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Final Dissertation

Essays on the Co-Evolution Between Strategies and Technologies

PhD in Management – XXXIII Cycle

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To my "nonno Nello"

Who taught me the beauty of a life spent to learn

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Acknowledgements

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Introduction

The current thesis is about innovation, interpreted as the outcome of the matching between technological knowledge and the social environment in which this knowledge is used and designed. The four essays composing this final dissertation all share the idea that innovations are not the inevitable outcome of some pre-established pattern but, instead, the result of a continuous effort to provide novel solutions to, and make profits out of, an ever-changing set of needs arising within our societies.

To this extent, the understanding of the innovation process calls for the understanding of the interactions between three fundamental elements: the agents looking for new business opportunities, the social environment (e.g., consumers, firms, institutions) expressing social needs, and the technological realm providing the hitherto attainable solutions to these needs. These elements can be seen as a triad in continuous evolution; or better, co-evolution, for each component of the system influences and reacts to changes coming from the other two. Indeed, the agents must interpret the environment to pinpoint new opportunities, technology is modified based on agents' actions and knowledge, and the environment transforms after the introduction of new products, processes, or organisational forms.

Under this perspective, innovation is therefore a complex and multi-faceted phenomenon, characterised by three dimensions. The first one is the direction: any artefact serves one or more functions which provide the direction for its improvement. Sometimes the matching between the technological means to achieve the functions and the functions themselves emerge out of the blue -as in the case of the subject at the centre of chapter 1- while other times the functions come first, and the architecture is adapted around them. Either way, any innovation is characterised by the functions it serves, and it is not a mere improvement in quality of something that existed before. Moreover, functional evolution is important to understand technological bifurcations and the connected social phenomena, such as the emergence of new markets and niches. The second dimension is path dependency, a feature characterising all the evolutionary processes. Path-dependency derives from direction: if innovations are generated to serve a purpose by re-combining the technological knowledge at disposal, then, from an historical perspective, today's knowledge depends upon yesterday's one. Finally, the third dimension is place-dependence and represents the spatial version of path dependency. Although we live in highly interconnected societies, knowledge transmission often requires physical interactions whereby tacit elements are transferred and learned. To this extent, the evolution of knowledge does not only hinge on the knowledge available at one point in time, but on the knowledge available at one point in time in a specific place.

To this extent, the following four essays study four different phenomena related to technology evolution by adopting these co-evolutionary lenses. In particular, each one of them focuses on a specific mechanism of technological evolution to understand also the consequences on the economic side.

Chapter 1 presents a study on exaptation. Exaptation is an evolutionary mechanism whereby some characteristics of an organism are selected based on functions that were not the ones originally steering their evolution. In technology, exaptation represents a process whereby an artefact acquires, all of a sudden, a new function, different from those devised when the artefact was conceived, creating, in such a way, a technological bifurcation bringing about the emergence of new markets. By adopting the perspective described before, the work seeks to understand under what circumstances and conditions firm's search strategies are more likely to be associated to the discovery of latent functions. To do that, the work builds a novel simulation model based on the generalised NK framework (Altenberg, 1997) and centred around the evolution of a multifunctional artefact operated by an agent. Specifically, while trying to improve the performance of her current artefact following the social needs expressed by the environment, the agent may discover new functions associated to artefact's components. These discoveries are related to the strategies the agent adopts to improve her current design, to the difficulty whereby she can learn from the underlying technology, and to the degree of dynamism of the external environment. Overall, this work provides a novel framework to study the generation of technological bifurcations.

Chapter 2 is connected to chapter 1 as it presents a study on the technological evolvability in presence of different types of modular architectures. Technological evolvability refers to the property of the technology to generate new varieties through time. These latter are the result of agents' search activities in a technological space which connects components to possible functions. To this extent, the difficulty whereby agents can search for the implementation of new functions in their artefacts depends upon the structure of the technology. Although many technological structures are nowadays represented by modular architectures, they are not alike. In particular, by means of a simulation model based on generalised NK, the study in this chapter shows how the different relationships between components and functions with a modular architecture leads to different degree of evolvability of the technology. Moreover, the model also shows the presence of a trade-off between the speed whereby new variants are discovered and the performance of the artefacts produced by one architecture. In economic terms, the results of the simulations indicate the existence of a relationship between the structure of a technology and the emergence of connected markets.

Chapter 3 focuses on another type of differentiation. Instead of studying the evolution of technologies through the emergence of novel functions, it investigates the evolution of a market through the emergence of niches, each one characterised by a specific product variety. It proposes a novel product life-cycle model in which firms compete for consumers in a market for a multi-functional artefact. Within this framework, consumers have heterogenous preferences over the different functions, while firms conduct R&D activities that alter artefact's architecture to improve the performance of their product in accordance with customers' tastes. The model is able to reproduce some important stylised facts highlighted by the literatures in economics and innovation studies. In particular, it shows how modular architectures are related to market organisation which, in return, depends on customers' preferences.

Finally, Chapter 4 introduces the geographical dimension to technological evolution by looking at technological variety at the regional level. The underlying idea of this empirical study is to investigate the contribution of firms' collaboration strategies for the evolution of regional variety of technological knowledge. By measuring university-industry collaborations through the patenting activity involving academic inventors, the study offers some evidence on the role of firms' collaboration choices for the evolution of regional capabilities. Results suggest that the mere collaboration with universities is not sufficient for firms to have an impact on the variety of regional knowledge but, instead, it is also important that the knowledge produced by the collaboration can be accessed by more than one organisation.

CHAPTER 1

Sensitivity, Innovation Attitudes, and Perseverance as the Strategic Foundations of Exaptation[1]

1.1 Introduction

Innovations represent an attempt to provide solutions to problems expressed within society. The history of technology shows there are many mechanisms through which the innovative process has been carried out (Dew, Sarasvathy,and Venkataraman, 2004). Sometimes the solution to a problem has been achieved through a process of adaptation, by designing artefacts with ad-hoc characteristics capable to fulfil the desired functions. Other times, the solution to problems has been reached by co-opting a characteristic of an already existing artefact for a use that was not accounted for by the original design (Mokyr, 2000). The latter innovation pattern is labelled exaptation and it is extremely relevant not only because it is at the basis of the generation of successful products (Osepchuk, 1984), but also because it represents the mechanism behind new market niches following from the technological bifurcations brought about by the emergence of alternative uses of the artefact (Andriani, Ali, and Mastrogiorgio, 2017).

Despite its importance, however, there are still few studies focusing on the complex process whereby exaptation is brought to light and on the roles played by the different elements at its roots (Andriani and Cattani, 2016). Hitherto the literature has pointed out that exaptation unfolds in three phases (Andriani and Carignani, 2014): an initial one characterised by the serendipitous emergence of a new function for an existing product/technology, a second one centring around the deliberate selection of the newly

[1] *Co-authored with Luigi Marengo (Professor of Economics, Luiss University, Rome, Italy) and Mariano Mastrogiorgio (Assistant Professor of Strategy, IE Business School, Madrid, Spain)*

emerged function and the redesign of the artefact's architecture around it, and a third phase dealing with the adaptation of the new product/technology on the basis of the characteristics of users' needs. These three phases involve the interaction between the artefact, the external context, and the agent (Andriani and Cattani, 2016). As a matter of fact, the emergence of new uses/functionalities for the artefact occurs when it is exposed to a specific external context. At the same time, the external context legitimates the functionalities of the artefact and modifies agents' perceptions regarding new possible uses.

These perceptions are connected to learning processes associated with agent's activity (Malerba, 1992). To this extent, the possible development of new uses for current artefacts is bound to firms' strategies. In this sense, strategic behaviours represent the gear of a co-evolutionary process involving technology and the external environment (Felin et al., 2016; Von Uexkiill, 2013).

Although the literature has started to dig deeper into the foundations of exaptation, there are still few studies focusing on the relationship between specific aspects of firms' strategies and this peculiar way to innovate (Querbes and Frenken, 2017). Moreover, very often exaptation has been hitherto investigated through case studies and historical anecdotes, providing a rich set of detail of the mechanisms underlying each case but also a wide range of differences that have to be gathered under the same umbrella. It is therefore important to provide a theoretical framework able (i) to explain the evidences emerging from the literature, and (ii) to expand the investigation of exaptation along co-evolutionary patterns between technology and strategies.

By starting from the literature results and drawing on behavioural (March, 1994) and evolutionary theories (Nelson and Winter, 1982), this work aims to contribute to the literature on the genesis of exaptation by developing a simulation model that allows to study its foundations. In particular, the proposed formal representation allows to investigate (i) the roles played by different levels of perceptions and by different types of operational procedures in the development of newly emerged functionalities of an already existing artefact and (ii) how these roles change depending on the type of the external context and of the technology involved.

In the next section the whole framework is described in detail while in section 3 we provide the results of our simulations. Section 4 concludes.

1.2 The Model

1.2.1 Pillars and General Overview

By drawing on the literature, our model builds upon the three pillars backing the emergence of exaptation (Felin et al., 2016): (i) the artefacts generated by a common set of components, (ii) the external environment in which the artefact is used (e.g., formal and informal institutions, social needs, and economic players), and (iii) the agent inventing and improving the artefact (firms) (Fig.1). These three pillars generate the dynamics of the model through their interactions.

[FIGURE 1 ABOUT HERE]

The general idea is the following. In every period, societal needs are expressed in two forms. On the one hand, the external environment evaluates the functions fulfilled by the artefacts in circulation. On the other, it also expresses the need for a new function not yet developed.

By observing the functional evaluation, each agent seeks to improve her artefact to better meet the requirements of the external environment. In particular, efforts are devoted to improve the ability of the product to fulfil functions perceived as the most relevant ones. The number of attempts each agent devotes to the improvement of a function is represented by the degree of perseverance. Moreover, improvements are carried out by working on the product's components connected to the function of interest: the more an agent operates on a component, the more she gains knowledge about it. After a certain number of times an agent has operated on one component she perceives (either serendipitously or because of her cognitive ability) the possibility to create an entirely new function with that component. If that new function is the same requested by the external environment in the subsequent period, then the agent creates a new bundle of functions and exaptation occurs. Otherwise nothing happens and the process starts again.

Given this general overview, the next subsections describe in detail eachaspect of these dynamics.

1.2.2 Model Description

1.2.2.1 The Artefact(s)

The whole exaptation phenomenon centres around the evolution of artefacts and, in particular, around the implementation of new bundles of functions/creation of new artefacts when new functions are discovered for some components. For instance, in the microwave-oven example, the magnetron (a component of the radar) was discovered to possess the ability to melt candy bars (new function) and was re-employed to create a new artefact taking advantage of this possibility (Andriani and Carignani 2014).

To account for the relationship between functions and components, we follow the *artefact-centred* approach to technologies (Dosi and Nelson 2010) conceiving artefacts as bundles of functions provided by a set of components combined together through technological knowledge. The formal way whereby we represent these relationships is through a *generalised NK* model (Altenberg 1997; Frenken 2006). Generalised NK models represent a variation of traditional NK models (Kauffman et al. 1993; Levinthal 1997; Marengo et al. 2000) in which the functions of the complex system do not need to coincide with the elements of the system (Fig.2). In other words, generalised NKs provide a degree of freedom with respect to NK models because they allow to distinguish between the functions of the system and its elements, enabling in this way to account for a larger number of system architectures (Frenken 2006).[2]

[FIGURE 2 ABOUTE HERE]

In our case, the elements of the system are the artefact's components. Each component is represented as a dummy variable, $n_i = \{0,1\}$, whose values indicate the possible characteristics (e.g., the i-phone camera can be simply 'wide' or 'wide and ultra-wide').[3,4] To this extent artefacts are represented by binary strings of length N, $S = \langle n_1, n_2, \dots, n_N \rangle$, that can take on 2^N combinations.

Technology associates each one of the F functions provided by the artefact to a subset of these components. For example, both the engine and the chassis contribute to a car's maximum speed. Technological complexity, on the contrary, is given by the interrelations between the different functions brought about by the underpinning common components. As a matter of fact, a single component may be important for more than one function and, moreover, it can affect the functions it is connected with in differing ways. In the car's example, for instance, the power of the gear is positively associated to speed but negatively associated to stability. Generalised NK can reproduce these dynamics through the architecture of the *genotype-phenotype map* and the construction of the landscape associated to it. In our model, the degree of complexity of technology is controlled through the degree of *polygeny* which sets the number of components needed to provide each specific function.[5]

Akin to what occurs in traditional NK models, the string S is evaluated for its degree of fitness. Differently from traditional NK, however, the generalised version does not evaluate the components of the system but its functions. To this extent, in our context, the degree of fitness ω_j represents the ability of an artefact to fulfil function f_j. In particular, ω_j depends on the setup of those components $n_i \in S$ that are technologically associated to f_j. In order to allow for the presence of complex relationships between components and functions, the values for each ω_j under each combination of the related components are randomly drawn from a uniform distribution between 0 and 1 (ω_j~uniform[0,1]). When n_i changes its value (from 0 to 1, or viceversa) the associated ω_js will change as well.

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[2] The generalised NK was introduced in the evolutionary biology literature to study genome evolution on the basis of the relationships between genes and phenotypes (Altenberg 1997). A representation of these relationships is given by the so-called genotype- phenotype map: a matrix with a number of rows equal to the number of phenotypes and the number of columns equal to the number of genotypes. Whenever the ij-th cell of the matrix is non-empty, it means that the j-th genotype affects the performance of the i-th phenotype.

[3] In the evolutionary biology literature the values of components are the alleles of the genes.

[4] Components are treated as binary just for sake of computational simplicity. It has been proven that NK models results are similar even when n_i can take on more values.

[5] The generalised NK framework allows to shape technological complexity either by determining the degree of *polygeny* -i.e., the number of components associated to each function - or by determining the degree of *pleiotropy* -i.e., the number of functions associated to each component. To keep the structure of technology as simple as possible and focus on the strategic foundations of exaptation, we opted to construct the genotype- phenotype maps of our simulations by setting the degree of polygeny. Yet, the dynamics of the model works as well if instead we opted for the degree of pleiotropy.

By interpreting ω_j as a measure for the ability of the artefact to provide the j-th function, the technological quality of an artefact is defined as

(1) $$W = \frac{1}{F}\sum_{j=1}^{J} \omega_j(S)$$

its average ability to fulfil the functions implemented in its design.

Differently from basic generalised NK, however, the number of implemented functions is not fixed. As exaptation relates to the emergence of new functions, our model accounts for the evolution of artefacts' architectures via the inclusion of new functions (Figures 3 and 4).

[FIGURE 3 ABOUT HERE]

[FIGURE 4 ABOUT HERE]

Throughout the simulation agents can discover *latent functions* associated to one or more components of their artefact. The agent(s) who discovers (discover) first a latent function creates (create) a *new bundle* by adding the new function to the design of her (their) artefact (artefacts). Figure 5 depicts the possible patterns for the evolution of an artefact with two functions ($\langle f_1 f_2 \rangle$) at the beginning of the simulation and two latent functions (f_3 and f_4) that are discovered throughout the simulation. As it can be noticed, the figure hypothesizes that f_4 is the first discovered function, thus generating the new bundle $\langle f_1 f_2 f_4 \rangle$. As to the emergence of f_3 the model accounts for three different possibilities:

1. f_3 is discovered by one (or more) agent(s) associated to $\langle f_1 f_2 \rangle$, leading to the emergence of $\langle f_1 f_2 f_3 \rangle$;
2. f_3 is discovered by one (or more) agent(s) associated to $\langle f_1 f_2 f_4 \rangle$, leading to the emergence of $\langle f_1 f_2 f_3 f_4 \rangle$;
3. f_3 is discovered at the same time both by one (or more) agent(s) associated to $\langle f_1 f_2 \rangle$ and by one (or more) agent(s) associated to $\langle f_1 f_2 f_4 \rangle$, leading to the contemporaneous emergence of $\langle f_1 f_2 f_3 \rangle$ and $\langle f_1 f_2 f_3 f_4 \rangle$.

The relevance of these three possible patterns is related to the focus of our paper. As a matter of fact, exaptation deals with the emergence of a new function associated to one or more components. As such, once the function is discovered, there cannot be another exaptation related to that function, but there can only be new recombinations of that function with other bundles. To keep the model as simple as possible and centred around exaptations, we decided not to incorporate recombinations in this version.

[FIGURE 5 ABOUT HERE]

The discovery of a latent function passes through a *learning-by-searching* process over the artefact's components: every time one agent operates on n_i, she learns more about it. After a certain number of times she worked on n_i, if this component is connected to some latent function, the agent is able to spot this new opportunity. Notice that this mechanism is equally valid in presence of serendipitous events -as in the case of the fist antidepressant drug, Marsilid, reported by Andriani and Cattani (2016)- or in presence of superior abilities in pinpointing new affordances.

The number of trials required to discover a latent function is a parameter reflecting the *difficulty of learning-by-searching* of the technology. As a matter of fact, the different patterns of exaptation observed across sectors may be partly due to the differences in the difficulty to gain knowledge about the underpinning technology.

Once a function is discovered, a new genotype-phenotype map is created, by adding a new row to the genotype-phenotype map of the parent artefact. As it is illustrated in subsection 1.2.2.3, from the emergence of a new bundle onward, agents associated to other artefacts can shift to the new artefact.[6]

1.2.2.2 External Environment

The second pillar of the model is represented by the *external environment*. As underlined by Felin et al. (2016) affordances are context-related. To this extent, the emergence of exaptations must be related to the contexts in which artefacts are exposed and used. In our model the external environment plays two distinct roles.

On the one hand, it evaluates the functions implemented in existing artefacts. The idea is that, in each specific historical period, in a society some functions are more relevant than other ones: for example, before the pandemic, the possibility to travel was regarded as highly important, while after the arrival of the pandemic public health functions have taken over.

On the other hand, the external environment provides some signal -to be spotted by social actors- on the societal needs that would be important to meet. This signal can be either explicit, i.e. already structured in a potential demand for products, as in the case of the first antidepressant drug (Marsilid), or latent, as in the case of Viagra, for which Pfizer needed to set up a marketing campaign to stimulate the emergence of the niche (Dew and Sarasvathy 2016).

We model the first role through a mechanism producing one weight β_j for each function f_j implemented in the artefacts in circulation. More specifically, we regard the functional evaluation as the outcome of the interaction between formal (norms) and informal (culture, habits) institutions and other social aspects in which the artefacts are embedded. To this extent, we set up a second generalised NK made of E binary elements $T = \langle e_1, e_2, \dots, e_E \rangle$, in which each $e_i \in \{0,1\}$ represents one of the aforementioned external factors. At the beginning of the simulation, societal dynamics associate (a subset of) these elements to each one of the functions. For example, cars' functions (speed, stability, size) are judged on the basis of traffic rules, commuters' habits, level of pollution, infrastructures etc. The degree of complexity is given, as before, by the degree of polygeny of the system, i.e. by the number of social factors related to the evaluation of one specific function.

[6] This version of the model is not designed to study the dynamics underpinning the movements across artefacts. Shifts are accounted for in order to have more than one agent searching on the different landscapes generated by the model.

The setup of T represents the position within the NK landscape and indicates the situation in which society judges the artefacts. Whenever one (more) bit(s) switches (switch) from 0 to 1 (or viceversa) it implies that the corresponding factor(s) has (have) changed its (their) setup (e.g., traffic rules become tighter/looser, commuters change their habits in terms of transports etc.).

Different combinations of external factors bring about different judgments of the functions. The latter are represented by the degrees of fitness produced by the NK and associated to each emerged function f_j. Akin to what occurs with the technological NK, each function is associated to a degree of fitness $\theta_j \in [0,1]$ under all the possible combinations of T. As before, the values of each θ_j are drawn from a uniform distribution to create complexity in the relationship between functions and combinations of T. Yet, differently from the technological case, these evaluations are normalised to provide the environmental weights β_js

(2) $$\beta_j = \frac{\theta_j}{\sum_{k \in \boldsymbol{F}^e} \theta_k} \quad \text{for all} \quad j \in \boldsymbol{F}^e$$

where $\boldsymbol{F}^e$ indicates the set of functions already discovered in that period of the simulation.

Once computed, environmental weights may change for two reasons. The first one is the emergence of a latent function. In this case the new function starts to be evaluated by the environment and, therefore, all the β_js are recomputed. The second reason for β_js to change is associated to changes of the underpinning factors. When one or more e_is change, the θ_js of the associated functions change as well, leading to a re-normalization of all the environmental weights. For example, if traffic rules become tighter, the speed of a car can decrease its importance while its ability to promptly stop becomes more relevant. The frequency whereby β_js change due to changes in the environmental factors gives the *degree of environmental dynamism* of the context in which artefacts are discovered and improved.

Environmental weights are important insofar as they provide an evaluation of artefacts. As a matter of fact, the artefact of each agent can be judged by its overall technical performance (eq.1) as well as by its degree of appreciation by the external environment

(3) $$\Theta = \sum_j \beta_j \omega_j$$

computed as a weighted average of the technological quality of the artefact. In other words, Θ represents the quality of the artefact from the environment perspective.

Finally, the environmental degrees of fitness θ_js are also important for evaluating the relative importance of each bundle of functions a within the environment (ψ^a). ψ^as represent the *inter-artefacts weights* indicating which bundle of functions is appreciated more and which is appreciated less in a specific setting of the environment. Alternatively, ψ^as can be seen as the relative importance of the different market niches stemming from the same technology. Each ψ^a is computed as

(4) $$\psi^a = \frac{\bar{\theta}^a}{\sum_{b=1}^{A} \bar{\theta}^b} \quad \text{for } a = 1, \ldots, A$$

where $\bar{\theta}^a = \frac{1}{F^a} \sum_{j|f_j \in a} \theta_j$ is the average fitness of the functions implemented in the bundle a. Whenever exaptation occurs -bringing about a new combination of functions- then ψ^as decrease for the emergence of a new market niche. On the contrary, when environmental factors change, then each ψ^a changes but in an unpredictable way: if the functions included in a bundle become more relevant after the change, then the bundle may acquire importance with respect the other ones.

As to the second role of the external environment, the signals regarding social needs to be met are given every iteration of the model by randomly drawing one among the hitherto hidden functions. Whenever these signals match with the functions discovered by agents in the previous period, then exaptation occurs; if instead there is a mismatch between the signals and the findings - or there is no discovery at all - then nothing happens (Fig.6).

[FIGURE 6 ABOUT HERE]

When a new function emerges, then it is immediately associated to the factors of the external environment upon which it depends on.

<u>1.2.2.3 Agents</u>

The third pillar of the model is represented by the agents (firms) searching for new technological solutions to satisfy the requests coming from the external environment. In such a sense, agents represent the gear generating *co-evolutionary patterns* for they link the external environment with technology.

As already described, the technological solutions accounted for by the model fall within two categories: (i) improvement of already existing artefacts, (ii) construction of new artefacts through the inclusion of newly discovered functions. Throughout a simulation, each agent can in principle alternate both activities; yet the latter passes through her discovery of a latent function. At the same time discovery depends upon *learning-by-searching* processes which, in return, hinge upon the way agents decide to act on their current artefact. As a matter of fact, by adopting a boundedly-rational perspective (March 1994), the strategy followed to improve an artefact determines the direction in which new knowledge is gained, increasing in such a way the likelihood of pinpointing some affordances while overlooking other ones.

The model accounts for three distinct, but interconnected, aspects of agents' strategy that can have an impact on exaptation.

The first element deals with the *degree of sensitivity* to the external environment, i.e. to the ability of an agent to sense the evaluations of the functions implemented in her artefact made by the external environment. To this extent, sensitivity provides the spectrum of alternative possibilities taken into consideration by agents when deciding how to improve their artefact. Under this perspective, sensitivity is the first element needed for the construction of dynamic capabilities (Teece, Pisano, and Shuen 1997).

In the model sensitivity is represented by an exogenous parameter $\eta \in (0,1)$ setting the minimum threshold above which agents perceive the environmental weight β_j of a function f_j implemented in her artefact. In other words, given η, agents are able to sense only those functions with $\beta_j > \eta$. Highly sensitive agents are those with an η very close to 0. Indeed, as every emerged function has a strictly positive weight, η very close to 0 implies that agents are able to sense all the β_js associated to the functions included in their artefact. On the contrary, agents with very high η (over 0.50) are able to perceive only those functions whose environmental weight β_j is greater than 0.50. These latter are then low sensitive agents (Fig. 7).[7]

[FIGURE 7 ABOUT HERE]

The second strategic element is bound to the way whereby agents decide to setup the improvement of their artefact once they have identified the functions they want to act on through sensitivity. Indeed, they can still rely on the environmental weights β_js or, rather, they can focus on the abilities of the artefact to provide the sensed functions (ω_j). In the first case the direction of improvement is given by the external environment only, while in the second case it is given by technology. These alternative behaviours identify two different *attitudes toward innovation*: we label the first *market oriented* and the second *technology oriented*.

The main characteristics of *market oriented agents* are the following:

- they set the agenda to improve their artefact by putting in decreasing order the sensed functions on the basis of their environmental weights;
- they consider as improvements all the changes in the artefacts' components that increase the degree of external appreciation Θ.

On the opposite side, *technology oriented agents*:

- set the agenda to improve their artefact by putting in decreasing order the sensed functions on the basis of functional fitnesses ω_j;
- consider as improvements all the changes in the artefacts' components that increase the degree of technological quality W.

Both types of agents improve the artefact by starting to operate from the function regarded as the most important one - according the two different criteria - and, then, pass to the subsequent ones until the list of functions is over.

The third strategic element refers to the *degree of perseverance*, i.e. the number of attempts the agents decide to undertake in order to improve each sensed function before passing to the next one. To this extent,

[7] Notice that, in presence of two functions only, $\eta = 0.50$ agents can perceive at most one out of the two, for β_js are computed by normalizing functional fitness values. In presence of three functions and $\eta = 0.50$, in order to perceive one function, the variance of fitness values has to be high enough to make one function count more than 50% while the sum of the other two must count less than 50%.

perseverance is a measure for the effort devoted to the amelioration of each specific function. In the model, we represent this through a parameter λ, exogenously set, indicating the number of iterations spent by the agent in the off-line search (Levinthal 1997) over a specific function. More precisely, in each one of the λ iterations devoted to one function, each agent randomly draws one of the components associated to it and switches it from 0 to 1 or viceversa. If this change brings about an improvement according to the agent's yardstick then it is accepted, otherwise no change is made. After λ iterations on one function, the agent shifts to the next one in her agenda.

Whilst perseverance is different from learning-by-searching, for it is bound to functions and not to components, these two aspects are correlated: the larger the amount of time spent improving one function, the higher the amount of knowledge learned on the components associated to that function.

Finally, exaptation is not the only way whereby agents change their artefact. In order to allow for the presence of more agents searching over an artefact (once its underpinning latent functions are discovered), the model accounts for the possibility of shifts from one artefact to an already existing one. Every time an agent expires the list of sensed functions, she confronts the degree of environmental appreciation of her artefact Θ with the average value of the Θs associated to the other agents producing the same artefact. [8] If the former is larger, then the agent can decide to shift to another existing artefact. This decision is taken by randomly drawing one of the remaining existing artefacts with probabilities proportional to ψ (i.e. on the basis of the relevance of the targeted artefact within the environment) and by comparing her own current performance with the one she would obtain with the targeted artefact. If the latter is greater, then the shift occurs.

1.2.2.4 Model Algorithm

What has been described in the previous pages represents the framework of the model. In order to create a simulation with this framework it is necessary to setup the algorithm whereby the dynamics of the model unfold.

Before the beginning of any simulation:

- technology and external environment relationships with functions are constructed and the corresponding landscapes are estimated;
- the latent and the emerged functions are identified and environmental weights are computed accordingly;
- the initial position of the environment on the external environment landscape is randomly drawn from a uniform distribution over the set of integers $[0, 2^E - 1]$;
- a population of agents is created and equally split between the *market oriented* and *technology oriented* types;

[8] This is a mild version of competition. As the model deals with the emergence of latent functions and exaptation, we did not model in detail competition. The idea is that1 once in a while agents have sufficient resources to enter into new productions.

- each agent is randomly assigned an initial position over the technological landscape by drawing an integer from the uniform distribution $[0, 2^N - 1]$. In order not to have any bias as to the type of agents, each position is associated both to one market oriented agent and to one technology oriented agent.

During each iteration of the simulation:

1. the external environment randomly draws the signal for the need of a latent function: if in the previous iteration some agent has discovered the corresponding function then exaptation occurs; otherwise nothing happens;
2. if an environmental change has to occur during the iteration, then a new position for the environment is randomly drawn and all the β_js, Θs, and ψs are computed accordingly;
3. each agent operates her activity:
    a. if she is starting a new improvement phase either because she has just changed her artefact - due to exaptation, or to a shift to another existing product- or because she has expired the previous list of functions, she scans the external environment to set her agenda for the improvement of the artefact on the basis of her degree of sensitivity;
    b. if the list of perceived functions is not yet expired, she continues with the improvement of her artefact;
    c. if she has expired the list of functions in the previous period she checks whether she can shift to another artefact and, in case, she does it.

1.2.3 Simulations Setting & Experiments

In order to study the role of agent's strategic elements for exaptation we look at the emergent properties of the model by using our framework as a laboratory setting in which we run experiments through the manipulation of the parameters of interest.

In particular, to study the role of sensitivity, we run a set of 6 experiments in which the only changing parameter is η; while, to study the role of perseverance, we run a set of 6 experiments in which the only changing parameter is λ. In each experiment of the first set, η takes on one among the following values $\{0.001, 0.11, 0.21, 0.31, 0.41, 0.51\}$ while λ is kept fixed at 1. On the contrary, in each experiment of the second set η is kept fixed at 0.21 while λ takes on one value among $\{1, 10, 20, 30, 40, 50\}$. As to innovation attitude, each experiment includes a population of 80 agents split in two halves: one-half market oriented and one-half technology oriented. This strategy guarantees that the different outcomes between the two groups are solely due to the differences in their behaviours.

In order not to incur in biased results, each experiment controls not only for the remaining exogenous parameters, but also for the possible distortions given by those elements of the model randomly drawn from uniform distributions (e.g., landscapes, initial agents' positions, positions of the environment).

Regarding the remaining parameters, all the simulations have been carried out with the following parametrization

- number of components $N = 14$;
- overall number of functions $F = 9$, of which 7 latent at the beginning of the simulation;
- polygeny of the function-component technology = 7;
- number of elements of the external environment $E = 14$;
- polygeny of the functions-external environment relationship = 14.

To deal with the second issue, we set up each experiment as a set of 1000 repetitions of independent simulations with identical parametrization and we took the average results (or the variance of the average). Moreover, for some analyses we also computed the 95% confidence intervals to be sure of the statistical difference of the outcomes.

As exaptation is a long-run phenomenon (especially in certain techno- logical areas), we set each repetition to last 1000 iterations. Our results, therefore, must be interpreted as *long-run* results.

Moreover, exaptation's anecdotes have underlined the differences across technologies in terms of the emergence of hidden functions as well as of environmental conditions in which these phenomena occurred. Put in another way, exaptation seems to be also bound to the characteristics of the two remaining pillars: technology and external environment. To this extent we repeat our experiments within four different scenarios. Table 1 summarizes the main characteristics of each scenario.

[TABLE 1 ABOUT HERE]

The *first* one is the simplest and deals with a situation in which the environment is stable throughout the simulation -hence, β_js change only in response of exaptations - and the difficulty to gather knowledge about technological components is low as well. This scenario represents situations in which discoveries are fairly easy, and, at the same time, actual and potential demands for artefacts are quite stabilized (as in the case of Marsilid).

The *second scenario* is equivalent to the first one in terms of environmental stability while it is different as to the learning-by-searching difficulty. In order for an agent to discover a latent function associated to one component, the agent must work on that component for at least 22 times. The scenario represents a situation in which it takes time to gather experience on a specific technology and, thus, be able to discover new functions. One case of this type may be represented by the radar technology giving rise to the microwave oven.

The *third scenario,* on the contrary, differs from the first one in terms of dynamism of the external environment. In this case, discoveries are relatively simple to be carried out, but, at the same time, the environment in which new artefacts are produced is not stable. Specifically, within the experiments in this scenario, the position of the landscape changes randomly every 3 iterations. In other words, every 3 iterations β_js, Θs, and ψs change in a random way. A situation like the one delineated by this scenario is the one in which technology is relatively simple to be searched, but the demand for the newly emerged artefacts is not stable. An example is given by Viagra, whose niche construction was not stable at its birth.

At last, the *fourth scenario* is represented by a situation in which both the dynamism of the external environment and the difficulty of discoveries are high. A situation like this one, may have been that of laser, which was born as a proof of a theoretical paper and then it took time to be redeployed in different areas.

1.3 Analyses

As exaptation is a complex phenomenon, our analyses deal with three aspects related to it: the first one is the *number* of new artefacts rising after the discovery of latent functions, the second one is the *degree of uncertainty* of this process, and the third one is its *timing*. In the following subsections we report the analyses of the results of the experiments for each strategic aspect.

1.3.1 Sensitivity

Figure 8 plots the average number of exaptations (measured in terms of artefacts incorporating one or more emerged functions) per degree of sensitivity. In particular, this picture refers to the first scenario which represents the simplest one. We start our analyses from the simplest case in order to highlight the main characteristics of the relationship between exaptation and sensitivity. Subsequently, we compare these results with those associated to the remaining scenarios to understand how they change across different contexts.

[FIGURE 8 ABOUT HERE]

From the figure it emerges a positive relationship between the degree of sensitivity and exaptation: the higher the degree of sensitivity to the external environment the higher the number of artefacts created through the discovery of latent functions. This result can be explained in the following way. As illustrated in fig. 7, for a given artefact with a given environmental evaluation, higher sensitivity means a larger number of functions accounted for during the improving phase. At the same time, the larger number of accounted functions translates into a larger number of explored components, and, as such, a higher likelihood of discovering some latent function.

Yet, there is also the other side of the coin related to the dynamic nature of exaptation. As a matter of fact, from fig. 8 it is possible to see that the relationship between sensitivity and the number of artefacts is concave rather than linear. In particular, concavity implies that unitary increments in η are associated to decreasing increments in exaptations. This is given by the combination between the aforementioned relationship between sensitivity and the number of accounted functions, on the one hand, and the effect of exaptation on artefacts, on the other. Indeed, if instead of varying η, we keep it fixed and increase the number of functions of an artefact -as it occurs when a latent function is discovered- then the redistribution of environmental weights β_js, triggered by the emergence of the new function, may lead the agent to decrease the number of functions accounted for in the following improvement phase. As a result, through the emergence of new functions, in presence of stable environments, the rate of discoveries are negatively associated to artefact's size. In other words, the process of adding new functions to an artefact slows down exaptation because it makes more difficult for agents to consider all the possible functions when deciding how to improve the artefact, thus leading them to overlook some source of *learning*.

This relation, however, is extremely *context-dependent*. Figure 9 plots the results of the same analyses of figure 8 for each type of scenarios.

