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Spinoffs in context: entry and performance across different industries

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Abstract

Four major stylized facts about spinoffs have been identified by the literature: (i) spinoffs perform better than *de novo* entrants, (ii) there is an inverted U-shaped relationship between the age of a firm and spinoff formation, (iii) better parents generate more spinoffs, and (iv) better parents originate better spinoffs. These stylized facts hold in some industries (e.g., automobiles) but not in others (e.g., lasers, disk drives, and asbestos). Existing theories of spinoff formation and performance explain these stylized facts but not the differences across industries. Inspired by the history-friendly models of industry evolution, the article presents an agent-based simulation model in which technological and demand conditions contribute to determine both the emergence and the performance of spinoffs. We assume that three main factors characterize the emergence of spinoffs: first, spinoffs emerge out of innovation activities within the parents; second, spinoffs share knowledge with their parents; third, spinoffs have some degree of product differentiation with respect to their parents. The model is able to generate the stylized facts identified by empirical research in the automobile industry and also to replicate the regularities and exceptions holding in lasers, disk drives, and asbestos.

JEL classification: B52, C63, L26

1. Introduction

In early 1903, Henry Ford founded the Ford Motor Company that would soon become one of the most successful players in the emerging automobile industry. Just a few months earlier, Ford had left another company, the Henry Ford Company (renamed later as Cadillac Automobile Company), which was very successful in the first decade of the 1900s, until it was acquired by General Motors and became its luxury brand. The link between a successful spinoff and a successful parent was not peculiar to the Ford–Cadillac case: it was the rule in the early automobile industry and in many other industries, such as disk drives, tires, semiconductors, or legal services (Klepper, 2016). However, in another industry, such as lasers, the spinoff–parent link was irrelevant: better parents did not generate better spinoffs. For example, Laser Diode Laboratories spun off in 1967 from RCA to develop a new manufacturing technology for laser diodes, but it was not successful.

So far, analyses about spinoffs have generally ignored exceptions to the empirical regularities or treated them as statistical nuisance.[1] In this article, we explore the possibility that these exceptions do not emerge by chance but are generated by the structural characteristics of industries. We build a simulation model where the industry context explains the empirical regularities as well as the exceptions.

The spinoff–parent link is definitively not the only empirical regularity about spinoffs in the domain of industrial dynamics. The most well-known stylized fact about spinoffs—probably the very reason why there is so much attention to them—is that they perform better than *de novo* entrants. The evidence is quite robust, and it ranges from the classical cases of automobiles, tires, disk drives, medical devices, and lasers to the (more exotic) ones of wine, video games, and fashion industries. However, even this regularity has an exception: in the asbestos abatement industry, when the performance of spinoffs is compared with the one of *de novo* entrants, spinoffs do not perform better—actually they perform worse—than other entrants. Another empirical regularity is that parents' propensity to generate spinoffs first increases and then decreases with age. Again, we find an exception: in disk drives, age had no impact on parents' propensity to generate spinoffs. Memorex entered the industry in 1968: in 1973, it spun out Shugart Associates, but it also generated many spinoffs when it was relatively old (International Memories in 1977, Priam in 1978, Ibis in 1980, and Evotek in 1981). Some of these entrants, although very young, quickly spun out other firms: International Memories was the parent of Atasi (founded in 1981), and Ibis was the parent of Applied Information Memories (founded in 1982). Finally, we also know that better parents generate a higher number of spinoffs. Quite surprisingly, given the discussion so far, there is no evidence in the literature against this regularity.

Different models have successfully explained one or more of the stylized facts listed above, by looking at distinct causal mechanisms, ranging from asymmetric information to learning and from cannibalization to disagreements. However, none of these mechanisms has been able to explain the exceptions to these empirical regularities. Learning occurred both in automobiles and disk drives, but the relation between parents' age and the spinoff rate held in one industry and not in the other. Disagreement was an important driver of spinoff formation both in tires and in lasers, but in the former industry, spinoffs from better parents had better performance, whereas in the latter, this did not happen. So, why are these models not able to explain the between-industry variation emerging from the stylized facts? Although they highlight different mechanisms, they all share an important feature: they focus on the internal characteristics and dynamics of incumbent firms leading to the generation of spinoffs.

In this article, on the contrary, we focus on the industry context as a factor explaining both regularities and exceptions. We propose that the emergence and performance of spinoffs as well as of *de novo* entrants are related to some basic properties of the technology of the industry, which we call technological regimes; some characteristics of the demand, which we call demand regimes; and the discontinuous changes occurring in these dimensions.

We present a simulation model, inspired by the history-friendly models of industry evolution (Malerba *et al.*, 2016), in which industry conditions contribute to determine both the emergence and performance of spinoffs and their between-industry variation. We do not propose any specific assumption regarding the within-firm mechanisms leading to the generation of spinoffs, as we focus our attention on the industry characteristics. We assume only that spinoffs share something with their parent in terms of knowledge transmitted to employees and research teams and that they have at least some degree of product differentiation with respect to their parent.

On these grounds, our model is able to generate the stylized facts uncovered by the empirical research. By choosing a set of parameters representing the characteristics of the paradigmatic automobile industry, the model shows that spinoffs perform better than *de novo* firms; there is an inverted U-shaped relationship between the age of a firm and spinoff formation; better parents generate more and better spinoffs.

Then by changing the parameters and the rules governing technological regimes, demand regimes, and discontinuities to represent the main features of the asbestos abatement, lasers, and disk drive industries, the model is also able to replicate both the regularities and the exceptions about spinoffs occurring in these industries.

Our results suggest that the stylized facts and their exceptions are the outcome of different processes taking place in different sectoral contexts. In particular, the superior performance of spinoffs is strongly related to the

1 Agarwal *et al.* (2004) include age (linear and squared) in their analysis of spinoff generation patterns but do not comment that it has no effect. In his review, Klepper (2009a) presents a list of regularities and industries in which they hold and briefly mentions the existence of exceptions.

characteristics of the demand, specifically the degree of market fragmentation in several niches: the existence of a large number of such submarkets favors the generation and the growth of these new firms. Indeed, almost all the empirical studies refer to differentiated markets. This process is reinforced when technical change is driven by cumulativeness, and a direct link is established between spinoff and parent performance. The patterns of spinoff generation, finally, are strongly influenced by the regular or discontinuous arrival of new technological and market opportunities.

This article makes several contributions to the literature. First, it points out that, in addition to within-firm dynamics, industry-level variables should not be neglected when considering the role played by spinoffs in the evolution of industries and the overall economy. In fact, sectoral differences in terms of demand and technology explain why some empirical regularities hold in some industries and not in others. Second, the article suggests that demand conditions may play a role as relevant as technology in determining the dynamics and effectiveness of spinoffs, whereas the literature so far has mostly focused on capabilities inheritance and knowledge transmission (Elfenbein *et al.*, 2010), although the early work by Garvin (1983) identified the existence of multiple submarkets as an important driver of spinoff formation. Third, the article contributes to the evolutionary theory modeling (Nelson and Winter, 1982) of entry and industrial dynamics. Evolutionary models of industrial dynamics have provided interesting insights in important phenomena such as Schumpeterian competition (Nelson and Winter, 1982; Winter, 1984), the industry life cycle (Klepper, 1996), the dynamics of submarkets (Klepper and Thompson, 2006), and other industry regularities (Marsili, 2001). However, all these models assume entry of new firms as an exogenous mechanism, which is quite at odds with one of the pillars of the evolutionary theory—the generation of new varieties as fundamental in determining the outcomes of the system. Our model provides a first step toward a theory of endogenous entry in an evolutionary framework.

