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

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Abstract

We propose a new *co-evolutionary* computational *two-sector approach* to the design of national innovation policy that recognizes the importance of inter-sectoral *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 new role for innovation policy to create a balanced, sectorally-targeted approach.

Keywords: Innovation, coevolution, Neo-Schumpeterian models, absorptive capacity.
JEL-Code: B52, C63, O31.

1 Introduction

The twin pillars of modern *innovation policy* literature are economic analysis of the production of new information under uncertainty (Nelson 1959, Arrow 1962a), and the evolutionary economic model of innovation diffusion (Schumpeter 1939, Nelson and Winter 1982). Innovation policy seeks institutional solutions to market failure in the production of new knowledge in order to support innovating firms to adopt new technologies and to develop new markets and industries (Martin and Scott 2000). The theory of innovation policy is mostly developed within a representative market or representative industry approach, with policy attention directed to resolve market failure and guide industrial dynamics. Consideration of how other sectors affect innovation is generally treated as an additional complexity in an essentially monosectoral analysis.

The absence of a multisectoral approach in innovation policy is striking when compared to its centrality in the modern *innovation strategy* literature, which builds on the same evolutionary economic foundations – namely in 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 organisational boundaries. A multisectoral approach is fundamental to strategic analysis because value creation in complex technological systems is an interdependent process across multiple firms. Such analysis of the balance of knowledge 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 (Baldwin 2018, Adner and Kapoor 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), but 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 shifts to an entire economy, in which innovation is 'upstream'of consumer markets, and 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 through bottlenecks such as the balance of capabilities, technological overshooting, and absorptive capacities.

In this paper, we 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 corresponding to innovation policy settings. Our model builds on Nelson and Winter (1982), Almudi *et al*. (2013) and Dosi *et al*. (2013) and 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 analysing 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 emphasised the importance of dynamic competence, bottlenecks, and industry architectures to an understanding of how innovation creates value in complex technology systems. A core contribution of this paper 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 as outcomes from statistical distributions operating in a complex model, and as a result of learning by doing and adaptation efforts, the strategies and capabilities of innovating firms. Then, we characterize as knowledge coordination problems such as bottlenecks arising from overshooting and absorptive capacity constraints the simulated probability of collapse of intersectoral trading in our multisector model. Our stochastic computational model is able to 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 over a sectoral technology (what we will call the 'understanding radius') – are dynamically interdependent with innovation properties of firms in other sectors. This provides a model of how industry architectures and business ecosystems can be understood from an innovation policy perspective.

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. 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. Finally, Section 5 reviews the implications of our co-evolutionary model for innovation theory and policy. We also comment on potential 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. Perhaps the most developed bodies of theoretical work supporting innovation policy in this stream are those around the concepts of National Innovation Sytems (Freeman 1987; Lundvall 1988, 1992; Nelson 1993) and Sectoral Systems of Innovation (Malerba 2005), which are 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 understanding the direction of technological change. According to Rosenberg (1969) technological imbalances (or bottlenecks) may arise since 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 the correct design of institutional frameworks (within theoretical limits) and the engagement and participation of a range of organizational players involved in technological change.

Unlike innovation policy approach, the multisectoral approach to innovation is well developed in the organisational strategy literature. Management scholars have focused on innovation strategy, that is, the strategic dimensions through which the innovating firm create and captures value. This literature is centred about the concepts of capabilities, industry architectures, and ecosystems (Baldwin and Clark 2000, Jacobides 2008, Jacobides et al 2006, Jacobides 2018, Adner and Kapoor 2010). Sectors are seen as complex architectures (or ecosystems) whith 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 (Jacobides et al 2006, Teece et al.1997, Jacobides and Tae 2015). 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, Baldwin 2018, Jacobides *et al.* 2014, Jacobides and Tae 2015).