[FIGURE 9 ABOUT HERE]

To begin with, the difficulty of *learning-by-searching* and the degree of *environmental dynamism* exert two opposite effects on the sensitivity-exaptation relation. The increment in the number of attempts needed to discover a function associated to a component shifts downward the line, especially when sensitivity is high. In other words, ceteris paribus the degree of environmental dynamism, the number of discovered artefacts decreases with the difficulty of learning from the components, even if agents are highly sensitive. This evidence may underpin the different rates of emergence of exaptations across technologies. Indeed, the majority of works documenting exaptation focus on, or mention, examples drawn from the pharmaceuticals or the chemistry industries. Results in figure 9 suggest that this may be due to the relatively high easiness in studying the components of these technologies. On the contrary, when technology requires much more time to be understood, the number of exaptations is much smaller.

As to the degree of environmental dynamism, the reverse happens. By comparing the relationship emerging from scenario 3 with the relationship emerging from scenario 1, it is possible to observe that environmental dynamism increases the average number of exaptations per each degree of sensitivity, especially for the very low values of η. Such a flattening effect can be interpreted as the outcome of the increased number of stimuli received by the agents populating highly dynamic environments. As a matter of fact, even if scarcely sensitive, firms operating on churning markets are always exposed to new stimuli and can easily gather knowledge and spot new affordances in presence of technologies with a low difficulty of learning- by-searching.

The combination between high difficulty in learning-by-searching and high degree of environmental dynamism (scenario 4) reshapes completely the relation between sensitivity and exaptation by exacerbating some aspects of scenarios 2 and 3. The large amount of time required to understand the technological mechanisms together with the continuous changes in the stimuli coming from the external environment make it impossible for agents with very low sensitivity to discover any latent function. Yet, as soon as we pass from very low to reasonably low levels of sensitivity (i.e. from $\eta = 0.51$ to $\eta = 0.41$) the situation changes dramatically. The effect of dynamism dominates the one of technological complexity making the number of exaptations to soar. At the same time, further increments in the degree of sensitivity seem to exert no effects on the number of exaptations. Indeed, the number of artefacts including an emerged function remains quite stable when η is in-between 0.41 and 0.001. In this cases, the combination of the churning effect with the difficulty of the learning-by-searching creates an upper-bound to the expansion of exaptations.

The second aspect related to exaptation is its degree of uncertainty. The relationship between uncertainty of exaptations and sensitivity is relevant insofar as it provides us with an information about the variation of outcomes over 1000 repetitions. In figure 10, we plot -for all the four scenarios- the variance of the averages presented in the previous graphs against the degrees of sensitivity.

[FIGURE 10 ABOUT HERE]

The lines delineated by the data in scenarios 1 and 2 represent two concave functions with peaks at $\eta = 0.31$. This means that exaptation's outcomes are more uncertain when agents fall within the intermediate levels of sensitivity. On the contrary, when agents are either extremely sensitive or extremely insensitive, the outcome of their search activities is more certain. As a matter of fact, in stable environments, being at an intermediate level of sensitivity is highly risky because the evaluation of the environment may or may not be large enough for triggering search processes over some specific artefact's function. At the same time, being extremely sensitive ($\eta = 0.001$) implies being able to sense all the β_js given by the environment, while being extremely insensitive ($\eta = 0.51$) implies being unable to spot any function at all.

Moreover, the line associated to scenario 2 lies below that of scenario 1. The difficulty of learning-by-searching decreases exaptation's uncertainty by increasing the time needed for a new function to emerge. In presence of a context with very complex technologies to understand, agents need to spend a lot of efforts in studying the components before being able to come up with many artefacts.

Yet, environmental dynamism decreases exaptation's uncertainty more than the learning-by-searching difficulty. As a proof for that the lines associated to scenarios 3 and 4 lie below the other ones, especially for intermediate levels of sensitivity. On top of that, instead of being concave, these lines tend to be flat (scenario 4) or slightly decreasing (scenario 3). By exposing agents to a continuous flow of stimuli, environmental dynamism creates less uncertainty in the exaptation phenomenon given any level of sensitivity. In particular, concerning scenario 4, the combination between high learning-by-searching difficulty and environmental dynamism dampens variability of exaptation outcomes for all the degrees of sensitivity.

The final aspect is related to the timing of exaptation. Figure 11 reports the average iteration for the first and the last exaptation in each set of repetitions.

[FIGURE 11 ABOUT HERE]

When the difficulty of learning-by-searching is low, exaptation tends to start and terminate in advance with respect to the other scenarios. Moreover, the timing of these events seems to be constant with respect to the degrees of sensitivity, except for low and very low levels of sensitivity in highly dynamic contexts. In the latter cases, the emergence of latent functions is postponed because the churning of the environment makes it more difficult for an agent to promptly accumulate the sufficient knowledge to spot new affordances.

On the contrary, the difficulty of learning-by-searching shifts both the beginning and the conclusion of exaptation ahead in time. Both the line associated to scenario 2 and the line associated to scenario 4 lie well above those related to scenarios 1 and 3. However, while the mere presence of a high difficulty of learning-by-searching (scenario 2) transfers on a higher level the relationship between sensitivity and the timing of exaptation, the combination between a high difficulty in learning-by-searching and a high degree of environmental dynamism reshapes this relation into a convex function. To this extent, by increasing the degree of sensitivity, agents in scenario 4 speed up the whole exaptation process in an exponential way.

1.3.2 Perseverance

The second strategic element studied in relation to exaptation is the degree of perseverance. Figure 12 reports the average number of exaptations per degree of perseverance in presence of a stable environment and an easy technology to learn from.

[FIGURE 12 ABOUT HERE]

According to the data, there is a bump in the number of artefacts when passing from no perseverance ($\lambda = 1$) to moderately low ($\lambda = 10$) perseverance. On the contrary, further increments in the number of iterations spent to improve each function are not associated to significant improvements in the number of exaptations. This implies that, in scenario 1, improvements in learning are easily achievable even with few trials, while a very long period of time spent on single functions won't be beneficial in terms of new discoveries.

[FIGURE 13 ABOUT HERE]

However, even in this case, learning-by-searching difficulty and environmental dynamism have an impact on the level and the shape of the relationship. Indeed, when comparing the average number of emerged artefacts per degree of perseverance across scenarios it is possible to notice that the effect of learning-by-searching difficulty is to shift downward the whole line while the effect of dynamism is to flatten it (Fig. 13). As such, in presence of technologies highly difficult to learn from, discoveries of a new function are uncommon, and only few firms succeed in it. At the same time, it is still valid the argument used for scenario 1: even in scenario 2, overcoming a certain amount of perseverance won't bring about any increment in the number of discoveries. These results have to be interpreted by keeping in mind that exaptation can be seen as a, more or less conscious, race for the discovery of latent functions. In such a sense, a little bit of perseverance is important not to overlook affordances difficult to be spotted at first sight. Yet an excessive degree of perseverance may lead to a waste of time, allowing another competitor to find the latent function.

The differences across perseverance levels are neutralized in presence of highly dynamic environments. In fact, when the external context changes frequently, firms are continuously pushed to change the function they focus on to improve their products. Given that the number of functions is finite, a high functional turnover implies a high likelihood that the firm will work again on the same component in the future leading to an accumulation of technological knowledge. This dynamics widens the set of firms that are able to discover one function in the same period and, as such, it increases the number of exaptations even in presence of $\lambda = 1$. At the same time, this does not add any effect for the cases with moderately low, medium, and high levels of perseverance: firms that spend already a bit of effort to improve their artefact's functions don't gain any extra knowledge through the dynamism of the environment.

All these results translate into a specular relation between perseverance and exaptation's uncertainty (Fig. 14). According to our simulations, high uncertainty occurs only in absence of perseverance ($\lambda = 1$) and in stable environments. As soon as λ passes from 1 to 10, the variance of the average number of discovered artefacts sharply decreases and stabilizes on the same level for all the remaining values of λ. At the same time, environmental dynamism, by providing more opportunities to accumulate knowledge, stabilizes uncertainty on low levels for all the perseverance values.

[FIGURE 14 ABOUT HERE]

Finally, in terms of exaptation's timing, perseverance does not seem to play any role in scenarios with technologies easy to learn from. On the contrary, in presence of high difficulty in the learning-by-searching processes, the whole exaptation phenomenon is on average quicker when agents do focus even a minimum amount of periods on the improvement of their artefacts, i.e. when $\lambda > 1$ (Fig. 15). At the same time, in these cases, exaptation unfolds quite late in the simulations if compared with the cases in scenarios 1 and 3 for it takes more time for agents to learn all the possible affordances of each component.

[FIGURE 15 ABOUT HERE]

1.3.3 Innovation Attitudes

The last strategic element relates to the attitude towards innovation. Differently from sensitivity and perseverance, we do not investigate its relationship with exaptation in isolation. Rather, what we do is to check whether different behaviours in setting up the improvement phase act on the relationships highlighted so far. To this extent, we replicate the same analyses of previous paragraphs by dividing the population of agents between technology oriented and market oriented.

Figure 16 reports the results of figure 10 by disentangling the outcomes of the two subgroups. In three scenarios out of four, the way firms approach the improvement of their current artefacts does not matter for the relationship between sensitivity and exaptation. Indeed, neither learning-by-searching difficulty nor environmental dynamism in isolation interact with the two attitudes. On the contrary, when both these elements combine together (scenario 4), the type of attitude towards research matters for the relationship between sensitivity and exaptation. As a matter of fact, as soon as agents become slightly sensitive to the external environment ($\eta < 0.51$), technology oriented agents outmatch market oriented agents in the ability to discover new functions and create exaptations. Moreover, by increasing sensitivity, the gap between the two groups increases as well.

[FIGURE 16 ABOUT HERE]

This discrepancy in the performances can be explained in the following way. By ordering the sensed functions on the basis of their technological fitnesses (ω_j) rather than on environmental weights (β_j), technology oriented agents are able to partially counterbalance the negative effects of churning on learning. As a matter of fact, even though a high degree of dynamism helps firms to meet a larger number of stimuli in their search activity, an excessive adherence to what the external environment dictates may affect the ability of the firm to focus on specific technological elements. When it is highly difficult to learn from a technology, as it is the case of scenario 4, this translates into a lower amount of accumulated knowledge and, hence, into a lower number of exaptations.

[FIGURE 17 ABOUT HERE]

These results are also confirmed in the analyses on the timing of exaptation (Fig.17). Whilst there are few differences across the two groups, and not even extremely significant, the data regarding the average iteration of the last exaptation show that technology oriented agents tend to finish exaptation later than the market oriented ones. Provided the results in figure 16, this evidence confirms that technology oriented firms are able to continue exaptation for a slightly longer period of time.

[FIGURE 18 ABOUT HERE]

A slightly different picture emerges from the data regarding exaptation and persistence (Fig. 18). Differently from the sensitivity case, environmental dynamism evens out differences across agents even in presence of low levels of persistence and high learning-by-searching technologies. However, technology oriented agents agents now outmatch market oriented agents in scenarios 1 and 3. As a matter of fact, in the first case, even though both types of firms face the same environment throughout the simulation, technology oriented agents possess an advantage over market oriented agents for the specular reason identified for the results in figure 16. While in that case, ranking functions through ω_j helped firms to counterbalance environmental churning, in this case it helps to counterbalance the stasis generated by the combination of stable environments and high persistence. Indeed, with a high degree of persistence in a stable environment market oriented agents repeat the same operations until the end of the simulation (for β_js do not change). On the contrary, technology oriented agents may change the way they rank the perceived functions due to the interconnections generated by the degree of pleiotropy of single components. In fact, if by acting on the i-th component to improve the j-th function also the k-th function is improved, then the order of fs for the subsequent improvement period may change and technology oriented firms may be able to discover new functions in advance with respect to the market oriented ones.

When environmental dynamism is high (as in scenario 3), on the one hand, this effect is slightly increased by the fact that technology oriented agents get in touch with more stimuli and more search opportunities while, on the other hand, it is partly counterbalanced by the fact that market oriented agents go through the same environmental dynamics. On the whole, however, technology oriented agents still outmatch the market oriented ones in terms of discovered exaptations.

1.4 Conclusions

The paper has investigated the role of three elements of firms' strategies (sensitivity, perseverance and innovation attitudes) for exaptation under different technological and environmental contexts. Analyses have taken advantage of an original simulation model centred around the evolution of artefacts through the discovery of hidden functions via learning-by-searching processes. Our framework is not only able to generate branching processes similar to those delineated by the literature, but it is also able to connect these phenomena to firms' strategies providing a first step for the investigation of the strategic foundations of exaptation.

The results of our analyses suggest that:

1. the way firms operate to improve their products has an impact with respect to the number of exaptations, the uncertainty of the process, and its timing;
2. sensitivity is important for exaptation as it widens the set of sources of knowledge, increasing the number of discoveries;
3. at the same time, there is also a negative side as functional growth of artefacts hampers the effect of sensitivity on exaptation because it makes more difficult for firms to pinpoint a set of functions to improve;
4. moreover increments in sensitivity not always reduce uncertainty about exaptation: the starting point matters. As incrementing sensitivity is costly, because firms have to invest more in market research activities, they may not always regard it as an attainable option;
5. perseverance is relevant insofar as it helps firms to pinpoint affordances;
6. yet in order to pinpoint affordances firms do not need to be excessively perseverant;
7. the roles both of sensitivity and of perseverance for exaptation are highly context-dependent for they hinge upon the degree of dynamism of the context in which firms operate and on the easiness whereby it is possible to learn from a technology;
8. innovation attitudes further moderates the relationships between sensitivity and perseverance, on the one hand, and exaptation, on the other: firms that focus on technological aspects of their products, without exclusively following the external environment, are better able to create new artefacts with emerging functions.

Our analyses provide also an explanation for the different rate of exaptation across different technologies: heterogeneity in contexts and strategies bring about heterogeneity in exaptation.

It is also important to underline that our framework can be easily adapted to study other aspects of co-evolutionary processes between technology, strategies, and the environment.

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Tables and Figures

TABLE 1. SCENARIOS FOR THE SIMULATION

		Learn.-By-Search. Difficulty	
		Low	High
Environment	Stable	Scenario 1	Scenario 2
	Dynamic	Scenario 3	Scenario 4

FIGURE 1. THE PILLARS OF THE MODEL

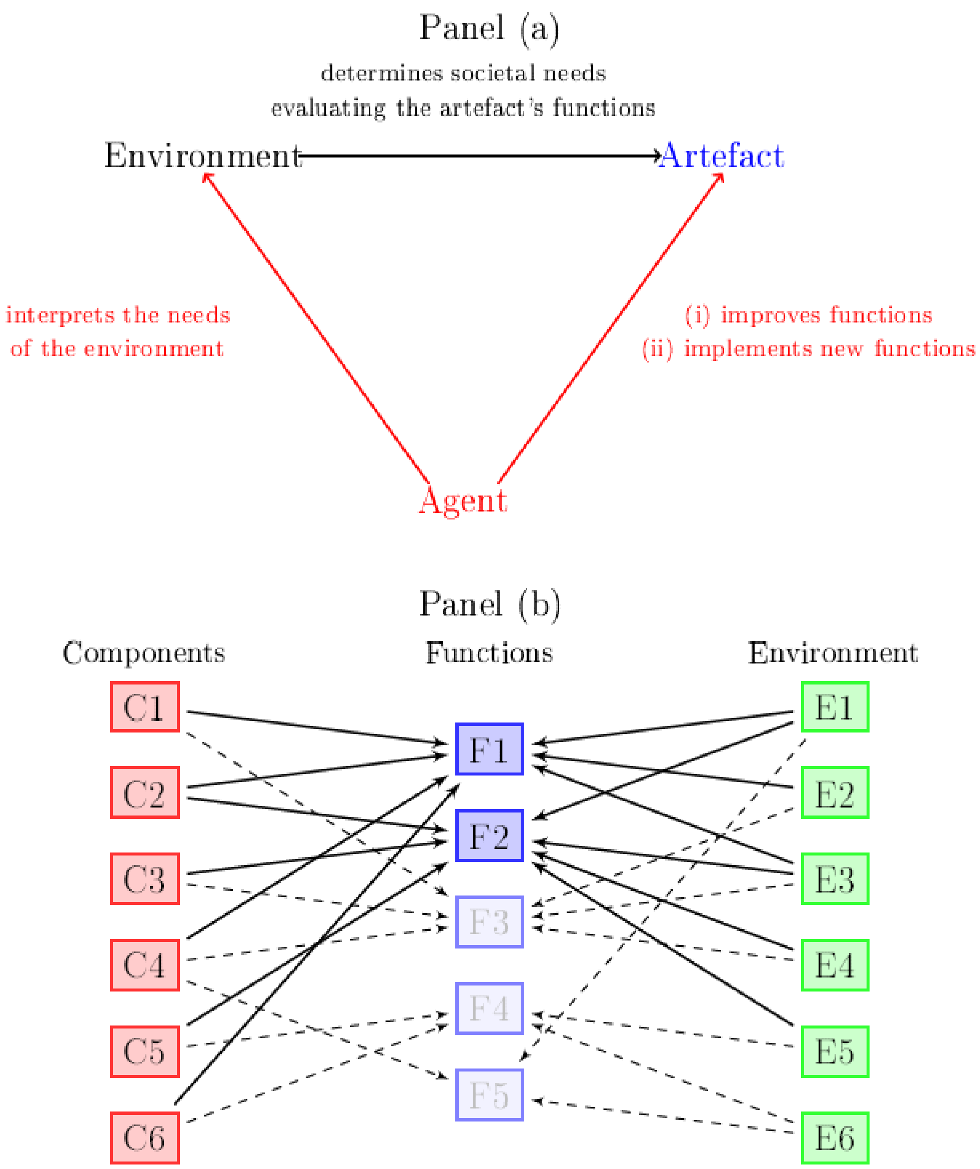


FIGURE 2. COMPARISON OF THE GENOTYPE-PHENOTYPE MAPS FOR TRADITIONAL AND GENERALISED NK MODELS

	$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{n_3}$	$\mathbf{n_4}$	$\mathbf{n_5}$
$\mathbf{f_1 = n_1}$	x	x		x	
$\mathbf{f_2 = n_2}$		x	x	x	
$\mathbf{f_3 = n_3}$			x	x	x
$\mathbf{f_4 = n_4}$	x			x	x
$\mathbf{f_5 = n_5}$		x	x		x

(A) *traditional NK*

	$\mathbf{n_1}$	$\mathbf{n_2}$	$\mathbf{n_3}$	$\mathbf{n_4}$	$\mathbf{n_5}$	$\mathbf{n_6}$	$\mathbf{n_7}$	$\mathbf{n_8}$	$\mathbf{n_9}$
$\mathbf{f_1}$	x	x	x	x	x	x	x		
$\mathbf{f_2}$	x			x	x	x	x	x	x
$\mathbf{f_3}$	x	x	x	x			x	x	x
$\mathbf{f_4}$	x	x	x	x	x	x	x		

(B) *generalised NK*

FIGURE 3. ALTERNATIVE EVOLUTIONS OF THE GENOTYPE-PHENOTYPE MAPS

	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9
f_1	x	x	x	x					
f_2	x			x	x				x
f_3	x	x	x						x
f_4			x	x	x		x		
f_5					x	x	x	x	

(A) *Starting artefact* $< f_1 f_2 f_3 >$

	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9
f_1	x	x	x	x					
f_2	x			x	x				x
f_3	x	x	x						x
f_4			x	x	x		x		
f_5					x	x	x	x	

(B) *Artefact* $< f_1 f_2 f_3 f_4 >$

	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9
f_1	x	x	x	x					
f_2	x			x	x				x
f_3	x	x	x						x
f_4			x	x	x		x		
f_5					x	x	x	x	

(C) *Artefact* $< f_1 f_2 f_3 f_5 >$

FIGURE 4. EXAMPLES OF POSSIBLE ARTEFACTS EMERGING THROUGHOUT A SIMULATION

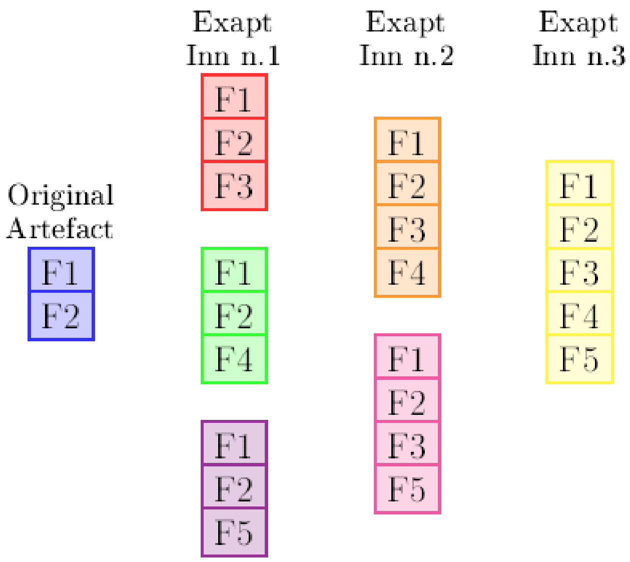


FIGURE 5. EVOLUTION PATTERNS OF EXAPTATION

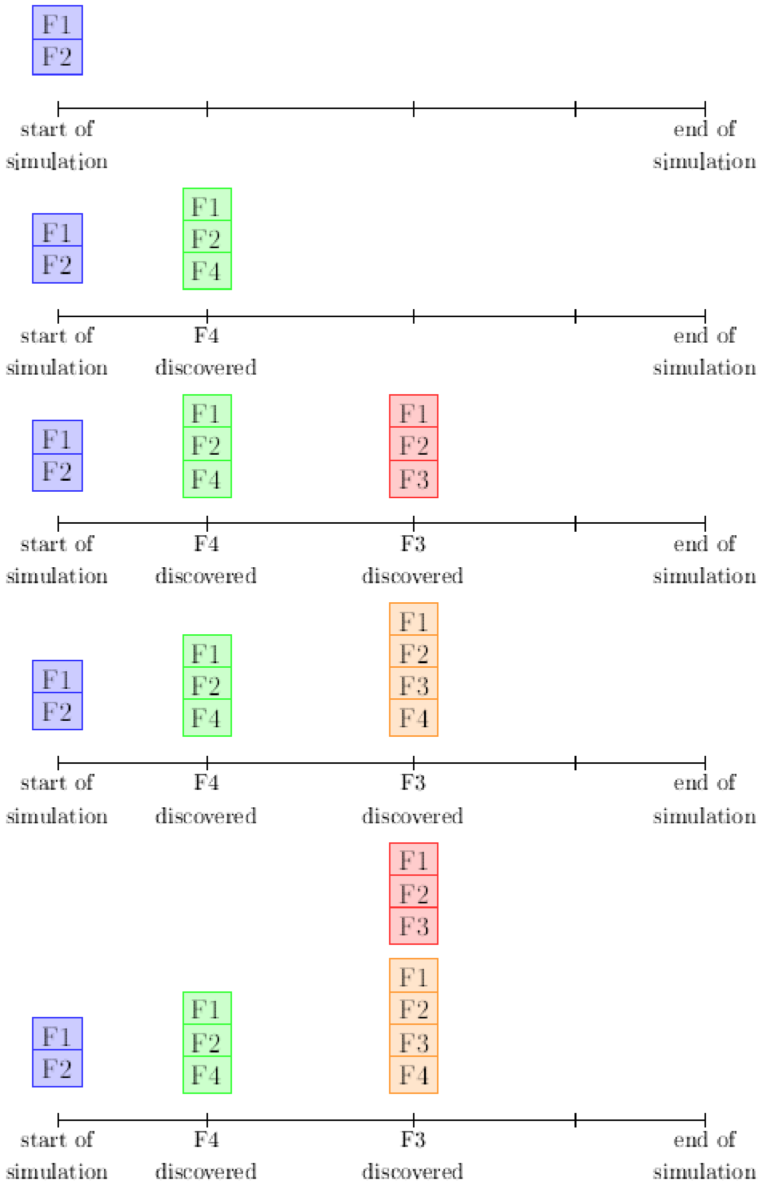
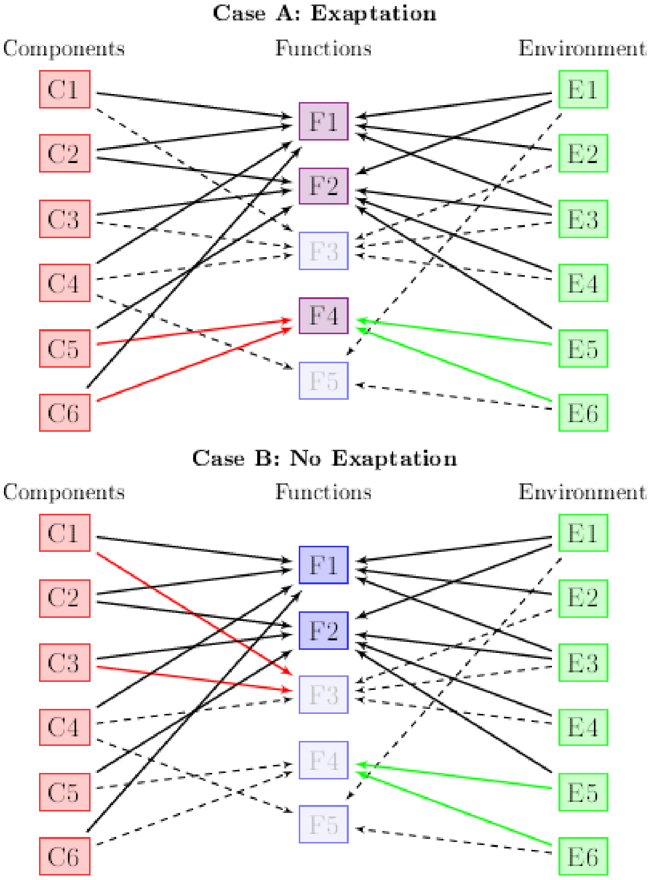
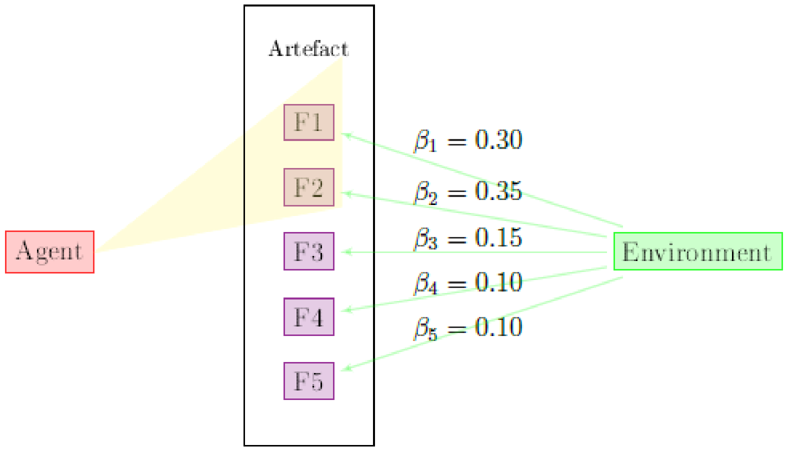


FIGURE 6. EXAMPLES OF MATCHING

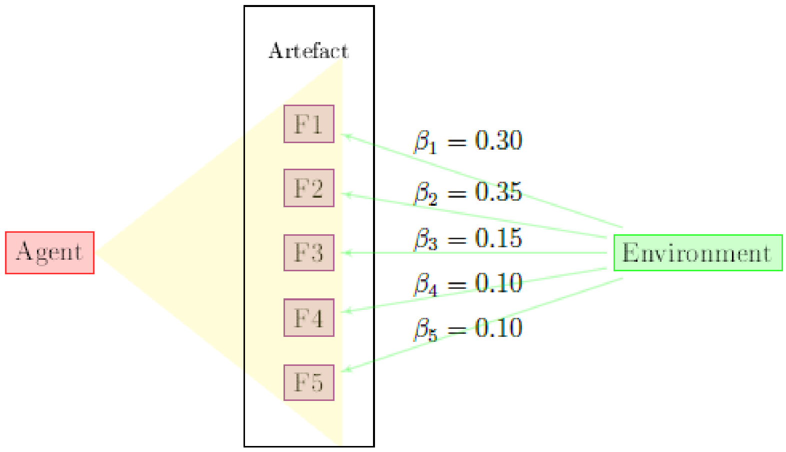


Case A: the environment draws F4 AND an agent discovers a new function (F4) associated to C5 or C6; Case B: the matching fails.