The article is structured as follows. In Section 2, we review the empirical literature and the theoretical models about spinoffs, as well as the current work on technology regimes, demand regimes, and discontinuities. Then, in Section 3, we present the theoretical framework that inspires our model. A qualitative description of the model is provided in Section 4: it focuses on the characteristics of consumers, technologies, and firms and on the basic mechanisms of entry of spinoffs and other firms. In Section 5, we present the results emerging from the model, by simulating industry conditions analogous to those examined by the empirical literature. Finally, we conclude by discussing the relevance of our results within the current discussion about spinoffs and provide implications for future research. A detailed and formal description of the model is presented in the Appendix.

2. Literature review

Past studies have provided different classifications of firms entering an industry, and the "spinoff" label has been used to refer to different types of firms. Following Klepper (2009a), we consider spinoffs those new firms entering an industry that (i) are founded by employees of incumbent firms (the parents) and (ii) engage in the same industry in which the parent firm is active (intra-industry spinoffs). We label as *de novo* entrants all other start-ups. Finally, we do not consider diversifying entrants (firms active in other industries before entering the focal one).

2.1 Empirical evidence

Since the seminal work by Garvin (1983), a large body of empirical work about spinoffs has been published. Most of these studies focus on the early stages of specific industries located in the United States: legal services (Philips, 2002), biotechnology (Stuart and Sorenson, 2003), disk drives (Agarwal *et al.*, 2004; Franco and Filson, 2006), lasers (Klepper and Sleeper, 2005), automobiles (Klepper, 2007), medical devices (Chatterji, 2009), semiconductors (Klepper, 2009b; Cheyre *et al.*, 2015), tires (Buenstorf and Klepper, 2009), and asbestos abatement (Hunt and Lerner, 2012). A smaller, but increasing number of studies focus on industries in countries other than the United States: automobiles in the UK (Boschma and Wenting, 2007) and in Germany (von Rhein, 2008), book publishers in the Netherlands (Heebels and Boschma, 2011), lasers in Germany (Buenstorf, 2007), motorcycles in Italy (Morrison and Boschma, 2018), the wine industry in Australia and New Zealand (Roberts *et al.*, 2011), and the worldwide fashion design (Wenting, 2008), local area network (Fontana and Zirulia, 2015), and video games industry (De Vaan *et al.*, 2013). Finally, some studies consider multiple industries: Gompers *et al.* (2005) examine spinoffs backed by venture capital firms; Eriksson and Kuhn (2006) exploit a matched employee–employer data set to study spinoffs in the whole private sector in Denmark over 20 years; Muendler *et al.* (2012) and Dick *et al.* (2013) analyze a similar data set over a shorter period for Brazil and the Netherlands, respectively.

All these studies address one or more of the following three themes: the performance of spinoffs *vis-à-vis* other entrants; the rate at which parent firms generate spinoffs, and its determinants; and the geographical location of spinoffs and their role in the creation of industrial clusters. Klepper (2009a) and Klepper and Thompson (2010) summarize the findings from these studies and present them in the form of empirical regularities or stylized facts. With respect to the purposes and the scope of this work, four of these stylized facts are relevant[2]: a schematic overview is presented in Table 1.

The first empirical regularity (which we label *Stylized Fact I*) is that in most of the industries listed above (automobiles, book publishing, disk drives, fashion design, lasers, medical devices, motorcycles, plastic molds, tires, video games, and wine), spinoffs have better performance than *de novo* entrants. Work done on the Danish data set used by Eriksson and Kuhn (2006), as well as on other matched employee–employer data sets (Muendler *et al.*, 2012; Dick *et al.*, 2013), confirms that spinoffs perform better than other entrants. Hunt and Lerner (2012), however, find that the opposite pattern holds in the asbestos abatement industry in Colorado and attribute this result to left truncation owing to a missing-data problem potentially affecting all the previous studies.

The second empirical regularity (*Stylized Fact II*) is that older parents tend to generate more spinoffs up to a certain point, which is around 14 years. Firms older than 14 years have spinoff rates decreasing with age. As a consequence, the general relationship between age of parents and spinoff generation rate has an inverted U shape. This pattern holds in automobiles, lasers, legal services, local area networks, and semiconductors. However, it does not hold in disk drives (Agarwal *et al.* 2004).

The third empirical regularity (*Stylized Fact III*) is that high-performing firms have a higher spinoff generation rate: there is supporting evidence in automobiles, disk drives, lasers, local area networks, plastic molds, semiconductors, and tires. So far, no study has found a different pattern.

The fourth empirical regularity *(Stylized Fact IV)* is that high-performing parents generate high-performing spinoffs. This is so in automobiles, disk drives, legal services, motorcycles, semiconductors, tires, and video games, but not in lasers (Klepper and Sleeper, 2005; Buenstorf, 2007).

So, it is possible to conclude that although all the stylized facts hold in the majority of the industries that have been studied, there is also an interesting between-industry variation characterizing stylized facts I, II, and IV.

2.2 Theory

Four main groups of models have been proposed so far to explain the phenomenon of spinoffs and the emerging empirical regularities. A summary is presented in Table 2. The first group of models (Anton and Yao, 1995; Hellman, 2007) is based on asymmetric information mechanisms: employees have private information about the quality of their innovation, and they opportunistically decide to set up their own firm whenever this is more convenient for them rather than revealing the innovation to the firm. These models effectively explain the higher performance of spinoffs with respect to *de novo* firms: employees know the value of their innovation and create a spinoff only when the quality of the innovation is high.

The second group of models is based on learning mechanisms (Franco and Filson, 2006): employees of incumbent firms learn over time the tacit know-how embedded in their employers routines and capabilities, and later they use it to start their own firm. Stylized facts I, III, and IV follow from this formulation: employees from high-performing firms learn more, and therefore perform better once they leave the parent to found a spinoff.

The third group of models assumes that both the firm and the employee know the value of the innovation, but the firm fears that its commercialization would cannibalize its existing products (Klepper and Sleeper, 2005) or would stretch too far the scope of its activities (Cassiman and Ueda, 2006). These models are consistent again with stylized

2 Klepper and Thompson (2010) list a fifth stylized fact, linking the spinoff generation rate to acquisitions and CEO changes: this is not discussed here, as our model does not include these elements. In addition, Klepper (2009a) presents some stylized facts about the geographical location of spinoffs, which is also beyond the scope of this article. Recently, the literature has also focused on the effects of spinoff generation on the performance of the parents: the findings describe a negative effect on the parent in service industries (Philips, 2002; Wezel *et al.*, 2006) and a positive one—with some temporal patterns—in manufacturing industries (McKendrick *et al.*, 2009; Ioannou, 2014).