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 bottlecnecks can arise inter-sectorially 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

The key insight of our multisector approach to innovation policy is that 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 forwards and backwards; 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 increasingly and 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). Modern innovation economics is increasingly recognising that an intrinsic characteristic of evolutionary technical change is extreme inter-field unevenness and that technological progress emerges from the co-evolution of practice and understanding in coupled multisector domains (Dosi and Nelson 2010, Dosi and Grazzi 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.

Innovation policy can work differently in a multisectoral economy compared to a single sector economy. To show this, we develop a new class of computational model (an agent-based coevolutionary model) built around two key mechanisms in the multisectoral revolution: *aborptive capacity* (Cohen and Levintal 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 builds on Nelson and Winter (1982), Almudi *et al*. (2013) and Dosi *et al*. (2013). It 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 micro-foundations, general equilibrium models (e.g. CGE, DSGE) developed in the 1980s have subsumed the input-output 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 macro-industrial planning (IO models for *industry policy*) and macro-dynamic 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 inter-linked 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, each sector can absorb and adopt technologies from every other sector. Sectoral innovation constrains, in a balanced economy, can only be a consequence of variation in resources, prices and income, as in IO and GE models. Note the standard absorptive capacity literature focuses on intra-sectoral constraints, not inter-sectoral constraints. In an *unbalanced* innovation economy, absorptive capacity constraints (i.e. bottlecnecks) 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 inter-sectoral 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 wasted private and public innovation effort because the benefits cannot be diffused owing to absorptive capacity constraints.

3 The Model

This section describes our agent-based computational neo-Schumpeterian model of a multisectoral economy (Dosi *et al*. 2013; Metcalfe *et al*. 2006; Saviotti and Pyka 2013). The model description can be completed with the equations, technical details and the pseudocode in Appendix A and Appendix 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 (Bloch and Metcalfe 2018, Winter

1984, Vives 2001) with a mark-up 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 (intra-sectoral) 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 Levintal 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 Sector 1 and Sector 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. 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. In fact, we propose it as a general framework to carry out 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, considering the limited scope of a single paper, in this current initial work we 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?

To tackle these questions in our model, let us begin by explaining (from a technical point of view) that the model is implemented in JAVA and the statistical analysis is carried out with R-Project (see the formal structure of the model in Appendix A and Appendix B). The model dynamics reach limit states in approximately 5,000 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, 2017b). Because of stochasticity, we run the model 100 times and average the data for each setting of parametric values.

In this specific paper, we focus computational analysis on the role played by *absorptive capacity* in the downstream machine-using Sector 2 as a key driver of intersectoral coevolution and innovation. We consider how the generative stochastic structure *Beta (a,b) distribution* (from which machine-user firms emerge) affects multisector coevolution. The shape of the distributions varies depending on parameters (*a,b*) (ses Fig.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 are going to 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 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 coevolutionary 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 Nornal, 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 radius* $\rho_j \in (0,1)$ emerge (see Appendix A and B).

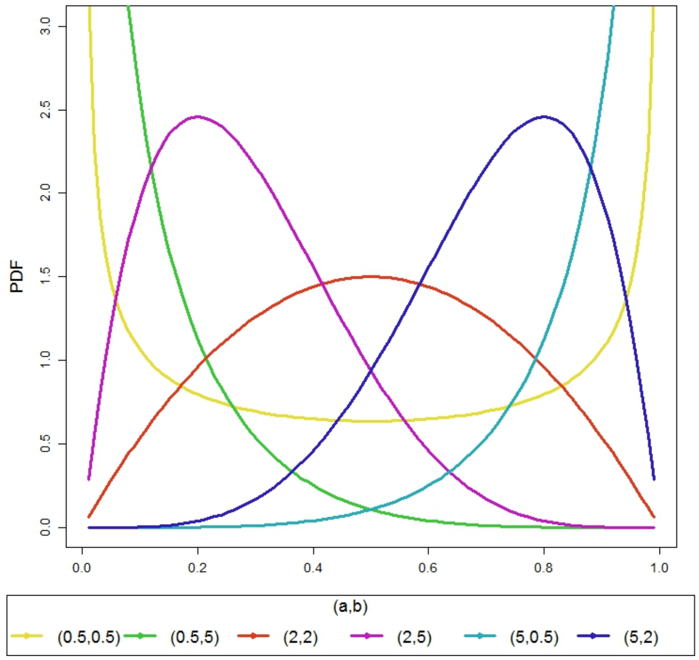

Figure 1. Density functions for the Beta (a,b) distribution.