FIGURE 7. THE ROLE OF SENSITIVITY



(A) *low sensitivity*



(B) *high sensitivity*

Note: lighted functions are those perceived as relevant

FIGURE 8. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF SENSITIVITY

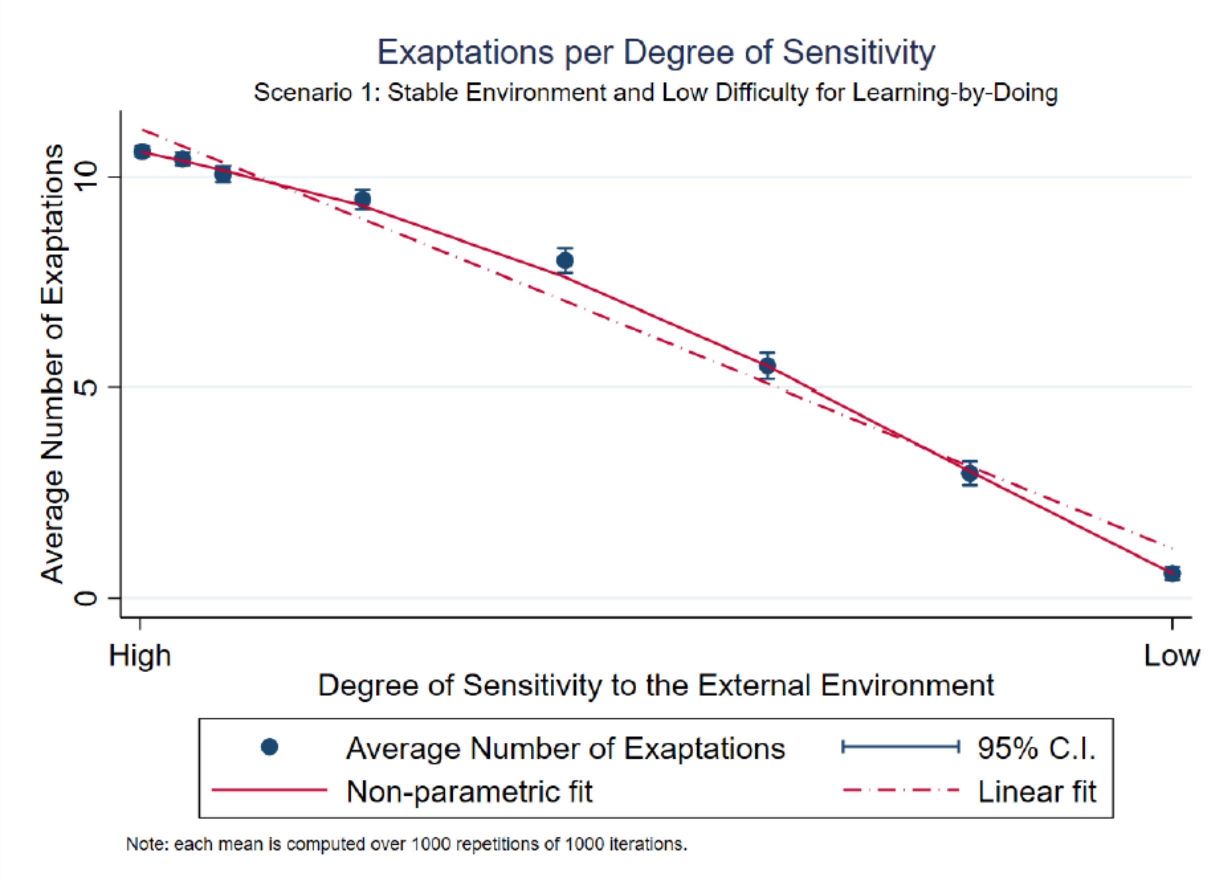


FIGURE 9. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF SENSITIVITY ACROSS DIFFERENT SCENARIOS

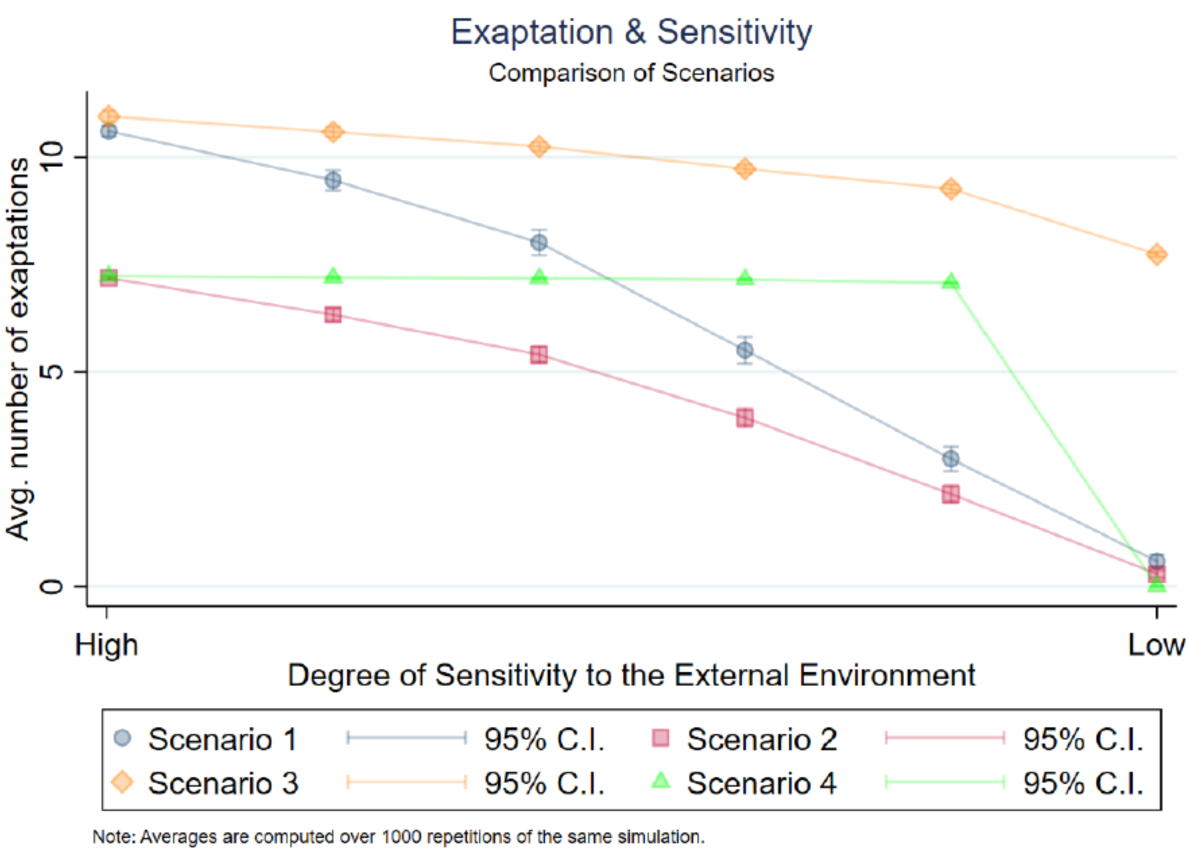


FIGURE 10. VARIANCE OF THE NUMBER OF EXAPTATIONS PER DEGREE OF SENSITIVITY ACROSS DIFFERENT SCENARIOS

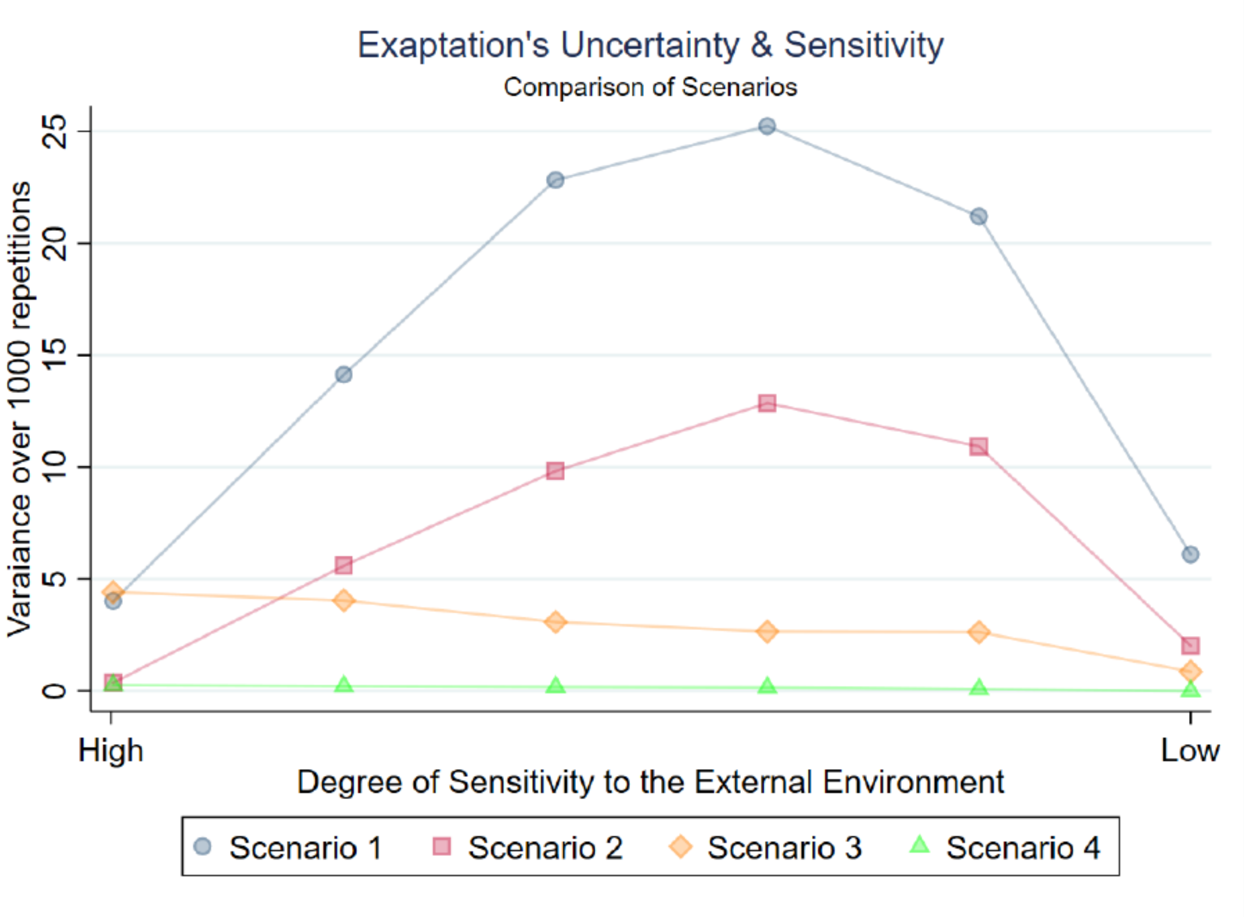
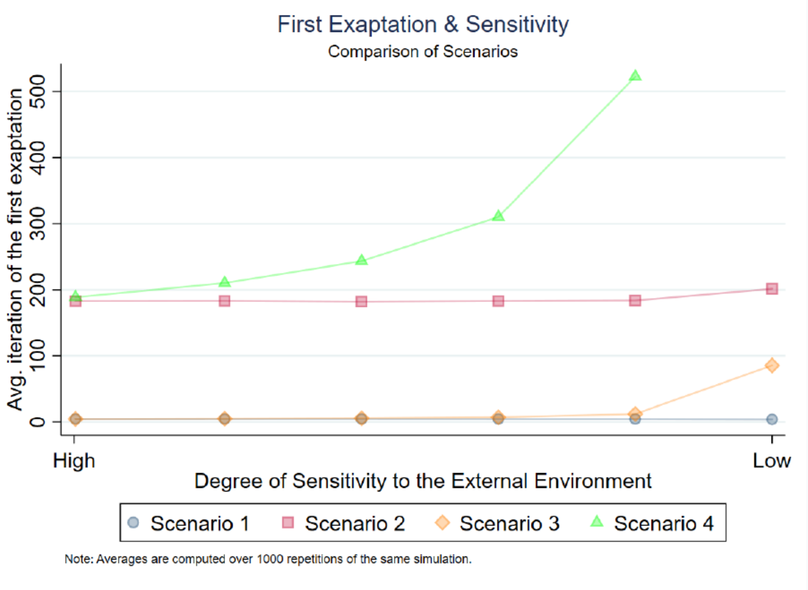
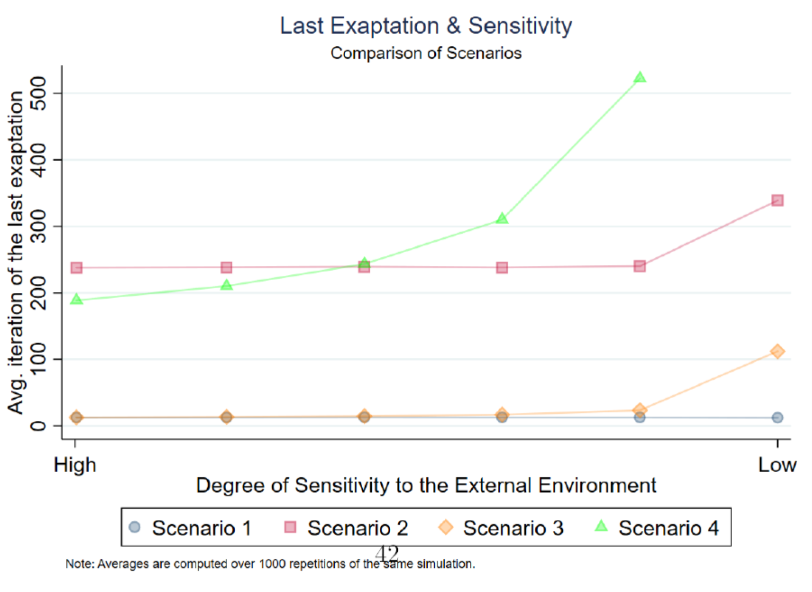


FIGURE 11. TIMING OF EXAPTATIONS PER DEGREE OF SENSITIVITY ACROSS DIFFERENT SCENARIOS



(A) *Avg. Iteration of First Exaptation*



(B) *Avg. Iteration of Last Exaptation*

FIGURE 12. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF PERSEVERANCE

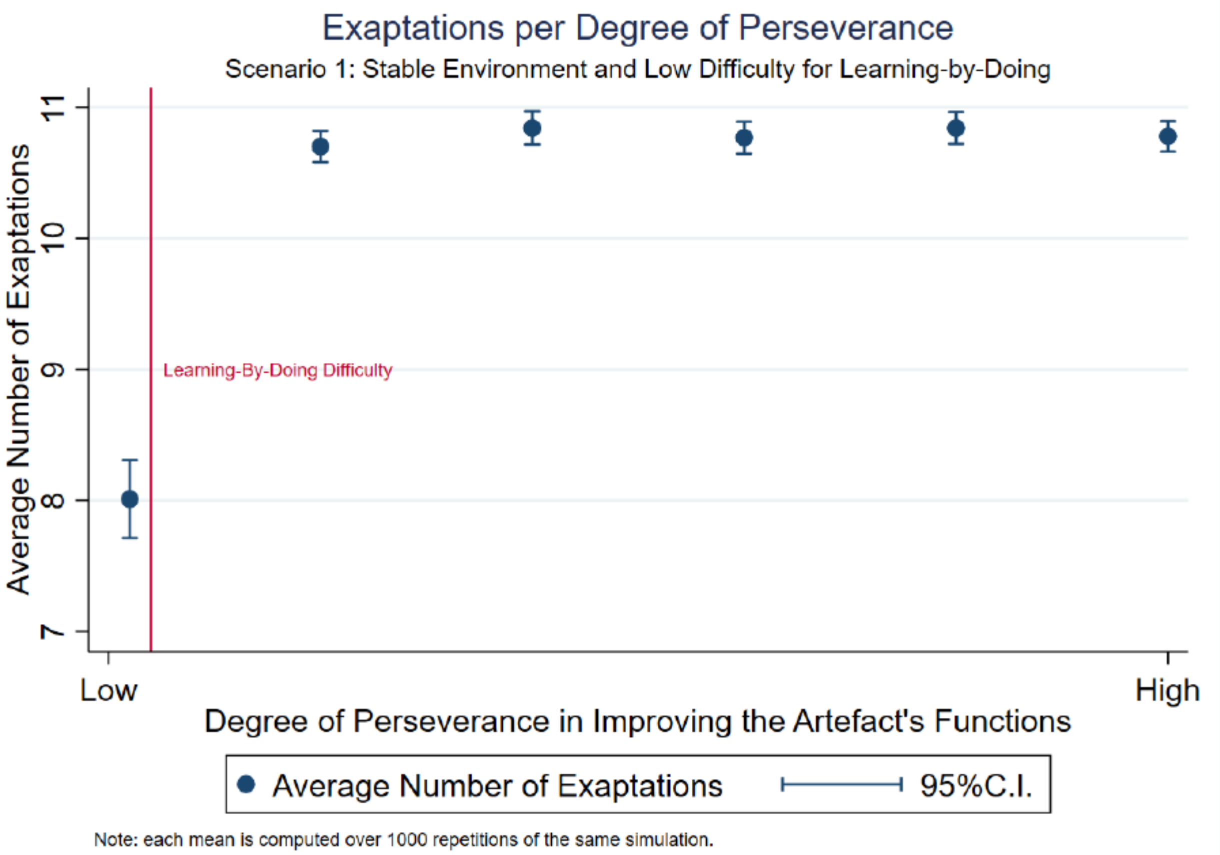


FIGURE 13. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF PERSEVERANCE ACROSS DIFFERENT SCENARIOS

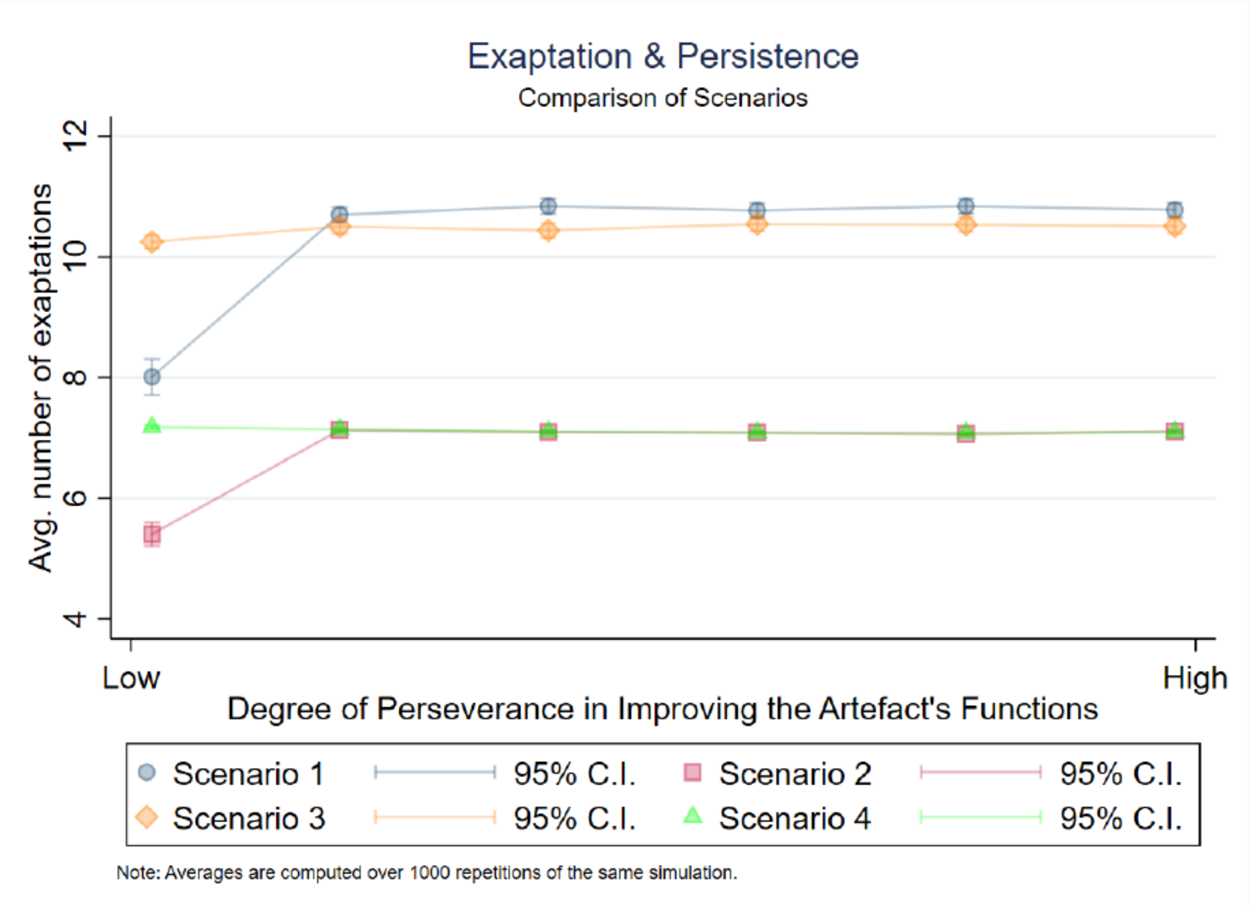


FIGURE 14. VARIANCE OF THE NUMBER OF EXAPTATIONS PER DEGREE OF PERSEVERANCE ACROSS DIFFERENT SCENARIOS

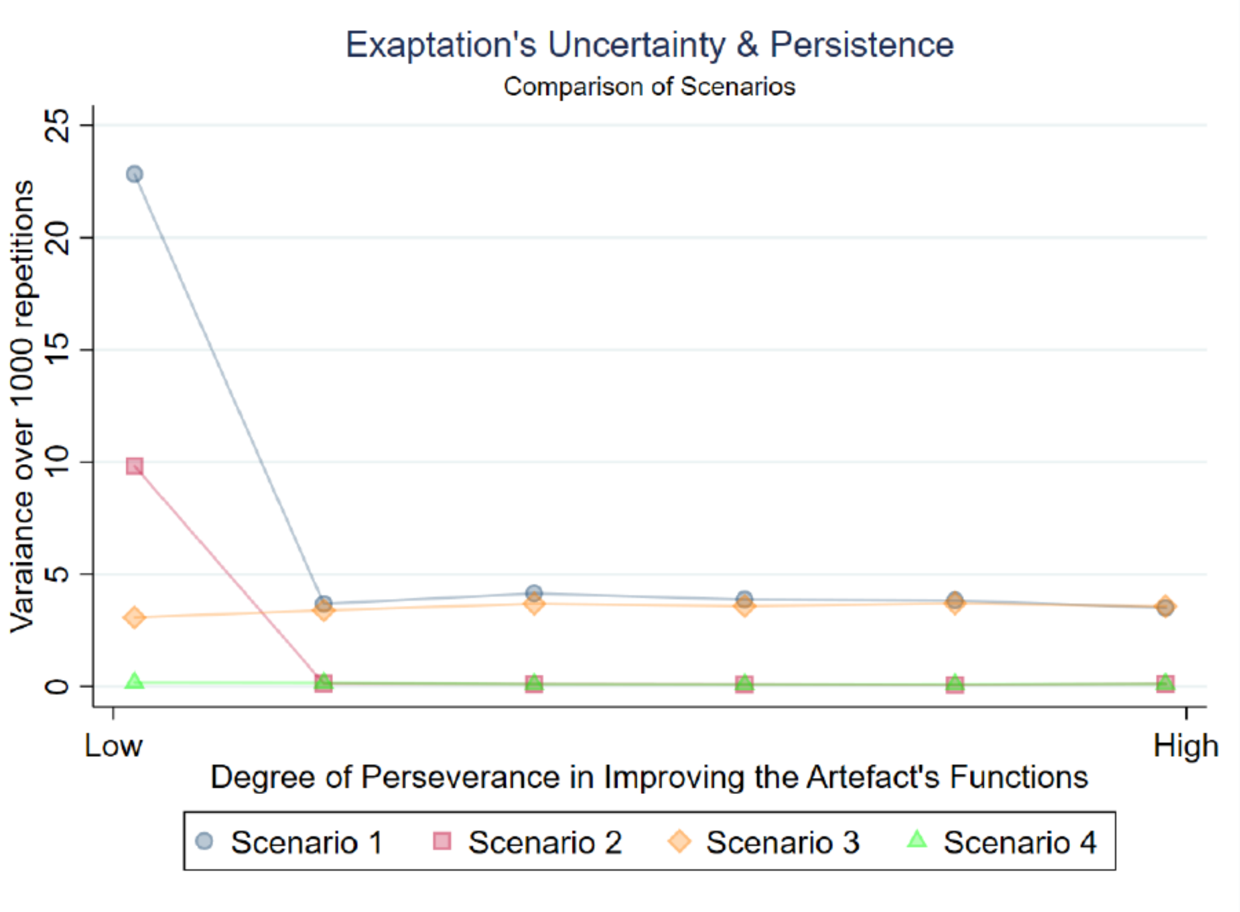
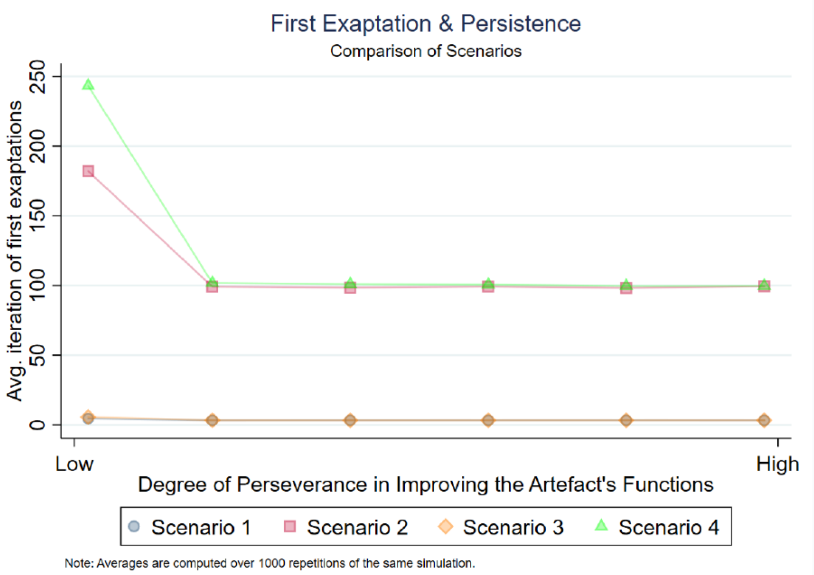
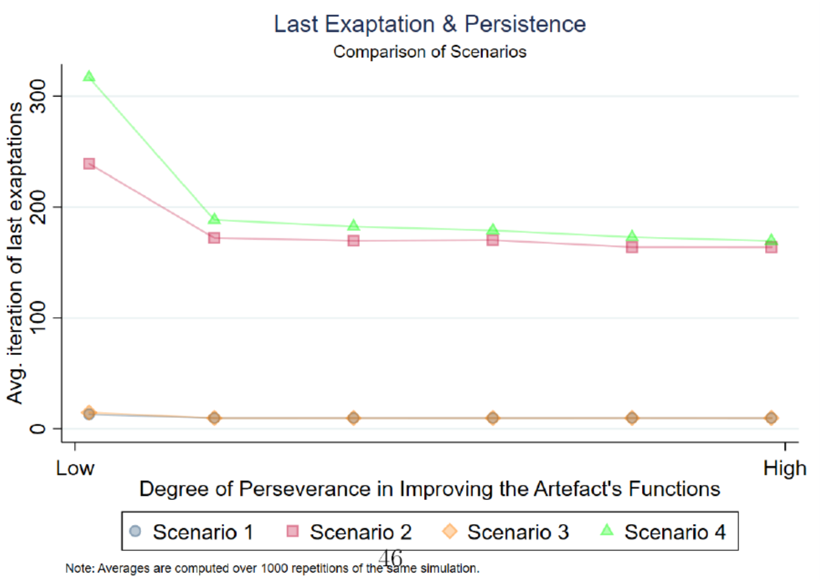


FIGURE 15. TIMING OF EXAPTATIONS PER DEGREE OF PERSEVERANCE ACROSS DIFFERENT SCENARIOS

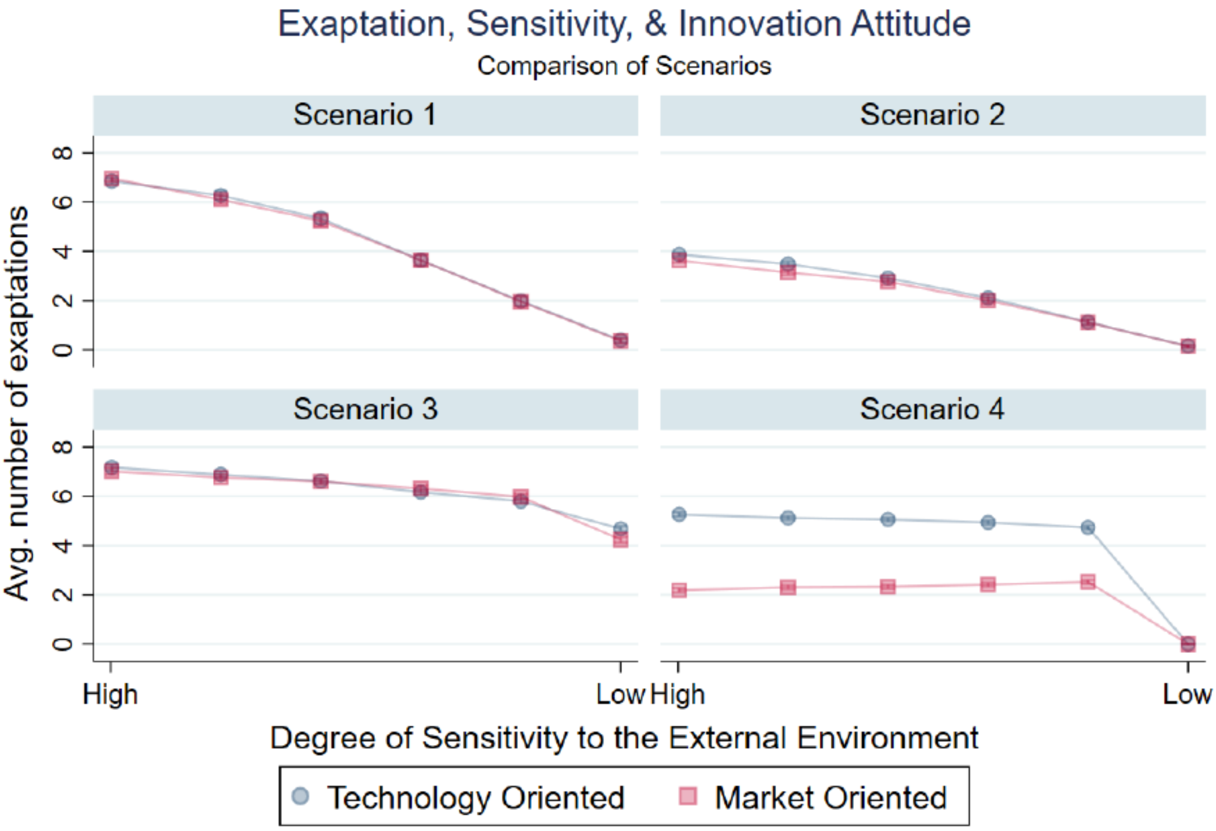


(A) *Avg. Iteration of First Exaptation*



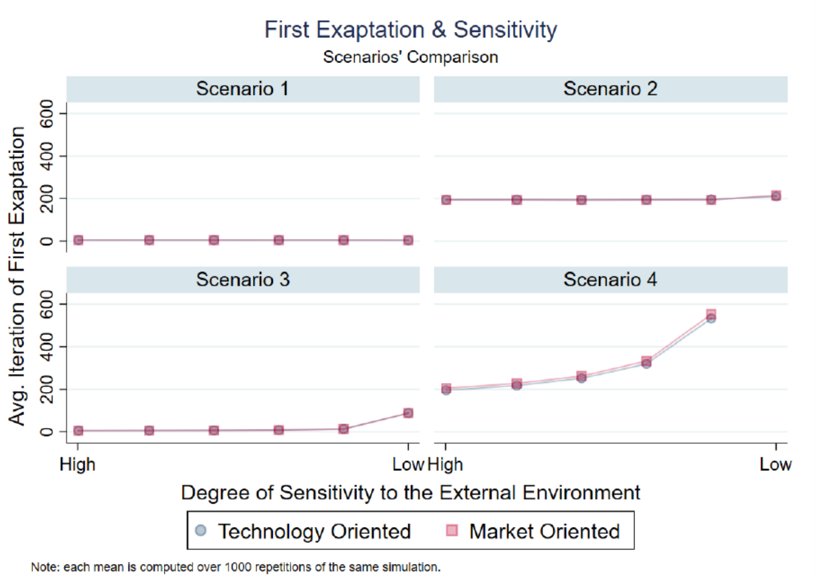
(B) *Avg. Iteration of Last Exaptation*

FIGURE 16. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF SENSITIVITY ACROSS DIFFERENT SCENARIOS AND AGENTS' INNOVATION ATTITUDES

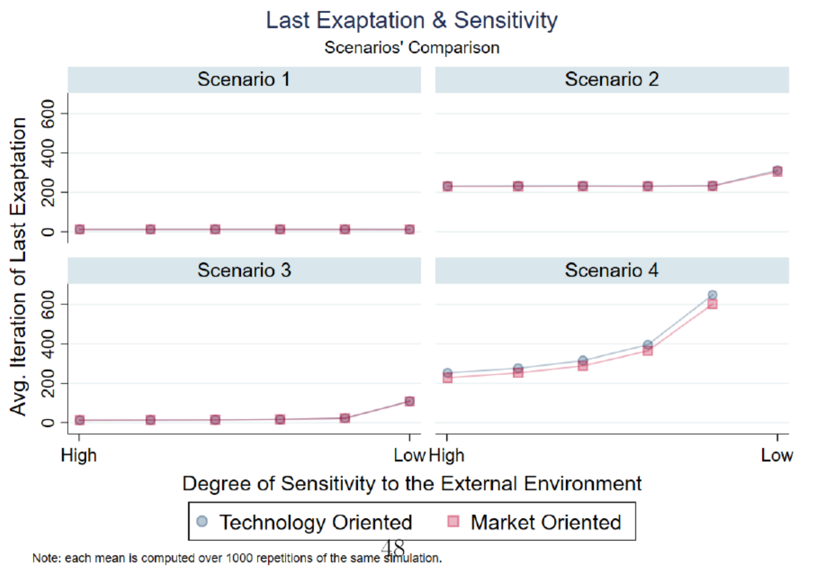


Note: each mean is computed over 1000 repetitions of the same simulation.

FIGURE 17. TIMING OF EXAPTATIONS PER DEGREE OF SENSITIVITY ACROSS DIFFERENT SCENARIOS AND AGENTS' INNOVATION ATTITUDES

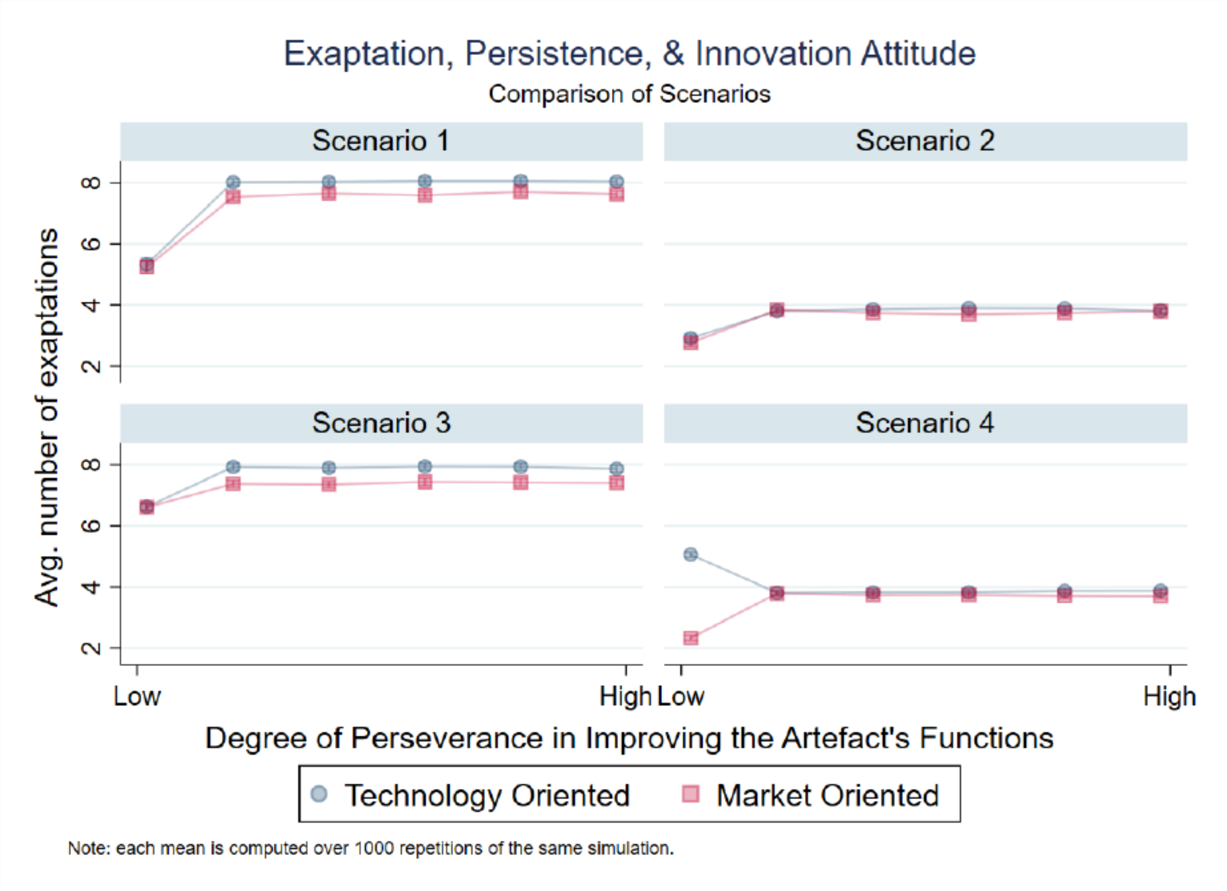


(A) *Avg. Iteration of First Exaptation*



(B) *Avg. Iteration of Last Exaptation*

FIGURE 18. AVERAGE NUMBER OF EXAPTATIONS PER DEGREE OF PERSEVERANCE ACROSS DIFFERENT SCENARIOS AND AGENTS' INNOVATION ATTITUDES



CHAPTER 2

Functions, Modular Architectures, and Technological Evolvability[9]

"…how technology evolves is the central question in technology."

(W. Brian Arthur, 2009, p.15)

2.1 Introduction

Technologies are evolving systems characterized by mechanisms of variation, inheritance, retention and selection. In his book *The Nature of Technology*, Brian Arthur gives a powerful account of the evolutionary approach to the study of technologies and traces it back to such early contributions as Samuel Butler's and Seabury Colum Gilfillan's who found in Darwin's ideas a powerful toolbox to interpret the evolution of technologies and of human societies in general.

The evolutionary approach has proven very effective in developing a better understanding of the dynamics of technological knowledge in its interaction with the economic forces that contribute to shape the directions of technological change (Nelson and Winter, 1982, Dosi and Nelson, 2010).

More recently, this evolutionary perspective has been enriched and extended by merging with complexity studies. Starting from Hebert Simon's seminal work (Simon, 1962 and 1981), connections between the architectural and evolutionary properties of a complex system have been investigated. In

[9] *Co-authored with Luigi Marengo, Professor of Economics, Luiss University, Rome, Italy*

particular, the observation that most complex systems we observe are nearly decomposable and hierarchical, is attributed to the evolutionary advantages that such systems enjoy over systems with different architectures.

In a posthumously published paper, Herbert Simon sets this argument in the clearest way (Simon, 2002) and argues that nearly decomposable and hierarchical systems enjoy two sources of evolutionary advantage. First - he claims - if we begin with a set of simple elements that can form (possibly through random combinations) stable structures and the latter can then also combine in other larger structures and so on and so forth, then the resulting complex system will almost always be nearly decomposable and hierarchical. The second property is that nearly decomposable hierarchical systems will increase their fitness much faster than other systems of comparable complexity and will therefore tend to prevail in a population.

Simon's view offers a connection between the architecture of a system and its evolutionary properties, where by architecture we mean the elements that compose the system and their – typically hierarchical – organization in subsystems or modules at various layers. Scholars of technologies found in Simon's work a rationale for explaining what was happening mainly in the computer industry, where the modularization of products, production and functions was clearly happening, especially at IBM (Starr, 1965). Baldwin and Clark's seminal work provided a vocabulary, a set of concepts and an analytical framework for the study of modularity and its evolution (Baldwin and Clark, 1997 and 2000). They highlighted three fundamental "design rules" governing modular technological systems: architecture, interfaces, and standards. Their analysis, still mainly based on the computer industry was later extended with reference to other technologies. In particular, Sako and Murray (1999), referring to the automotive industry, distinguished between modularity in design, modularity in production and modularity in use.

Ulrich (1995) sets the basic elements of a modular product which have inspired the main features of the model we propose in this paper: the functions that a product performs, the mapping between such functions and the physical components of the product, and the interfaces between interdependent physical components. Functionality driven modularity is indeed at the core of our investigation in the present paper.

Whereas in natural systems modularization is the outcome of a random and purposeless, though constrained, process, in human-made systems modularization are at least partly directed and purposeful. In addition, whereas in biological system only genetic codes may undergo recombination, in artificial systems modules can be directly recombined and this possibility of using modules as basic recombinant units gives great opportunities for producing novel and more complex structures very quickly, as recognized at least since Schumpeter (1912). Finally, humans are also capable of modifying the architecture of the system. Baldwin (2015) discusses such architectural capabilities, i.e. "the ability to see a complex technical system in an abstract way and change the system's structure by rearranging its components" and argues that a fundamental aspect of such capabilities lies in the management of bottlenecks, i.e. components or modules that somehow put the most binding constraints to the evolution of the system and are also often source of value creation and capture.