Table 1. Stylized facts about spinoffs

Stylized fact	Description	Positive evidence	Negative evidence
Fact I	Spinoffs have better performance than other entrants	*Automobiles* (UK: Boschma and Wenting, 2007; United States: Klepper, 2007; Germany: von Rhein, 2008); *Book publishing* (The Netherlands: Heebels and Boschma, 2011); *Disk drives* (United States: Agarwal *et al.*, 2004); *Fashion design* (Worldwide: Wenting, 2008); *Full private sector* (Brazil: Muendler *et al.*, 2012; Denmark: Eriksson and Kuhn, 2006); *Lasers* (United States: Klepper and Sleeper, 2005; Germany: Buenstorf, 2007); *Medical devices* (United States: Chatterji, 2009); *Motorcycles* (Italy: Morrison and Boschma, 2018); *Plastic molds* (Portugal: Costa and Baptista, 2012); *Semiconductors* (United States: Cheyre *et al.*, 2015); *Tires* (United States: Buenstorf and Klepper, 2009); *Video games* (Worldwide: De Vaan *et al.*, 2013); *Wine* (Australia / New Zealand: Roberts *at al.*, 2011)	*Asbestos abatement* (United States: Hunt and Lerner, 2012)
Fact II	The relation between the age of parents and their spinoffs generation rates has an inverted U shape	*Automobiles* (United States: Klepper, 2007); *Lasers* (United States: Klepper and Sleeper, 2005; Germany: Buenstorf, 2007); *Law firms* (United States: Philips, 2002); *Local area networks* (Fontana and Zirulia, 2015); *Semiconductors* (United States: Klepper, 2009b).	*Disk drives* (United States: Agarwal *et al.*, 2004; United States: Franco and Filson, 2006)
Fact III	High-performing firms have higher spinoffs rates	*Automobiles* (United States: Klepper, 2007); *Disk drives* (United States: Agarwal *et al.*, 2004; United States: Franco and Filson, 2006); *Lasers* (United States: Klepper and Sleeper, 2005; Germany: Buenstorf, 2007); *Local area networks* (Fontana and Zirulia, 2015); *Plastic molds* (Portugal: Costa and Baptista, 2012); *Semiconductors* (United States: Klepper, 2009b); *Tires* (United States: Buenstorf and Klepper, 2009)	
Fact IV	High-performing parents generate high-performing spinoffs	*Automobiles* (UK: Boschma and Wenting, 2007; United States: Klepper, 2007; Germany: von Rhein, 2008); *Disk drives* (United States: Agarwal *et al.*, 2004); *Fashion design* (Worldwide: Wenting, 2008); *Full private sector* (Denmark: Dahl and Reichstein, 2007; The Netherlands: Dick *et al.*, 2013); *Law firms* (United States: Philips, 2002); *Motorcycles* (Italy: Morrison and Boschma, 2018); *Semiconductors* (United States: Klepper, 2009b); *Tires* (United States: Buenstorf and Klepper, 2009); *Video games* (Worldwide: De Vaan *et al.*, 2013)	*Lasers* (United States: Klepper and Sleeper, 2005; Germany: Buenstorf, 2007)

facts I, III, and IV, because better firms generate more and better innovations, and the resulting spinoffs benefit from the superior quality of their parents' ideas.

The model by Klepper and Thompson (2010) is based on the concept of disagreements within the firm. Neither the employer nor the employee knows the real value of the innovation: both can only observe noisy signals. Whenever their evaluation differs too much, a spinoff is generated. If the leaving employees have superior ideas, then the spinoffs perform better than other entrants, spinoff-generating firms have high performance until these employees

Table 2. Theoretical models about spinoffs

Theory	Basic mechanism	Explained stylized facts	References
Asymmetric information	Firms are not able to evaluate *ex-ante* the value of an innovation developed by the employees, who find it more profitable to commercialize by spinning out.	I	Anton and Yao, 1995; Hellman, 2007
Learning	Employees can learn the specific routines and capabilities of their employing firm and try to use them to set up their own firm.	I, III, and IV	Franco and Filson, 2006
Cannibalization	Firms and employees share the evaluation of an innovation, but the firm prefers not to commercialize it because it would cannibalize its existing businesses.	I, III, and IV	Klepper and Sleeper, 2005; Cassiman and Ueda, 2006
Disagreements	Individual within organizations have different evaluations about the value of an innovation. When it is not possible to find an agreement, some members leave and create their own firm.	I, II, III, and IV	Klepper and Thompson, 2010; Thompson and Chen, 2011

remain within the firm, and the high-performing firms will generate more spinoffs. Moreover, the model also explains the temporal pattern of spinoff generation (Stylized Fact II). Thompson and Chen (2011) adapt this model to study also the differences between spinoffs pursuing innovations and spinoffs remaining on old products because they disagree with the adoption of an innovation by the parent firm.

In sum, all four models, more or less successfully, are able to replicate the stylized facts discussed above. However, none of them considers the variation between industries that characterizes stylized facts I, II, and IV, and that it is exemplified by the cases of lasers, disk drives, and asbestos. Indeed, these models focus on the internal functioning of the firms and abstract completely from the structural characteristics of an industry.

2.3 Industry context

Our model differs from existing theories, because we explicitly consider the industry context and we characterize it in terms of technological regimes, demand regimes, and discontinuities. Technological regimes are technology-specific patterns in the ways firms learn and deal with the fundamental characteristics of the technological environment (Winter, 1984): the empirical literature has shown their role as determinants of several aspects of industrial dynamics, and in particular of entry patterns (Malerba and Orsenigo, 1999). Technological regimes include three broad dimensions: (i) the level of technological opportunities, that defines the extent to which new technological solutions are potentially available to innovative firms; (ii) the degree of appropriability of returns from innovations, that determines the extent to which innovative products are protected from imitation; and (iii) the cumulativeness of knowledge, that defines the extent to which future knowledge depends on the current level of knowledge (Breschi *et al.*, 2000). The literature has also identified strong associations between these dimensions, so that it is possible to define two extreme, opposite technological regimes: the entrepreneurial regime, characterized by high innovative opportunities, low degree of appropriability, and low cumulativeness of knowledge; and the routinized regime, characterized by a lower level of opportunities, high degree of appropriability, and high cumulativeness of knowledge (Winter, 1984).

Demand regimes are rooted in two well-established dimensions of demand heterogeneity. First, consumers have different opinions about the features that are necessary or preferable in a product—we call this dimension horizontal fragmentation (Hotelling, 1929; Klepper and Malerba, 2010). Second, consumers have different minimum quality requirements that a product must satisfy to be taken into consideration for purchase—we call this dimension vertical fragmentation (Adner and Levinthal, 2001; Malerba *et al.*, 1999). By combining these dimensions, we obtain two opposite demand regimes: the fragmented demand regime, in which both horizontal and vertical fragmentations are relevant, and the homogeneous demand regime, in which there is no consumers' heterogeneity.

Technological regimes and demand regimes are a useful tool to describe "regular" industry evolution. In these periods, new technologies and submarkets may appear, but they do not alter the basic rules of the game in the industry. However, it is well known that industries are also characterized by abrupt changes, that are called discontinuities and can be considered as a change of paradigm (Dosi, 1982). Tushman and Anderson (1986) refer to technological

Table 3. The Dimensions of Demand Regimes, Technology Regimes, and Discontinuities

Demand Regimes	Homogenous		Fragmented	
Horizontal Fragmentation	Low		High	
Vertical Fragmentation	Low		High	
Technology Regimes	**Entrepreneurial**		**Routinized**	
Technological Opportunities	High		Low	
Appropriability Conditions	Low		High	
Cumulativeness of Knowledge	Low		High	
Discontinuities	**Regular**	**Endogenous**	**Disruptive**	**Generational**

discontinuities as major advances that offer big improvements in the quality–price ratio over existing technologies and have also consequences on the demand side, as they determine the emergence of new submarkets. Quite often these changes are "endogenous," meaning that they are driven by the research activities of the firms operating in the industry. Christensen (1997) has further explored the role of new and growing submarkets, labeling as "disruptive" innovations a specific class of discontinuities where at the beginning the new technology is not necessarily better than the existing one. Discontinuities have also been characterized according to their frequency: Lawless and Anderson (1996) defined "generational" discontinuities those changes where new technologies and submarkets appear repeatedly, but older ones still survive, as in the case of multiple generations of mobile communications (Li *et al*., 2018).

Table 3 summarizes the dimensions of demand regimes, technology regimes, and discontinuities.

