously changing) knowledge endowment or absorptive capacity that allows them to understand (or not), and choose among the set of machine-varieties or formal parts of it offered by Sector 1. Therefore, the dynamics linking both sectors depend on the emergent *co-evolution* of innovation and absorption activities taking place and developing across both sectors.

The computational results of our model highlight the importance of intersectoral *absorptive capacity* constraints in innovation linkages between the two sectors in the economy. Innovation in the upstream sector (Sector 1) can be stimulated—but can also be slowed or even blocked—depending on the *absorptive capacity* of the downstream-user sector (Sector 2). We have found that not only the absorptive capacity of the user-Sector 2, but also the evolution of this sector in interaction with the final consumers are crucial for the sustainability of activities in Sector 1 (upstream).

Balanced sectoral knowledge requires solving a meso–macro coordination problem. In a complex evolving economy, this is a major task for innovation policy. Thus, drawing on the model, we could suggest that the lack of absorptive capacity in certain realms of activity in modern economies might be preventing the timely adoption of radical contemporary innovations. Moreover, it could be the case that whereas we observe increasing innovation rates in certain (upstream) activities, the overall effects of technological change could be difficult to be seen if downstream sectors were insufficiently absorptive of innovation. Indeed, the consequences of innovation slowdowns due to knowledge-coordination problems can be unpredictable from the viewpoint of standard macroeconomic policy, and may end up in income distribution problems, fluctuating growth paths and employment pathologies such as those analyzed in Fatas-Villafranca *et al.* (2012).

The model we have presented in this article can help make sense of the widely observed low productivity performance of modern innovation policies as a consequence of sectorally unbalanced knowledge and frictions in intersectoral co-evolution. The innovation policy problem lies in aligning innovation and absorptive capacity in a two-sector nonlinear stochastic complex framework. New roles for innovation policy are suggested, such as combining supporting and intersectoral connective institutions. In this regard, *the slump effect*, according to which improving the generative structures in downstream sectors could have very sharp effects in upstream R&D, highlights promising new ways for innovation policy in the near future.

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Appendix A: The model equations

We formally state the model assumptions (see also Appendix B).

The capital-good sector (Sector 1)

Prices and performance

At time t, we have a changing set of firms in Sector 1: $S_t^1 = \{C_{i,t}^1\}$. We denote by $C_{i,t}^1$ each individual firm i in Sector 1 at t. These firms produce different varieties of a capital-good we call machine. We assume profit-seeking firms that compete in price $p_{i,t}$ and machine performance $x_{i,t}$ (performance is normalized on the unit interval). Firms in Sector 1 set prices using an endogenously changing mark-up ($\mu_{i,t} > 1$) over expected unit cost. Thus the price set up by firm i at t is:

$$p_{i,t} = \mu_{i,t} c_{i,t}^e \tag{A1}$$

We highlight two aspects in the pricing routine. On the one hand, we consider that the higher the expected market share of each firm, the higher the margin it applies (Almudi *et al.*, 2012; Winter, 1984). On the other hand, we state that each firm i delineates at t the set of "perceived close rivals" depending on performance distance. This set is determined according to information from t–1, and is a firm-specific strategic trait. We define this set as:

$$\Lambda_{i,t} = \left\{k : |x_{k,t} - x_{i,t}| \leq \sigma_i x_t^{max}\right\}, \quad \sigma_i \in (0,\ 1) \tag{A2}$$

From (A2) each firm estimates the rivals' overall market power by adding up the market shares of the close rivals: $\left(\sum_{k\epsilon\Lambda_{i,t}} s_{k,t-1}\right)$. If we now consider this intensity of direct competition $\left(\sum_{k\epsilon\Lambda_{i,t}} s_{k,t-1}\right)$ as an element that makes the demand for the specific machine more elastic (it erodes the perceived market power of the firm), the mark-up set up by firm i at t can be obtained as follows:

$$\mu_{i,t} = \frac{\eta + \sum_{k\epsilon\Lambda_{k,t-1}} s_{k,t-1}}{\eta + \sum_{k\epsilon\Lambda_{k,t-1}} s_{k,t-1} - s_{i,t}^e}, \quad \eta > 1 \tag{A3}$$

$$s_{i,t}^e = \frac{1}{card(S_t^1)} \text{for new firms, and } s_{i,t}^e = s_{i,t-1} \text{ otherwise}$$

Finally, regarding firm performance $(x_{i,t})$ we assume that firms improve their machines through innovation (below).