Architectural capabilities are particularly important to overcome some drawbacks of modularity, arising from the observation that the high speed of adaptation which characterizes modular systems comes at the cost of suboptimality (e.g. Ethiraj and Levinthal 2004, Brusoni et al. 2007). A modular system can quickly climb a local optimum in the evolutionary landscape, but finding another, possible better, local peak often requires redesigning the system and escaping from the constraints posed by the current modular structure.

In this paper we try and enrich this evolutionary/complexity perspective. Our point of departure is the observation that technological evolution passes through the evolution of the artefacts it generates. Therefore, to understand this process we must understand how artefacts evolve and what are the factors shaping the patterns of this evolution.

To begin with, artefacts are characterised by two important factors: the bundles of functions they deliver through their use and the architecture of components generated by the technical solution needed to provide those functions. These two factors join together the social dimension, given by the relevance of an artefact within a context, with the technical dimension.

Evolutionary processes evaluate artefacts on the basis of their usefulness, i.e. on the basis of their ability to fulfil specific functions. In this sense, the artefact's architecture is relevant insofar as it enables improvements in this ability.

As argued by Simon, modular architectures possess higher adaptive capacities with respect to other types of complex structures. In fact, the possibility to operate in isolation on single modules to improve the performance of the connected functions, allows that system to quickly increase its fitness to a specific environment.

At the same time, adaptation is only one side of the coin. Indeed, evolutionary processes are based on the selection of the fittest among a set of alternative structures. In this sense, an extremely relevant aspect is related to the mechanisms whereby a system generates through time new varieties. This property is called evolvability and it is connected to the development of new phenotypes by organisms (Dawkins, 1989, Alberch, 1991, Wagner and Altenberg, 1996, Pigliucci, 2008). From a technological point of view, evolvability can be seen as the mechanism whereby one or more artefacts acquire new functions, generating new bundles. Differently from the development of phenotypes, however, the development of a new function is (almost always) an intentional activity carried out through R&D activities devoted to the solution of specific technical problems by starting from the already possessed knowledge. As artefact's architecture encapsulates the possessed knowledge -through the technical solutions embedded in its design- it also determines the distance with the functions that can potentially be implemented. To this extent, the architecture plays an important role for technological evolvability.

Following these lines, the paper investigates the role of modularity for technological evolvability. Specifically, by starting from the main features characterising any artefact's architecture -the degrees of pleiotropy of its component and the degree of polygeny of its functions- our analyses investigate what type of modular structure is associated to the highest artefact's evolvability. To do that, we build a simulation model based on the generalised NK framework (Altenberg, 1997; Frenken, 2006) in which a population of firms modify their artefacts to improve their performance and reach new market niches.

Our results indicate that not all modular architectures provide the same degree of evolvability. In fact, ceteris paribus the degree of polygeny of functions, evolvability is higher the higher the degree of pleiotropy associated to the lower-level modules of a technology for recombinant processes are quicker. Yet, our simulations also show that evolvability advantages are as well associated to a lower average fitness of artefacts generated by a technological architecture. Hence, the analyses suggest the presence of a trade-off between fitness and evolvability, at least in the short run.

The paper is organized as follows. In section 2 we present our generalized NK model and in section 3 we present the main simulation results and discuss their implications for the modularity debate. Finally, in section 4 we draw some conclusions and implications for future research.

2.2 The model

To study the relationship between the variety of artefacts emerging from a technology and the architectural characteristics of its functions we set up a simulation model centred around the processes of search and development of an artefact. The model is built upon three pillars: (i) the technology connecting each component of the product to the function(s) it contributes to provide; (ii) the evaluation of the bundle of functions implemented within the artefact's design expressed by the external environment (e.g. consumers with their needs) in which that artefact is employed; and (iii) the agents (e.g. firms) devoted both to improve the performance of their current artefact and to discover the techniques to implement new functions within their product.

In a nutshell, by drawing on the idea that the carrier of value of an artefact is related to what that artefact can be used for (Baldwin 2018, Saviotti and Metcalfe, 1984), the dynamics of our model starts from an external environment expressing a set of social needs that can be fulfilled through some functions. These social needs not only express an evaluation on each single function, but also on their different combinations. For example, the possibility to take pictures with a mobile phone increases its relevance whenever these pictures can also be sent with the same phone. At the same time, the possibility to watch a movie on the same phone may require an increase of its screen size which may hamper the portability of the phone itself. As such, societal needs generate a network connecting functions through complementarities and trade-offs.

This request for artefacts able to satisfy specific bundle of needs is taken on by firms seeking to increase performances through (i) the dominance of the market niche in which they operate and (ii) the search for niches of higher value. To this extent their strategy seeks, on the one hand, to increase the ability of their current product to provide the functions requested by the corresponding niche while, on the other hand, to look for new market opportunities whenever able.

The first operation is bound to the improvement of the existing artefact given a specific technological architecture. This is the case, for example, of the launch of a new version of a mobile phone presenting the same components of its earlier version but with better performances on (some of) its functions.

On the contrary, the second activity calls agents for modifying the product architecture in order to change the number of the provided functions. This is the case of the launch of a new mobile phone with new functions or of a tablet whose characteristics are similar to those of the original mobile phones but providing different functions.

More specifically, in our model whenever the firm pinpoints a new function to be introduced in its artefact, it faces two possible challenges. If this function has not been discovered yet, it starts a search process to find the technical solutions to bring its new concept to light while, if the function has already been implemented in some other artefact, it imperfectly copies the technical solution from one of the products already incorporating it.

The discovery phase encompasses the identification of the *recipe* needed to introduce the new function within the current product. This recipe requires (i) the identification of the components underpinning the new function and (ii) the definition of the procedure whereby these components have to be combined to provide the function. This highly uncertain process fails if any of the two conditions are not met. Yet, whenever successful, the artefact’s architecture is modified and the firm is able to shift to a new production and a new niche.

Imitation, on the contrary, does not require the firm to discover the recipe to implement the new function, but it requires to absorb some already existing knowledge from other producers and to copy their technical solution. This can only be done imperfectly, both because of the complexity of the technique and, possibly, of the presence of intellectual property rights impeding perfect replication. As such, imitators may not be able to provide artefacts with the same performance quality as the incumbents.

Within this framework, the technological architecture is relevant insofar as it provides the technological distance between the functions already implemented in one product with those that can be discovered and implemented in the near future. As such, different architectures may provide different degrees of difficulty to discover new functional combinations (and the emergence of new niches).

In the following subsections, we describe in detail the single elements of the model to better explain how these dynamics hitherto delineated unfold during the simulations.

2.2.1 The External Environment

In our framework, the external environment provides the evaluation of the different combinations of functions on the basis of societal needs. In other words, the external environment represents the compass that firms use to pinpoint the direction for the development of their products.[10] Yet, these evaluations may not be linear: a greater number of functions does not necessarily imply a higher evaluation of the whole bundle. As in the mobile phone case mentioned before, the combination of some functions within a bundle may generate trade-offs decreasing the overall evaluation of the artefact. In other cases, the contemporaneous presence of two functions within one design may bring about synergies from a societal point of view, leading to a more than proportional increment in the evaluation of the whole bundle of functions.

To encompass all these cases, we decided to model the evaluation of the bundle of functions through an NK model (Kauffman, 1993). NK models represent a category of models originally introduced in evolutionary biology and extensively used in economics, management and organization sciences (Levinthal 1997; Dosi, Levinthal, and Marengo, 2003; Levinthal and Marengo, 2016, Rahmandad 2019) that allows to study the fitness of complex systems characterised by K interdependencies among its N components. In particular, by acting on the structure of the interdependencies – called

[10] It is important to underline that this version of the model does not account for changes in the evaluation of the different bundle of functions. This choice has been made not to overload the model with possible variations and to allow a representation of product evolution in the short-to-medium run. In future works the model can be accommodated to incorporate environmental changes.

epistatic relationships following from the relationships between the genes and the phenotypes of an organism – it is possible to study complex systems characterised by different architectures.

In our case, the complex system is represented by the network of functions generated by the external environment's evaluation of the different bundles. To this extent, the N components are here represented by the F functions while the K interdependencies are generated by the *complementarities* and the *trade-offs* among these functions. When two functions are not subject to any interdependence, then they can be bundled without any 'more-than-proportional' or 'less-than-proportional' effect on the overall evaluation of the artefact.

In traditional NK models the setup of the system is represented by a string s of N elements s_i, $s =< s_1, s_2, \dots, s_N >$. Conventionally, it is assumed that each s_i can take on only two states $A_i = \{0,1\}$ (*alleles* in biological terms).[11] As such, it is possible to delineate the *design space*

(1) $$S = \prod_{i=1}^{N} A_i$$

including all the possible $A^N = 2^N$ combinations of s.

In our case, a string s represents a specific bundle of functions while each s_i indicates the presence (when =1) or absence (when =0) of the corresponding function within the bundle. For example, if we assume $F = 5$, then $s =< 01101 >$ represents a bundle made of functions 2, 3 and 5 while $s =< 11010 >$ represents a bundle made of functions 1, 2 and 4. Overall, then, for any given F the number of possible bundles amounts to $2^F - 1$ (as we exclude the bundle without any function).

The final pillar of the NK model is represented by the fitness level of each string s. In particular, the model associates to each element s_i a specific real value f_i in-between 0 and 1 representing the degree of functioning of that element. To this extent, the level of fitness of the string s is represented by the sum[12] of the degrees of functioning across the N elements of the system:

(2) $$W = \sum_{i=1}^{N} f_i$$

This is exactly the matter in which interdependencies play their role. Indeed, any $K > 0$, implies that the degree of functioning of s_i (i.e., f_i) does not depend solely on the state of s_i but also on the state

[11] Notice that this restriction is made only for easiness of computation, as it has been shown that the properties of NK models do not change when the number of alleles is greater than 2.

[12] The choice to take the sum instead of the average is guided by the criterion whereby agents decide to pass from one bundle of functions to another. Imaging one agent starting from the bundle $< 10110 >$ is evaluating the introduction of the 5th function, leading to the bundle $< 10111 >$: according to the behavioural rule of the model, she will accept to add the new function insofar as W increases during the passage. If W is represented by the sum of f_is this means that the agent is willing to accept the function insofar as the overall evaluation of its artefact increases. On the contrary, if W is represented by the average f_i this implies that the agent is willing to accept the new function if the value it brings to the artefact is greater than the average f_i.

of other K elements s_j among the other $N - 1$ ones. In this way, f_i changes not only when s_i switches from 0 to 1 (or viceversa), but also whenever each one of the other K connected elements change the status. The maximum degree of interdependency occurs when $K = N - 1$, since any change in any element of s affects all the degrees of functioning f_is. Moreover, as the value of each f_i is randomly drawn from a uniform distribution between 0 and 1, the higher the degree of interdependence K the larger the number of non-linearities between s and W, i.e. the larger the number of local peaks.

In our case each value f_i represents the evaluation of each function in a specific bundle while W, computed as the sum of f_is is the evaluation of the whole bundle. Akin to the traditional NK, complexity is modelled through interdependencies among functions that affect their evaluations. In our case, interdependencies can be interpreted as functions whose contemporary presence in the same bundle brings about complementarities or less-than-proportional effects on the overall evaluation of the bundle by the external environment.

However, whilst in traditional NK models the parameter K is very often treated as the *degree of polygeny* - the number of the other functions s_is affecting the evaluation of a specific function f_i (i.e. the extent of interdependency among functions) - in our model the parameter K is treated as the *degree of pleiotropy* – the number of evaluations f_is affected by one specific function s_i.[13] This different perspective on K allowed us to better control the design of the network of functions without affecting the dynamics of the model. Moreover, our model accounts also for the possibility of different degrees of K across functions. Figure 1 reports four examples of networks generated by a model with $F = 8$. In each network the nodes represent the functions while the directed edges indicate what evaluations are affected by the presence of the function from which the edge originates. Notice that in the networks in the upper part of the graph K is constant across nodes, while in the two networks in the lower part of the graph the inclusion of some functions within the bundles affects the evaluation of the overall value of the bundle more than other functions (i.e. K varies across functions).

[FIGURE 1 ABOUT HERE]

2.2.2 The Technological Architecture

The second element of the model is represented by the technology connecting each component of one product to the function(s) it contributes to provide. As a matter of fact, the F functions composing the bundles evaluated by the external environment can be provided through ad-hoc technological solutions represented by artefacts whose design is conceived to provide a set of specific functions.

[13] It is possible to treat K as either the polygeny or the pleiotropy because in traditional NK the number of components s_i equal the number of degrees of fitness f_i. This assumption is relaxed by the Altenberg's (1995) variant described in the next subsection.

For example, a mobile phone conceived to communicate through phone calls, to navigate on the internet, and to write mails must embed the components needed to provide all these functions.

As the focus of our model rests on the diversification of functional bundles, we decided to pre-set the whole technological space in which functions are associated to the corresponding components according to specific techniques, while leaving to the agents the ability to compose their artefact by joining together in the same design the different components providing the targeted functions.

To model the technological space, we employed the generalization of the NK model proposed by Altenberg (1995). This is a refinement of the traditional framework delineated in the previous subsection that allows to relax some of the binding assumptions characterizing the original NK model (Frenken, 2006). Indeed, differently from the original NK, Altenberg's generalization keeps distinct the components of the string s from the degrees of fitness f_j, thus allowing to consider cases in which the number of s_i differs from the number of f_j. In Altenberg's case, this distinction was introduced to separate the genotypes of an organism – represented by s_i – from the phenotypes of the same organism – represented by f_j. In our case, this characteristic is useful to distinguish the components of an artefact (s_i) from the functions it provides (f_j).

As such, the technological space associates to each one of the F functions evaluated by the environment a subset of components among the possible N, with $N \geq F$. In this way, an artefact A designed to fulfil $F_A \leq F$ functions can be defined through the string $s^A =< s_1, s_2, \dots, s_{N_A} >$ made of the $N_A \leq N$ components necessary to provide F_A. Therefore, an artefact providing all the F functions is represented by a string $s =< s_1, s_2, \dots, s_N >$ made of N components.

As before, $s_i$can take value 0 or 1. However, differently from the functional network's case, here the two alleles represent two different states of the same component s_i: for example, a plastic or a metallic chassis for the mobile. Provided that, an artefact with F_A functions can take on up to 2^{N_A} combinations while an artefact including all the F functions can take up to 2^N variations of its design.[14]

Another reason that led us to opt for Altenberg's variant instead of traditional NK relates to the greater degree of freedom in the design of technology's architecture. As a matter of fact, the distinction between F and N generates a distinct differentiation between the *degree of polygeny* and the *degree of pleiotropy*. In other words, in the Altenberg's the number of components affecting one specific function seldom equals the number of functions affected by one specific component. This allows for a wider range of architectures that can be studied through this model. In this sense, Figure 2 reports

[14] Notice that, now, a string s made of zeros, such as $< 0000 >$, is perfectly allowed because it does not mean absence of all the components but, instead, it means that all the components take on their statuses associated to 0.

six examples of different architectures that can be implemented when passing to the generalized NK. More specifically: each panel of the figure describes a technology through a *genotype-phenotype map*. In biology this type of maps is used to describe the relationships between phenotypes (rows) and genotypes (columns). In our case they describe the relationship between functions (rows) and components (columns).

[FIGURE 2 ABOUT HERE]

As for the architecture, it is possible to notice that the two figures in the upper panels represent two complex architectures. As a matter of fact, adjacent components affect at least one common function, generating both direct and indirect links across all the functions. On the contrary, the middle panels report the genotype-phenotype map for two modular systems with the first component acting as technical standard across all the functions. In particular, the left-hand-side panel delineates a technological space made of two modules, while the right-hand-side panel delineates a modular system made of four modules. Finally, the two panels in the lower part of the figure report two special cases related to modules (Frenken, 2006; Frenken and Mendritzki, 2012).

The left-hand-side panel delineates a decomposable system, solely made of four modules, while the right-hand-side panel reports a hierarchical system in which each technical standard is a module of modules. This is the case of many modern artefacts that are created by constructing modules out of other modules.

Provided these differences, then, Altenberg's NK associates fitness values $f_j$to phenotypes (in our case to functions). In particular, each f_j is a function of the components associated to it. In other words, the ability of an artefact to fulfil one specific function (f_j) depends on the components (s_i) associated to that function. It is important to underline that the same component s_i may affect in different ways different functions. For example, a larger screen may increase the easiness to use a mobile for navigating internet but, at the same time, it may decrease its portability. As such, by switching s_i from 0 to 1 (or viceversa) it is possible to generate different effects on different f_j.

Finally, the overall quality of an artefact A is given by its performance θ^A, represented by the average fitness of the functions implemented in its design, i.e.

(3) $$\theta^A = \frac{1}{F_A}\sum_{j=1}^{F_A} f_j$$

2.2.3 The behaviour of firms

The third pillar of the model is represented by the behaviour of firms. Indeed, these ones seek to improve their performance either by improving their position within the market niche in which they currently operate or by looking for a new market niche to reach. To this extent they can operate two different types of activities.

On the one hand, the first activity relates to the improvement of the ability of their artefact to fulfil the functions already implemented in its design. This is carried out by switching from 0 to 1 (or viceversa) the values of the components s_i of their product s^Ain search for higher values of θ^A. In particular, in each period of the improvement phase, each firm

1. randomly draws s_i, one of the components included in its artefact;
2. switches s_i from 0 to 1 (or viceversa) and checks whether θ^A increases after this change;
3. accepts the change insofar as θ^A has increased, otherwise it waits for the next period to continue this improvement strategy.

The *offline search* thus delineated lasts for a number of periods exogenously set through a parameter. Once this number of periods has expired, the firm compares its value θ^A with all the θ^A of the other firms producing the same artefact (and hence populating the same niche). If its θ^A is greater than the average value $\bar{\theta}^A$ then the firm can look for a new niche to migrate to. The underpinning idea is that firms with the higher performance in one niche have accumulated the necessary resources to look for new niches.

To pinpoint a possible new niche B, the firm randomly draws one of the functions not yet incorporated in its product and compares the hypothetical degree of appreciation of the new bundle B (W^B) from the external environment with the degree of appreciation of its current bundle (W^A). In other words, the firm evaluates whether the new niche could be more profitable than the current one. There are two possible outcomes of this process:

1. $W^B \geq W^A$, which implies that the firm decides to shift to the new niche;
2. $W^B < W^A$, in which case the firm, before discarding the opportunity to introduce the new function in its artefact checks whether, by creating a new bundle C through the replacement of one of the functions in A with the new function, it can reach a higher value niche (i.e., $W^C > W^A$). If this is the case, then the firm attempts to enter the niche C, otherwise it remains on niche A.

If the comparison process led the firm towards a new niche, then its next step requires the implementation of the new function within its product. Yet this can occur in two ways:

1. if the function has not been discovered yet, the firm has to set off an R&D process looking for the technological solution needed to provide the pinpointed function;

2. if the function has already been implemented by other firms it does not need to discover a new technique but it can imitate those adopted by others.

In the first case the R&D process is made of two separate but interdependent phases:

1. in the first phase the firm needs to discover the process whereby the new function is produced by guessing the number of components needed to provide it (through a random draw);
2. in the second phase it has to correctly understand it by identifying (through another random draw) the identity of the components that have to be included in its artefact to generate the new function.[15]

To this extent, the new function is discovered whenever both conditions are met: should it fail any of the two attempts, then it would not be able to continue the development of the new artefact and it would remain in its original niche. When the firm successfully discovers the new function, the architecture of its product changes by including the components needed to generate the new function. From a genotype-phenotype perspective, the inclusion of the new function would add the row associated to new function to the original map.

In the imitation case, the firm does not need to discover the recipe to provide the new function. However, it has to copy the technical solution from another firm already incorporating it in the artefact's design. Although this process is less risky, its outcome is still uncertain for imitation is always imperfect due to the complexity of the technology to be imitated and to the property rights that might hamper the diffusion of the right knowledge across firms. To this extent, imitation makes it possible for the firm to identify all the components needed to produce the function but not their correct setup. As a matter of fact the model randomly draws the number of components that the firm is not able to correctly imitate. Notice that, due to the technological nonlinearities, imperfect imitations may lead the newcomer both to a lower and to a higher position than the incumbent.

2.3 Results

2.3.1 Simulation Strategy and Setup

The framework we have delineated in the previous section is quite complex and can be used to investigate different issues regarding the processes of artefacts' search and development. As the current work focuses on the relationship between technology's architecture - more specifically different types of modular architectures- and technology's evolution, we decided to take advantage

[15] If its artefact already possesses all the necessary components this second phase is automatic.

of the model insofar as it was necessary for our study, leaving to future research interesting aspects including other dimensions. To this extent, in all the simulations we kept fixed the aspects related to the external environment, while manipulating the parameters associated to the technological generalised NK. In particular, our strategy is based on the architectural differences arising when passing from a modular system characterised by modules connected to one single interface standard – likewise the apps with the mobile operating system – to systems characterised by nested modules, representing themselves smaller interface standards – as it is the case of many high-tech products. As a matter of fact, within the former type of architecture the degree of polygeny of each function -i.e. the number of components connected to the function – and the degree of pleiotropy of each component – i.e. the number of functions a component contributes to provide- are strictly connected. Indeed, by being associated to one module only, each component contributes to the provision of the functions associated to that module. For example, the lines of code of TripAdvisor will not serve any other app on the mobile phone. To this extent there is a rigid relationship between the two measures defining an architecture.

On the other hand, the hierarchical structure relaxes these relationships for each component can be seen, at the same time, as part of a module and as an interface standard for the lower levels modules. For example, the camera incorporated in a mobile phone represents a module of the broad architecture, together with the display, the mic, the speaker, the GPS module, the battery etc. However, that same camera is itself the result of the combination of a sensor, 'capturing the image', and a lens, 'focusing the light onto the sensor to make the image crisp and clear'. Moreover, both these components are made of other components. For instance, the sensor is a complex integrated circuit itself including, among others, the phototedectors, which are responsible for the resolution of the photos that can be taken with the camera-module. In this sense, the ratio between the degree of polygeny of one function and the degrees of pleiotropy of its associated components may vary on the basis of the architecture of the sub-modules.

These differences can be seen by comparing in figure 3 the first four panels with the fifth one. The five pictures represent the matrix forms of five different architectural structures. In each matrix, rows *j* are specific functions, while each column *i* represents one specific component and blue squares in the *ji*-th position indicate that the *i*-th component contributes to the provision of the *j*-th function. Within this logic, the degree of polygeny is represented by the number of blue squares per row, while the degrees of pleiotropy are the numbers of blue squares within every column. The first four matrices describe four different types of hierarchical architectures as their elements are associated to modules that are nested within higher order modules. For example, in the first panel, the first second-order module is made of components 2, 4, and 5. However, components 4 and 5 represent, in turn, two submodules nested within the second interface. The lowest-level modules are named *child modules* (Frenken and Mendritzki, 2012) and the four hierarchical structures feature four different numbers of these modules. The fifth matrix, on the contrary, depicts one simple modular structure. In this case, in fact, all the child modules are nested within the unique interface of the artefact represented by the first component.

[FIGURE 3 ABOUT HERE]

Polygeny and pleiotropy are not only important to describe one technology, but they also represent two important aspects in the dynamics of the evolution of an artefact. As a matter of fact, the degree of polygeny of one function indicates the degree of difficulty of providing that function while the degree of pleiotropy of one component points to its degree of polyvalency. In other words, by conceiving technologies as a series of recipes and procedures needed to achieve the production of one product or service (Dosi and Nelson, 2010), the degree of polygeny indicates how many '*ingredients*' we need to '*cook*' our functions while the degree of pleiotropy indicates '*how many recipes*' require my ingredient. To this extent, the easiness whereby a new function can be implemented in one artefact depends 1) on the difficulty of its recipe and 2) on the number of missing ingredients.

At the same time, polygeny and pleiotropy are related to the improvements in the performance of the artefact. In fact, if I want to improve the quality of one recipe I need to use ingredients of higher quality.

As such, our strategy has been to fix *a priori* the number of functions and the degree of difficulty of their recipes (i.e., the degree of polygeny) while building around these parameters alternative architectures for the creation of the landscapes in which agents operate their choices. In particular, we opted for technologies with seven functions, each one generated by the combination of three components.

Given that the aim of the work is to study artefact's diversification in terms of functional bundles, we impose that, at the beginning of each simulation, agents start with the same artefact made of the first two functions of the genotype-phenotype map. Moreover, each simulation lasts 100 iterations and is populated of 100 agents, whose initial position in the sub-landscape of the two-functions artefact is randomly drawn from a uniform distribution. In order to ensure that our results are not driven by a specific setting of the landscape, we repeated the same simulation for 1000 times, each time on a newly drawn landscape and with new randomly drawn agents.

For each repetition, we register the number of functional bundles discovered by agents during the 100 periods-interval and their average degree of fitness. We also compute the average and the standard deviation across the 1000 repetitions. In this way, we make sure that the differences across the simulation averages are driven by differences in the underlying architectural structures of the genotype-phenotype maps of the whole technology.

2.3.2 Results

The first aspect we study is the relationship between technological architecture and the degree of products' diversification. Figure 4 reports the average number of artefacts discovered by agents in each set of replications of the simulations associated to the architectures depicted in Figure 3. First of all, it is possible to observe that, on average, hierarchical architectures are associated to a larger number of product variety than simple modular architectures. In this sense our simulations suggest that it is more likely to observe higher diversification when technologies are structured through nested modules rather than when technologies are made of simple modules bound together by one platform. Moreover, this difference is higher the lower the number of child modules of the hierarchical architecture. In other words, the lower the number of the lowest-level modules, the higher the number of recombined functional bundles discovered by agents.

[FIGURE 4 ABOUT HERE]

These two results can be interpreted on the basis of the different relationships between polygeny and pleiotropy in the five architectures. As a matter of fact, when there are few child modules the average degree of pleiotropy of technology's components is higher. In other words, in presence of hierarchical technologies with a relatively small number of child modules, each component has many uses. To this extent, by having at disposal a relatively small set of components, an agent can quickly implement new functions within her artefact by recombining these same components. On the contrary, the more hierarchical architectures approach the simple modular architecture, the more each component is associated to one module only. In this second case the discovery of one component does not open up as many recombinant possibilities as the ones in the previous example. This is also highlighted by two further evidences. On the one hand, the easiness of the recombination process is also associated to the number of components embraced by a technology: architectures characterised by high average pleiotropies require a lower number of components while architectures characterised by low average pleiotropies are generally made of a larger number of components which increase the space in which agents have to look for the technological solutions they need. On the other hand, simulations with hierarchies characterised by higher pleiotropies are associated to a lower degree of variation of the possible outcomes, as demonstrated by the standard deviations of the number of artefacts discovered in each repetition and reported in Figure 5.

[FIGURE 5 ABOUT HERE]

By interpreting the standard deviation of the simulations' results as the degree of uncertainty associated to one architecture, these data indicate that search processes are less uncertain when the overall architecture is made of nested modules instead of simple modules. As such, not only hierarchical structures lead on average to a wider spectrum of artefacts through functional recombination, but they also decrease the risk of this process. The mechanism underpinning this result resides once more in the possibilities opened up by single components. By retrieving the metaphor of technology as a recipe, *given* the degree of difficulty to discover a new recipe, the grater the degree of polyvalence of ingredients, the lower the risk I am not able to find new recipes by recombining them.

Yet, this advantage in terms of evolvability comes at a cost. As a matter of fact, the higher possibilities for diversification are offset by a higher difficulty to reach the best performances. As a matter of fact, when looking at the average fitness values across the different simulations (Figure 6), the ranking of the five architectures is the opposite with respect to the one emerging from the previous analysis. Indeed, whilst the shape of fitness presents a downturn -due to the discovery of new functional bundles[16]- in all the five cases, it is also evident that architectures with more child modules outperform hierarchical architectures with fewer child modules. As such, when tackling the issue of product quality, simpler modular structures outmatch hierarchical architectures and, among these, those with the highest pleiotropy display the poorest performances.

[FIGURE 6 ABOUT HERE]

Even in this case pleiotropy plays a central role. Given that higher degrees of pleiotropy imply higher degrees of interconnection across functions, agents conducting search activities on hierarchical architectures with few child modules are more likely than others of being unable to improve the fitness of each function in isolation. To this extent, they find themselves more often in a paralysis due to the fact that any 'one-bit mutation' at their disposal may actually deteriorate the overall performance of their artefact (Frenken and Mendritzki, 2012). On the contrary, simpler modular structures are associated with higher fitness levels because each component contributes to the provision of a lower number of functions. In the latter case, then, 'one-bit mutations' have an effect on a narrower number of functions, allowing for easier hill-climbing processes.

On the whole, all these outcomes suggest the presence of a twofold effect of hierarchy for technology: on the one side, hierarchical structures can facilitate the emergence of a larger number of products'

[16] Notice that, by construction, when an agent shifts from one niche to a new one characterised by a larger number of functions the average fitness can increase insofar as the fitness of the new function is already greater than the average fitness. If it is lower, as it is probably the case, then the overall quality of the product decreases. At the same time, this is in line with empirical evidence which shows that products improve their quality throughout their life-cycle.

varieties while, at the same time, they can also hamper the right improvement in its quality. Therefore, these results point out the presence of a short-run variety-fitness trade-off generated by architectural structures. From an evolutionary perspective, this is a relevant matter for both of these properties are at the basis of any technological change.

At the same time, in the long-run, architectures cannot be taken as given for they can be modified through the introduction of new components and the implementation of new modules that are eligible of dampening the trade-off. Yet, even though our model does not incorporate these features, it is reasonable to assume that the new components will be introduced by tapping into existing knowledge which may bring back the issue of modularity for the new structure. We leave this possibility for future work.

2.4 Concluding remarks

We started from the consideration that technology is a complex system whose evolution unfolds through mechanisms of variation, inheritance, retention and selection. In this respect, the literature has shown that modularity has some advantage over the other types of architectural forms because of (i) its tendency of arising spontaneously and (ii) the speed whereby it increases its degree of fitness (Simon, 2002). Yet, we argued that modular architectures are not all equivalent in terms of evolvability but, on the contrary, there are different types of modular systems whose performance differs due to the relationship between the components, on the one hand, and the functions generated through these components, on the other. In particular, by adopting a 'technology-as-artefact' perspective (Dosi and Nelson, 2010), we suggested that the dimensions characterising the discrepancies across the types of modular structures play an important role for technological evolution.

To investigate the modularity-evolvability link, we built a new simulation model based on the NK tradition (Kauffman, 1993; Altenberg, 1995) and centred around firms' strategies to improve current artefacts and create new ones to reach new niches. Specifically, the framework stands on three pillars: (i) an external environment providing an evaluation of all the possible bundles of functions implementable in an artefact's design, (ii) a technological landscape characterised by a specific modular technology connecting all the functions accounted for to the set of components needed to provide them, and (iii) a set of agents (firms) seeking to improve their performance either by improving the performance of their current artefact or by embarking on R&D activities to discover new functions to implement in their product design.

The results of the simulations showed that the several modular structures differ each other both in terms of the ability to generate artefact's variations and in terms of the level of fitness reached by these variations through time. In particular, our results suggest the presence of a variety-fitness trade-off since architectures displaying the highest levels of variability are also those with the lowest levels of fitness and vice versa. Both results hinge on one key characteristic of any modular system: the degree of pleiotropy of its components. Indeed, modular systems characterised with high pleiotropy, on the one hand, facilitate recombination -hence variety- while, on the other hand, they easily incur lock-in into local optima. These phenomena follow from the versatility of each component which can lead quickly to new recombination but it can also hamper changes because 'many recipes can go wrong at once by changing one ingredient'. On the contrary, modular systems whose components have low degrees of pleiotropy tend to generate less varieties, for 'adjacent recipes require very different ingredients', but, at the same time, they present the ability to reach superior fitness levels by allowing for small improvements of single 'recipes' without affecting all the 'remaining courses'.

From a technological perspective, we regard this variety-fitness trade-off as relevant for the following reasons. To begin with it places a spotlight when the mechanism is 'on the move', posing new issues on what are the aspects to be privileged when trying to devise new technologies. At the same time, we regard our results as contributing to the understanding of the recent evidence regarding the innovation rate slowdown. Indeed, as modularity has become a standard in product design and competition has exacerbated the need for fitness, product architecture may have contributed to this trend (without of course being the only reason).

At the same time, we think it is important to mention few caveats regarding our model. As mentioned in the previous pages, the framework we have delineated is more apt to describe technological change on the medium-to-short run, for the number of components are exogenously fixed, while it is reasonable to assume structural changes in the long-run. In a similar and specular vein, also the external environment evaluation is fixed throughout the simulation, while, in the future, it could be interesting to investigate whether the different types of modular architectures differ in their ability of allowing evolvability in presence of dynamic external environments. As mentioned, we are aware of all these points and we will address them in future works.