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 Fig.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 79x79=6,241 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).

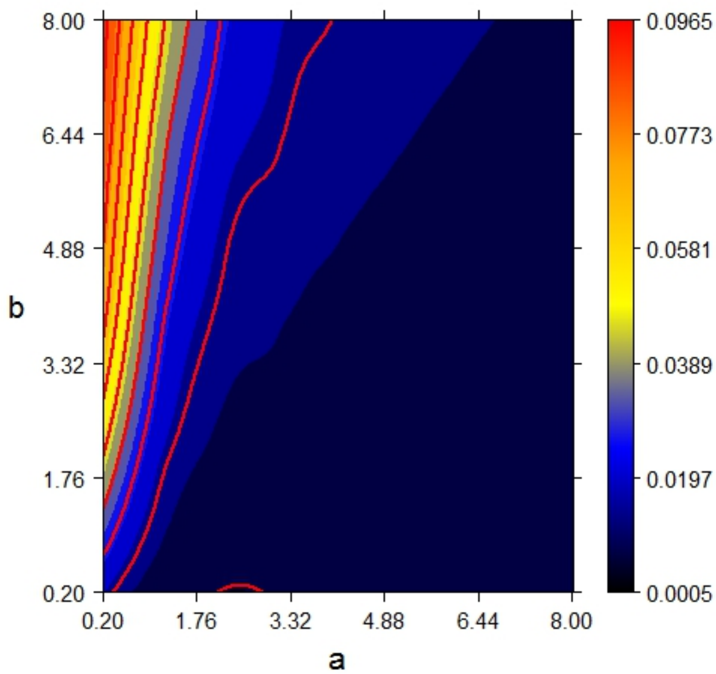

Figure 2. Probability of collapse related with the Beta (a,b) parameters.

In we relate Figure 2 with the PDFs 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, -hot colours) 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.

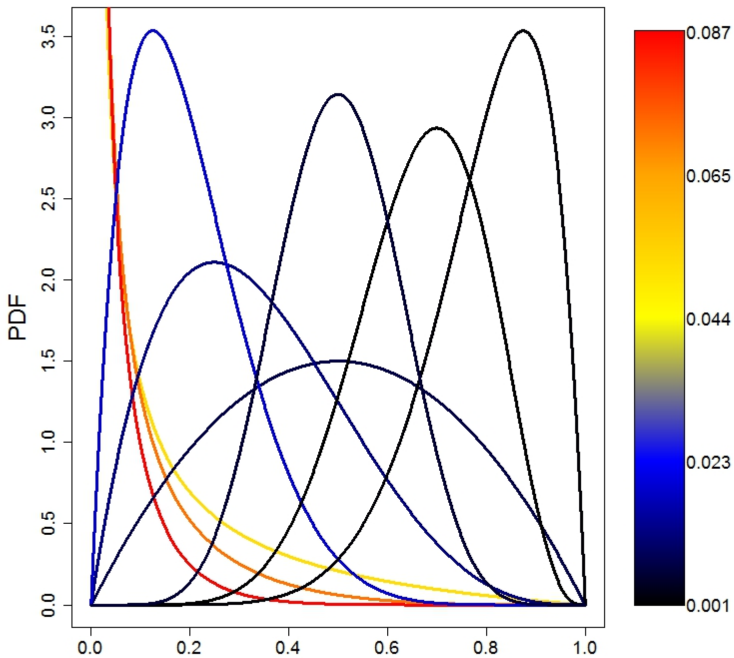

Figure 3. Beta distributions and probability of collapse

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 the interested reader, a detailed explanation of the econometric methology for polynomial regressions, the use of p-values as indicators of statistical significance, and the nonlinear regression methodology that we are going to use below can be seen (e.g.) in Montgomery *et al*. (2006, chapters 7 and 13) or in 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 $P(x,y) = a_0x^0y^0 + a_1x^1y^0 + \cdots + a_nx^0y^n$. In the third column, we present the estimated coefficient value with confidence interval [5% and 95%] and the p-value (H_0: a null coefficient). As we see, the $R_{adjusted}$ becomes acceptable (>0.9) for a 3-polynomial degree.