Demand-driven production and costs

We assume demand-driven production in Sector 1, so that $q_{i,t} = q_{i,t}^d$. Likewise, we assume that total costs include production costs and R&D costs. We consider constant and common unit production costs (c). Firms will differ in their unit R&D efforts. To set prices (see (A1)), firms use *ex ante* expected unit costs. They must use expected unit costs because they still do not know their demand-driven level of production and sales. We assume naïve expectations about the production level, so the expected unit cost is:

$$c_{i,t}^e = c + \frac{R_{i,t}}{q_{i,t}^e} = c + \frac{R_{i,t}}{q_{i,t-1}}, \quad c > 0 \tag{A4}$$

Once the structure of demand arises (below) and the exchanges between Sectors 1 and 2 have occurred, firms will know the effective production and the effective unit costs. Then, they will calculate the real profit for i at t as:

$$\pi_{i,t} = (p_{i,t} - c_{i,t})q_{i,t}; c_{i,t} = c + \frac{R_{i,t}}{q_{i,t}} \tag{A5}$$

Only profitable firms remain in the market (see Appendix B).

We also assume that firms devote a specific proportion of profits to R&D with a lag, so that:

$$R_{i,t} = r_i \pi_{i,t-1}, \quad r_i \in (0,\ 1) \tag{A6}$$

We often find slightly different R&D spending routines in the literature, but all of them render essentially similar results (see Fatas-Villafranca *et al.*, 2008, 2012, 2014; Almudi *et al.* 2012, 2013; Bloch and Metcalfe, 2018).

We also assume that every firm in Sector 2 demands, at most, one unit of a specific variety of the capital-good from Sector 1 and uses this machine to produce a consumption good in Sector 2. For simplicity, we assume that every unit of capital totally depreciates and disappears at no cost at the end of each period. When selecting a specific type of machine at t, downstream firms assess the prevailing levels of price and performance in Sector 1. Observe that if we define the set of customers for each capital-firm i at t in Sector 1 as $\Omega_{i,t}$, we have $q_{i,t}^d = card(\Omega_{i,t})$.

R&D-based innovation

Let $\gamma_{i,t}$ be the flow of new knowledge generated by each firm i in Sector 1 at t. Assume this flow is a random realization of a (truncated) Pareto distribution, so that $\gamma_{i,t} \sim Dist.$, with "*Dist*" representing the truncated Pareto distribution, supporting values $L = 0$ and $H = 1$. We endogenize the typical Pareto-parameter (the slope of the density function θ) so that $\theta = \frac{1}{\phi \cdot imitation + (1-\phi) \cdot research}$, where (*a la* Nelson, 1982; Fatas-Villafranca *et al.*, 2009; Dosi *et al.*, 2017) we have:

$$\begin{aligned} imitation &= \frac{x_t^{max} - x_{i,t}}{x_{i,t}}, \text{ assimilation of external knowledge from the gap to the frontier;} \\ research &= \frac{R_{i,t}}{R_{i,t}^{max}}, \text{generating knowledge from (normalized) inner R\&D;} \end{aligned} \tag{A7}$$