3. Theoretical framework

In this work, we model the internal organization of firms in a very simple way, trying to be as agnostic as possible with respect to the individual motivations behind the creation of spinoffs. Our assumptions regarding the creation of spinoffs are compatible with all four theories described in the previous section, as well as with most empirical evidence. In particular, first, we assume that the creation of spinoffs is related to some form of innovation: there is evidence in many sectors that spinoffs are associated to the detection of innovation opportunities (Costa and Baptista, 2015). This assumption is now a standard element in spinoff models (Golman and Klepper, 2016). Second, we assume that spinoffs have similarities with their parents in terms of knowledge and capabilities. Again, this is a common assumption in spinoff models, and although most empirical evidence about it is indirect (Chatterji, 2009), there are a few works showing that capabilities (Agarwal *et al*., 2004) and routines (Philips, 2002; Wezel *et al*., 2006) are transferred from parents to spinoffs, and accurate descriptions of how this process of *imprinting* occurs (Ferriani *et al*., 2012). Third, we assume that spinoffs have differences in terms of products with respect to their parents. There is actually some debate about similarities and differences between spinoffs and parents. The earlier literature on spinoffs has emphasized mostly the similarities between the parent and the spinoff (Klepper and Sleeper, 2005), but more recent contributions have also showed how spinoffs quite often have a tendency to differentiate from their parent—especially when they emerge from a strategic disagreement (Klepper and Thompson, 2010) or when they are located geographically closer to the parent (Berchicci *et al*., 2011). In some cases, spinoffs even move to other, vertically related industries, as the user-industry spinouts reported by Adams *et al.* (2016). Klepper (2016) reports detailed information about spinoffs occurring exactly because of strategic disagreements about new products to commercialize, including very famous cases in the automobile industry (such as the Cadillac–Ford) or in semiconductors (where Amelco and Signetics were formed to develop and exploit the integrated circuit technology that was neglected by the parent Fairchild). The focus on a different market niche—as we hypothesize in our model—can also determine the selection of specific organizational traits, that leads over time to increasing differences between the spinoff and its parent, in a process that Garnsey *et al.* (2008) call speciation.

The relation between the internal processes driving spinoff generation and the industry characteristics, and how this interaction affects the stylized facts about spinoffs, is illustrated in Figure 1. The pentagon at the center of the figure lists the three most important features of the processes that occur within a parent organization and lead to the creation of a

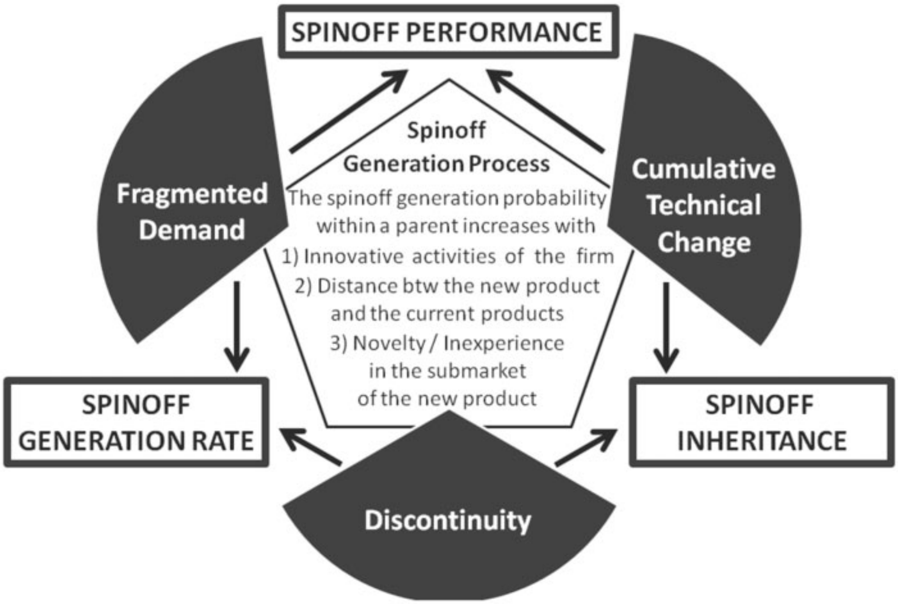

Figure 1. Spinoff generation process and industry characteristics.

spinoff. In our theoretical framework, a spinoff is associated to innovation—and in particular to the discovery of a new product by an existing firm. Therefore, more innovative firms tend to generate more spinoffs. Once a new product has been found, the probability that a spinoff will occur from it is higher if the product is distant from the current productive structure of the parent and if the submarket to which the product is associated is new to the industry or to the firm.

This internal process interacts with the industry characteristics to determine the performance of spinoffs, their overall generation patterns, and the relevance of the inheritance mechanism. The demand regime—and more specifically a fragmented demand—positively affects the spinoff generation rate, because the existence of multiple submarkets increases the chances that new products are distant from what parent firms are doing. For similar reasons, it also increases the chances of good performance by spinoffs, because they will not suffer from the competition from their own parents. The technological regime—and more specifically the cumulativeness of technical change—affects the inheritance mechanism between the parent and the spinoff: when knowledge is accumulated within existing firms, spinoffs' performance advantages are also driven by their link with the parent, in addition to the mechanisms related to the structure of submarkets. Finally, discontinuities—conceptualized as the arrival of new products associated to new submarkets—determine the temporal patterns of spinoff generation and can strengthen or weaken the role of the inheritance mechanism.

4. Model

In this section, we provide a qualitative description of the model. There are two types of agents: consumers and firms. We characterize their behavior by highlighting the dimensions that are relevant in their choices. We also provide a brief description of the dynamics of the model.[3]

4.1 Consumers' preferences

In each period, all consumers must choose whether to purchase any product and which product to purchase, in case more than one is available on the market. Consumers consider two elements in their purchasing decisions: the price

3 The model used in this article extends the one developed by Capone et al. (2013). Simulation code is written in Java through the Netbeans IDE. The code is available from the contact author upon request. We acknowledge the use of the COLT library developed by CERN and the SSJ library developed by Pierre L'Ecuyer and colleagues at the University of Montréal.

and the quality of products. For all consumers, the lower the price and the higher the quality of a product, the higher the probability of purchasing it. However, consumers' evaluation of products varies along two dimensions.

First, consumers are grouped in submarkets according to differences in "ideal locations" and "distances" from products (Hotelling, 1929). The quality of products is perceived by consumers depending on the distance from their "ideal" product: when a product is too far from it, consumers perceive a very low quality and do not consider it for purchase. The higher the similarity that consumers perceive across all products, the lower the horizontal fragmentation of the industry. At one extreme (horizontally homogeneous demand), consumers in any submarket consider any product as "ideal." At the other extreme (horizontally fragmented demand), consumers in any submarket consider only their "ideal" products for purchase.

Second, within each submarket, consumers differ in the evaluation of the minimum quality requirements that satisfy their needs (Adner and Levinthal, 2001). A product is not taken into consideration for purchase if its quality does not meet the consumer-specific requirements. The weaker the heterogeneity in the minimum quality requirements, the lower the vertical fragmentation of the industry. At one extreme (vertically homogeneous demand), all consumers in a submarket have the same requirements. At the other extreme (vertically fragmented demand), each consumer in a submarket has her own requirements.

4.2 Firms' activities

In each period, all firms perform their activities—including innovation, pricing, and internal allocation of resources—according to their own set of routines and capabilities.

Firms' innovation activities are of two types. First, firms can try to improve the quality of their current products by increasing their level of knowledge. An increase in the level of knowledge always determines an increase in the level of quality, but the extent of the increase depends on the technological trajectory of a product (Dosi, 1982), that is, a product-specific function that associates a level of quality to each level of knowledge. The process of discovery of new knowledge is affected by an industry-level parameter—the cumulativeness of knowledge, which is the degree by which future knowledge depends on the current level of knowledge. At one extreme (high cumulativeness), the starting point for the generation of new knowledge is the current level of knowledge. At the opposite extreme (no cumulativeness), the current level of knowledge is irrelevant and the increase of knowledge depends only on the financial resources of firms and their innovation capabilities.