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

	a^0b^3	$-0.000002270 \pm 0.000009228393$	0.68572
	$R_{adjusted} = 0.9168$		
	$P - value = \ 0.00000000000000022$		

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

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 polinomyal. Thus, we have a very good fit and a significant statistical relation linking *probability of collapse* -through a cubic polinomyal- with (*a,b*) *parameters of the Beta distribution* in the model. The results in Table 1 support statiscally 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 2-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 polinomyal 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):

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

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*	$skew^0$	$0.00664250 \pm 0.000086206$	0.0000000000000002
	$skew^1$	$0.01192869 \pm 0.00008093$	0.0000000000000002
	$skew^2$	$0.00402343 \pm 0.000039975$	0.0000000000000002
	$R_{adjusted} = 0.9334$		
	$P - value = 0.00000000000000022$		
3	$skew^0$	$0.00664250 \pm 0.000085733$	0.0000000000000002
	$skew^1$	$0.01141738 \pm 0.000129326$	0.0000000000000002
	$skew^2$	$0.00402343 \pm 0.0000397563$	0.0000000000000002
	$skew^3$	$0.00010179 \pm 0.0000201477$	0.0000000000000002
	$R_{adjusted} = 0.9341$		
	$P - value = 0.00000000000000022$		

Table 2. Polinomial regressions for 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 polinomyal, 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.

Regarding the interpretation of the results, 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 fastly-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 meso-level 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).

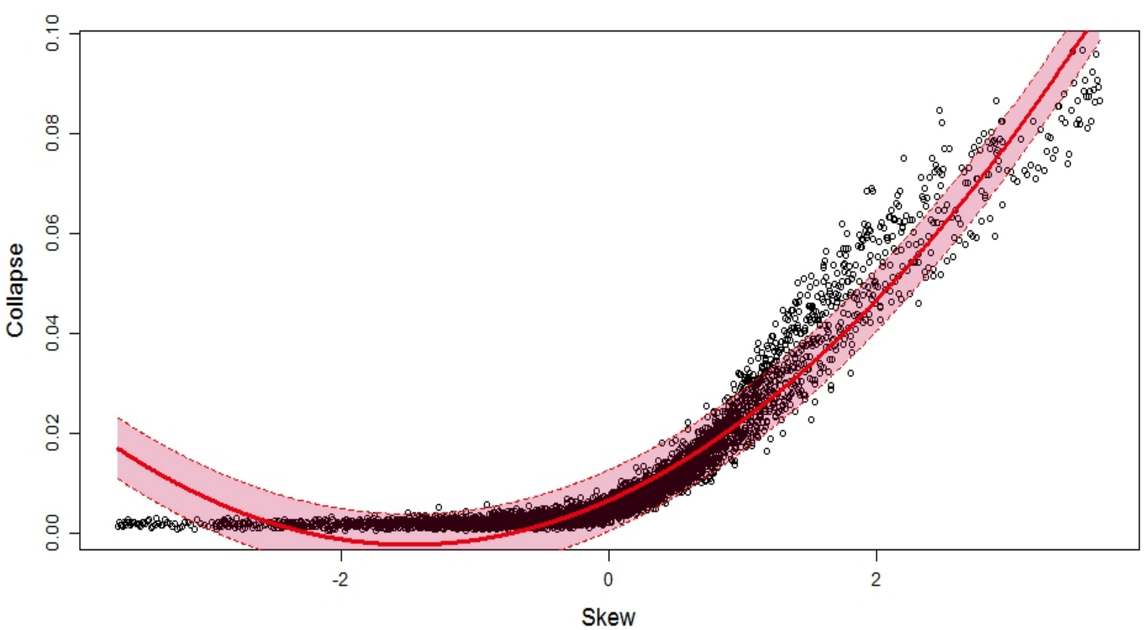

Figure 4. Second order polinomial fit (Collapse/skew).