In (A7), we assume that the productivity of R&D reflected in the flow of new knowledge $\gamma_{i,t}$, depends on both complementary sources, with a sectoral bias denoted by parameter ϕ that determines the relative importance of imitation. The lower the firm-specific value of θ at t, the higher the probability of obtaining a large flow of new knowledge $\gamma_{i,t}$. Finally, we assume that the relative performance of each Sector 1 firm is updated through a mechanism in which those firms generating higher than average flows of new knowledge, i.e. $\gamma_{i,t} - \bar{\gamma}_t > 0$, increase their relative performance compared to rivals in Sector 1. Thus:

$$\frac{x_{i,t+1} - x_{i,t}}{x_{i,t}} = \gamma_{i,t} - \bar{\gamma}_t; \quad \bar{\gamma}_t = \sum_h x_{h,t}\gamma_{h,t} \tag{A8}$$

Firm entry-exit

Firms in Sector 1 with profit $\pi_{i,t} \leq 0$ exit the market. Also, at each time step, one new firm enters the sector. With probability "λ", the new firm's traits are selected randomly (so that the new entrant enters into the sector by carrying genuine novel traits). With probability "$1 - \lambda$", the new firm copies one of the incumbents with probabilities proportional to market shares and by bearing an implementation cost (Appendix B).

The consumption-good sector (Sector 2)

At time t, there exists a set of firms in Sector 2, $S_t^2 = \{C_{j,t}^2\}$. Each firm (denoted by j) produces a different variety of consumption-good (with different prices $p_{j,t}$ and quality levels, $y_{j,t}$). Firms in Sector 2 produce with different techniques or machine-varieties depending on the technological performances of their respective capital-good provider. The technological level of the machines used by firms in Sector 2 determines the corresponding quality of the consumption good. Firms in Sector 2 with superior machines will supply quality-superior consumption goods. Considering the prevailing distribution of machine-performance levels on the supply side (Sector 1 at t), and the distribution of cognitive endowments corresponding to the consumption firms in Sector 2 ($X_{1,t}, \ \ldots, \ X_{card(S_t^2),t}$), each firm j in Sector 2 decides which firm to buy from Sector 1. Assume full-capacity use and total depreciation of machines in one period. For simplicity, the production level in Sector 2 is normalized to 1 and fully sold to consumers. The market in Sector 2 is driven by a replicator equation (see below).

The process of machine choice by each *j*-firm in Sector 2

We represent the limits of user-firms' absorptive capacity as follows: we assume that each firm is endowed with a firm-specific capacity to understand, incorporate and use new technology. This firm-specific capability depends on each firm's experience, but it also rests on the knowledge-based traits of the firm (cognitive capacities), each firm's culture regarding risk-taking, and the different abilities to manage technological and organizational change. We assume that each firm j has, at t, a specific performance interval capturing what she can understand and assimilate. These intervals are distinct among firms, and they get updated in a path-dependent way as firms learn by using specific machines (Arrow, 1962b). Each user-firm j is endowed at t with a specific and changing *absorption interval* defined by a path-dependent *center* $X_{j,t}$ and a specific *understanding radius* $\rho_j \in (0, 1)$.

We also consider that firms not only care about machine performance but also about prices. Thus, we consider that firms make their choices within the set of machines that they can understand, and they compare performances and prices of understandable machines. When they buy, they incorporate the price of the machine as a cost. This cost will be the referential upon which user-firms charge their margins to make the prices for final consumption. The quality of the machines determine the quality of the final goods to be sold in Sector 2. Formally, we propose the following process of assessment and choice for each machine user-firm j in Sector 2:

1. Firm j delimits the set of (cognitively) feasible options, which will be conditioned by the firm specific cognitive capabilities $\rho_j \in (0, 1)$. This *understanding radius* is a way of parameterizing absorptive capacity in a firm.