Second, firms can try to find new products to be launched on the market. The probability of finding a new product depends on the resources invested by the firm, its innovation capabilities, and two industry-level parameters: the level of technological opportunities and the level of appropriability of returns from innovation. The former defines the extent to which new technological solutions are available to innovative firms. At one extreme (high level of opportunities), finding a new product is a rather easy task. At the opposite extreme (low level of opportunities), the innovation process may require a lot of time and financial resources to be successful. The level of appropriability defines the extent to which innovative products are protected from imitation. At one extreme (strong appropriability conditions), a firm cannot imitate the successful products of other firms. At the other extreme (weak appropriability conditions), a firm is allowed to produce and sell any product that it was able to develop irrespectively if it is already produced by others.

Each product of a firm is associated to a team, which carries on its research activity independently, and randomly chooses whether to use its financial resources in the current period to improve an existing product or to search for new products. Therefore, firms can pursue both innovation activities at the same time, provided that they have multiple teams.

The allocation of financial resources between different teams depends on their past performance: a team has more resources if the associated product earns a higher share of the firm's profits and if its innovation activities generate quality improvements or the discovery of new products. For the sake of simplicity, all firms use all their profits to finance innovation activities, once they have repaid the initial debt to set up the activities. Finally, firms are profit seekers and set prices based on the past market shares of all their products to avoid competition between their own products.

4.3 Model dynamics

A simulation run represents the evolution of an industry over time. An industry is composed by several submarkets that appear, grow, and disappear. The appearance of new submarkets follows different patterns according to the specific industry features: a regular pattern, in which new submarkets appear at regular intervals over time; an endogenous pattern, in which the emergence of submarkets is driven by firms' search activities; a generational pattern, in which new submarkets appear in bunches in specific periods; and a disruptive pattern, in which new submarkets quickly absorb existing submarkets.

The simulation starts as soon as one firm enters the industry and it ends T periods after the last submarket has appeared. The first entrant is followed by other *de novo* firms that find an appealing technological opportunity. The number of these firms entering at the beginning is set exogenously and acts as a seed for the entry of all other firms in later periods. Each period, potential *de novo* firms look at the performance of recent entrants and choose whether entry is feasible.

Entry of *spinoffs* follows a different logic. First, it is strictly linked to the innovation activities of existing firms. Whenever an incumbent firm discovers a new product, a new firm might actually spin off. This assumption reflects the idea that spinoffs can be generated out of learning occurring within the parent firm (Franco and Filson, 2006). Second, spinoff formation is positively related to the distance of the new product from existing ones: the farther the new product is from the current productive profile of the existing firm, the higher the probability that the firm will not exploit that innovation and a spinoff will come out pursuing it. This assumption reflects mostly spinoff theories based on cannibalization fears (Klepper and Sleeper, 2005), but it is also consistent with asymmetric information (Anton and Yao, 1995) and disagreement (Klepper and Thompson, 2010) views. Third, the probability of spinoff formation is also higher if the product is located in a submarket that has recently appeared and in which the parent firm has a limited innovative experience. Owing to the novelty of the submarket, there is a higher probability that the firm will suffer from asymmetric information (Anton and Yao, 1995) or that strategic disagreements occur (Klepper and Thompson, 2010). Once a spinoff firm is created, it inherits some of the knowledge of the parent firm.

All the existing firms perform their activities in the following order: first, they allocate the existing financial resources among teams; then, each team chooses and executes its specific innovative activity. Once new products have been discovered and existing products have been improved, firms set the prices and try to sell their products on the market. Market shares and profits are determined according to the utility that products provide to consumers.

Finally, exit of products and firms occurs. A product that does not reach a minimum market share in at least one submarket is withdrawn from the market. A firm that does not have any product to sell on the market fails and exits from the industry.

5. Results

5.1 Methodology

A simulation model of industrial dynamics describes the rules that govern the evolution of an industry over time. The actual realization of the model is a run. It is a function of a set of initial conditions, which include both the values of the parameters and the initial values of the variables. The variables are the elements of the model whose value is updated according to the rules of the model. The parameters are the elements of the model whose value does not change within a single run.

In a simulation model of industry evolution, the parameters may refer either to specific objects of the model (firms, products, and submarkets) or to the whole industry. Their values are determined through a process of calibration (Fagiolo *et al.*, 2007) that ensures the viability of the industry and the replication of the historical evolution of specific industries (Malerba *et al.*, 2016). In this model, we use the history-friendly models of the computer industry (Malerba *et al*, 1999) and the pharmaceutical industry (Garavaglia *et al.* 2013) as a reference for the calibration of most of the parameters of the model. As a further element of robustness, we keep the value of these parameters constant across the different simulated industries, so to attribute our findings only to the elements defining demand regimes, technological regimes, and discontinuities, which are purposefully chosen in a consistent way to replicate the characteristics of the simulated industries.

In this article, we select four sectors among the many ones studied empirically by spinoff scholars. The automobile sector is selected as an example of industry in which all regularities hold. Three more sectors—lasers, disk drives, and asbestos—are selected because characterized by some exception to the spinoff empirical regularities. A summary of regularities and exceptions in the selected sectors is presented in Panel A of Table 4.

For each of the selected industries, we choose appropriate values of the parameters and model rules controlling technology regimes, demand regimes, and discontinuities. The hypotheses about each industry are discussed below,

Table 4. Comparison between real-world and simulated industries

Panel A Real-world industry	Autos	Lasers	Disk drives	Asbestos
Fact I Spinoffs perform better than *de novo*	Y	Y	Y	N
Fact II Age of parents affects spinoffs (invU)	Y	Y	N	–
Fact III Better parents: more spinoffs	Y	Y	Y	–
Fact IV Better parents: better spinoffs	Y	N	Y	N
Panel B Simulated industry	**Autos**	**Lasers**	**Disk drives**	**Asbestos**
Fact I Spinoffs better than *de novo*	Y	Y	Y	N
Fact II Parents: age	Y	Y	N	Y
Fact III Parents: more spinoffs	Y	Y	Y	Y
Fact IV Parents: better spinoffs	Y	N	Y	N

Y: holds; N: does not hold; NS: nonsignificant; -: lack of evidence.

Table 5. Simulated industries' characteristics

Parameter	Automobiles	Lasers	Disk drives	Asbestos
Horizontal fragmentation	0.8	1	1	0.1
Vertical fragmentation	1	1	1	0.1
Level of opportunities	0.5	0.9	0.7	0.1
Appropriability	0.9	0.1	0.9	0.1
Cumulativeness	1	0.5	0.9	0.1
Discontinuity pattern	Endogenous	Regular	Generational/disruptive	Regular

and the corresponding parameter values and rules are reported in Table 5. To study each simulated industry, we perform 1000 runs keeping constant the parameters, to reduce the impact of random elements on the results. We then analyze the data generated by each simulated industry and collect information about (i) firms' performance metrics (survival and profits), focusing on the difference between spinoff and *de novo* firms; (ii) spinoff generation rates, focusing on the role of age and performance (survival and profits) of the parent firm; and (iii) spinoffs' performance, focusing on the role of performance of the parent firm. Performance results are reported in the form of averages within each firm category (spinoffs vs. *de novo* firms and spinoffs from best parents vs. spinoffs from other parents). However, within each category, there is also some degree of heterogeneity in performance metrics: these patterns of heterogeneity also differ across simulated industries.