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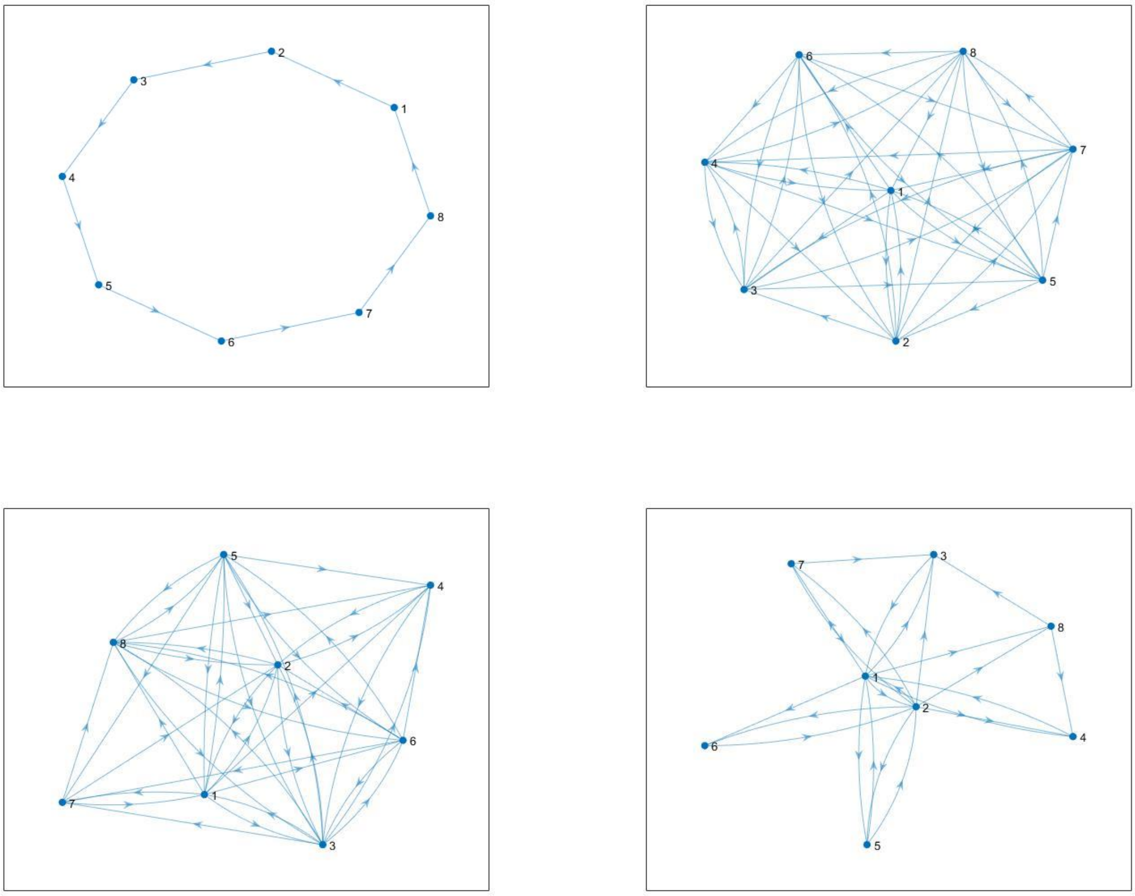
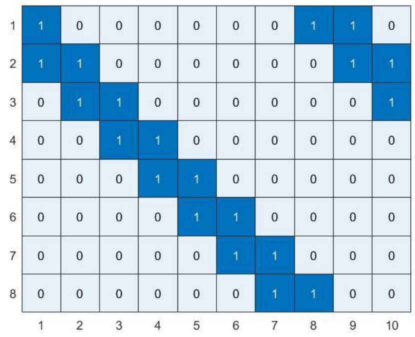
Figures

FIGURE 1. EXAMPLES OF NETWORK OF FUNCTIONS

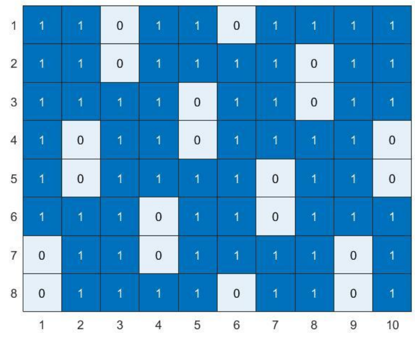


Note: the four panels represent four examples of directed networks of functions that can be generated by the model. Vertices correspond to functions while edges represent the links between each pair of functions stemming from the evaluation of the external environment. The arrow over each edge indicates the direction of the relationship. For example, in the network represented in the upper panel on the right, function 1 influences the evaluation of function 2. The set of edges coming out from one node represent the pleiotropy of the corresponding function within the environmental NK. The two examples reported in the upper panels represent two networks in which every function has the same degree of pleiotropy. The wo examples reported in the lower panels represent two networks in which the degree of pleiotropy differs across functions.

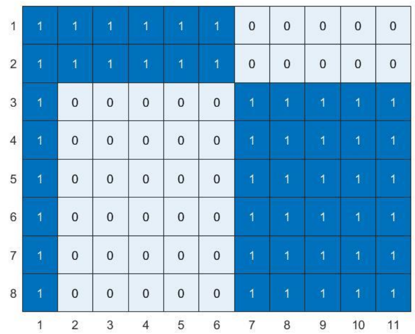
FIGURE 2. EXAMPLES OF TECHNOLOGICAL ARCHITECTURES



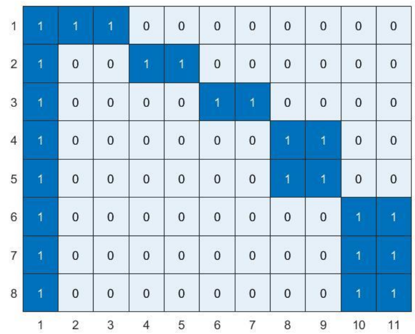
(a)



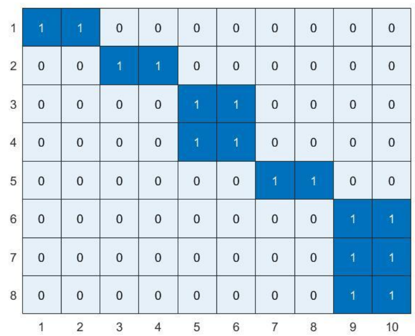
(b)



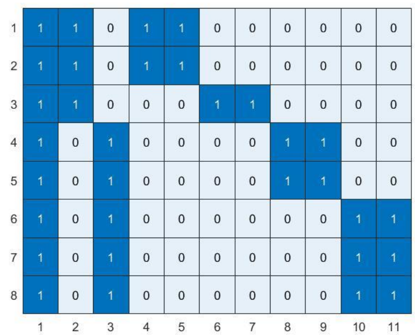
(c)



(d)



(e)

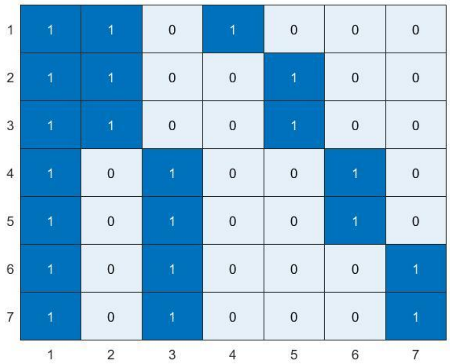


(f)

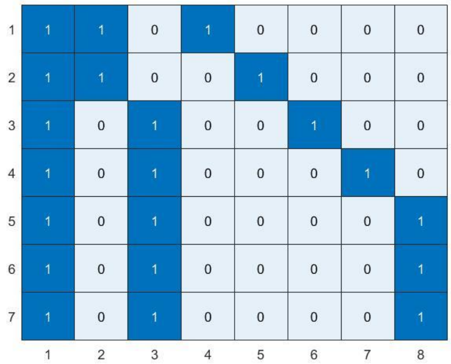
Note: the six panels report six examples of architectures for a technology with eight functions. Each figure represents a genotype-phenotype maps where rows correspond functions *j* while columns correspond to components *i*: blue squares in position *ji* indicate the cases in which component *i* affects function *j*. Panel (a) describes a complex technology without modules in which every component has a degree of pleiotropy equal to two. Panel (b) describes a complex technology without modules in which every component has a degree of pleiotropy equal to six. Panel (c) represents a modular technology with one platform and two modules, each one made of five components. Panel (d) represents another modular technology with one platform and five modules, each one made of two components. Panel (e) represents a decomposable system made of five modules, each one consisting of two components each. Finally, Panel (f) represents a hierarchical system, in which each layer is made of submodules.

FIGURE 3. ARCHITECTURES EMPLOYED IN THE SIMULATIONS

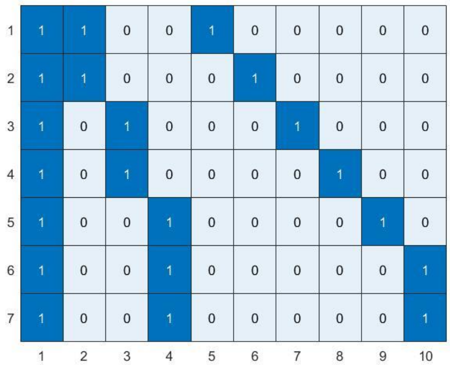
(a) Hierarchical – 4 child modules



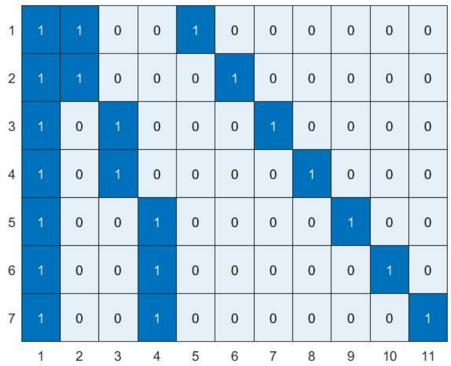
(b) Hierarchical – 5 child modules



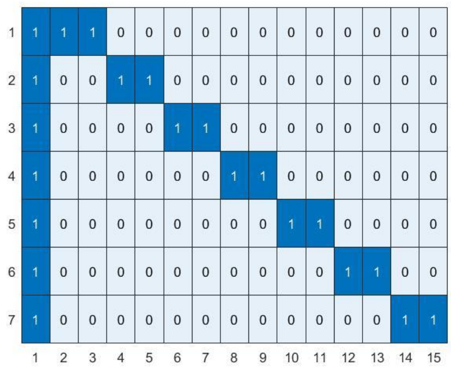
(c) Hierarchical – 6 child modules



(d) Hierarchical – 7 child modules

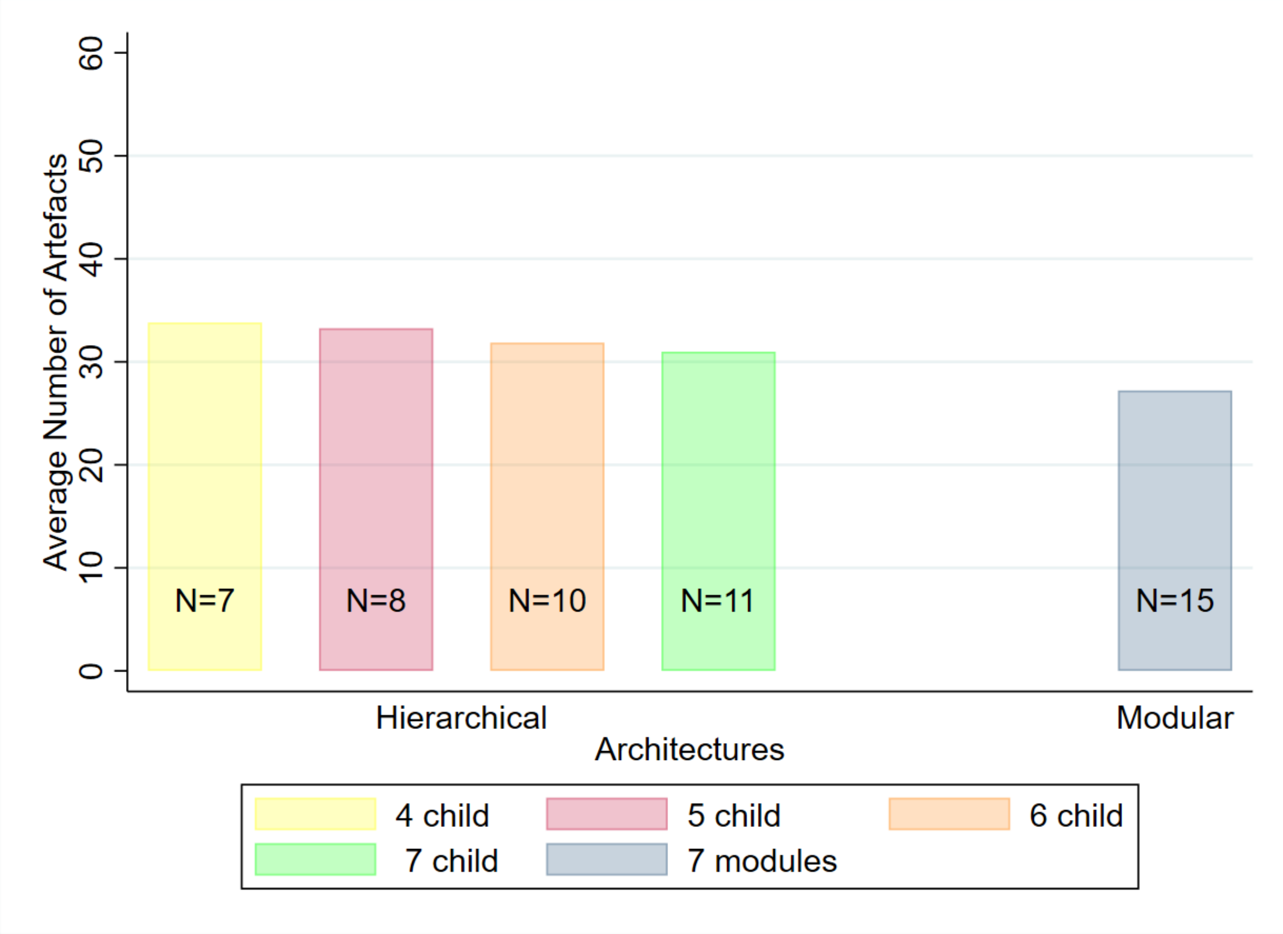


(e) Modular



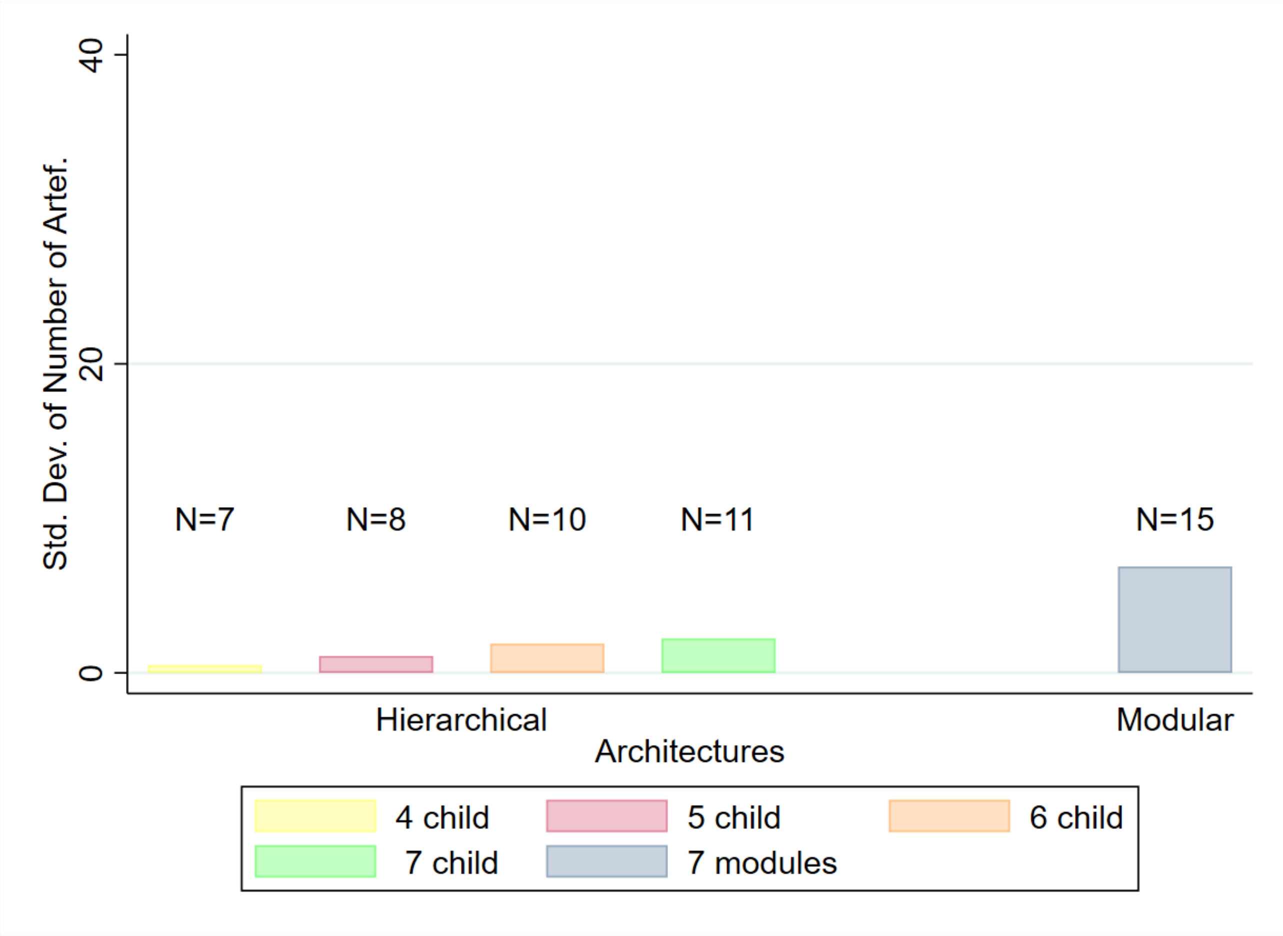
Note: the five panels report the five genotype-phenotype maps for the architectures investigated by the analyses. All of them refer to a technology with 7 functions and degree of polygeny equal to 3. Panels (a)–(d) represent four technologies with a hierarchical architecture of nested modules while Panel (e) represents a simple modular technology with one standard only and five separate modules. Panel (a) is characterised by the presence of 4 child modules. Panel (b) is characterised by 5 child modules. Panel (c) is characterised by 6 child modules. Panel (d) is characterised by 7 child modules.

FIGURE 4. AVERAGE NUMBER OF ARTEFACTS DISCOVERED ACROSS ARCHITECTURES



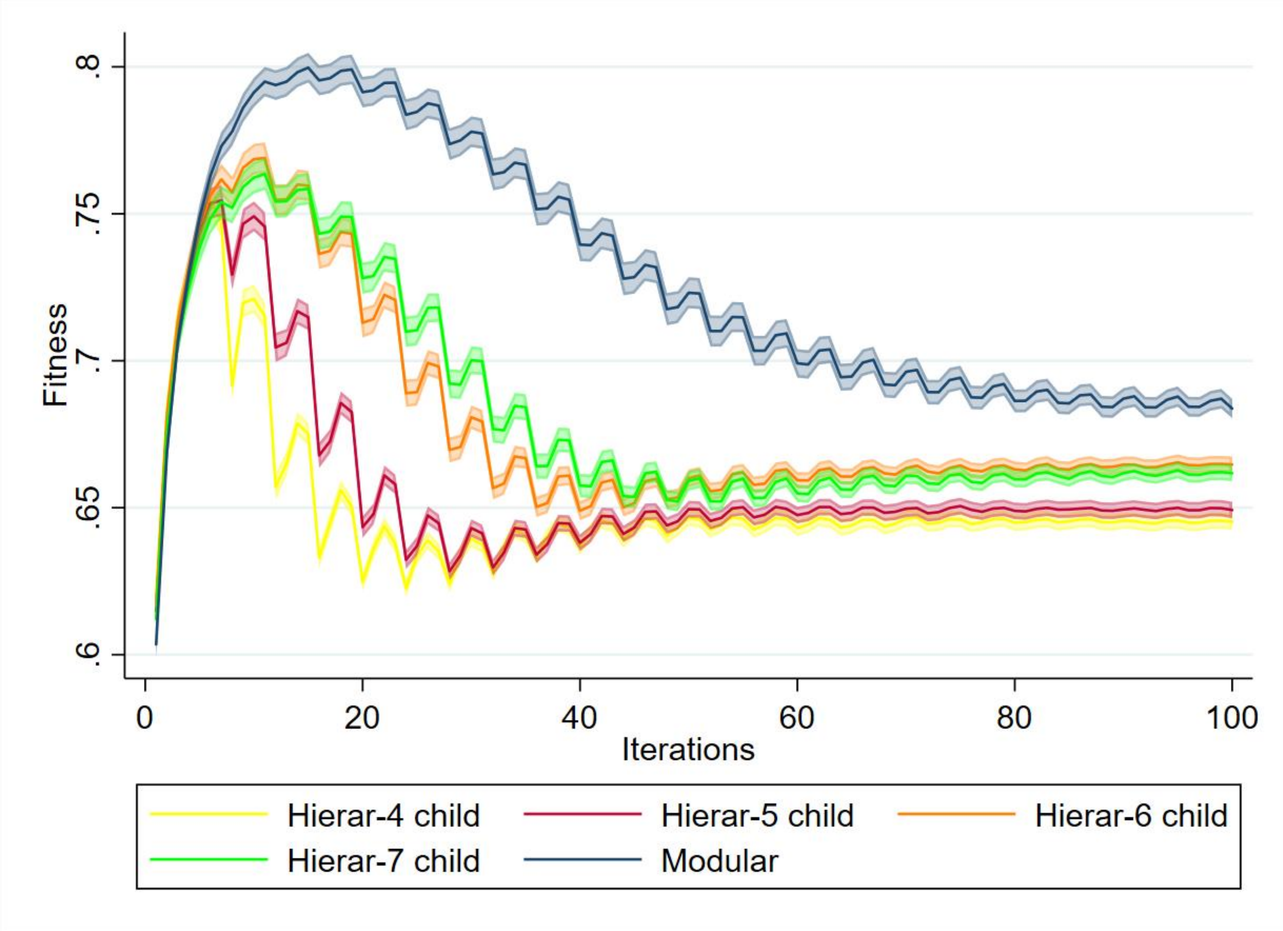
Note: each bar is computed by taking the average number of artefacts over 1000 repetitions of the same simulation. Each repetition lasts 100 periods and artefacts are defined on the basis of bundles of implemented functions. The five simulations differ in terms of the architectural structure of the underpinning technology. The first four simulations refer to four hierarchical architectures with nested modules, but different number of child modules, while the fifth simulation refers to a modular architecture with one standard and five simple modules. The remaining parameters of the model setup are the same across simulations: the number of agents is 100, the number of functions is 7, the degree of polygeny of the technology is 3, the degree of pleiotropy of the environmental network equals 2, and the number of periods each agent spends to improve her artefact equals 3. Even though not reported in the graph, the 95% C.I.s confirm the differences across bars are significant.

FIGURE 5. STANDARD DEVIATION OF THE AVERAGE NUMBER OF ARTEFACTS DISCOVERED ACROSS ARCHITECTURES



Note: each bar the standard deviation for the average number of artefacts computed over 1000 repetitions of the same simulation. Each repetition lasts 100 periods and artefacts are defined on the basis of bundles of implemented functions. The five simulations differ in terms of the architectural structure of the underpinning technology. The first four simulations refer to four hierarchical architectures with nested modules, but different number of child modules, while the fifth simulation refers to a modular architecture with one standard and five simple modules. The remaining parameters of the model setup are the same across simulations: the number of agents is 100, the number of functions is 7, the degree of polygeny of the technology is 3, the degree of pleiotropy of the environmental network equals 2, and the number of periods each agent spends to improve her artefact equals 3.

FIGURE 6. AVERAGE FITNESS ACROSS ARCHITECTURES



Note: the graph reports the average fitness values and the 95% C.I.s computed over 1000 repetitions of the same simulation. Each repetition lasts 100 periods while fitness levels are computed as simple averages across 100 agents. The five simulations differ in terms of the architectural structure of the underpinning technology. The first four simulations refer to four hierarchical architectures with nested modules, but different number of child modules, while the fifth simulation refers to a modular architecture with one standard and five simple modules. The remaining parameters of the model setup are the same across simulations: the number of agents is 100, the number of functions is 7, the degree of polygeny of the technology is 3, the degree of pleiotropy of the environmental network equals 2, and the number of periods each agent spends to improve her artefact equals 3.

CHAPTER 3

A Generalized NK-Framework to Study the Co-Evolution Between Industry Dynamics and Artefact's Architecture[17]

3.1 Introduction

The centrality of industrial dynamics stems from the fact that industries lie at the intersection of the economic and technological realms. As a matter of fact, in order to survive the market-based competition, firms devote their efforts to look for new products, new processes and new organisational forms advancing, in this way, knowledge and technology (Dosi and Neson, 2010; Nelson and Winter, 1982). The outcome of these activities is a multi-faceted phenomenon in which both realms co-evolve.

The literature has analysed these dynamics from two different perspectives. On the one hand, the way industries evolve has been analysed starting from the movements and performances of the underlying population of firms. On the other hand, works in the evolutionary tradition have been placing their focus on the technologies behind the products and the ways these evolve through time thanks to demand conditions. Although both approaches have provided many insights, their accounts remain partial, leaving us with an insufficient understanding of the co-evolutionary forces between the two aspects. In particular, the lack of formal models able to gather under the same umbrella firms' dynamics and technological evolution hampers

[17] *Co-authored with Koen Frenken, Professor in Innovation Studies, Utrecht University.*

our understanding of important phenomena such as the changes in product's architecture, the emergence of different dominant designs, and their effects on submarkets.

We try to fill this gap by putting forth a novel simulation model embedded within the evolutionary tradition able to replicate the stylised facts of product life cycle theories concerning (i) product diffusion, (ii) shakeout events, (iii) modularity in product design, and (iv) size of products in terms of components. In particular, the framework presented in this paper can replicate these phenomena by means of a rich illustration of firms, technology, consumers, and their interactions while hinging on a parsimonious set of parameters. To achieve this goal, we adopted a complexity perspective on technology and introduced a formal representation of artefacts based on the generalised NK model (Altenberg, 1997, Frenken, 2006). This approach allowed us to treat in an explicit form the relationship between product components and the corresponding functions as well as to include a constructional selection mechanism to study how product architecture changes in relation to firm's search strategies and the demand it faces. Therefore, differently from the current literature on industry life cycle, our model is able to generate back-and-forth influences between industrial and technological domains. Moreover, the general results of our model are found to be robust to different preference regimes of customers. At the same time, the differences emerging from the different preference scenarios highlight that both industry dynamics and technological branching are influenced by the type of consumers faced by firms. In so doing the model opens new possible research avenues regarding the reciprocal influences between the two domains.

More specifically, our results enrich the industry life cycle perspective by showing that hierarchical product architectures emerge in response to firms' need to improve the product's performance to meet customers' tastes. As a matter of fact, to improve the ability of a multifunctional artefact to fulfil a specific function without jeopardising the remaining ones, firms adopt technological solutions affecting a circumscribed number of functions. This is especially true when the artefact has already included a large number of components.

The paper is organised as follows. The next section traces the different connections between our model and the previous literatures by highlighting the similarities as well as the differences with past and current modelling approaches. Section 3 provides an in-depth description of the model as well as of its constituting parts. Section 4 presents the results of the simulations and their interpretation. Section 5 concludes by summarising the main points and indicating both limitations and possible future extensions.

3.2 Related works

The present work puts forth a novel simulation model able to represent the co-evolution of a market for a complex product and its underpinning technology. The idea of interrelation between the economic and technological domains traces back to the birth of the evolutionary research program which conceives industry dynamics in terms of firms seeking for better performances through the search for novel technological solutions (Nelson and Winter, 1982). By following this tradition and adopting an artefact-centred perspective (Arthur, 2009), our framework reconnects to two streams of research -the theoretical literature on industry dynamics and the literature on technology as a complex system- that have investigated distinct aspects at the centre of the co-evolutionary mechanism.

The models in the industry dynamics field can be broadly divided into two different categories: the first one can be ascribed to the equilibrium tradition, while the second one is connected to the evolutionary perspective. The adherence to different schools of thought leads the models falling within either of these groups to place the focus of the analysis on different aspects of such a complex process. The works inspired by equilibrium theories tend to focus more on issues related to firm-level heterogeneity in terms of structural characteristics and performance, by seeking to reconcile the empirically rooted differences with agents' optimising behaviours (Klepper, 1996; Klette and Kortum, 2004; Klepper and Thompson, 2006). In particular, heterogeneity is interpreted as the result of stochastic processes connected to specific dimensions such as the innate capabilities to innovate (Klepper, 1996), the ability to make profits out of new products (Klette and Kortum, 2004), or the luck of entering and expand in new submarkets (Klepper and Thompson, 2006). In general, such a methodological approach leads these contributions to treat innovation as a mono-dimensional phenomenon that increases the quality of products, while search activities are reduced to a mere problem of optimal investments and luck. When submarkets are accounted for, they are represented either as temporary deviations from the homogeneous product case (Klepper, 1996) or as the number of exogenously rising market segments in which firms can enter through different mechanisms (Klette and Kortum, 2004; Klepper and Thompson, 2006). In such a sense, diversification is not seen as a qualitative phenomenon but, rather, as a quantitative one -the mere number of submarkets a firm is present into- overlooking any consideration as to the underpinning feature of each submarket.

At the opposite side, the models embedded in the evolutionary perspective start from different premises as they are built with the aim of studying technological development. Instead of trying to justify heterogeneity, which is assumed as a necessary condition for the working of the whole system, they set artefacts and products at the centre of the stage. The starting point of this approach is represented by life cycle theory (PLC henceforth) and its considerations on innovation phases and industry demography (Utterback and Abernathy, 1975). Yet, differently from the PLC approach, evolutionary models do not interpret artefacts as technological devices developed outside the social context but, rather, as the outcome of a process connecting firms with consumers (Windrum, Birchenall, 1998). To this extent, dominant designs and submarkets are reconnected to demand conditions which, in return, hinge upon consumers' preferences over a multitude of product's characteristics (Lancaster, 1966; Valente, 2012). As a result, the evolutionary strand of literature introduces a qualitative dimension in the analysis of technology, looking at what artefacts are used for (Saviotti, Metcalfe, 1984) and interpreting innovation as the outcome of a tension between technological feasible solutions and functional demand (Malerba, Nelson, Orsenigo, Winter, 1999, 2007). Finally, from a methodological standpoint, the dynamic perspective of evolutionary analyses translates into simulations models that overcome the need to constrain the system into closed form solutions.

Provided that, it is also important to highlight that the first wave of evolutionary industry dynamics models tend to focus primarily on technologies and artefacts in terms of functions, while generally not accounting for the underpinning structure. In so doing they do not connect to issues related to the design of products as well as to the organisation of production following from it. To be able to represent technology in a more realistic way, we resort to the literature on complex systems (Simon, 1962) and its application to innovation studies (Frenken, 2006; Murmann and Frenken, 2006). This perspective posits that products are complex artefacts, in which hierarchically nested subsystems of different sizes are combined into an architecture designed to provide specific functions. The architecture represents the outcome of technological knowledge while hierarchy is associated to the property of technologies of being decomposable and modular.

To translate these concepts into a model, Frenken (2006) proposes the employment of the generalised NK framework (Altenberg, 1997). This is a generalisation of the NK model introduced by Kauffman (1993) in theoretical biology and widely used in economics and management to study the performance of a system in presence of interconnections among its elements (Levinthal, 1997; Gavetti and Levinthal, 2000; Marengo and Dosi, 2005). However, many of the works in this tradition, tend to propose models in which the NK structure is the central pillar, representing either really stylised competitive environments (Levinthal, 1997) or specific aspects of reality (Frenken and Mendrizki, 2012; Querbes and Frenken, 2017) to focus more on search strategies in presence of bounded rationality (Simon, 1972; March, 1994).

As our interest lies in a parsimonious but realistic representation of industry dynamics, the approach we follow is to nest the generalised NK framework within a detailed competitive environment. In so doing we want to combine the rich account on industry evolution with a compelling representation of the technological change.

Our work is not the first trying to combine industry dynamics with complexity theory. Recently, a few papers have started to include NK models within more detailed competition frameworks. Lenox, Rockart, and Levine (2007), for example, study industry patterns (entry, exit, and shakeout) in presence of highly interdependent decisions by means of a Cournot model in which marginal costs are determined by firm's position on an NK fitness landscape. In a similar vein, Adner, Csaszar, and Zemsky (2014) propose a framework to study a multi-attribute product market in which firms' business policies determine the position over the product attributes' landscapes while performances are determined through competition over a set of consumers with heterogeneous tastes for attributes. In such a sense, both models reconnect to the tradition following from equilibrium theory while taking advantage of complexity theory to provide an explanation for firm-level heterogeneity.

Our model departs from these works for a number of reasons. First, by following an evolutionary perspective, our approach places a lot of attention to technology, by providing a thorough representation of artefacts. Where Lenox, Rockart, Levine (2007) and Adner, Csaszar, Zemsky (2014) adopt an NK framework to represent a generic set of firm's decisions, we take advantage of generalised NK (Altenberg, 1997) to specifically model technology. At the same time, our representation of firm behaviour is more realistic being based upon subsequent routines (Nelson and Winter, 1982) not only related to single-bit mutations. Moreover, our framework is better able to account for consumers' taste heterogeneity as it does not restrict the number of attributes – or functions in our terminology- possessed by the product. As a matter of fact, on the one hand, Lenox, Rockart, and Levine (2007) are still connected to the mono-dimensional perspective of technology and consider at most the dichotomy between price and quality while, on the other hand, Adner, Csaszar, and Zemsky (2014) create an NK setup for an artefact with two attributes only which represents a particular case of Altenberg's model.

More in tune with our work are the contributions of Marengo, Valente (2010), Mueller, Schrempf, Pyka (2015), Garas, Lapatinas (2017), and Schlaile, Mueller, Schramm, Pyka (2018). Marengo and Valente (2010) can be regarded as the closest to our framework as they propose a model on the evolution of a complex product industry in presence of consumers with heterogenous tastes and different firm's innovation strategies. Through their simulations they show that innovation rates and market concentration are intertwined with the condition of technology and competition. However, differently from us, they model complex products via a pseudo-NK framework (Valente, 2008). This choice bears two important consequences. First, they do not explicitly treat product functions but, instead, assume consumers evaluate artefacts on the basis of their components. Whilst small, this divergence with our model implies that the same concept of submarket is different: in our case submarkets are defined by "what can be done" with one product while in their case by "what the product is made of". Secondly, the use of pseudo-NK makes them assuming technology as exogenously given, whereas in our context the employment of the generalised NK allows us to include technology evolution within the dynamics of our model.

Mueller, Schrempf, and Pyka (2015) focus instead on the relationship between submarkets and the heterogeneity of consumer's tastes. In particular, they propose an agent-based model, relying on a framework having common features with the NK one, in which niches hinge upon tastes' departure from the global standard of a multi-characteristic product. Schlaile, Mueller, Schramm, and Pyka (2018) extend this model to study the role of consumers in the generation and diffusion of responsible innovations. Finally, Garas and Lapatinas (2017) propose a location-analysis spatial model in which firms compete in a multi-characteristics space for a set of consumers whose preference opinions are influenced through network effects.

All these works, share with ours the idea that boundedly rational consumers with heterogenous tastes for multi-functional artefacts play an important role in shaping industry and the direction of its evolution. Yet, their perspective on artefacts remains on functions/characteristics only, without any connection to the underpinning technology. To this extent, the models they put forth do not allow to connect demand dynamics with architectural change as we do in our model.

All in all, the framework presented in the next section can be regarded as a step forward with respect to the previous evolutionary literature because it produces a general, yet rich, representation of industry dynamics with a parsimonious set of parameters, by directly connecting economic with technological evolution. Moreover, the flexibility of the whole structure makes it eligible to incorporate all the characteristics of previous models, allowing to further expand the understanding of the underlying phenomena.

3.3 Description of the model

3.3.1 General framework

To combine industry dynamics with artefact's evolution, we build our framework upon three pillars: (i) a multifunctional artefact at the centre of the market, (ii) consumers representing the demand side, and (iii) firms designing and producing the artefact. These three elements can be conceived as three nodes of a system whose properties emerge during the simulations via the web of interactions among them. In particular

- firms compete by selling a multifunctional artefact to attract consumers with heterogenous preferences over artefact's functions;
- each consumer makes a purchase as long as there is at least one product on the market reaching (or overcoming) the minimum performance threshold she requires from a product;
- when there is more than one product on the market meeting the previous condition, the consumer chooses the alternative with the highest matching between artefact's technical performances and her preferences over functions;
- to survive and increase their customers' base, firms carry out R&D strategies aimed at improving artefact's performance: in particular, each firm infers the direction of R&D from the preferences of her past customers' base;
- artefact's improvements can translate into (a) incremental or (b) radical product innovations: the former relate to changes in the components already present within the product architecture while the latter involve a change in the product architecture through the introduction of a new component;
- radical innovations are riskier than marginal innovations for their search process may not necessarily be successful;
- the amount of resources a firm can invest into the development of radical innovations is proportional to its past market shares.