Each firm's radius of understanding, together with the firm-specific changing center $X_{j,t}$ of the absorption interval, determine the set of feasible providers for firm j which is: $\Xi_{j,t} = \{i : |X_{j,t} - x_{i,t}| \leq \rho_j x_t^{max}\}$;

2. Firm j chooses a feasible-provider (a cognitively feasible type of machine) with a probability which is proportional to $\alpha_1 x_{i,t} + (1-\alpha_1)\left(1 - \frac{p_{i,t}}{\sum_{k\epsilon\Xi_{j,t}} p_{k,t}}\right), \ \alpha_1 \in (0, \ 1)$
3. The quality of firm j becomes: $y_{j,t} = x_{i,t}$
4. Each firm in Sector 2 has a cost equal to the price of the machine bought: $c_{j,t} = p_{i,t}$

Since this process takes place for all the firms in Sector 2 (see also Appendix B), we can define now the set of customers for every single firm in Sector 1: $\Omega_{i,t} = \{i - customers\}$.

As long as a firm in Sector 2 uses one specific type of machine, we asume that this level of performance becomes the firm's cognitive endowment for the next period: $X_{j,t+1} = y_{j,t}$.

Market competition in Sector 2

Sector 2 firms compete in price and quality in the consumption good market. We have already defined how to obtain the quality level of each firm, $y_{i,t}$. Regarding price, we propose that consumption firms also apply a mark-up pricing routine. Then, we consider

$$p_{j,t} = \left(\frac{\delta}{\delta - s_{j,t}}\right) c_{j,t}, \quad \delta > 1 \tag{A9}$$

In (A9) $c_{j,t}$ is the cost of the chosen machine, and $\delta(> 1)$ is just a parameter. As in Winter (1984), or more recently in Fatas-Villafranca *et al.* (2008), and Almudi *et al.* (2012), we consider that each firm's market share is a good proxy for market power and, then, it is positively related to the margin. As in Almudi *et al.* (2013), to represent the market process, we define a firm-competitiveness (fitness) level for each firm j that combines normalized quality and price:

$$f_{j,t} = \alpha_2 \frac{y_{j,t}}{y_t^{max}} + (1-\alpha_2)\left(1 - \frac{p_{j,t}}{p_t^{max}}\right); \quad \alpha_2 \in (0, \ 1).$$

It is clear that we are representing both dimensions as related to maximum quality and price in Sector 2 at t. Now, from this fitness indicator we represent the market process in Sector 2 as follows:

$$\frac{s_{j,t+1} - s_{j,t}}{s_{j,t}} = f_{j,t} - \bar{f}_t; \quad \text{with } \bar{f}_t = \sum_h s_{h,t} f_{h,t} \tag{A10}$$

Firms entry-exit

Firms in Sector 2 with a share lower than 0.005 leave the market, while at every time step one new firm enters the sector. The new entrant may carry novel traits, or it may copy one of the incumbents (see Appendix B). Regarding these two possibilities, we consider that with probability λ (a *mutation rate*) the new entrant *carries fully-novel traits*. With probability $1-\lambda$ the new entrant *copies* one of the incumbent firms. In the case of *fully-new entrants* (with probability λ), we assume that these firms randomly draw, as a specific feature, their *understanding-cognitive radius* $\rho_j \in (0, 1)$) from a *Beta distribution* with positive parameters (a, b). These parameters appear as exponents in the random variable and thereby control the shape of the distribution. We consider this distribution because it allows us to represent a wide range of alternative scenarios regarding the institutional structure engendering machine-user firms with different degrees of *absorptive capacity*. This element of the model allows us to represent the effects of more or less skewed generative structures, which will be our proxy to characterize alternative institutional systems from which more or less absorptive *fully-new* user-firms emerge. Observe that the expected value and variance of a *Beta distribution*, given $a > 0$, $b > 0$, are E$= \frac{a}{a+b}$, and variance Var$= \frac{ab}{(a+b)^2(a+b+1)}$. Finally, for those cases in which (probability "$1-\lambda$") the *entrant firm copies one of the incumbents*, we consider that this process takes place with probabilities proportional to market shares. We assume that the initial market share of the new entrant is 0.005, with other market shares being re-calculated accordingly (Appendix B).