5.2 Simulated industries: automobiles

The automobile industry is the paradigmatic example of the typical industry life cycle identified by Klepper (1997). The early phases of the industry (from 1895 to 1924) were characterized by an intense dynamics of entry and exit, with entry peak in 1907 and firms' peak in 1909 (Klepper, 2009a). Spinoffs accounted for about 20% of the entrants, and their entry was limited to the first two decades of the century. Although they were only a minor fraction of entrants, in general they outperformed other automobile producers—actually, the Big Three can all be classified somehow as spinoffs. In the early era of the industry, before Detroit emerged as the leading center, producers were present across different states in the United States, and the market was somehow geographically fragmented. Consumers located in the cities and in the rural areas had quite different needs, and there was no model that could satisfy both. Both elements suggest some level of horizontal fragmentation. Vertical fragmentation was more important, as many potential consumers could not afford the product until mass production made it cheap enough. New submarkets were included in the industry in an endogenous process driven by firms' innovations (rather than by exogenous discontinuities), which increased the quality of the autos and spectacularly reduced their price (Hounshell, 1984). Innovation opportunities were quite high at the beginning, but declined rapidly as a dominant design emerged (Klepper, 2016). Strong cumulativeness characterized the process of technical change, as exemplified by the

Table 6. The dimensions of firm performance: spinoffs versus *de novo*

Industry	Automobiles		Lasers		Disk drives		Asbestos	
	De novo	Spinoff	*De novo*	Spinoff	*De novo*	Spinoff	*De novo*	Spinoff
Profits	49.32	72.59	8.34	24.32	3.09	9.51	91.67	70.94
Survival	13.26	15.28	18.37	23.29	5.1	6.41	12.2	6.3
Failure rate	0.925	0.898	0.683	0.592	0.903	0.853	0.919	0.954

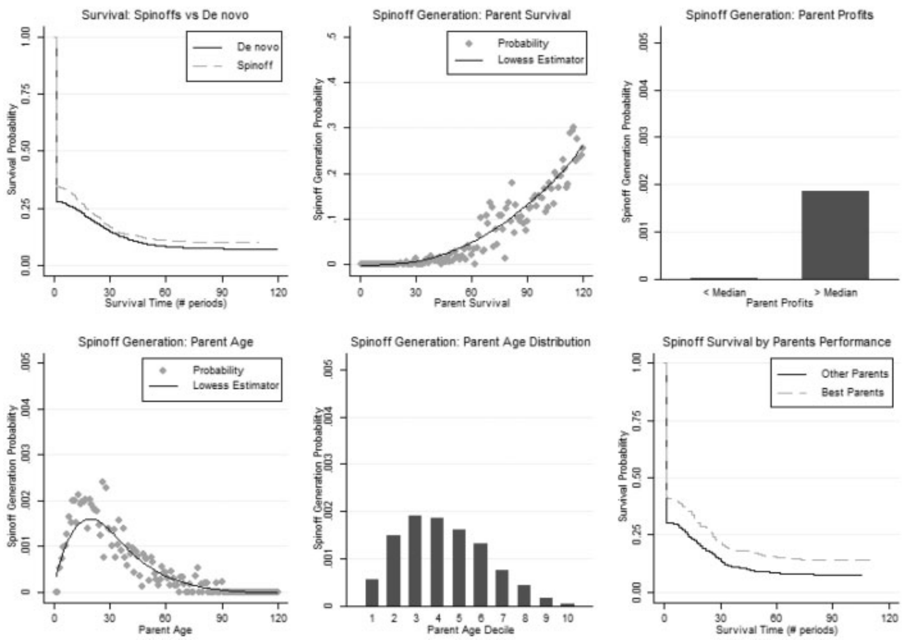

Figure 2. Stylized facts in the simulated automobile industry.

impressive number of related incremental changes that characterized the establishment of mass production by Ford. The speed of technical change and the quickly increasing capital intensity determined a strong appropriability regime (Hounshell, 1984).

All spinoffs' regularities are observed in this industry: this is confirmed by the results derived from our model using the parametrization provided in Column 1 of Table 5. Table 6 (Columns 1 and 2) presents different performance metrics for *de novo* and spinoff firms: the latter are characterized by higher average profits, higher survival time, and lower overall failure rates. The top-left panel of Figure 2 shows the survival function for *de novo* and spinoff firms estimated using the Kaplan–Meier estimator: at any age, spinoff firms have higher survival chances than *de novo* firms, and the difference between the two estimated curves is statistically significant.

In the automobile industry, better parents generate more spinoffs: this is confirmed in the simulated industry measuring parent performance in terms of both survival (Figure 2, top-center panel) and profits (Figure 2, top-right panel). The third regularity concerns the link between parent age and spinoff generation rate. Again, the simulated industry replicates the pattern observed in the real-world automobile industry: there is an inverted U-shaped relation between age and spinoff generation probability considering both absolute age (bottom-left panel of Figure 2) and its distribution (bottom-center panel of Figure 2).[4] Finally, the link between parent performance and spinoff

4 We exclude from the first graph those absolute values that are rarely observed. We exclude from the second graph firms aged 1. The same rules apply to all simulated industries.

performance emerges clearly from the last panel of Figure 2 (bottom-right): spinoffs enjoy higher survival rates at all ages if they originate from better parents, defined as the firms that are ranked at the top in terms of knowledge in the period in which the spinoff occurs.[5]

5.3 Simulated industries: lasers

The laser industry is instead the most well-known example of a sector not conforming to the regular industry life cycle (Klepper and Thompson, 2006), although a shakeout eventually occurred (Bhaskarabhatla and Klepper, 2014). The most remarkable feature of the industry is the large presence of submarkets, to be intended as particular applications serviced by specific lasers, with little relationship on the demand side, and in some cases also on the technology side (Klepper and Thompson, 2006): in our terminology, this results in a very high horizontal and vertical fragmentation. On the technology side, the industry was characterized by plenty of technological opportunities, emerging quite regularly from developments in the materials technology, and by a weak appropriability regime (Klepper and Sleeper, 2005). The importance of cumulativeness was limited, owing to the many tradeoffs in performance measures determined by the physical characteristics of the material used to amplify the light (Bhaskarabhatla and Klepper, 2014). Finally, the appearance of new technologies and submarkets driven by scientific developments was quite regular over the history of the industry and without any big discontinuity until diode-pumped solid state lasers were developed in the early 1980s (Klepper, 2016).

These characteristics of the industry are replicated in our model using the parametrization presented in Column 2 of Table 5. The simulated laser industry replicates the regularities about spinoffs observed in the real-world industry. Spinoffs perform better than *de novo* entrants in terms of profits, survival times, and (lower) failure rates (Table 6, Column 2). The top-left panel of Figure 3 shows that spinoffs have a higher survival probability than *de novo* firms at all ages. The probability to generate a spinoff is higher for parents that survive longer (Figure 3, top-center) and that earn more profits (Figure 3, top-right). The relation between age of the parent and spinoff generation probability has an inverted U shape using both age absolute values (Figure 3, bottom-left) and their distribution (Figure 3, bottom-center). The model is also able to replicate the exception to Stylized Fact IV, as there is no difference in the performance of spinoffs when they are sorted according to their parent performance (Figure 3, bottom-right). In fact, in this industry, owing to the limited role of cumulativeness, the superior performance of spinoffs is driven more by the availability of many, new submarkets and less by knowledge inheritance from the parents.

5.4 Simulated industries: disk drives

The disk drive industry has been extensively studied by industrial dynamics scholars since the seminal work by Christensen (1993) and is considered the paradigmatic example of disruptive innovation (Christensen, 1997). Actually, disk drives were characterized by both horizontal and vertical fragmentations, because of the emergence through multiple generations of new submarkets along both the vertical and the horizontal dimensions. The new submarkets were initially neglected by incumbent firms but quickly grew to absorb the existing submarkets. Within each generation, technology evolution was characterized by a high level of technological opportunities and cumulativeness of change, as testified by the dramatic increase in storage capacity over the years (Agarwal *et al.*, 2004), in which most of the returns from innovation were appropriated by leading firms, relying on tacit knowledge rather than on patents (Lerner, 1997).