[FIGURE 1 ABOUT HERE]

In the next subsections, the three pillars of the model - and their interactions - will be described in greater detail to provide a thorough description of the whole framework.

3.3.2 The multifunctional artefact

The model is anchored in the *artefact-centred* view of technology (Frenken, Nuvolari, 2004; Dosi, Nelson, 2010). This approach interprets products as technical solutions to specific problems, placing the attention to the design emerging from the combination of their components. This design determines the links between two sets of vertices of a *bipartite network* represented, on the one hand, by the same product components and, on the other, by the functions fulfilled through their combinations (Saviotti and Metcalfe, 1984). For example, the mobile phone is made, among others, of a processor, an antenna, a display, and a software, and their specific combination allows to make phone calls, to navigate on the internet, to send messages and even more.

In order to formally represent these relationships, we make use of the *generalised NK* model (Altenberg, 1997; Frenken, 2006), a variant of the traditional NK originally introduced in evolutionary biology by Kauffmann (1993) and widely employed in the economics and management literatures (Dosi, Faillo, Manara, Marengo, Moschella, 2017). NK models, both in the Kauffman and in the Altenberg versions, are designed to provide a representation of the complex relationship between the different solutions to a problem -may it be of biological, technical or organizational nature- and their performance. In our case, the problem at hand is represented by the functions an artefact is called to perform, the technical solutions are all the possible artefact's design conceived to provide those functions while the performance is the ability of a specific design to fulfil each one of the functions. As we want to keep the model as general as possible, we opted to employ the *generalised NK* version rather than the traditional NK as the former does not impose any restriction on the relationship between the number of artefact's components and its functions.[18]

According to the generalised NK an artefact is defined as a set of F functions f_j, with $j = 1, \dots, F$, provided through the technical combination of N components n_i, with $i = 1, \dots, N$. Every $n_i$can take on either of two values, $n_i = \{0,1\}$, each one indicating a possible variant of the same element.[19] For example, in the mobile case, the display can be either OLED or LCD, the size can be small or large, the camera system can be single or dual, etc. Accordingly, the design of an artefact is given by a binary string $S =< n_1 n_2 \dots n_N >$ which can take on a total of 2^N possible combinations.

Technology associates each n_i to the related functions f_js. Akin to what occurs in biology with epistatic relations between genes and phenotypes, the number of functions affected by n_i represents i-th *degree of pleiotropy*, while the number of components required to provide f_j is j-th *degree of polygeny*. As such, product's architecture is described through a *genotype-phenotype map*, an $F \times N$ matrix whose rows are associated to f_js, columns to n_is and nonempty elements indicate that the corresponding n_i affects f_j's performance, ω_j (figure 2).

[FIGURE 2 ABOUT HERE]

[18] The traditional NK framewrork equates the number of components N with the number of functions, making it difficult to study the evolution of artefact's architecture throughout the evolution of a market.

[19] In the evolutionary biology terminology, the values each element of the string can take on are called *alleles*. In reality, the number of variants of a specific element may be greater than two. The literature of NK has nevertheless demonstrated that this simplification does not bear any consequence on the dynamics of the model, therefore we stick to the two-alleles case for a matter of computation.

The latter, therefore, hinges upon the setup of the n_is included in the j-th polygeny and whenever one of these elements change from zero to one (or viceversa), ω_j changes as well. To make the analyses as general as possible, the model does not impose any specific type of relationship between n_is and the functions they affect: the performances of each f_j under each specific combination of its polygeny is randomly drawn from a uniform distribution over 0 and 1, i.e. $\omega_j \sim uniform[0,1]$. Given a specific design S, then, an artefact is associated with F performances ω_js. This information is usually boiled down by taking the (simple or weighted) average of the ω_js given S generating a *fitness landscape*.

Within this framework *complexity* arises whenever the same n_i contributes in differing ways to different functions. For instance: the larger the size of the display, the *fitter* the mobile is for reading documents or writing long mails, but the more uncomfortable it is for portability. As a result, the choice of the size of the device generates trade-offs in the design of the artefact.

Provided this description of the generalised NK framework, our model takes advantage of a dynamic version, similar to the one employed by Altenberg (1997) and Querbes and Frenken (2017). Indeed, to account for the artefact's evolution throughout the evolution of the market, the model includes a *constructional selection* mechanism whereby firms do not produce pre-established artefacts but instead they create their own architectures on a set of given functions. More specifically, at the beginning of the simulation firms produce an artefact providing the same F functions and made of one component only whose pleiotropy amounts to F.[20] Each firm possesses its own technology for each artefact is represented through a different NK.

Throughout the simulation each firm can either (a) change the variant of an element already present in the architecture by switching it from 0 to 1 -or viceversa- (*incremental innovation*) or (b) add a new component to the architecture (*radical innovation*). While the first type of change implies the discovery of a new solution with the same disposable n_is, the second one deals with a change in the number of n_is to solve the same problem. When a firm opts for this latter process the model generates a new component n^*_{N+1} with a random pleiotropy falling within the $[1, F]$ interval and impacting in a random way the corresponding ω_js. As it will be explained in a few, the only requirement for this new component is to be connected with the function at the centre of the firm's R&D strategy. The performance of the new *prototype* including the candidate component n^*_{N+1} differs from the one of the old product only in terms of the ω_js directly connected with n^*_{N+1}. Indeed, the ω_js affected by n^*_{N+1} are redrawn from the same unform distribution for a number of combinations amounting to $2^{polygeny+1}$.

If the inclusion of n^*_{N+1} improves the artefact's performance computed according to the firm's criteria, then the *prototype* takes over the old product, n^*_{N+1} enters permanently the artefacts architecture as n_{N+1}, and functions' pleiotropies are updated accordingly. To this extent, the architecture of each artefact is not given,

[20] The choice of starting the simulation with a product made of one component only is purely computational and bears no consequences on the dynamics of the model.

but it can change throughout the simulation depending on the number of new components added and on their pleiotropies. In particular, the set of n_is' pleiotropies can be used to describe the degree of modularity of the system's architecture for the narrower the number of functions affected by single components, the more localised the effects of changes in the latter ones on the whole performance of the artefact (Frenken, 2006).

[FIGURE 3 ABOUT HERE]

On a final note, the choice of generalised NK to model an artefact not only allows to study the evolution of product design, but it also allows to account for the *direction* of technical change, for the choice of the function to improve provides a yardstick of architecture's evolution.

3.3.3 Consumers

The demand side of the market is represented by a set of E individuals that are interested in the functions -or a subset of them- provided by the artefact. To this extent we follow Lancaster (1966)'s idea according to which consumers are not interested in an artefact *per se* but, rather, in its functions. For example, people buy mobile phones not simply because they exist but, instead, because mobile phones allow them to make phone calls, to write messages or even to signal their social status.

A consequence of this perspective is that preferences are related to product functions- or characteristics, in Lancaster's terms- and their role is to provide a ranking to consumer's choice.[21] In the model this ranking is obtained by associating each individual e with a set of F weights β_j^e

(1) $$\text{with } 0 \leq \beta_j^e \leq 1,\ \ j = 1, \dots, F \quad \text{and} \quad \sum_{j=1}^{F} \beta_j^e = 1$$

that provide e with a yardstick to evaluate the different artefacts she can find on the market. In particular, the evaluation of the artefact produced by a generic firm i is attained through a *weighted average* combining e's preferences with the ability of i's artefact to fulfil a specific function

(2) $$W_i^e = \sum_{j=1}^{F} \beta_j^e \cdot \omega_j^i$$

where ω_j^i is j-th function's fitness level of i-th artefact.

This framework also accommodates consumers' *heterogeneity* through the assignment of different β_j^es across e. In particular, the program employed in simulations does not assign β_j^es in a deterministic way but, instead, it sets the maximum weight each individual places on one among the F functions through a parameter δ, then it randomly draws the remaining weights, and, finally, it randomly assigns each function to a specific weight.

[21] '*…Utility or preference orderings are assumed to rank collections of characteristics…*' (Lancaster, 1966, p.133).

As a result of this procedure consumers have the same preference structure but differ in their distribution across functions.

The choice among the products that can be found on the market is made on the basis of W_i^es. More precisely, each consumer pinpoints the artefact matching more closely with her preferences, $W^{e,*}$, as follows

(3) $$W^{e,*}=\max\{W_1^e, W_2^e, \dots, W_F^e\}$$

However, the presence of a preferred type of artefact among the one present on the market does not immediately make an individual a consumer – especially in this case where costs and prices are kept implicit. To account for this fact, the model includes E consumer-specific thresholds γ^e, randomly drawn from a uniform distribution over [0.5,1], and allows an individual to purchase her preferred artefact insofar as $W^{e,*} > \gamma^e$. Therefore, if no artefact satisfies this condition, e does not make any purchase and waits for the next period.

Once a consumer e buys the product sold by firm i, she immediately enters its customers' base, i.e. $\text{customers}_{i,t} = \text{customers}_{i,t} + 1$. Revenue and market shares are then computed over the customers' bases formed in a specific period.

3.3.4 Firms

In line with the evolutionary tradition (Nelson and Winter, 1982) firms are modelled as boundedly rational agents guided by a satisficing behaviour and operating through routines to increase their market share. In particular, each firm's strategy is devoted to the design of a multifunctional product to be placed on the market.[22] This activity is made itself of two subphases (i) the definition of the search direction on the basis of past customers' revealed preferences and (ii) the innovation phase in which search is conducted on the basis of the accumulated resources.

The first subphase is inspired by the fact that firms do not conduct R&D in a random direction but, rather, they seek to infer customers' tastes on the basis of market research strategies. To this extent, these strategies provide the firm with the *direction* for their product's improvement. The framework accounts for these dynamics in the following way. At the beginning of each period t, every firm with a positive number of customers in $t-1$ retrieves the weights each customer places on artefact's functions, β_j^es, and sums them function-by-function

(4) $$B_j = \frac{1}{e}\sum_{h=1}^{e}\beta_j^e$$

[22] To place the focus on the role of artefact's design for industry evolution, production costs and prices are not explicitly modelled in this version. To this extent the model implicitly assumes that firms can sell their products without incurring in losses. At the same time, even though production costs and prices are not explicitly modelled, it is possible to conceive 'cheapness' as one of the functions of the artefact, thus indirectly accounting for them. Moreover, as firms are assumed never to incur in losses when selling their products on market, it is also possible to see the satisficing behaviour as devoted to increase total profits.

by obtaining a set of F indices B_js. In order to transform these indices into the *weights*, B_js are *normalised*

(5) $$\beta_j = \frac{B_j}{\sum_{h=1}^{F} B_h}$$

to obtain β_js. These weights are then ordered in a descending way and the firm identifies the function at the centre of its research and development efforts by picking the f_j corresponding to the highest β_j. In other words, each firm decides to act on the function whose past customers' base regarded as the most important among the F ones.

The second subphase deals with innovation. As described in the section devoted to the NK model, the framework accounts for two types of innovations: incremental and radical. The choice between either of the two depends on the results of a *greedy search* strategy (Querbes and Frenken, 2017) on the components associated with the function identified by market research activity. At first, firm i explores the possibility to improve the overall weighted performance of its artefact through a one-bit change of the components directly connected to the function. In case such *local* change is possible, the firm realises an *incremental innovation*, as its new artefact differs from the old one in terms of the variant of one of its components only. On the contrary, if incremental innovations are not possible within the current architecture, the firm embarks on a riskier search for a new component to be added to the artefact. The search unfolds as described in the subsection on NK as long as a good candidate is found or i expires its resources. To be a good candidate, the new component n_{N+1}^* must fulfil two requirements: (1) it must act on the function of interest and (2) its inclusion must improve the overall weighted fitness of the artefact. Notice that the first point only requires that the function identified through the market research strategy falls within n_{N+1}^*'s pleiotropy but it does not place any constraint as to its degree of pleiotropy which, on the contrary, is randomly drawn from a uniform distribution over $[1, F]$. This is of paramount importance because it implies that our framework does not force the evolution of the artefact's architecture towards any direction and that the results presented in the next section are *emerging properties* of the framework.

If a good candidate is found, then i realises a *radical innovation*. Yet, in line with the evidence in the literature, this process is more uncertain than the incremental innovation one for it hinges on the combination between the randomly re-drawn part of the landscape, on the one hand, and the available resources $y_{i,t}$, on the other. The first element deals with the outcome of a specific attempt, while the second deals with the overall number of attempts i can make for a specific search in t. As a matter of fact, each firm can't go on testing an infinite number of candidates n_{N+1}^* until it finds the right one, but it is instead constrained by the available resources

(6) $$y_{it} = y_{i,t-1}^{p} + \text{customers}_{i,t-1}$$

where $y^p_{i,t-1}$ are the resources passed on to the previous period and $\text{customers}_{i,t-1}$ is the number of customers that purchased i's product in $t-1$.[23] Therefore, if firm i does not find a good candidate after y_{it} trials, then the innovation process is unsuccessful and i must stick with the old product. On the contrary, if i finds a good candidate within the y_{it}trials at its disposal, the innovation process is successful, and any exceeding resource is passed on to the next period.

3.3.5 Dynamics of the model

Provided the description of the main parts of the model, each period of the simulation unfolds as follows:

1. each surviving firm computes the resources y_{it} available in the current period and retrieves preferences β^e_j from its past customers' base;
2. on the basis of this information each firm pinpoints the function f_j at the centre of its R&D strategy and start the search activity, ending up with (i) an incremental innovation, (ii) a radical innovation, or (iii) a failure of its R&D project;
3. depending on the outcome of the previous point, each firm places on the market (a) a new product or (b) the old one;
4. each consumer enters the market and, on the basis of her preferences, she evaluates all the available products by computing W^e_js:
    a. if none of W^e_js outmatches the minimum performance level (γ^e) of a consumer e, then e does not make any purchase in the current period and decides to wait for the next one;
    b. if there exists one artefact only with $W^e_j > \gamma^e$, then e purchases that artefact;
    c. if there are multiple artefacts meeting the $W^e_j > \gamma^e$ condition, then e picks the one with the highest W^e_j among the eligible ones;
5. after consumers have made their decisions market shares are formed and firms with a null customers' base for three consecutive periods go bankrupt.[24]

3.4 Simulations and results

3.4.1 Simulation strategy

The framework introduced in the previous section provides a stylised representation of the pillars and the structures involved in a market for a multifunctional artefact. The aim of such representation is to create a *flexible tool* whereby it is possible to study together the phenomena connected to market and technology

[23] This setup of the model is consistent with evidence supporting the presence of credit constraints bound to innovation processes or, in any case, with any vision whereby investments in innovation are proportional to the size of the firm. Future works can be made to test the results of our framework under different setup of financial markets.
[24] We opted for three periods before bankruptcy to allow firms for a rebound. However, this choice does not drive the results of our model.

evolution. To this end, simulations of the model serve to 'make the system in motion' while the patterns emerging from a group of simulations represent its emerging properties.

Akin to what occurs with laboratory experiments, the first step requires to set the exogenous parameters of the model. As the intention in building the framework has been to create a representation able to endogenously generate the majority of the system's elements, only four parameters need to be set before the beginning of the simulation: the number of artefact's functions, the number of firms, the number of consumers, and the maximum weight within consumer's preference distribution across functions (δ). Moreover, we decided to keep the first two parameters equal, boiling down the overall number of exogenous parameters to three.[25]

As a result, the simulations carried out for this work centre on a market for an artefact with 8 functions, in which 8 firms compete to attract 800 potential consumers. As to δ, we decided to test our framework on four different values identifying four different types of consumers. The first type ($\delta = 0.125$) defines a situation in which consumers do not have any specific preference but, instead, evaluate all the functions equally.[26] We labelled this as the *tabula rasa* case. At the opposite extreme of the spectrum lies the situation in which consumers are interested in one function only among the F possible ones ($\delta = 1$). This is the *polarised* case. Between these two, we tested two further situations. The first one is a situation in which half of each consumer's preferences are absorbed by one function while the remining 50% by the remaining $F - 1$ ones ($\delta = 0.5$). In this case, therefore, consumers are strongly attracted by one function, but the remaining ones are altogether equally important. Finally, the last case ($\delta = 0.7$) accounts for a situation in which there is one function absorbing 70% of each consumer's preferences, leaving the remaining 30% to the remaining functions. In this case, consumers are mostly interested in one function without disregarding (some of) the other ones.

To account for any possible distortion due to specific initial random values, each simulation has been repeated 1,000 times, with all the NK landscapes redrawn before the beginning of every repetition.

The next section reports the results of these groups of simulations over 100 periods. In particular, the results focus on four aspects representing three stylised facts of the industry dynamics and technology evolution literatures: *product diffusion*, *industry shakeout*, *architecture evolution*, and *product size*.

3.4.2 Results

The first aspect to be analysed is the pattern of product diffusion. Figure 4 reports the average share of consumers purchasing one artefact over 100 periods for each set of simulations. In line with product life cycles theories (Utterback and Abernathy, 1975), the model predicts that the market expands at different growth rates throughout the product lifecycle: at the beginning it is possible to observe a surge in the number of purchasing

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[25] This choice has been driven by the sake of simplicity only: higher or lower number of firms would not change the essence of the model and its simulations. By keeping the number of firms equal to the number of functions it implies that, in principle, each firm can specialise in a specific function, generating F niches.

[26] $\delta = 0.125$ is the result of an equal splitting of the sum of each consumer's weights, i.e. 1, among the eight functions.

consumers but, as the time goes by, the pace of this increment slows down considerably. To this extent the model is able to reproduce the main phases of industry evolution, from infancy to maturity.

[FIGURE 4 ABOUT HERE]

Yet, two aspects are worth pointing out. First of all, in none of the four sets of simulations the share of purchasing consumers reaches its maximum level. This suggests that, even when the market is mature enough and technology is already developed, some consumers will not purchase any of the available variants. Such result can be explained through consumer-specific performance requirements γ^e. The direction of the development taken on by technology through time will never satisfy alle the potential consumers: some of them will always be dissatisfied with the performance of the products on the market and will prefer to restrain from purchasing any variety.

The second point worth mentioning relates to the different market evolutions dynamics in correspondence with the different types of customers faced by firms. Whilst in all four cases the general pattern is the same, the pace whereby the different stages of evolution unfold and the degree of expansion of the market differ across the values of δ. In presence of *tabula rasa* individuals, the market slows down its growth rate mildly -especially if compared with the *polarised* situation– but its expansion remains the lowest among the four ones. On the contrary, the more consumers' preferences are gathered around one specific function the more the market reaches sooner its saturation level. At the same time, however, the maximum degree of market expansion increases with δ. In other words: the more consumers are interested in one specific function, the faster a larger share of them will start purchasing the artefacts available on the market. As a matter of fact, if consumers have specific preferences for specific functions firms are better able to pinpoint a direction for further developments of their artefact and create their own niche. The more the niche is characterised by customers interested in a narrower number of functions the higher the chances that firms are able to meet the majority of consumers-specific performance requirements γ^e. On the contrary, when potential consumers do not have a clear preference for any function, firms do not have a strong direction to improve their artefacts and, as a consequence, their product innovations may disappoint some of the interested individuals.

From the firm side perspective, product diffusion is mirrored by market shakeout events. Figure 5 reports the average number of firms alive during 100 iterations in each of the four groups of simulations. The results show a clear decreasing trend of this index by implying that not all the original firms are able to survive as the market matures.

[FIGURE 5 ABOUT HERE]

Nevertheless, the extent and the speed of these shakeouts differ across different values of δ. When consumers' preferences are equally split across the F functions the model almost immediately boils down to a monopoly for all but one firms exit the market. In this case, in fact, market niches cannot be created because products are evaluated on their average performance[27], which implies that consumers will immediately purchase from the producer with the highest fitness product while its competitors will have zero market shares. On top of that, zero-market shares imply that competitors of the winning producer won't be able to improve their artefacts and try to take over the market leader. Notice that this is equivalent to the standard case in which consumers have preferences over a simple measure for product quality.

Yet, when one function captures a large share of individuals' interest for the artefact ($\delta = 0.5$ and $\delta = 0.7$), firms are better able to create their own niche and survive. Indeed, in these cases the average number of surviving producers is higher than one and it is an increasing function of δ: the more consumers' preferences gather around some function, the better firms can split the market among themselves and the more they can better pinpoint the direction for the development of their artefact. Therefore, shakeout events may occur because two or more niches are close enough such that they end by fusing and generate a single bigger niche served by one firm only.

The final case is represented by the *polarised* situation, in which consumers are interested in one function only. Akin to what occurs for the intermediate situations, when $\delta = 1$ the model does not boil down to a single-market monopoly. However, the shakeout seems to be more severe than in the previous cases at least in the beginning of the simulation. As a matter of fact, the average number of surviving firms when $\delta = 1$ falls slightly below the $\delta = 0.5$ case until about period 20 and the $\delta = 0.7$ case until about period 50. Such an effect may be due to the exit of the least performing producers and the fusion of different niches. This implies that preferences' polarisation does not constitute *per se* the market niche, but it is instead the *matching* between preference's polarisation and the classes of artefacts that determine the number of niches.

So far, the analysis has focused on the evolution of economic aspects. Yet, this is only one side of the coin; the other side is represented by technology. Indeed, to innovate firms have to look for new solutions to improve the performance of their products. As described in the previous section, generalised NK allows to represent in a stylised way the artefacts, the underpinning technology, and its evolution. In particular two dimensions of technology are of interest for the current analysis: the degree of modularity and the number of components included in their designs. The former deals with the internal architecture of the product while the latter indicates how many components are required to design such architecture.[28]

To measure the degree of modularity we take advantage of the index proposed by Frenken (2006)

[27] When β_j^es are all alike W_i^e reduces to the *simple average* across functions' degree of fitness.

[28] Both measures are connected to a change in product architecture and, hence, to radical innovations. We focus on this type of innovations for incremental innovations do not imply any change in the structure of technology.

(7) $$M = \frac{\log_F(F^N) - \log_F(\prod_{n=1}^{N} P_n)}{\log_F(F^N)} = 1 - \frac{P}{N}$$

where

- P_n, with $1 \leq P_n \leq F$, is the degree of pleiotropy of n-th artefact's component;
- $P = \log_F(\prod_{n=1}^{N} P_n)$ is the system pleiotropy of an artefact with N components and F functions;
- $\log_F(F^N) = N$ is the maximum degree of system pleiotropy of an artefact with N components and F functions occurring when each component is connected with every function.

The underpinning idea is to measure the degree of modularity as the difference between the maximum system pleiotropy and the actual system pleiotropy. The larger this difference, the higher the degree of modularity of the product architecture.[29]

[FIGURE 6 ABOUT HERE]

Figure 6 reports the evolution of the average value of this index in each one of the four scenarios by further distinguishing between the artefacts produced by surviving firms and those produced by firms exiting the market. Irrespective of the level of δ, surviving firms' products exhibit the highest degree of modularity, and this value increases throughout product lifecycle. Moreover, increments in modularity are coupled with increments in the number of architecture's components. As a matter of fact, figure 7 shows that the average number of product components is higher for surviving firms and increases through time as well, while figure 8 shows that modularity and the number of product components are positively correlated even at the micro-level.

[FIGURES 7 AND 8 ABOUT HERE]

The explanation underlying this pattern stems from the superior evolutionary properties of modularity (Frenken and Mendritzki, 2012). Indeed, radical innovations are more likely to succeed when the newly added components do not jeopardize the performance of the whole artefact. When a technology is mature -i.e. when its core is already formed- this translates into the necessity of impacting a small number of functions with the additional component, i.e. the new component must have a low degree of pleiotropy. To this extent, the more

[29] Notice that, the minimum system pleiotropy for an artefact with $N-1$ components with $P_n = 1$ and one component with $P_n = F$ amounts to $\log_F F = 1$. To this extent $0 \leq M \leq \frac{N-1}{N}$.

a technology becomes rich in terms of components, the more its architecture will increase its degree of modularity.

Provided that, the differences across the scenarios observed in figures 6 and 7 stem from the differences in industry evolution shown in figure 5. As a matter of fact, the probability of discovering a component with low pleiotropy which is able to improve artefact's performance is positively correlated with the number of attempts a firm can make during its R&D activity. In return, attempts are correlated with the resources accumulated in the past and, therefore, with the size of customers' base. To this extent, the larger the customers' base, the higher the likelihood of discovering new components leading to successful innovations. As different δs are associated with different industry setups and market niches, then also the number of product components and the degree of modularity are indirectly functions of δ.

3.5 Conclusions

This work contributes to the literature on the life cycle of products and industries by proposing a novel simulation model able to combine a rich representation of industry dynamics with a rich representation of technological evolution. The past research on the topic has often tackled the subject by focusing on specific aspects of the phenomenon without creating a framework integrating both sides of the coin. Whilst those works have provided useful insights on the role of demand in shaping the trajectory of technological change and facilitating the rise of multiple dominant designs, their perspective does not allow to fully study co-evolutionary forces, leaving room for further investigation to explain the empirical evidence.

To this extent we set up a model based upon a parsimonious set of parameters which is, nevertheless, able to replicate four important stylised facts related to both domains: product diffusion, shakeout events, modularity in product design, and the increasing number of its components. To do that, we brought together two modelling traditions: the one dealing with rich representations of industry dynamics in presence of consumers with heterogenous preferences and the one focusing on a detailed characterisation of multifunctional artefacts through the complex system perspective.

As to this second aspect, we followed Frenken (2006) and adopted the generalised NK framework (Altenberg, 1997), a variant of Kauffman (1993)'s model in which the number of fitnesses may differ from the number of bits, thus providing a higher degree of freedom to portray the relationships between components and functions. By introducing a constructional mechanism based on search behaviours depending on the resources at firm's disposal and on past customers' preferences, we endogenized the making of artefact's architecture to study how it evolves in relation to the type of demand faced by firms.

Simulations' results suggest that the distribution of preferences over the functions are relevant for industry development. When consumers equally evaluate all the functions (*tabula rasa*) the market boils down to a monopoly very quickly, leading to the emergence of a unique product design. On the contrary, the more consumers are polarised around the different functions, the more submarkets arise naturally, and multiple dominant designs coexist in the long run. The emergence of a unique dominant design is also associated to the lowest expansion of the market, for many potential customers will not buy any product being dissatisfied with the variety on sale. At the opposite side, the coexistence of multiple designs allows the market to expand more, given that many more consumers will easily find a product matching with their tastes.

In terms of architecture, the outcomes of our analyses confirm that the products on the market tend to increase their modular structure through time. This is the result of search strategies aimed at improving the matching between functional performances and customers' tastes. Indeed, prototypes are accepted only if the newly added components do not jeopardise the whole artefact's fitness, which is more likely when the impact of the new component is relegated to few functions only (Altenberg, 1997). Moreover, increments in the degree of modularity are coupled with the increase in the number of components.

As these processes are connected to search activities, and these latter are related to the resources accumulated by firms, different preference regimes influence in the extent of product modularity and size. Indeed, in presence of a large number of submarkets -when consumers favour some function more than others- the quantity of resources per firm is lower than in the tabula rasa case. This implies that firms have a smaller number of attempts for their innovative activities and, as such, less occasions to develop them along the aforementioned patterns.

Apart from the product life cycle literature, our model also connects to the studies looking at variety and economic development (van Dam and Frenken, 2020; Hausmann et al., 2007). Specifically, it provides a microeconomic justification for the observation that the complexity of products produced in one country increases through time. The framework put forth in this paper provides a possible explanation for this phenomenon based on the combination between demand preferences and firms' search behaviours. Indeed, complexity increases because established firms need to reshape their products' architectures not to lose the market shares they have acquired in the past.

Provided that, we are aware the framework can be improved to include some issues that are not hitherto treated in the current version. First, the model does not contain entry dynamics: there are only incumbent firms and market turnout is absent. Yet, the structure of the model is flexible enough to adapt to a situation with firms trying to enter the market throughout the whole simulation. Moreover, some results won't change with this modification: for example, in presence of tabula rasa consumers' preferences, monopoly would arise irrespective of the rate of entrance for it represents a "winner takes it all" situation.

Second, the model can also be improved in terms of behavioural realism. For example, as consumers' preferences are so relevant for the emergence of submarkets and modularisation of products, we are currently working on an extension in which firms undertake marketing strategies to analyse how results change when they can influence preferences. Another possible improvement can be bound to the branching of functions implemented within artefacts. Up to now the set of implemented functions if fixed; however, it could be interesting to setup a model in which the number of functions can change depending on their "proximity" in the demand and technological spaces. Such a model could be used to understand under what conditions related and unrelated diversifications may occur and providing a reference point to the economic geography literature.

On the whole, despite its limitations, we think the current model represents a simple yet rich framework for a deeper understanding of co-evolutionary mechanisms between technology and industries.

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Figures

FIGURE 1. PILLARS OF THE MODEL

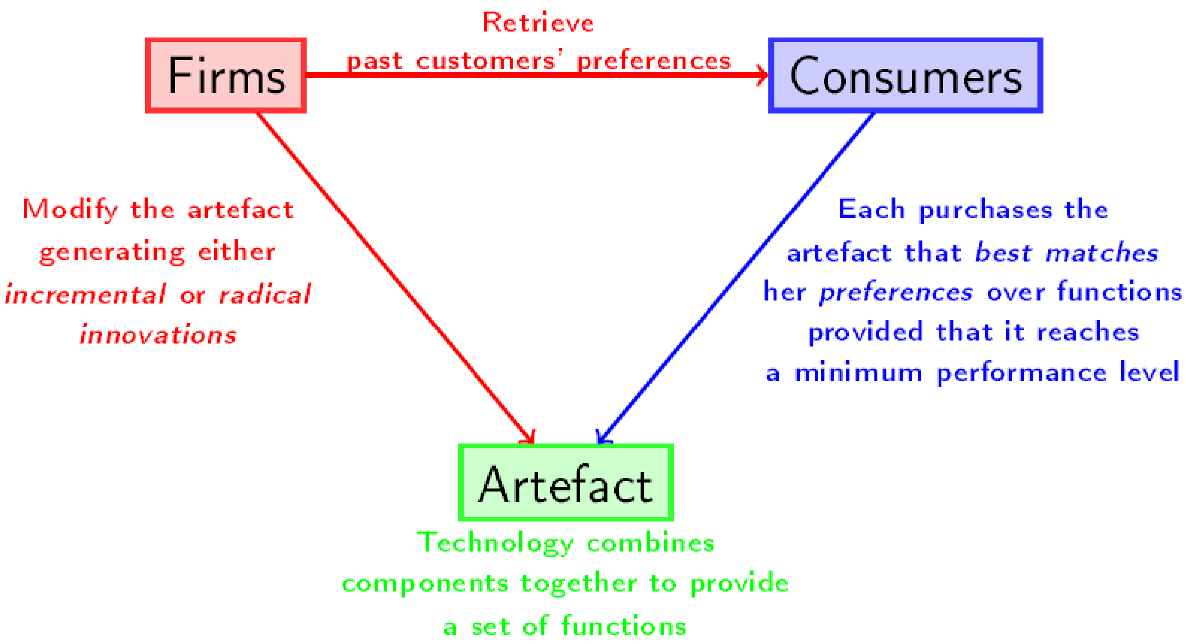


FIGURE 2. GENOTYPE-PHENOTYPE MAPS IN NK MODELS

Traditional NK

	n_1	n_2	n_3	n_4	n_5
$f_1 = n_1$	x	x		x	
$f_2 = n_2$		x	x	x	
$f_3 = n_3$			x	x	x
$f_4 = n_4$	x			x	x
$f_5 = n_5$		x	x		x

Generalised NK

	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9
f_1	x	x	x	x	x	x	x		
f_2	x			x	x	x	x	x	x
f_3	x	x	x	x			x	x	x
f_4	x	x	x	x	x	x	x		