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

Let us move to 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 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 stationarity in 5,000 steps.

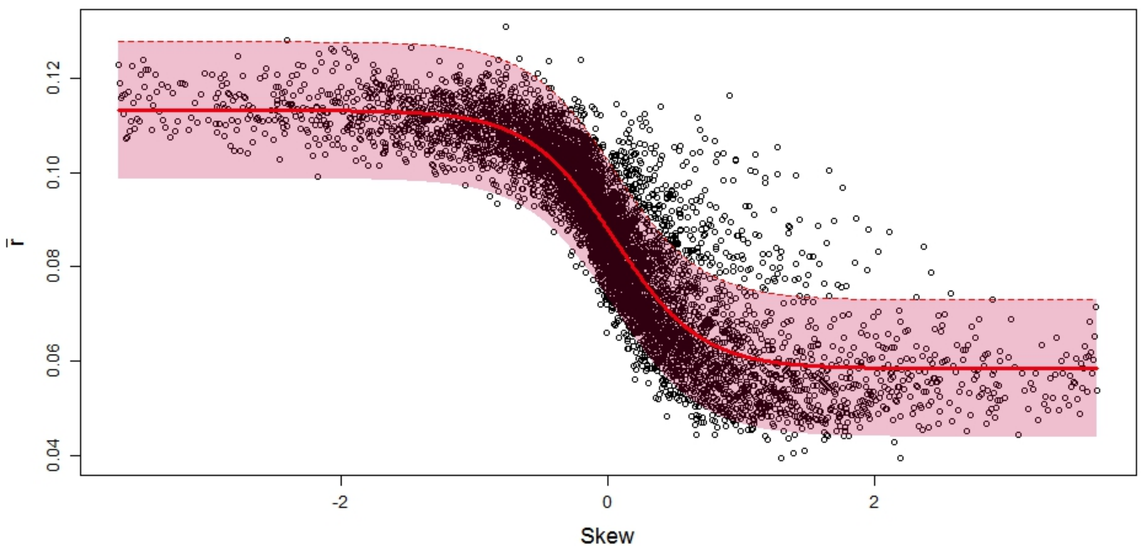

Figure 5. Sigmoidal fit (Average R&D to profits ratio/skew).

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 absorbtive 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 percent of net profits devoted to R&D (on average in Sector 1 as a stationary value) in the best cases, to two percent 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).

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

Table 3. Sigmoidal fit for the result in Figure 5.

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 what we call the "slump effect" of R&D intensity. In economic terms, we find a non-linear relationship which 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 Fig.5 indicates that, as the generative structure in the downstream sector becomes less generative of aborptive 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 percent of profits to R&D in Fig.5, we quickly fall to values of five percent along the vertical axis. This is the slump effect. As we see in Fig. 5, in our model, absorptive capacity in the user-sector influences in a highly non-linear 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 a very important result which poses additional arguments in favour of procurement policies capable of unchaining technological progress with no need to rely on taxes, pickig winners, subsidies and other traditional policies.

Finally, we would like to point out that our model formally supports previous results in the literature -such as Adner (2017), Adner and Kapoor (2010) or Jacobides *et al.* (2018)- in which it is shown how coordination failures within industry ecosystems may block innovation adoption and technological change. Nevertheless, our model adds something very important to these results, namely, the dangerous possibility that the mechanisms underlying innovation slowdowns may be highly non-linear (the *slump effect*). In these cases, silent and even moderate deteriorations of the socio-economic and institutional frames engendering user-firms have only minor effects (at first!) in the innovation rates; but unexpectedly and in a very quick manner, an slightly higher deterioration of the generative structure near the inflection zone (see Fig. 5) can produce a very 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).