5 The fourth stylized fact is very challenging from a methodological point of view. Once a spinoff is created, it can easily become a competitor of its own parent, affecting its performance. Empirical studies have mostly used survival measures as proxy for performance of both parents and spinoffs. However, in the case of parents, survival time is measured at the time in which the spinoff occurs—which implies that the performance measure of parents is their age. A simulation model does not provide any solution to the problem, because the interdependence of spinoffs and parent firms is a structural characteristic of the model and not a random factor to be controlled for by multiple runs of the model. However, it offers the opportunity to measure variables that are usually unobservable, such as knowledge. To avoid any effect that can be attributed to changes in knowledge over periods and across simulations, we use a period-specific relative rank of knowledge: in each period, all firms are ranked according to their knowledge, and those with the highest rank are categorized as best firms.

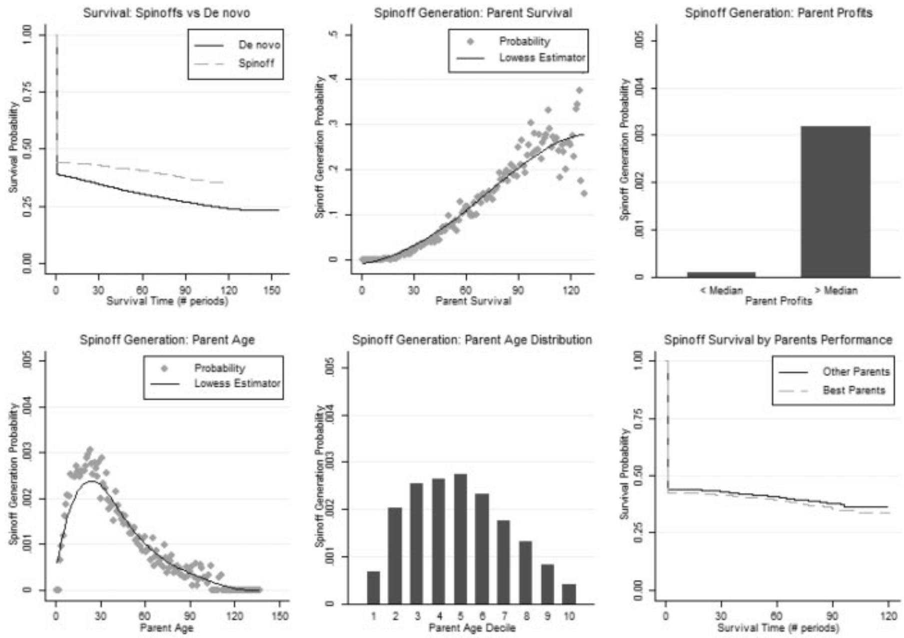

Figure 3. Stylized facts in the simulated laser industry.

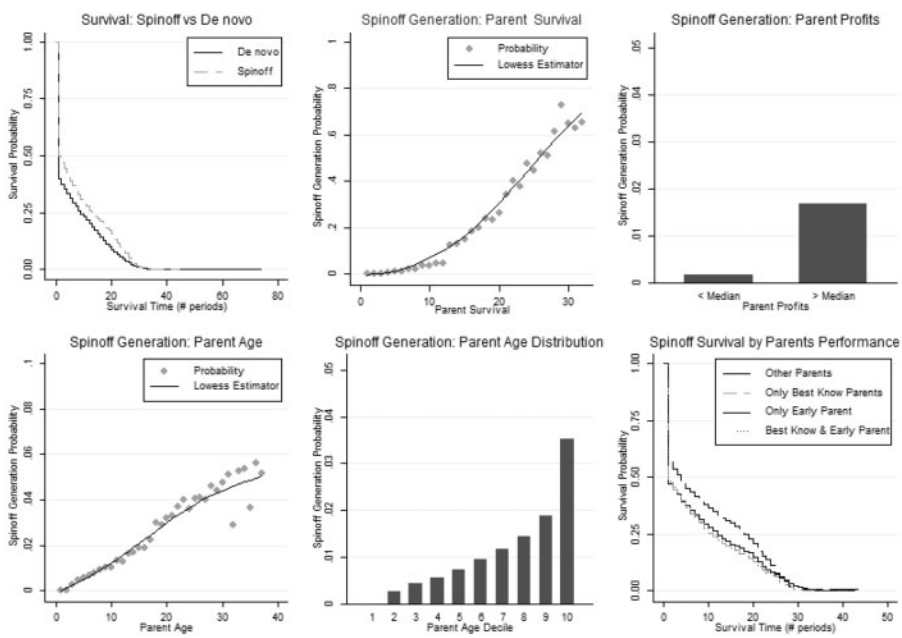

Figure 4. Stylized facts in the simulated disk drive industry.

The characteristics of the simulated disk drive industry are summarized in Column 3 of Table 5. Given the prevailing technological and demand regimes (i.e., the presence of a fragmented market and a cumulative process of technical change), the empirical regularities concerning spinoff performance and inheritance are verified in this industry. More in detail, spinoffs earn more profits and survive more than *de novo* firms (Table 6: Column 3; Figure 4: top-left).

Analogously to what emerges from empirical findings (Franco and Filson, 2006), spinoff superior performance is not associated to higher know-how of the parent but to early entry in the previous disk drives generation (Figure 4: bottom-right). As in other cases, spinoff generation probability is positively associated to parent performance measured through survival (Figure 4: top-center) and profits (Figure 4: top-right): parents with longer survival spans or earning more profits than the median firm have a higher probability to generate spinoffs. However, in this industry, the relation between parent age and spinoff generation probability does not have an inverted U shape (Figure 4: bottom-left and bottom-center). This effect can be attributed to a sort of censoring that occurs owing to the arrival of the new, disruptive generations.

5.5 Simulated industries: asbestos abatement

Among the industries we have selected, the asbestos abatement industry is definitively the less well known and studied by industry evolution scholars. However, there are two important features that make it an interesting case to analyze. First, it is the only sector in which it is documented a spinoff disadvantage *vis-à-vis de novo* firms. Second, it is a sector where opportunities for differentiation are removed by strong governmental regulation, and therefore, it is a good proxy for a homogeneous demand regime.

Hunt and Lerner (2012) report some information about the origin and the characteristics of this industry in Colorado. Although some concerns about the negative effects of asbestos on human health existed since the 1930s, its use in productive activities was not banned until the 1980s. In the United States, its use was prohibited in 1985, and strict regulation about its removal was demanded to state-level agencies. In Colorado, all firms involved in these activities needed a state-issued license to operate, and the allowed procedures were strictly regulated. Government regulation eliminated most of the heterogeneity in the technical realm and therefore also the possibility of vertical fragmentation, although some form of horizontal fragmentation still remained in the distinction among few big niches such as families, private firms, and public bodies. Actually, although they interpret their results as evidence of sample selection issues in the spinoffs literature, Hunt and Lerner (2012) found that the only successful spinoffs were characterized by nontechnical market experience that allowed them to exploit this limited form of demand fragmentation. On the technology side, although some innovative procedures have been developed over time, the overall level of technological opportunities has been very limited, the possibility of appropriating returns from them negligible, and cumulativeness did not play any role. Finally, owing to the stable conditions of the technological environment and of the regulatory framework, no discontinuity is reported in this industry.