Appendix B: List of symbols and pseudocode

We use subscript i for any firm in Sector 1; j for firms in Sector 2; we use k otherwise.

Parameters in Sector 1 and base-setting	
$\alpha_1 = 0.5$	Performance/price sensitivity of demand
$\eta = 1.5$	Common parameter in pricing routine
$c = 0.01$	Unit production cost
$\phi = 0.5$	Relative importance imitation *vs* inner R&D.
$\epsilon = 0.75$	Entry cost for new imitative entrants
$\lambda = 0.05$	Probability of entering doing innovation (identical in both sectors)

Firm-specific parameters in Sector 1	
$r_i \sim U(0,\ 1)$	Share of profits devoted to R&D
$\sigma_i \sim U(0,\ 1)$	Radius delimiting perceived direct competitors

Firm-specific variables Sector 1	
$x_{i,t} \in [0,\ 1]$	Technological level in relative terms
$q^e_{i,t} \geq 0$	Expected sales (in real terms = number of expected customers)
$R_{i,t} \geq 0$	R&D spending
$c^e_{i,t} > 0$	Expected total unit cost
$\mu_{i,t} > 1$	Unit profit mark-up on costs
$p_{i,t} > 0$	Price
$\gamma_{i,t} \in [0,\ 1]$	Firm knowledge
$q_{it} > 0$	Sales (in real units = number of customers)
$s_{it} \in [0,\ 1]$	Market share
$c_{i,t} > 0$	Total unit cost (ex post)
$\pi_{i,t} \geq 0$	Total firm profit

Notation regarding Sector 1

$C^1_{i,t}$: firm i from Sector 1 at time t.
$S^1_t = \{C^1_{i,t}\}$: set of firms operating in Sector 1 at t.

Notation regarding Sector 2

$C^2_{j,t}$: firm j in Sector 2 at t.
$S^2_t = \{C^2_{j,t}\}$: Set of firms in Sector 2 at t.

Aggregates

- Number of firms in each sector: $card(S^1_t)$ and $card(S^2_t)$.
- Industrial concentration index (Herfindhal) in each sector: H^1_t and H^2_t.

Parameters in Sector 2 and base-setting	
$\alpha_2 = 0.5$	Performance/price sensitivity of demand
$\lambda = 0.05$	Probability of entry doing innovation (equal in both sectors)
$\delta = 1.06$	Common parameter in pricing routine
$a = 1$	Parameter beta-distribution
$b = 1$	Parameter beta-distribution

Firm-specific parameter Sector 2	
$\rho_j \sim$Beta $(a,\ \mathrm{b})$	Cognitive absorptive capacity (as a radius)

Firm-specific variables in Sector 2	
$X_{j,t} \in [0,\ 1]$	Knowledge to manage machines
$c_{j,t} > 0$	Cost of the machine
$y_{j,t} \geq 0$	Machine quality
$p_{j,t} > 0$	Price of the variety of consumption good
$f_{j,t} \in [0,\ 1]$	Consumption good firm-specific fitness (tradeoff quality/price)
$s_{j,t} \in [0,\ 1]$	Market share
$\pi_{j,t} \geq 0$	Firm profit

Parametric conditions when departing from the standard (base) setting

- $0 \leq \alpha_1 \leq 1$;
- $\eta > 1$;
- $c > 0$;
- $0 \leq \phi \leq 1$;
- $\epsilon \geq 0$;
- $0 \leq \lambda \leq 1$;
- $0 \leq \alpha_2 \leq 1$;
- $\delta > 1$;
- $a > 0$;
- $b > 0$;

Pseudocode (algorithm)

1. Initialize:
   1.1. Sector 1 (machines production). Initially empty sector- no firms ($S_0^1 = \varnothing$).
   1.2. Sector 2 (consumption goods production). Initially empty sector- no firms ($S_0^2 = \varnothing$).
   1.3. END;
2. For any t:
   2.1. Call Entry_Sector1;
   2.2. Call Entry_Sector2;
   2.3. Call Operate _Sector1;