FIGURE 3. DYNAMICS OF CONSTRUCTIONAL SELECTION

Beginning

	n_1
f_1	x
f_2	x
f_3	x
f_4	x
f_5	x

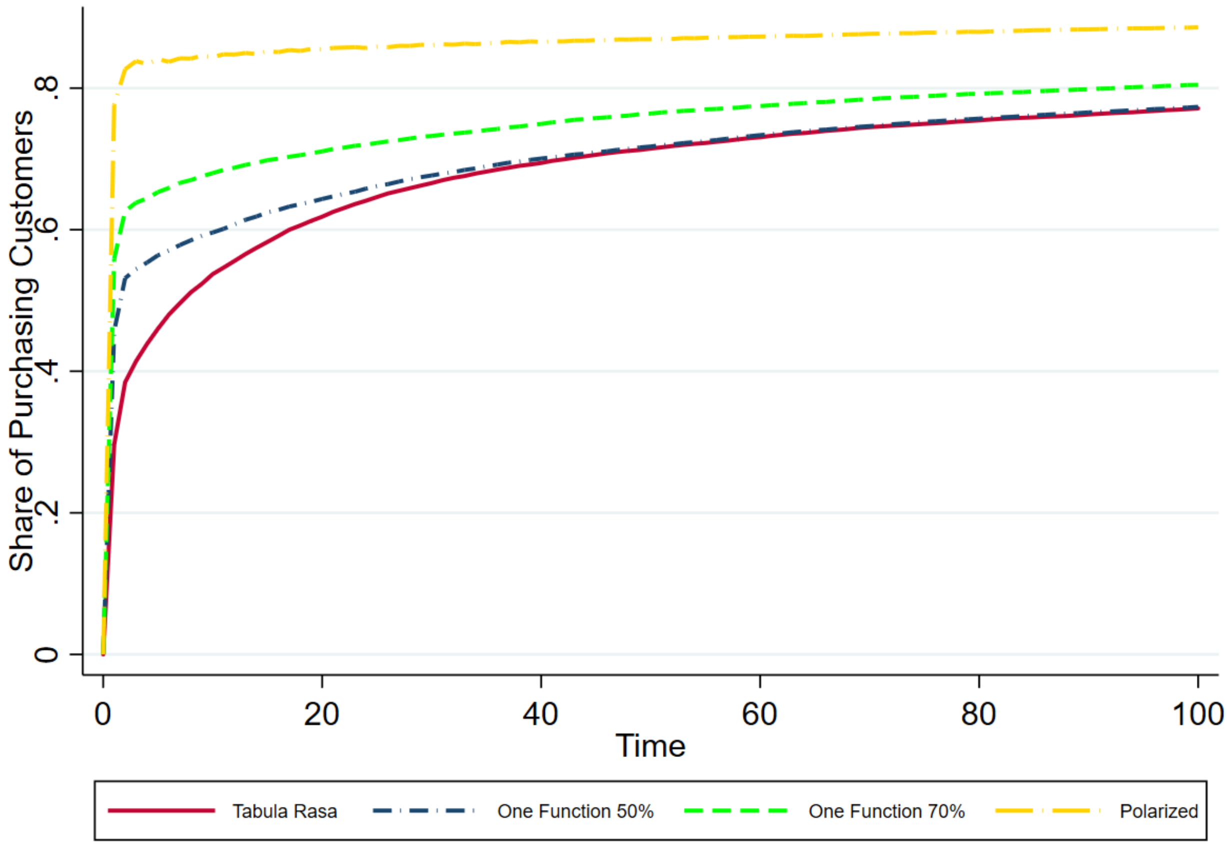
Adding new components

	n_1	n_2^*
f_1	x	
f_2	x	x
f_3	x	
f_4	x	x
f_5	x	x

Possible Architecture at the End

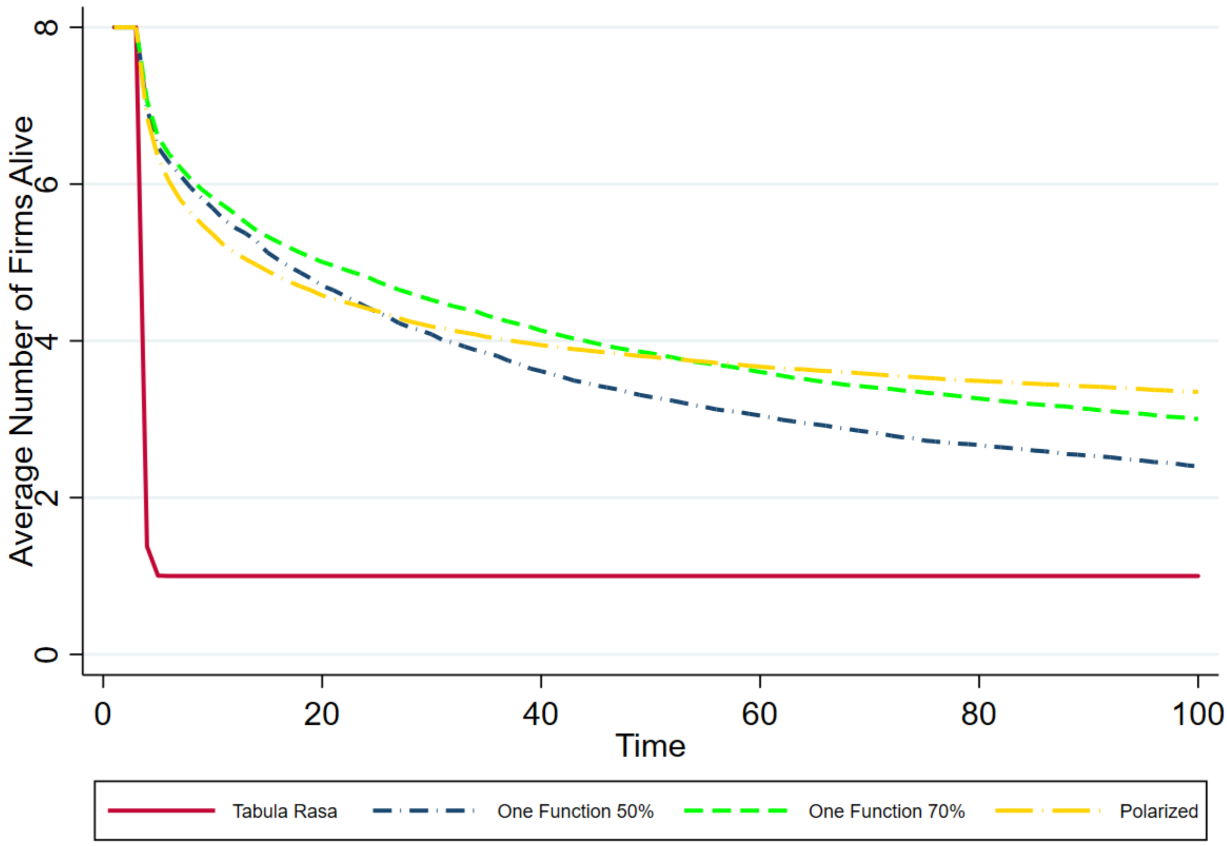
	n_1	n_2	n_3	n_4
f_1	x		x	
f_2	x	x		x
f_3	x		x	
f_4	x	x		
f_5	x	x		x

FIGURE 4. PRODUCT DIFFUSION



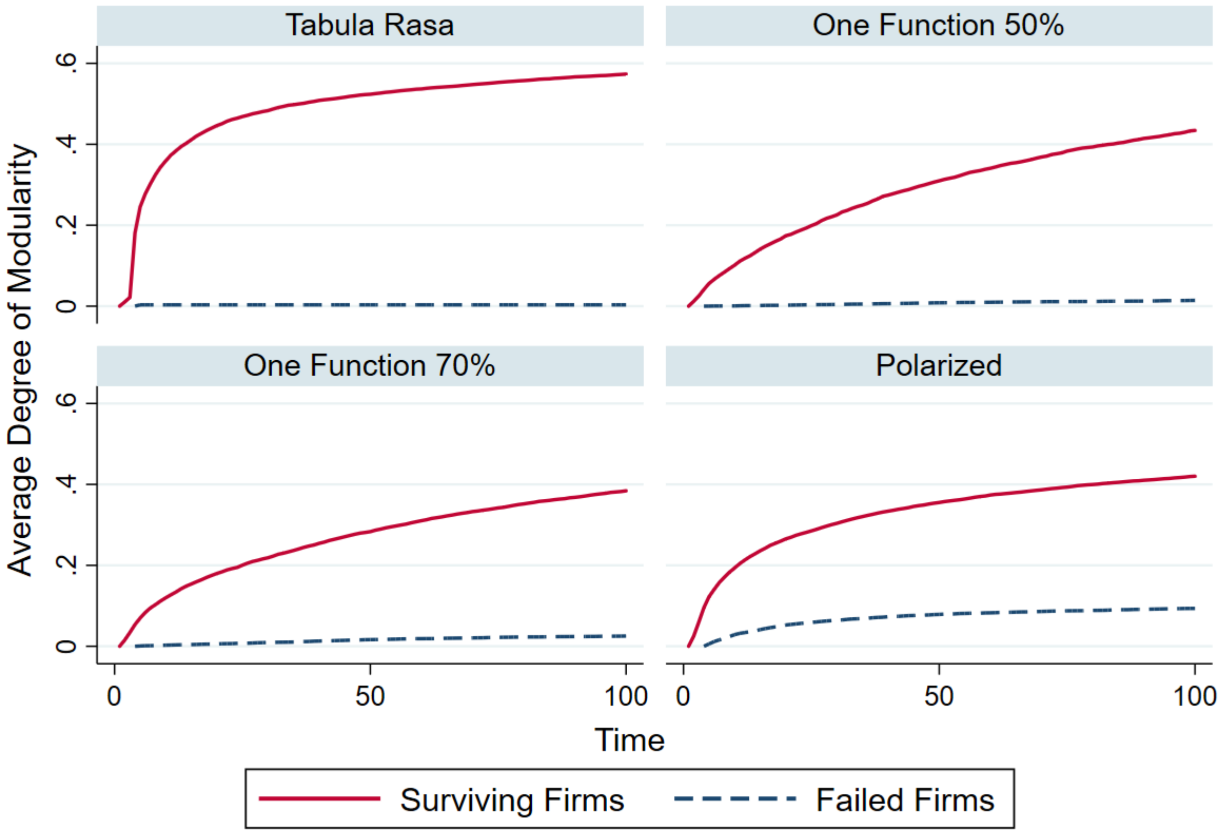
Note:shares of purchasing consumers are computed by summing the shares of consumers served by each firm within a simulation. The graph report averages over 1,000 repetitions.

FIGURE 5. INDUSTRY SHAKEOUT



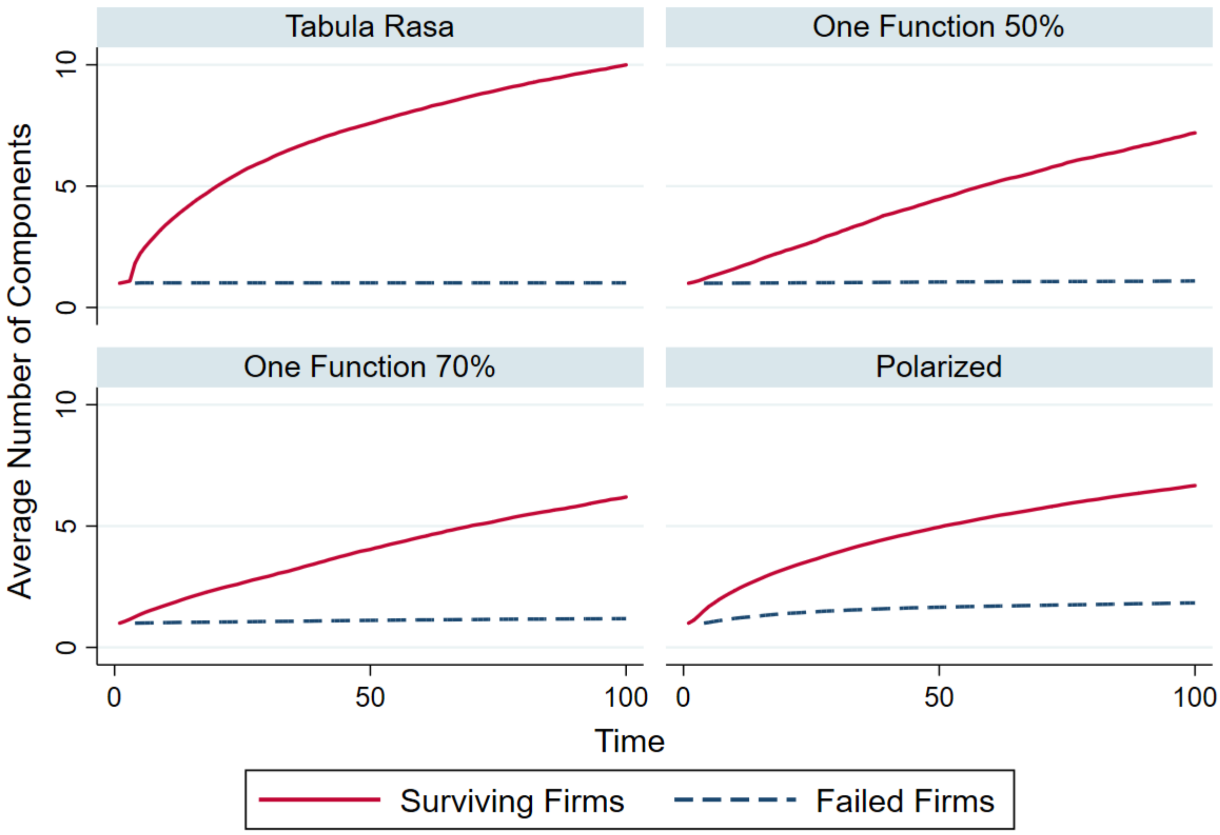
Note: the average number of firms alive is computed over 1,000 simulations for each customers' preference setting. In each simulation the number of initial firms is eight.

FIGURE 6. ARCHITECTURAL EVOLUTION OF ARTEFACTS



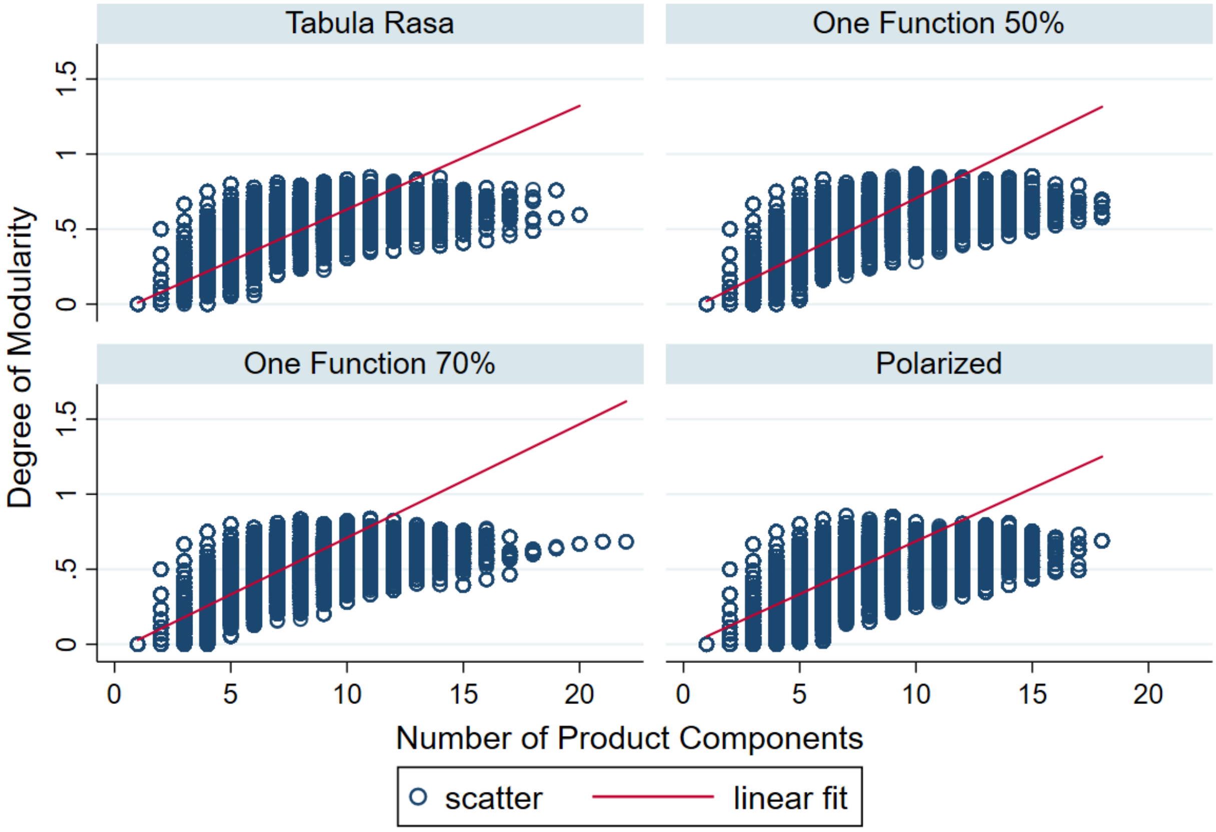
Note: the average degrees of modularity are computed over 1,000 simulations for each customers' preference setting. Modularity is computed with the index proposed in Frenken (2006).

FIGURE 7. AVERAGE NUMBER OF ARTEFACT' S COMPONENTS



Note: the average number of components are computed over 1,000 simulations for each customers' preference setting.

FIGURE 8. CORRELATION BETWEEN THE NUMBER OF ARTEFACT'S COMPONENTS AND MODULARITY



Note: each data point refers to the artefact of a firm in a specific time period in a specific simulation. Artefact's modularity is computed as in Frenken (2006).

CHAPTER 4

Local Technological Evolution & University-Industry Collaboration[30]

4.1 Introduction

The paper deals with the role of university-industry collaborations in shaping the evolution of the technological knowledge, skills and competences that can be found in a region.

Regional capabilities are fundamental for economic development as they are at the basis of regional specialization (Boschma, 2017). Indeed, the degree of connection between different production activities rests upon the set of technological knowledge, skills and competences needed for each activity to thrive. The more two production activities require similar endowments of capabilities the more they are regarded as related. On the contrary, the more two production activities are underpinned by very different and disconnected capabilities, the higher their degree of unrelatedness. To this extent the portfolio of capabilities within a region is associated with the varieties of industries therein located (Boschma and Frenken, 2011).

In a dynamic perspective, the portfolio of local capabilities is important because it influences the potential evolution patterns of the regional technological knowledge (Boschma, 2017; Castaldi, Frenken, and Los, 2015). According to evolutionary theories, new technologies derive from the recombination of already existing knowledge (Arthur, 2009; Becker, Knudsen, and Swedberg, 2012) and the type of innovation brought about by such a recombinant process (Weitzman, 1998) depends on the capabilities that agents can tap into as well as on the way they recombine them. The recombination of very close types of knowledge, skills and competences is usually associated with incremental innovations while the recombination of very unrelated types of capabilities is associated with radical and breakthrough innovations (Castaldi, Frenken, and Los,

[30] *Co-authored with Valentina Meliciani, Professor of Applied Economics, LUISS Guido Carli (Rome)*

2015). As the innovation process usually takes advantage of geographically localised knowledge, the current portfolio of local capabilities constrains its possible evolution and creates a path-dependent dynamic akin to a branching process (Fornahl & Guenther, 2010; Martin & Sunley, 2006; Boschma and Frenken, 2011). As a result, the tendency is that of an increment in the degree of relatedness of clustered technologies with a risk of lock-in effects for the region in the long-run. This is also corroborated by the evidence that increments in the degree of unrelatedness are rarer than increments in the degree of relatedness (Boschma, 2017; Neffke, Hartog, Boschma, and Henning, 2018).

Yet: where do regional capabilities come from? As Neffke et al. (2018) claim 'regions do not act themselves. Instead, their economies change as a result of the actions of the firms they host' (p.26). By assuming that strategies and actions are at the basis of the formation of new capabilities, in order to understand how regional capabilities evolve it is important to look not only to the nature but also to the behaviours of the firms and other regional players – such as universities or other types of institutions- whose behaviours can improve the knowledge of organizations residing in that territory. To this extent, the aim of this work is to contribute to the literature on the 'agent based'-perspective of structural change by studying how firms' collaboration with universities for R&D purposes are correlated to the emergence of new capabilities at the regional level.

In particular, by resorting to the firm-level evidence that firms' collaborations with universities are associated with the creation of radically new products (Fitjar and Rodriguez-Pose, 2013), we seek to investigate whether university-industry collaborations are eligible of producing new capabilities within the organization that can propagate in the surrounding area through the aforementioned transmission mechanisms and affect the evolution of the regional capability base.

To do that, we built a NUTS3 dataset on Italian provinces by merging patents data with information on academic inventors drawn from the APE-Inv database for the years 1997-2008. Our analyses take advantage of a set of different econometric techniques to investigate the relationship between the concentration of university-industry collaborations and regional technological variety. By adopting the entropy index to measure variety, we are able to analyse this topic with reference to total, related, and unrelated varieties. Our estimates point out two interesting results. First, not all firms-university collaborations are relevant for changes in regional technological variety: only when these collaborations allow more than one organisation to tap into the newly created knowledge, the spillover effects at the regional level seem to exert a significant impact on variety. Secondly, university-industry collaborations seem to be connected to unrelated rather than related changes in the variety of technological knowledge.

This evidence is in line with previous works highlighting the role of academic inventors (Quatraro, Scandura, 2020) and collaborations (Santoalha, 2019) for regional specialisation. However, it also adds to their findings at least along three dimensions. To begin with, we tackle university-industry collaborations from a search strategy perspective of firms. Secondly, our approach disentangles the collaboration with a university from the number of patent assignees, allowing for digging deeper into this phenomenon. Finally, we adopt a methodology that allows us to look at the way regional technological variety changes and not only at the relationship between new knowledge and the original regional knowledge base.

The paper is structured as follows. In the next section we briefly sketch the literature related to our approach and our study. In section 3 we describe the dataset, its variables and the empirical strategy we followed. Section 4 presents the results of the analyses and section 5 concludes.

4.2 Related Literature

The interest for the capabilities possessed by the agents populating a specific territory is linked to their role in the process of regional development. On the one hand, the variety of regional technological capabilities underpins the mix of products and services produced in that specific area (Boschma, 2017) for it defines the boundaries of what regional agents can do. On the other hand, the spectrum of these capabilities also plays a dynamic role, contributing to shaping the technological trajectory of the region, by providing the conditions for the emergence of different types of innovations and varieties of economic activities (Castaldi, Frenken, Los, 2015).

These latter are also associated to qualitatively different economic performances (Frenken, Van Oort, Verburg, 2007). Differentiation within sectors (related variety) triggers the emergence of Jacobs' externalities and it is usually coupled with the growth of employment by encouraging the generation of new niches and spin-offs. On the contrary, the degree of differentiation of regional economic activities (unrelated variety) is inversely proportional to unemployment: the more diversified the portfolio of sectors within a region, the less connected the underlying demands. As a result, negative shocks in one sector do not spread across the remaining ones. Yet, changes in unrelated variety are not as common as changes in related variety.

The role of agents is pivotal for the direction of the regional capability base evolution. The type of knowledge and resources they are able to tap into and recombine are associated to the types of innovation they can bring to life (Weitzman, 1998; Boschma, 2017; Neffke, Hartog, Boschma, Henning, 2018). Innovation activities seeking to mix highly unrelated sources of knowledge are, in fact, eligible of generating technological breakthroughs while, at the same time, being coupled with a quite high probability of failure. On the opposite side, the combination of related types of knowledge, whilst being a less risky activity, is generally bound to incremental rather than radical innovations.

To this extent, the understanding of search strategies, and the way they are linked with the variety of technological knowledge, becomes a central topic. According to behavioural and evolutionary accounts, search activities are usually conducted locally, being subject both to path- and to place-dependent dynamics (Martin, Sunley, 2006). The branching process stemming from these forces increases the degree of relatedness of the local activities (Boschma and Frenken, 2011) and may result into a regional lock-in where relatedness breeds higher relatedness. Increments in the degree of unrelated variety help escaping lock-in phenomena by introducing new elements hitherto weakly connected to the regional capability base.

The agents at the basis of a structural change introduce within the regional boundaries some capabilities and some knowledges that are loosely connected to the ones traditionally associated to that territory (Neffke, Hartog, Boschma, Henning, 2018). Some recent empirical works provide evidence that the ability of importing 'distant knowledge' within the region is generally connected to (i) the type and/or nationality of firms and entrepreneurs (Neffke, Hartog, Boschma, Henning, 2018; Colombelli, D'Ambrosio, Meliciani, and Quatraro; 2020); (ii) the ability of certain individuals of spanning knowledge boundaries (Quatraro, Scandura, 2020); and (iii) the structure of collaboration networks (Santoalha, 2019).

Whilst informative as to the role of some elements in the dynamics of regional specialisations, these works do not fully account for the search strategies followed by firms while seeking to innovate. As a matter of fact, the firm-level empirical literature shows that different search strategies are associated to different innovation outcomes (Laursen and Salter, 2006). In particular, cooperation between firms and universities is associated with new-to-the-market innovations (Fitjar and Rodriguez-Pose, 2013) for it allows firms to tap into a far more diversified range of knowledge sources with respect to the intra business interaction (Kaufmann and Tödtling, 2001). Moreover, At the local level, collaborations with universities can generate localised knowledge spillovers (D'Este, Guy, and Iammarino, 2013) thus increasing the knowledge base available to the population of local firms (Marzucchi, Antonioli and Montresor, 2013).

Quatraro and Scandura (2020) and Santoalha (2019) are the two works that closely touch upon some these themes without tackling them completely, thus leaving room for further studies in these topics. For example, Quatraro and Scandura (2020) study the role of academic inventors in the regional patterns of unrelated diversification by showing that the higher involvement of academic inventors within the local innovative activity and the higher number of patents involving academic inventors are associated to new technological specialisations with lower degrees of relatedness to the local knowledge base. Whilst accounting for the role of university-industry collaborations for innovative activities, they tackle the issue from an inventor perspective rather than from an assignee perspective (as we do in the current work). This implies that their investigations do not deal with firm's strategic level. Moreover, by looking at the inventors' side, they measure the extent of the influence of these collaborations through the number of regional patents involving an academic inventor. Yet, this measure is uninformative as to the size of the network of firms that can access the newly created knowledge: in principle all the patents can pertain different firms. Finally, their dependent variable looks at the entry into new technological specialisations (Colombelli, Krafft, Quatraro, 2014). Yet, diversification processes can start even without the region reaching a technological specialisation in a specific field, and the sole focus on new specialisations is not informative as to the change in the variety of regional technological knowledge.

As to Santoalha (2019), his analyses look at the role of innovation collaborations for regional technological specialisations. In particular, results highlight the presence of a complementary role for regional diversification between intra- and inter-regional research networks, which becomes even more important in the case of less developed regions. Differently from our work, Santoalha (2019) does not focus on a specific type of collaboration but looks at the co-patenting activity in general, making distinction only on the geographical location of collaborators. However, as already pointed out, firm-level empirical evidence on innovation collaborations underlines the relevance of the participants to the collaboration network. Moreover, by adopting a definition of collaboration based on co-applications, he rules out all those cases in which the firm calls for an external inventor but does not cooperate with another firm.

4.3 Data and empirical strategy

4.3.1 Data

The dataset we employ for our investigations is built by merging information from three different sources. The variables related to technological varieties and university-industry collaborations are computed starting from patent data. To geolocate patents, we took advantage of the open-source dataset made available by Morrison, Riccaboni, and Pammolli (2017), who use high-resolution geolocation to disambiguate inventors and assignees on about 8.5 million of patents from EPO, PCT, and USPTO.

Given the cross-country heterogeneity of the information about academic inventors contained in APE-Inv (described in few lines), we decided to restrict our analyses to the sole Italian case, leaving the comparison of results in different institutional contexts to future works. Provided that, a key decision in the construction of the dataset was related to the criterion to be adopted for the geolocation of patents. Indeed, Morrison, Riccaboni, and Pammolli (2017) provide information on both inventors' and assignees' addresses. Although some works geolocate patents on the basis of the former ones (e.g., Scandura and Quatraro, 2020), we regarded that, in our case, it is more appropriate to use the assignees' information. The reason behind this choice is twofold. First of all, likewise Santoalha (2019), we are interested in organisations', rather than single individuals', actions. It is true that patents are generated by one or more individuals, yet the perspective of the current study is to understand to what extent firms, which provide resources and create the milieu for inventors to operate, can influence knowledge evolution through their decisions. The second argument is still related to the idea of organisations -firms as well as universities and research institutes- as carriers of capabilities that go over and above the single individuals. It is true that spillovers can be produced by individuals, nevertheless these spillovers are amplified and have an impact on a geographical scale through organisations. To this extent, we retained from the Morrison, Riccaboni, and Pammolli (2017) dataset only those patents with at least one assignee residing within the Italian territory and used the assignees' addresses to allocate each patent within one among the Italian provinces. In case of multiple assignees, we applied fractional count (de Rassenfosse, Dernis, Boedt, 2014), not to add multiple times the same patent.

For measuring university-industry collaborations, we complement patent data with the information drawn from the project on "Academic Patenting in Europe", or APE-Inv (Lissoni, Pezzoni, Potì, Romagnosi, 2013). In particular, we accessed the open-source part of APE-Inv and retrieved data on the presence of academic researchers among the designated inventors for each Italian patent covered by the project. Although APE-Inv provides information for more than one country, we decided to focus on the Italian case due to the lack of homogeneity across countries in terms of years covered by the project. After the matching with Morrison, Riccaboni, and Pammolli (2017)'s database, we are left with 38,909 patents, for a total of 13,241 applicants over the 1997-2008 period.

These data are used to compute the variety and collaboration indices, boiling down to a NUTS3-level database for Italian provinces. To this database, we have also added some NUTS2 and NUTS3 variables drawn from Cambridge Econometrics and employed as controls in our econometric exercise.

In the next pages we describe both the construction of the indices of interest and the empirical strategy that we follow in our analyses.

4.3.2 Variables

The aim of the work is to study the role of R&D university-industry collaborations for the variety of regional technological knowledge. Differently from most of the recent literature, we decided not to tackle this issue from the specialisation perspective, but, instead, we opted to adopt a measure for variety that accounts for the whole set of capabilities and knowledges that are present in the province. The first reason for this choice follows from the idea of studying 'how variety changes' rather than 'what is the connection of new specialisations to the regional capability base'. Secondly, as reminded before, the literature on regional variety has shown that the different types have different impacts on economic performances. Yet varieties are an intermediate step between some factors and performance. As such, it is also relevant to understand what factors underpin the different types of variety to understand how regional performances can be triggered.

For these reasons, we used the *entropy index* to measure the spectrum of the different types of knowledges held by the actors residing in a territory.

Entropy is a widely used variable (Castaldi, Frenken, Los, 2015; Frenken, Van Oort, Verburg, 2007), although usually it is employed as a control or independent variable rather than a dependent one. In a nutshell, it measures how uneven is the distribution of a set of elements: the more the distribution is concentrated around few elements, the lower its entropy; the more it is equally distributed across them, the higher its entropy. Akin to Castaldi, Frenken, and Los (2015), we take advantage of this index to look at the distribution of technological fields associated to the patents held by applicants residing within a specific region. In this way, we seek to measure to what extent the patenting activity within a specific geographical area is diversified (in technological terms). Formally, by labelling p_i^r the proportion of technological class i, with $i = 1, \dots, n$, in region r, we define *total variety* of technological classes as the entropy index

$$TV^r = \sum_i p_i \cdot \log_2\left({}^{1}\!/_{p_i}\right) \tag{1}$$

with $TV^r = 0$ when the distribution is concentrated around one class only[31], and $TV^r = \log_2(n)$ when the distribution is evenly spread over all the possible n classes. Moreover, by using the IPC classification at 4-digit, $n = 622$ with a maximum level for TV^r amounting to $\log_2(622)$.

One of the most important properties of entropy is that it can be broken down into the varieties of the intermediate levels of classification (Castaldi, Frenken, Los, 2015). This implies that we can decompose the regional total variety of technological knowledge

(2) $$TV^r = UV^r + RV^r$$

into a term capturing the extent of diversity of macro-technological classes present in the region (*unrelated variety* UV^r) and a term capturing the average extent of technological diversity *within* each macro-technological class (*related variety* RV^r).

To compute *unrelated variety,* we start by aggregating the 4-digit technological classes employed for the construction of TV^r into the higher order 3-digit IPC groups. This implies, for example, that the 'planting; sowing; fertilising' group (4-digit IPC class 'A01C') and the 'harvesting; mowing' group (4-digit IPC class 'A01D') fall both within the 'agriculture; forestry; animal husbandry; hunting; trapping; fishing' 3-digit IPC class denoted as 'A01'. By defining $S_g$the set of 4-digit classes nested within the g-th macro-class, and $P_g^G = \sum_{i \in s_g} p_i^r$, with $g = 1, \dots, G$, the proportion of patents falling within the g-th macro-technological class in region r, the degree of *unrelated variety*

(3) $$UV^r = \sum_g P_g^r \cdot \log_2 \left({}^1\!/_{P_g^r} \right)$$

is represented by the entropy index computed over the 3-digit classification. As with equation (1), UV^r is bounded below by zero whereas its maximum level is equal to $\log_2(G) = \log_2(121)$ given that $G = 121$.

The residual part of total variety is represented by the (weighted) average degree of differentiation within the 3-digit classes. In other words, *related variety* in region r is given by

(4) $$RV^r = \sum_{g=1}^{G} P_g^r \cdot H_g^r \quad \text{and} \quad H_g^r = \sum_{i \in S_g} \frac{p_i^r}{P_g^r} \cdot \log_2 \left({}^{P_g^r}\!/_{p_i^r} \right)$$

with H_g^r representing the entropy degree within g-th class and measuring the variety of the 4-digit technological classes present in region r falling within the g-th 3-digit category.

Given diversification is a phenomenon unfolding through time, we do not measure varieties on a yearly basis but, instead, we split the 1997-2008 time-span into three 4-years' time-windows {1997-2000; 2001-2004; 2005-2008}, and compute varieties by grouping together the patents according to this partition. This is a common practice in the literature (e.g., Scandura and Quatraro, 2020; Santoalha, 2019), although usually the

[31] Notice that, when the distribution is concentrated around one class it implies that, for that class $p_i = 1$ and $p_i \cdot \log_2({}^1\!/_{p_i}) = \log_2 1 = 0$, while for the remaining classes $p_i = 0$ and $p_i \cdot \log_2({}^1\!/_{p_i}) = 0$.

length of each period is of five years. Unfortunately, the time dimension of our dataset combined with the specification of the models we want to test do not allow for 5-years' windows. In this sense, 4 years' windows represent the second best. Moreover, we also create a 2-years' time-windows dataset, partitioning the 1997-2008 time-span into six periods instead of three, to be employed in some of our econometric analyses.

Following from the adoption of these repartitions, from now on the time subscript to the variables will indicate time-windows rather than single years.[32]

As to the independent variable, we measure the regional intensity of university-industry collaborations

$$(5) \qquad IntColl_{r,t} = \frac{\text{\# patents in time window } t \text{ and region } r \text{ with at least one academic inventor}}{\text{\# patents in time window } t \text{ and region } r}$$

by looking at the share of patents with at least one academic among the inventors over all the patents held by assignees residing in the region r. Whilst similar, our variable differs from the one employed by Santoalha (2019) under a fundamental aspect. As a matter of fact, he defines collaborations in terms of co-applicants, thus looking at the organisations/persons applying for the patent. On the contrary, we geolocate patents in terms of assignees -the organisations that can use the patent- and define collaborations on the basis of APE-Inv information which refers to the inventors. To this extent, unlike Santoalha (2019), we regard as collaborations also those cases in which the patent is assigned to one organisation only, but the team working on the idea includes an academic professor.

The distinction between assignees and inventors allows us also to classify collaborations based on the number of organisations that can tap into the knowledge generated by the patent. Indeed, when the patent is held by one firm only the possibilities of spillover effects are smaller than the case in which the patent is assigned to multiple firms. To this extent the number of subjects that can tap into a specific knowledge is important for its circulation. As such, we also split $IntColl_{r,t}$ into two further variables: $IntColl_{r,t}^{single}$ and $IntColl_{r,t}^{multi}$. The first

$$(5.a) \qquad IntColl_{r,t}^{single} = \frac{\text{\# of patents in time window } t \text{ and region } r \text{ with at least one academic inventor AND one assignee only}}{\text{\# patents in time window } t \text{ and region } r}$$

represents the share of patents held by one firm and with at least an academic inventor, while the second

$$(5.b) \qquad IntColl_{r,t}^{multi} = \frac{\text{\# of patents in time window } t \text{ and region } r \text{ with at least one academic inventor AND multiple assignees}}{\text{\# patents in time window } t \text{ and region } r}$$

represents the share of patents held by more than one firm and with at least an academic inventor.

[32] We are perfectly aware of the trade-off generated by the combination between the nature of the technological variety phenomenon and the time-span covered by our dataset. On the one hand, the small number of years at our disposal calls for partitioning the dataset into small time-windows to be able to exploit the panel dimension. As it will be illustrated in the section dedicated to the empirical strategy, we sought a compromise between these two elements by investigating the subject with multiple techniques and two different time-windows, assuming the consistency of results across the different econometric exercises as a support for our arguments.

Finally, in order to single out as much as possible the role of university-industry collaborations for variety, we control for a set of variables that are related to both factors. From a technological point of view, the degree of variety and the number of collaborations hinge on the knowledge base that can be found in the territory. As such, we control for the number of patents and the average intramural R&D expenditures as proxies for this knowledge base. Whilst the information on the number of patents is at the NUTS3 level, the one related to R&D could be found at the NUTS2 level only.

From an economic point of view, the extent of knowledge and the degree of collaborations are connected to the size of local economy and its degree of interconnectedness. As such, we introduce in our regressions both the level of per capita GDP and the level of population at the provincial (NUTS3) level.

To homogenise our control variables to the time-windows' structure of the dataset, we took the averages of the yearly data falling within each interval.