5 Discussion

We have 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 producing and selling 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. This is because absorptive capacity constraints in the downstream sector can backpropagate to cause innovation overshooting in the upstream sector.

We have modeled this general knowledge coordination problem as a multisectoral process in which 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 performances in Sector 1 evolve 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 inter-sectoral *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 presended in this paper 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 non-linear 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:

$$p_{i,t} = \mu_{i,t} c_{i,t}^e \qquad \text{(A1)}$$

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:

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

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:

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

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

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:

$$c_{i,t}^{e} = c + \frac{R_{i,t}}{q_{i,t}^{e}} = c + \frac{R_{i,t}}{q_{i,t-1}}, \qquad c > 0 \qquad \text{(A4)}$$

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:

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

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

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

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

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, Bloch and Metcafe, 2018 and Almudi *et al.* 2012, 2013).

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 dissappears 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 $q_{i,t}^{d} = card\left(\Omega_{i,t}\right)$.

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:

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

(A7)

$$research = \frac{R_{i,t}}{R_{i,t}^{max}},$$ generating knowledge from (normalized) inner R&D;

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:

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

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 $(X_{1,t}, \cdots, X_{card(S_t^2),t})$, 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-base 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 assessement 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

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

In (A9) $c_{j,t}$is the cost of the chosen machine, and δ (>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:

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

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:

$$\frac{s_{j,t+1} - s_{j,t}}{s_{j,t}} = f_{j,t} - \bar{f_t}; \qquad \text{with} \quad \bar{f_t} = \sum_h s_{h,t} f_{h,t} \qquad \text{(A10)}$$

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.

Notation regarding Sector 1

$C_{i,t}^{1}$: firm i from Sector 1 at time t.

$S_t^1 = \{C_{i,t}^1\}$: set of firms operating in Sector 1 at t.

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.
$\varepsilon = 0.75$	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
$q_{i,t}^{e} \geq 0$	Expected sales (in real terms = number of expected customers)
$R_{i,t} \geq 0$	R&D spending
$c_{i,t}^{e} > 0$	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 2

$C_{j,t}^{2}$: firm j in Sector 2 at t.

$S_t^2 = \{C_{j,t}^2\}$: Set of firms in Sector 2 at 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	
$\rho_j \sim Beta\,(a,b)$	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

Aggregates

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

Parametric conditions when departing from the standard (base) setting

- $0 \leq \alpha_1 \leq 1$;
- $\eta > 1$;
- $c > 0$;
- $0 \leq \phi \leq 1$;
- $\varepsilon \geq 0$;
- $0 \leq \lambda \leq 1$;
- $0 \leq \alpha_2 \leq 1$;

- $\delta > 1$;
- $a > 0$;
- $b > 0$;

Pseudocode (Algorithm)

1. Initialize:

   1.1. Sector 1 (machines production). Initially empty sector- no firms ($S_0^1 = \emptyset$).

   1.2. Sector 2 (consumption goods production). Initially empty sector- no firms ($S_0^2 = \emptyset$).

   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:,

$\rho_j \sim Beta\,(a,b)$;

$X_{j,t} \sim U(0,m),\ m = x_{t-1}^{max}$ 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: $c_{i,t}^e = c + \varepsilon \frac{R_{i,t}}{q_{i,t}^e},\ \ q_{i,t}^e = q_{k,t-1}$;

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 ($i \neq k$): $\Lambda_{i,t} = \left(k: \left(x_{k,t} - x_{i,t}\right) \leq \sigma_i x_t^{max}\right)$;

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: $\frac{x_{i,t+1} - x_{i,t}}{x_{i,t}} = \gamma_{i,t} - \bar{\gamma}_t,\ \bar{\gamma}_t = \sum_k x_{k,t}\gamma_{k,t}$;

2. END;

- Define Apply_Replicator_Sector2:

1. For each j in Sector 2, calculate its market share from the replicator equation:

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

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;