2.4. Call Operate_Sector2;
2.5. Call Apply_Replicator_Sector1;
2.6. Call Apply_Replicator_Sector2;
2.7. Call Exit_Sector1;
2.8. Call Exit_Sector2;
2.9. END;
3. END;

- Define Entry_Sector1:
  1. Entry Sector 1: One new firm i enters in Sector 1 ($S_t^1 = S_{t-1}^1 \cup \{C_{i,t}^1\}$);
  2. With probability λ, or if the sector is empty, then $S_t^1 = \{C_{i,t}^1\}$ random initialization of traits:
     $r_i \sim U(0,\ 1)$;
     $\sigma_i \sim U(0,\ 1)$;
     $x_{i,t} \sim U(0, m),\ m = x_{t-1}^{max}$ if x_{t-1}^{max} exists, or $m = 1$ otherwise;
  3. If the new entrant copies, then: it copies firm $k \neq i$, with probability proportional to market share $s_{k,t-1}$, so that:
     $r_i = r_k$;
     $\sigma_i = \sigma_k$;
     $x_{i,t} = x_{k,t-1}$;
  4. Normalize $\sum_i x_{i,t} = 1$. The new entrant affects sectoral technology levels;
  5. END;
- Define Entry_Sector2:
  1. Entry Sector 2: A new firm j enters Sector 2 ($S_t^2 = S_{t-1}^2 \cup \{C_{j,t}^2\}$);
  2. Recalculate market shares: $s_{j,t} = 0.005,\ \sum_k s_{k,t} = 1 - s_{j,t} = 0.995$;
  3. With probability λ, or if the sector is empty, random initialization of traits:,
     $\rho_j \sim$Beta $(a,\ \text{b})$;
     $X_{j,t} \sim U(0, m),\ m = x_{t-1}^{max}$ if x_{t-1}^{max} exists, or $m = 1$ otherwise;
  4. If the new entrant copies: It copies firm k in Sector 2 with a probability which is proportional to its market share $s_{k,t-1}$, and:
     $\rho_j = \rho_k$;
     $X_{j,t} = X_{k,t-1}$;
  5. END;
- Define Operate_Sector1:
  1. For each firm i in Sector 1:
     1.1. R&D Investment:
        1.1.1. If it is a new imitative entrant: $R_{i,t} = R_{k,t}$;
        1.1.2. otherwise: $R_{i,t} = r_i \pi_{i,t-1}$;
     1.2. Expected unit cost:
        1.2.1. If it is a new imitative entrant: $c_{i,t}^e = c + \epsilon \frac{R_{i,t}}{q_{i,t}^e},\ q_{i,t}^e = q_{k,t-1}$;
        1.2.2. If it is a new entrant but it does not imitate: $c_{i,t}^e = c$;
        1.2.3. otherwise: $c_{i,t}^e = c + \frac{R_{i,t}}{q_{i,t}^e}$, $q_{i,t}^e = q_{i,t-1}$;
        1.2.4. END;
     1.3. Delimitation of direct rivals ($i \neq k$): $\Lambda_{i,t} = \left(k : (x_{k,t} - x_{i,t}) \leq \sigma_i x_t^{max}\right)$;
     1.4. Set Cournot mark-up: $\mu_{i,t} = \frac{\eta + \sum_{k \epsilon \Lambda_{k,t-1}} s_{k,t-1}}{\eta + \sum_{k \epsilon \Lambda_{k,t-1}} s_{k,t-1} - s_{i,t}^e}$, $s_{i,t}^e = \frac{1}{Card(S_t^1)}$ for new firms and $s_{i,t}^e = s_{i,t-1}$ otherwise;
     1.5. Pricing: $p_{i,t} = \mu_{i,t} c_{i,t}^e$;
     1.6. New knowledge at t: $\gamma_{i,t} \sim Dist.$, with "$Dist.$" representing a (truncated) Pareto distribution, supporting values $L = 0$, $H = 1$ and parameter θ (slope of density function). We have θ in our model as being determined by:
        $\theta = \frac{1}{\phi \cdot imitation + (1-\phi) \cdot research}$;