4.3.3 Empirical Strategy

To study the contribution of university-industry collaborations to the diversification process of the variety of regional technological knowledge we conducted three different sets of analyses based on just as many methodologies. To begin with, we sought to estimate the role of collaborations for variety with the following equation

(6.a) $$Var_{r,t} = \beta_0 + \alpha\ IntColl_{r,t-1} + \boldsymbol{X}_{r,t-1}\boldsymbol{\beta} + \theta_t + \varepsilon_{r,t}$$

where

- $Var_{r,t}$ is the log of the type of variety –TV_t^r, RV_t^r, or UV_t^r– in region r and time window t;
- β_0 is a constant term capturing the average value of variety in the reference year;
- $IntColl_{r,t-1}$ is the log of the intensity of university-industry collaboration in region r and time window $t-1$;
- $\boldsymbol{X}_{r,t-1}$ is a vector of NUTS3 and NUTS2 control variables in time window $t-1$;
- θ_t is a parameter for the time fixed effects capturing cyclical phenomena common to all regions during time window t;
- $\varepsilon_{r,t}$ is the normally distributed error term.

Within this specification, α represents the parameter of interest and it measures the elasticity of technological variety to university-industry collaborations.

When the intensity of collaboration is broken down to investigate the differences between one-applicant and multi-applicants patents, we modified equation (6.a) as follows

(6.b) $$Var_{r,t} = \beta_0 + \alpha_1\ IntColl_{r,t-1}^{single} + \ \alpha_2\ IntColl_{r,t-1}^{multi} + \boldsymbol{X}_{r,t-1}\boldsymbol{\beta} + \theta_t + \varepsilon_{r,t}$$

where $IntColl_{r,t-1}^{single}$ is the log of the intensity of university-industry collaborations in region r at time window $t-1$ producing patents with one applicant only while $IntColl_{r,t-1}^{multi}$ is the log of the intensity of university-industry collaborations in region r at time window $t-1$ producing patents with more than one applicant. To this extent, the parameters of interest in equation (6.b) are represented by α_1 and α_2.

In both equation (6.a) and equation (6.b), the proxies for the university-industry collaboration enter the specification lagged by one time window with respect to the dependent variable. This choice has been made to attenuate possible issues of simultaneity between technological variety and collaborations arising when taking both measures at t. As a matter of fact, it is reasonable to assume that firms and universities join into research projects to tap into complementary types of knowledge, and this may be more likely within regions in which knowledge is diversified already. If this is the case, however, by regressing Var on contemporaneous values of $IntColl$, we would obtain biased estimates for $E[IntColl_{r,t} \cdot \varepsilon_{r,t}] \neq 0$. To this extent, by taking lagged values of $IntColl$ we try to rule out any effect of variety on collaborations and retain only the information regarding the relationship going from collaboration to the variety. A similar argument has also been applied to the set of controls in $\boldsymbol{X}$.

As to the econometric technique, we used pooled OLS on a 4-years' time-window dataset for estimating the parameters of both equations, with each t representing one among the three periods {1997-2000; 2001-2004; 2005-2008}. This choice has been guided by the fact that technological diversification takes time to unfold, and inventions take time to be patented. Therefore, we grouped the observations together into 4-years' time-windows. To account for the possible presence of region-specific variances of the error term (σ_r^2), we clustered standard errors at the regional level.

Yet, apart from simultaneity, equations (6.a) and (6.b) may suffer from another form of endogeneity following from the correlation between $IntColl$ and some unobserved region-specific factors. For example, it is likely that both technological variety and university-industry collaborations are correlated with factors such as the historical role played by universities within a territory or the local entrepreneurial culture. By assuming that the error term $\varepsilon_{r,t}$ can be broken down into a time-invariant region-specific factor (μ_r) and an idiosyncratic term ($\epsilon_{r,t}$) such that

$$\varepsilon_{r,t} = \mu_r + \epsilon_{r,t}$$

with $E[\mu_r] = E[\epsilon_{r,t}] = 0$ and $E[\mu_r \cdot \epsilon_{r,t}] = 0$, then the preceding argument implies that $E[IntColl \cdot \mu_r] \neq 0$.

A second issue related to equations (6.a) and (6.b) is connected to the absence of path dependency. As a matter of fact, both models do not include the lagged values of the dependent variable among the control variables. Yet, technological variety unfolds through time and builds upon previous knowledge and capabilities. To this extent, the absence of the lagged dependent variable among controls may lead our coefficients of interest to be biased for they may capture part of the information belonging to path dependency.

Unfortunately, the time span covered by the dataset places a trade-off to the strategy to tackle both issues. Indeed, fixed effects estimates cannot be applied to a dynamic version of (6.a) and (6.b) due to the Nickell bias problem arising with short panels and dynamic specifications (Nickell, 1981). At the same time, if we introduced the lagged dependent variable among controls, the number of observations per region would prevent us from using internal instruments to cope with the correlation between the independent variables and the time-invariant region-specific component of the error term in a GMM framework. As a matter of fact, in the 4-years' time window dataset, each region has at most three observations (one per period), which boil down to two because controls are lagged by one time-window. Thus, if we want to introduce the lagged dependent variable within the set of regressors, the length of time-windows must be shortened to be able to include more observations. Given that we followed both choices: on the one hand, we kept specifications (6.a) and (6.b) estimating the coefficients of interest through FE; on the other hand, we introduced the lagged dependent variable among regressors and estimated the model on a 2-years' time window dataset.

For the first case, we modified (6.b) as follows

$$Var_{r,t} = \beta_0 + \alpha_1\, IntColl_{r,t-1}^{single} + \alpha_2\, IntColl_{r,t-1}^{multi} + \boldsymbol{X}_{r,t-1}\boldsymbol{\beta} + \theta_t + \mu_r + \epsilon_{r,t} \tag{7}$$

and applied fixed effects techniques to estimate the parameters. FE estimates make us estimate the contribution of $IntColl$ to Var over and above the average value of Var (and the remaining controls). Also in this case, we clustered standard errors at the regional level in order to control for possible specificities of the error terms at the NUTS3 level.

With reference to the second option, we built another dataset based on the same data but aggregating the information into 2-years' time-windows. To this extent, instead of three periods per region, we ended up with six observations for 95 NUTS3 provinces and four observations for the remaining 15.[33] Thanks to this reorganisation, we could employ GMM techniques and use internal instruments to estimate the parameters of a dynamic specification. At the same time, the reduction of the length of time-windows decreases the amount of information encapsulated by each variable. As already mentioned, this is not a secondary issue for both variety and collaborations are two phenomena unfolding through time, which are better measured when gathering multiple years together. To partially overcome this limitation, we modified (6.b) and estimated the following specification

$$\begin{aligned} Var_{r,t} = {} & \rho_1\, Var_{r,t-1} + \rho_2\, Var_{r,t-2} + \alpha_1^1\, IntColl_{r,t-1}^{single} + \alpha_1^2\, IntColl_{r,t-2}^{single} + \alpha_2^1\, IntColl_{r,t-2}^{multi} + \\ & \alpha_2^2\, IntColl_{r,t-2}^{multi} + \boldsymbol{X}_{r,t-1}\boldsymbol{\beta} + \theta_t + \mu_r + \epsilon_{r,t} \end{aligned} \tag{8}$$

[33] Starting from early 2000's new provinces have been created and the overall number of NUTS3 regions passed from 95 to 110.

introducing further lags both for the degree of variety and for the collaboration intensities. In this way, we allow the variety in time window t to directly depend upon the knowledge accumulated over the past four years.

In terms of technique, we preferred the system GMM (Blundell and Bond, 1998) to the difference GMM (Arellano and Bond, 1991) following from the fact that the literature in economic geography points out that changes in unrelated variety are rare (Boschma, 2017). If this is the case, the levels of technological variety are not sufficiently informative to instrument the changes, which suggests that we should also use changes to instrument the levels (Roodman, 2009). Apart from $Var_{r,t-1}$, we treated as predetermined $IntColl^{single}_{r,t-1}$, $IntColl^{multi}_{r,t-1}$, and per capita GDP. As stated before, the underlying idea is that collaborations may suffer from a simultaneity bias, which would imply that $E[\Delta IntColl^{h}_{r,t-1} \cdot \Delta\epsilon_{r,t}] \neq 0$ with $h \in \{single, multi\}$. In a similar vein, the literature has pointed out that varieties contribute in different ways to the regional performance (Frenken, Van Oort, and Verburg, 2007), which makes it likely that $E[\Delta GDPph_{r,t-1} \cdot \Delta\epsilon_{r,t}] \neq 0$. As a final note, all the GMM estimates reported in the next section have been obtained with a two-step procedure and small-sample corrections to the covariance matrix estimate.

4.4 Results

This section presents the results of the econometric analyses. As described in the previous paragraph, we estimated our specifications by means of three different techniques -pooled OLS, fixed effects, and system GMM- each one devised to deal with specific issues arising from the hypothesized statistical model. By mirroring the reasoning reported in the preceding pages, we start our presentation from the simplest case, and then we pass to the more advanced ones showing the differences in the parameters of interest.

Table 3 reports the pooled OLS results for equations (6.a) and (6.b) with total variety as the dependent variable. The first column of this table shows the estimated coefficients for a specification including only control variables, whereas columns 2 to 5 display the outcomes of a set of regressions also containing the proxies for university-industry collaborations. As to these ones, the model in column 2 employs the generic collaboration variable while the ones in the subsequent columns differentiate between one- and multi-applicants' patents.

[TABLE 3 ABOUT HERE]

The estimates in column 2 reveal the presence of a positive, albeit nonsignificant, correlation between the concentration of patents with an academic professor among the inventors and the degree of technological variety at the provincial level. However, when collaborations are broken down into two groups on the basis of the number of patent applicants, we observe that there is a stark distinction between collaborations whose patent is owned by one single entity and collaborations whose patent is owned by multiple entities. As a matter of fact, while the share of patents with an academic inventor and a single applicant is not significantly associated to the degree of technological diversification (column 3), the percentage of patents with an academic inventor and multiple applicants is positively and significantly associated to the variety of regional technological knowledge (column 4). Moreover, this difference persists even when we include both proxies within the same specification (column 5).

Having said that, the results presented so far refer to total variety and do not provide any information regarding the direction of its change. Yet, this is an important element adding a further dimension to the understanding of the movements of regions in terms of knowledge. To this extent, we further divide total variety into its related and unrelated components and investigate their relationships with the two types of collaborations. Table 4 reports the results of six regressions. The first three replicate the specifications in columns (3)-(5) of table 3 by using related variety instead of total variety, whereas the last three do the same by substituting total variety with unrelated variety.

[TABLE 4 ABOUT HERE]

According to these estimates, the concentration of university-industry collaborations on the same territory is not significantly associated to related variety for all the coefficients are never statistically significant. On the contrary, significant and positive coefficients are found between the share of multi-applicants' patents with academic inventors and unrelated variety: regions displaying higher shares of these types of patents are, on average, also associated to a higher presence of unrelated types of technological knowledges. These results bring two considerations about. First, it is possible to argue that the associations between total variety and university-industry collaborations highlighted in table 3 are steered exclusively by changes in unrelated variety. In other words, the new capabilities connected to the regional concentration of firms conducting R&D activities with the help of academic professors tend to generate new trajectories for the regional capability base. This in line with the boundary spanning argument (Hargadon, 2006) and the results of the literature on the role of university-industry collaborations for regional branching processes (Scandura and Quatraro, 2020). At the same time, the positive correlation between the co-patenting concentration and unrelated variety highlights that, not only the newly acquired capabilities are loosely connected with the regional capability base, but also that the previous capabilities tend to be retained and, therefore, it is the whole spectrum of regional knowledge to become more unrelated.

As to the second consideration, not all the types of collaborations are alike in this matter. Only those collaborations whose research outcome -the patent- is owned by a multiplicity of entities are found to produce sensitive results at the regional level. Therefore, it is not only important whether the research is conducted together with an individual that is able to expand capabilities' horizon, but also whether these new capabilities can be tapped into by more than one firm in order to generate spillovers eligible of reshaping the whole regional knowledge.

As mentioned in the previous section, it is reasonable to assume that the estimates in tables 3 and 4 suffer from a bias following from the correlation between the collaboration variables and some region-specific factors that are constant through time -or at least they can be regarded as such over the time span covered by our dataset-which fall into the residual part of the specifications. To this extent, we devised other two possible models to test whether the results found with pooled OLS hold when controlling for regional heterogeneities. The first one, expressed by equation (7), which allows for the use of fixed effects techniques. The results for this case are reported in table 5.

[TABLE 5 ABOUT HERE]

As before the first three columns of the table refer to related variety while the last three to unrelated variety. Even in this case, university-industry collaborations seem to play a significant role only with respect to the unrelated type of knowledge, whereas related variety is negatively but not significantly correlated with both variables. In particular, fixed effects estimates show that the statistical correlation that we found for the equation in levels remains valid also when we estimate a regression using the differences between levels and within-province averages. Stated differently: the positive correlation between the concentration of university-industry collaborations stemming from multi-applicants' patents and unrelated variety holds true even when we get rid of those parts of these phenomena that are associated to time-invariant regional characteristics, such as the historical role of universities within one territory or its entrepreneurial culture. On top of that, it is interesting to notice that the order of magnitude of estimates for α_2 remains the same across both models. As a matter of fact, according to pooled OLS estimates α_2 amounts to ~0.7, while in the table 5 results, the unrelated variety's elasticity with respect to university-industry collaborations with multi-applicants' patents amounts to 0.9 percent.

The second strategy to deal with the endogeneity issue linked to the correlation between cooperation and regional unobserved heterogeneity estimates a dynamic model on a 2-years' time window dataset through the system GMM technique. As described in the previous paragraph, we coupled the adoption of a reduced timespan per each window with the introduction of a further lag in the independent variable as well as in the variety control. Table 6 reports the results of this exercise together with the AR(1), AR(2), and Hansen's statistics for the validity of our results. As before, the first three columns refer to related variety while the last three to unrelated variety.

[TABLE 6 ABOUT HERE]

First of all, the positive sign and the significance of coefficients for the lagged dependent variables in almost all the specifications are in strong favour of the presence of path dependent processes. To this extent, the GMM estimates reported in table 6 represent the most accurate for they take into account also this fundamental aspect of variety's evolution.

Secondly, it is interesting to notice that the estimated coefficients for the $t-2$ lags are as significant as, if not more significant than, the estimated coefficients for the $t-1$ lags. As such, even when reducing the amount of information contained in each observation -due to the smaller number of years accounted for- the effects of our variables of interest persist through time.

Specifically, as before, we observe a positive and significant correlation between the regional concentration of multi-applicants' patents with one or more academic inventors and the degree of unrelated variety. In particular, the estimated coefficients suggest that these effects dwindle through time terms of significance (columns 5 and 6) and magnitude (column 6). In other words: the spectrum of today's technological knowledge at the regional level is strongly more associated with behaviours taken on in the farther past than in the most recent one.

Differently from the estimates carried out with the 4-years' time-windows, the share of single-applicants patents with one (or more) academic inventor(s) seems to be significantly associated to regional technological variety. In particular, the estimates in columns (1), (3), (4), and (6) display a negative and significant coefficient for the second lag of the cooperation proxy. Although less strong as evidence with respect to the one connected to multi-applicants' patents, this result suggests that R&D activities aimed at improving the capabilities of one firm only may not generate enough spillovers to keep, or increase, the level of regional variety constant.

We also conducted robustness checks on our GMM estimates which are reported in the appendices of the paper. In the first robustness check we treated per capita GDP as an exogenous variable to understand the sensitivity of table 6 results to the weakly exogeneity assumption while, in the second robustness check, we instead added a further lag of the number of patents to control for the size of innovative activities also in $t - 2$. In both cases the results are in line with our main findings.

Overall, our regressions suggest that the role of university-industry collaborations for the variety of regional technological knowledge is more complex than one could expect. As a matter of fact, our results seem to suggest that it is not the mere collaborations that matter but, rather, the collaborations carried out by multiple parties. Only when the new knowledge is shared by multiple parties, the region as a whole can benefit from collaborations. If this is the case, then, the variety of regional knowledge increases through diversification processes that enhance areas that are loosely related one each other.

4.5 Conclusions

This work has investigated the role of university-industry collaborations for the evolution of the variety of regional technological knowledge. By starting from the considerations that regional phenomena are the result of actions carried out by actors populating the same territory (Neffke et al., 2018), we tried to shed light on the role of university-industry collaborations in the research field for the trajectory of the set of capabilities that can be found within a specific geographical area.

Differently from previous literature our analyses aim to study variety and not specialisations. Albeit these concepts are strictly connected one each other, they represent two slightly different concepts which bear also two slightly different considerations on the policy ground. Specialisations, and especially the study of new specialisations, tackle the issue from a purely branching process, without considering how the whole set of regional knowledges become but rather focusing on the new knowledge only. On the contrary, our perspective seeks to look at the change of the whole set of capabilities, considering the regional knowledge network on the whole.

The main results of our econometric exercise indicate that university-industry collaborations are not always relevant for regional technological variety. The acquire importance when the new knowledge created through the collaboration with an academic inventor is shared by more than one organisation. Secondly, we also observe that, when they play a role in the diversification process, they seem to be associated to unrelated rather than related variety.

From a policy perspective, our work suggests that R&D consortia should be preferred to one-to-one university-industry collaborations when policymakers want to increase the set of regional capabilities.

Our results are far from being conclusive on this subject. Moreover, some caveats must be explicated in order to better appraise the analyses of this paper. First of all, we were limited in our exercise by the time span of the dataset. Whilst the 1997-2008 interval involves more than 10 years, technological diversification would require at least the double of time to be studied. In particular, longer time horizons would have allowed us to apply more robust panel data techniques with 4-years’ time windows, which represent the ideal range to measure diversification. Unfortunately, the dataset containing the information regrading academic inventors did not allow us to extend temporally our analyses.

A second drawback of the study, which is common to the literature, is the use of patents as a source to measure technological knowledge and capabilities. There are two main reasons for this. First, patents are unevenly distributed across sectors, which implies that we are overestimating some types of knowledge -mainly related to manufacturing- and underestimating some other type – related for example to services. On top of that, patents represent successful innovations. However, learning occurs even in presence of failures, which implies that, in an ideal world, one should account also for unsuccessful collaborations.

Thirdly, the use of IPC for measuring the technological distance among technologies may not be the best choice. Indeed, IPC does not capture the presence of common capabilities in the generation of two technologies. To this extent, our variety measures have to be regarded as dependent on the official classification rather than on a capability base as with Hidalgo, Klinger, Barbasi, and Hausmann (2007). In the future, we are planning to recompute the entropy measures by taking advantage of co-occurrence based hierarchical classifications, in order to test whether the results of our analyses change depending on the classification employed to compute the entropy index.

Having said that, we regard our work as further contribution to the study of firms as agents of structural change and their strategies as the means to influence the direction of this change.

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Tables

TABLE 1. DESCRIPTIVE STATISTICS – 4 YEARS WIDOW DATASET

	(1) Obs	(2) Mean	(3) Std.Dev.	(4) Min	(5) Max
Total Variety	195	4.14	1.49	0.00	6.86
Related Variety	195	0.65	0.42	0.00	1.86
Unrelated Variety	195	3.49	1.16	0.00	5.39
L.Collab. with acad.	195	0.07	0.11	0.00	0.67
L.Collab. with acad. - multi apps.	195	0.02	0.04	0.00	0.44
L.Collab. with acad. - one app.	195	0.05	0.09	0.00	0.67
L.GDP per head	195	22097.72	5637.71	11946.25	41194.50
L.Population	195	552208.10	578878.77	90108.50	3728454.50
L.R&D exp.	195	0.94	0.35	0.28	1.70
L.N. pats.	195	4.19	1.62	0.88	8.89

TABLE 2. CROSS CORRELATION MATRIX – 4 YEARS WINDOW

Variables	TV	RV	UV	Collab.	Coll. multi	Coll. one	GDPph	Pop	R&D	N.Pats
TV	1.000									
RV	0.827	1.000								
UV	0.979	0.697	1.000							
Collab.	-0.054	-0.031	-0.057	1.000						
Coll. multi	0.027	0.003	0.034	0.554	1.000					
Coll. one	-0.077	-0.039	-0.085	0.913	0.165	1.000				
GDPph	0.754	0.704	0.709	-0.158	-0.055	-0.161	1.000			
Pop	0.387	0.495	0.316	0.164	0.136	0.127	0.248	1.000		
R&D	0.267	0.214	0.264	-0.079	-0.042	-0.073	0.327	0.149	1.000	
N.Pats	0.885	0.896	0.807	-0.057	-0.016	-0.060	0.808	0.476	0.299	1.000

TABLE 3. TOTAL VARIETY AND UNIVERSITY-INDUSTRY COLLABORATIONS

	(1) Total Var.	(2) Total Var.	(3) Total Var.	(4) Total Var.	(5) Total Var.
L.Collab. with acad.		0.2508			
		(0.2437)			
L.Collab. with acad. - one app.			0.1651		0.1125
			(0.2953)		(0.2888)
L.Collab. with acad. - multi apps.				0.7585**	0.7248**
				(0.3156)	(0.2941)
L.GDP per head	0.5143**	0.5278**	0.5241**	0.5100**	0.5169**
	(0.2046)	(0.2095)	(0.2099)	(0.2054)	(0.2105)
L.Population	0.1120*	0.1019	0.1082*	0.0985	0.0966
	(0.0639)	(0.0662)	(0.0649)	(0.0654)	(0.0662)
L.R&D exp.	0.1041	0.1063	0.1052	0.1058	0.1065
	(0.1074)	(0.1066)	(0.1070)	(0.1071)	(0.1070)
L.N. pats.	0.1290***	0.1304***	0.1290***	0.1330***	0.1329***
	(0.0345)	(0.0353)	(0.0349)	(0.0353)	(0.0355)
Constant	-5.1285**	-5.1572**	-5.1889**	-4.9372*	-4.9868*
	(2.5356)	(2.5901)	(2.5889)	(2.5465)	(2.5949)
Time effects	Yes	Yes	Yes	Yes	Yes
R2	0.6245	0.6274	0.6254	0.6291	0.6295
N. of observations	195	195	195	195	195

Note: OLS regressions with clustered standard errors at the NUTS3 level on a 4 years-window dataset. *p<0.1, **p<0.05, ***p<0.01

TABLE 4. RELATED/UNRELATED VARIETIES AND UNIVERSITY-INDUSTRY COLLABORATIONS

	(1) Rel. Var.	(2) Rel. Var.	(3) Rel. Var.	(4) Unrel. Var.	(5) Unrel. Var.	(6) Unrel. Var.
L.Collab. with acad. - one app.	0.0010		-0.0058	0.0950		0.0474
	(0.1429)		(0.1455)	(0.2833)		(0.2784)
L.Collab. with acad. - multi apps.		0.0909	0.0926		0.6702**	0.6560**
		(0.1842)	(0.1920)		(0.3117)	(0.2923)
L.GDP per head	0.0823	0.0817	0.0814	0.6032**	0.5938**	0.5967**
	(0.1140)	(0.1144)	(0.1142)	(0.2353)	(0.2324)	(0.2359)
L.Population	0.0676**	0.0660*	0.0661*	0.1241	0.1144	0.1135
	(0.0340)	(0.0337)	(0.0343)	(0.0844)	(0.0851)	(0.0857)
L.R&D exp.	-0.0629	-0.0627	-0.0628	0.1344	0.1353	0.1356
	(0.0629)	(0.0631)	(0.0631)	(0.1282)	(0.1283)	(0.1284)
L.N. pats.	0.1630***	0.1635***	0.1635***	0.0807*	0.0842**	0.0841**
	(0.0192)	(0.0191)	(0.0192)	(0.0413)	(0.0416)	(0.0418)
Constant	-1.7314	-1.7081	-1.7055	-6.1579**	-5.9541*	-5.9750*
	(1.3420)	(1.3453)	(1.3425)	(3.1009)	(3.0800)	(3.1093)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.8001	0.8002	0.8002	0.5319	0.5356	0.5356
N. of observations	195	195	195	195	195	195

Note: OLS regressions with clustered standard errors at the NUTS3 level on a 4 years-window dataset. *p<0.1, **p<0.05, ***p<0.01

TABLE 5. RELATED / UNRELATED VARIETIES AND UNIVERSITY-INDUSTRY COLLABORATIONS– FIXED EFFECTS REGRESSIONS

	(1) Rel. Var.	(2) Rel. Var.	(3) Rel. Var.	(4) Unrel. Var.	(5) Unrel. Var.	(6) Unrel. Var.
L.Collab. with acad. - one app.	-0.1792		-0.1571	0.0339		-0.0164
	(0.2018)		(0.1983)	(0.1716)		(0.1647)
L.Collab. with acad. - multi apps.		-0.4260	-0.3910		0.8829***	0.8866***
		(0.2810)	(0.2771)		(0.2370)	(0.2464)
L.GDP per head	0.2174	0.2912	0.3097	0.4443	0.2330	0.2349
	(0.4792)	(0.4928)	(0.4916)	(0.7276)	(0.7056)	(0.7114)
L.Population	-0.4230	-0.5301	-0.5196	1.3705	1.5885	1.5896
	(1.1082)	(1.1054)	(1.1053)	(1.8325)	(1.8016)	(1.8108)
L.R&D exp.	-0.0254	-0.1011	-0.0440	0.5282	0.5643*	0.5703*
	(0.3022)	(0.2654)	(0.3062)	(0.3205)	(0.2946)	(0.3203)
L.N. pats.	0.1203***	0.1233***	0.1265***	-0.1170**	-0.1315**	-0.1312**
	(0.0386)	(0.0372)	(0.0378)	(0.0568)	(0.0563)	(0.0559)
Constant	3.4270	4.1213	3.7517	-20.1735	-20.8713	-20.9098
	(16.6092)	(16.3577)	(16.4573)	(29.2836)	(28.4856)	(28.6892)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed eff.s	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.1135	0.1185	0.1273	0.0790	0.1193	0.1194
N. of regions	106	106	106	106	106	106
N. of observations	195	195	195	195	195	195

Note: OLS Fixed Effects regressions with clustered standard errors at the NUTS3 level on a 4 years-window dataset. Lagged dependent variable is removed to avoid biased results. *p<0.1, **p<0.05, ***p<0.01

TABLE 6. RELATED AND UNRELATED VARIETIES EVOLUTION – GMM REGRESSIONS

	(1) Rel. Var.	(2) Rel. Var.	(3) Rel. Var.	(4) Unrel. Var.	(5) Unrel. Var.	(6) Unrel. Var.
L.Collab. with acad. - one app.	-0.0731		-0.0340	0.2002		0.1024
	(0.0998)		(0.0773)	(0.2028)		(0.1386)
L2.Collab. with acad. - one app.	-0.2847***		-0.3098***	-0.3264*		-0.4184***
	(0.0756)		(0.0576)	(0.1676)		(0.0927)
L.Collab. with acad. - multi apps.		-0.0357	0.0183		0.5709**	0.3724*
		(0.1063)	(0.1051)		(0.2299)	(0.2134)
L2.Collab. with acad. - multi apps.		-0.1145	-0.1494**		0.5352***	0.5646***
		(0.0913)	(0.0739)		(0.1569)	(0.1240)
L.Related Var.	0.0705	0.0156	0.1044*			
	(0.0720)	(0.0771)	(0.0613)			
L2.Related Var.	0.1198*	0.1056	0.1567***			
	(0.0609)	(0.0639)	(0.0527)			
L.Unrelated Var.				0.2326***	0.3825***	0.1959***
				(0.0583)	(0.0909)	(0.0610)
L2.Unrelated Var.				0.0945**	0.0797*	0.0514
				(0.0418)	(0.0455)	(0.0369)
L.GDP per head	0.1615	0.2306	0.1800*	1.1091***	1.7266***	1.2410***
	(0.1475)	(0.1522)	(0.1019)	(0.2110)	(0.2330)	(0.1908)
L.Population	0.0917***	0.1010***	0.0870***	0.1821***	0.2582***	0.2030***
	(0.0215)	(0.0224)	(0.0174)	(0.0438)	(0.0648)	(0.0391)
L.R&D exp.	-0.0312	-0.0398	-0.0312	0.0612	0.0526	0.0548
	(0.0320)	(0.0314)	(0.0253)	(0.0689)	(0.0974)	(0.0643)
L.N. pats.	0.1068***	0.1141***	0.0949***	-0.0338	-0.1687***	-0.0407
	(0.0317)	(0.0358)	(0.0212)	(0.0315)	(0.0534)	(0.0319)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed eff.s	Yes	Yes	Yes	Yes	Yes	Yes
N. of observations	370	370	370	370	370	370
N. of individuals	104	104	104	104	104	104
AR(1)p-value	0.0001	0.0000	0.0000	0.0094	0.0199	0.0093
AR(2)p-value	0.9535	0.9248	0.9238	0.2290	0.1858	0.2524
Hansen p-value	0.0873	0.2092	0.3001	0.1683	0.1533	0.4074

Note: GMM-sys regressions with on a 2 years-window dataset. Lagged dependent variable, collaboration variables, and GDP per head are treated as predetermined to account for correlation with lagged error terms. *p<0.1, **p<0.05, ***p<0.01

Appendix

TABLE 6B. RELATED AND UNRELATED VARIETIES EVOLUTION – GMM REGRESSIONS

	(1) Rel. Var.	(2) Rel. Var.	(3) Rel. Var.	(4) Unrel. Var.	(5) Unrel. Var.	(6) Unrel. Var.
L.Collab. with acad. - one app.	-0.0528		0.0275	0.1973		0.0390
	(0.1094)		(0.0866)	(0.2309)		(0.1295)
L2.Collab. with acad. - one app.	-0.2090**		-0.2116***	-0.2145		-0.2374**
	(0.0829)		(0.0699)	(0.1846)		(0.1162)
L.Collab. with acad. - multi apps.		-0.0953	-0.0648		0.2436	0.1679
		(0.1216)	(0.1227)		(0.2195)	(0.1973)
L2.Collab. with acad. - multi apps.		-0.2153**	-0.2371***		0.4770***	0.5061***
		(0.0965)	(0.0682)		(0.1288)	(0.1260)
L.Related Var.	0.0460	-0.0338	0.0893			
	(0.0852)	(0.0856)	(0.0740)			
L2.Related Var.	0.0897	0.1080	0.1305**			
	(0.0672)	(0.0662)	(0.0584)			
L.Unrelated Var.				0.1884**	0.2647*	0.1659**
				(0.0862)	(0.1592)	(0.0772)
L2.Unrelated Var.				0.0922	0.0878	0.0595
				(0.0637)	(0.0721)	(0.0505)
L.GDP per head	0.1786**	0.1011	0.1256*	0.5821***	0.5649***	0.6559***
	(0.0846)	(0.0775)	(0.0699)	(0.1560)	(0.1599)	(0.1380)
L.Population	0.0848***	0.0831***	0.0795***	0.0878*	0.1028*	0.1121**
	(0.0222)	(0.0214)	(0.0181)	(0.0509)	(0.0613)	(0.0472)
L.R&D exp.	-0.0428	-0.0412	-0.0315	0.1116*	0.1620**	0.1278**
	(0.0348)	(0.0378)	(0.0299)	(0.0623)	(0.0705)	(0.0561)
L.N. pats.	0.1161***	0.1405***	0.1096***	0.0600**	0.0423	0.0620**
	(0.0245)	(0.0230)	(0.0192)	(0.0296)	(0.0599)	(0.0282)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed eff.s	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	370	370	370	370	370	370
Individuals	104	104	104	104	104	104
AR(1)p-value	0.0001	0.0001	0.0000	0.0103	0.0047	0.0059
AR(2)p-value	0.9242	0.9432	0.8502	0.2304	0.1926	0.2281
Hansen p-value	0.1197	0.2615	0.2551	0.2732	0.5913	0.6710

Note: GMM-sys regressions with on a 2 years-window dataset. Lagged dependent variable and collaboration variables are treated as predetermined to account for correlation with lagged error terms. *p<0.1, **p<0.05, ***p<0.01

TABLE 6C. RELATED AND UNRELATED VARIETIES EVOLUTION – GMM REGRESSIONS

	(1) Rel. Var.	(2) Rel. Var.	(3) Rel. Var.	(4) Unrel. Var.	(5) Unrel. Var.	(6) Unrel. Var.
L.Collab. with acad. - one app.	-0.0767		-0.0328	0.2132		0.0699
	(0.0935)		(0.0732)	(0.2123)		(0.1348)
L2.Collab. with acad. - one app.	-0.2868***		-0.2659***	-0.3070*		-0.4209***
	(0.0835)		(0.0678)	(0.1682)		(0.0913)
L.Collab. with acad. - multi apps.		0.0607	0.1606		0.5265**	0.3362
		(0.1069)	(0.0987)		(0.2513)	(0.2132)
L2.Collab. with acad. - multi apps.		-0.1349	-0.1353		0.6031***	0.5584***
		(0.1026)	(0.0816)		(0.1501)	(0.1191)
L.Related Var.	0.0600	-0.0436	0.0331			
	(0.0724)	(0.0738)	(0.0598)			
L2.Related Var.	-0.0260	-0.0667	-0.0340			
	(0.0802)	(0.0905)	(0.0716)			
L.Unrelated Var.				0.2066***	0.3035***	0.1668***
				(0.0546)	(0.0743)	(0.0471)
L2.Unrelated Var.				0.0953**	0.1167*	0.0480
				(0.0477)	(0.0604)	(0.0500)
L.GDP per head	-0.4348**	-0.3295	-0.3258**	0.7891**	1.1269***	1.1542***
	(0.2103)	(0.2208)	(0.1565)	(0.3457)	(0.3616)	(0.1899)
L.Population	0.0969***	0.0963***	0.0985***	0.1379***	0.2193***	0.1978***
	(0.0239)	(0.0281)	(0.0193)	(0.0451)	(0.0650)	(0.0401)
L.R&D exp.	-0.0327	-0.0468	-0.0506*	0.0669	0.0924	0.0660
	(0.0315)	(0.0337)	(0.0263)	(0.0674)	(0.0923)	(0.0619)
L.N. pats.	0.0617**	0.0887***	0.0588***	-0.0057	-0.0697*	-0.0193
	(0.0240)	(0.0265)	(0.0171)	(0.0285)	(0.0410)	(0.0254)
L2.N. pats.	0.0849***	0.0900***	0.0895***	0.0123	-0.0387	-0.0007
	(0.0244)	(0.0291)	(0.0202)	(0.0254)	(0.0370)	(0.0228)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed eff.s	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	370	370	370	370	370	370
Individuals	104	104	104	104	104	104
AR(1)p-value	0.0001	0.0000	0.0000	0.0086	0.0146	0.0081
AR(2)p-value	0.8496	0.6963	0.9261	0.2242	0.1727	0.2456
Hansen p-value	0.1758	0.2577	0.3385	0.2299	0.1140	0.4295

Note: GMM-sys regressions with on a 2 years-window dataset. Lagged dependent variable, collaboration variables, and GDP per head are treated as predetermined to account for correlation with lagged error terms. *p<0.1, **p<0.05, ***p<0.01