imitation $= \frac{x_t^{max} - x_{i,t}}{x_{i,t}}$, that is, assimilation of knowledge from the gap to the frontier;

research $= \frac{R_{i,t}}{R_{i,t}^{max}}$, that is, knowledge obtained from inner R&D;

2. END;

- Define Operate_Sector2:
  1. For each firm j:
     1.1. Re-scaling $X_{j,t-1}$ to be comparable with the values $x_{k,t}$, since values $X_{j,t-1}$ range within $\left(0, \frac{1}{Card(S_t^1)-1}\right)$, whereas the values $x_{k,t}$ range in $\left(0, \frac{1}{Card(S_t^1)}\right)$, we have an additional firm in the current period: $X'_{j,t-1} = X_{j,t-1} \cdot \frac{Card(S_t^1)-1}{Card(S_t^1)}$;
     1.2. Selection of understandable machines: $\Xi_{j,t} = \left(k : \left(X'_{j,t-1} - x_{k,t}\right) \leq \rho_j x_t^{max}\right)$;
     1.3. Buy a machine from i with probability proportional to: (demand for Sector 1 firms) $\alpha_1 x_{i,t} + (1-\alpha_1)\left(1 - \frac{p_{i,t}}{\sum_{k \epsilon \Xi_{j,t}} p_{k,t}}\right)$;
     $c_{j,t} = p_{i,t}$;
     $X_{j,t} = x_{i,t}$;
     $y_{j,t} = x_{i,t}$;
     1.4. Pricing: $p_{j,t} = \left(\frac{\delta}{\delta - s_{j,t}}\right) c_{j,t}$;
     1.5. Firm j competitivenes (fitness) in the consumption goods market: $f_{j,t} = \alpha_2 \frac{y_{j,t}}{y_t^{max}} + (1-\alpha_2)\left(1 - \frac{p_{j,t}}{p_t^{max}}\right)$;
  2. END;
- Define Apply_ Replicator_Sector1:
  1. For each firm i in Sector 1, update performance by: $\frac{x_{i,t+1} - x_{i,t}}{x_{i,t}} = \gamma_{i,t} - \overline{\gamma}_t$, $\overline{\gamma}_t = \sum_k x_{k,t}\gamma_{k,t}$;
  2. END;
- Define Apply_Replicator_Sector2:
  1. For each j in Sector 2, calculate its market share from the replicator equation: $\frac{s_{j,t+1} - s_{j,t}}{s_{j,t}} = f_{j,t} - \overline{f}_t$, $\overline{f}_t = \sum_h s_{h,t} f_{h,t}$;
  2. END;
- Define Exit_Sector1:
  1. For each firm i in Sector 1:
     1.1. Calculate ex post unit cost: $c_{i,t} = c + \frac{R_{i,t}}{q_{i,t}}$;
     1.2. Calculate profit: $\pi_{i,t} = q_{i,t}(p_{i,t} - c_{i,t})$;
     1.3. Firm i exists the market when $\pi_{i,t} \leq 0$;
     1.4. Normalize: $\sum_i x_{i,t+1} = \sum_i x_{i,t} = 1$. Note that firm exist alters the relative values of technological levels in the sector, both, in the current period, and in the next one;
     1.5. Communicate to Sector 2 the re-scaling in the previous step;
  2. END;
- Define_Exit Sector2:
  1. Each firm j in Sector 2 exists the market when: $s_{j,t+1} \leq 0.005$;
  2. Normalize: $\sum_i s_{i,t+1} = 1$;
  3. END;