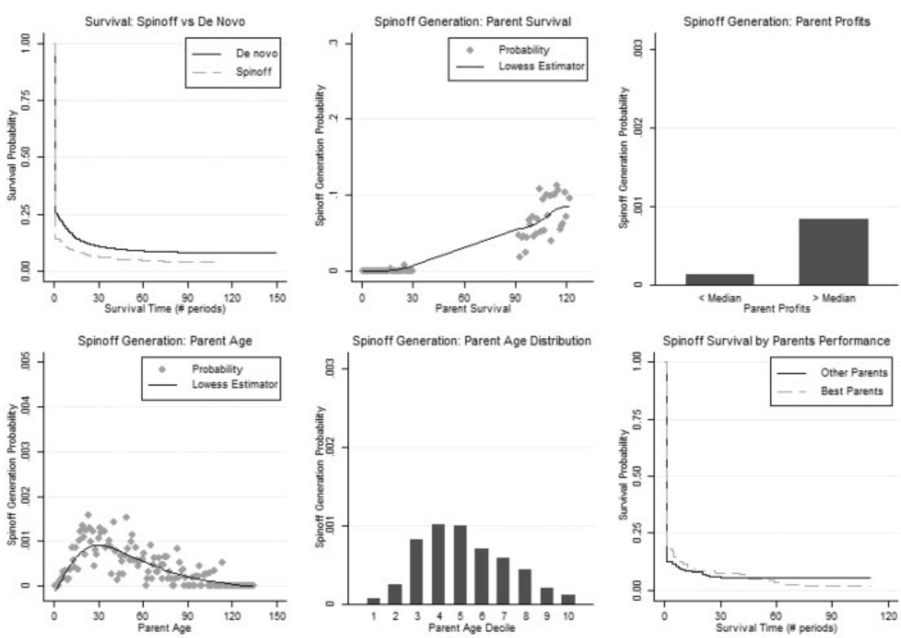

Figure 5. Stylized facts in the simulated asbestos abatement industry.

The last column in Table 5 summarizes the conditions of the simulated industry. Given our theoretical framework, we expect that a homogeneous demand determines unfavorable conditions for spinoff performance. Our results are consistent with this view: contrariwise to what we obtained in the other cases, spinoffs perform worse than *de novo* firms in terms of profits, survival length, and failure rate (Table 6: Column 4) and have lower survival probability at all ages (Figure 5: top-left). Parent knowledge is not relevant for survival, and therefore, we do not observe any difference between spinoffs from better and worse parents (Figure 5: bottom-right). As the pattern of arrival of new opportunities is regular, the two stylized facts about spinoff generation hold in this industry, although the absolute values are lower (Figure 5: top-center, top-right; bottom-left, bottom-center).

6. Discussion and conclusions

In this article, we have proposed a model that is able to replicate the four main stylized facts regarding spinoff formation and performance, as well as exceptions to these facts. The model is focused on sectoral variables regarding technological and demand conditions rather than on micro, firm-specific factors, such as the ones related to the asymmetry of information among agents, employee learning, the possible cannibalization of firms' current business, and the disagreements between individuals within an organization. The characteristics of the technological regimes and the demand regimes, and in particular the cumulativeness of technical change and the fragmentation of demand, explain why spinoffs perform better than *de novo* firms and why better parents generate better spinoffs. The specific pattern of discontinuous or regular changes in the technology and demand dimensions, instead, explains why there is an inverted U-shaped relationship between the age of firms and spinoff formation. The industry context determined by all these conditions explains also why some of these regularities do not hold in lasers, the disk drives, and asbestos abatement.

This article makes several contributions to the literature. First, we highlight that, in addition to within-firm dynamics, industry-level variables should be considered when examining the role played by spinoffs in the evolution of industries. This does not mean that firm internal factors are irrelevant in the generation and performance of spinoffs: in our view, they keep a central role as explanatory factors of the spinoff phenomenon. Second, our model suggests that demand conditions are as relevant as technology conditions in determining the dynamics and effectiveness of spinoffs, whereas the literature has so far mostly focused on the issue of capabilities inheritance and knowledge transmission (Elfenbein *et al.*, 2010). In fact, if we look at the formation of spinoffs over time and compare their evolution in different technological and demand regimes, demand emerges as the driving force. A fragmented demand is behind the verification of the empirical regularities about spinoff superior performance—and it is not by chance that most of the studies about spinoffs examine industries with many submarkets and niches. Discontinuities in the arrival of new submarkets explain why spinoff generation rates can follow alternative patterns to the regular inverted U shape. We do not deny the importance of the inheritance mechanism, however. Further developments of the model, coupled with ongoing empirical research, can also provide insights about the importance of the interaction between inheritance and differentiation in the phenomenon of spinoffs.

Third, we also contribute to the evolutionary theory modeling (Nelson and Winter, 1982) of entry and industrial dynamics. Evolutionary models have been very effective in explaining several regularities emerging from the research on empirical industrial dynamics (Marsili, 2001): the industry life cycle (Klepper, 1996), the dynamics of submarkets (Klepper and Thompson, 2006), and firms' size distribution and growth (Winter *et al.*, 2003). However, all these models assume that the entry of new firms is exogenous. This is quite at odds with one of the pillars of the evolutionary theory: the fundamental role of the generation of new varieties in determining the outcomes of the system. Our model provides a first step toward a theory of endogenous entry in an evolutionary framework. At least some of the firms entering the industry (the spinoffs) are not directly determined by our choices in terms of parameters: they actually emerge from the behavior and the interactions of the agents in the model.

Being a first attempt to shift the attention in spinoff analyses from the within-firm dynamics to the characteristics of the demand and the technological environment, our work certainly suffers from some limitations. In particular, one issue that deserves further attention concerns our assumption that links the creation of spinoffs to some difference that they have with respect to the parent. Klepper (2009a) considered the fact that in lasers as well as in semiconductors, spinoffs initially produced types of products that were a subset of those produced by their parents.

However, all the models developed so far[6] either assume or derive some elements of differentiation between spinoffs and parents. Moreover, the empirical evidence in other industries points in the direction of differentiation. Even in the laser industry spinoffs, although producing similar products, quite often targeted different submarkets and niches, such as civilians as opposed to military (Thompson and Chen, 2011). Still, in our model, we could explore the possibility that spinoffs differ with respect to their parents along not only the submarket dimension but also the quality dimension.

Another important issue in modeling the context conditions affecting spinoff dynamics and performance over a long-term process of industry evolution is the fact that spinoff generation has an impact on market structure that interacts with the direct effect of demand and technology conditions, and with the selection process of firms determined by market competition.[7] This is quite relevant for our work, given the comparative flavor of our analysis. A few measures are adopted in this work to control for this effect. First, we limit our analysis to a fixed number of periods after the emergence of the last submarket: therefore, industries characterized by different discontinuity patterns will have different temporal horizons of analysis. Second, we focus on a performance measure—survival—that is more robust to changes in market structure and competition dynamics. Finally, we draw our conclusions by looking at relative differences between spinoffs and *de novo* firms within the same industry context, without emphasizing differences in absolute values across industries.

In sum, this article shows that the major empirical stylized facts regarding spinoff formation and performance can be explained by an industry model that takes into account technological and demand conditions, and that this model is also able to propose an explanation of the different dynamics of spinoff formation over the evolution of industries. Moreover, the model suggests that two distinct processes govern the emergence and performance of spinoffs. The first is related to product differentiation. The second is linked to the process of development of knowledge and innovative capabilities within the parent firm and their inheritance by employees and research teams. This model therefore may complement other models that use more micro-, individual-, and firm-level explanations.

Our research agenda will try to move in two related directions. One direction is to empirically identify the specific dimensions of technology and demand in the different industries with quantitative indicators and not just with qualitative evaluations of the cases examined. The second direction is to support the results of our model by enlarging the types of sectors examined to industries characterized by homogeneous demand and by providing empirical evidence on the evolution of spinoff formation over time in different industries.

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References

Adams, P., R. Fontana and F. Malerba (2016), 'User-industry spinouts: downstream knowledge as a source of new firm entry and survival,' *Organization Science*, **27**, 18–25.

Adner, R. and D. A. Levinthal (2001), 'Demand heterogeneity and technology evolution: implications for product and process innovation,' *Management Science*, **47**(5), 611–628.

Agarwal, R., R. Echambadi, A. M. Franco and M. B. Sarkar (2004), 'Knowledge transfer through inheritance: spinout generation, development and survival,' *Academy of Management Journal*, **47**, 501–522.

Anton, J. J. and D. A. Yao (1995), 'Start-ups, spin-offs, and internal projects,' *Journal of Law, Economics, and Organization*, **11**, 362–278.

6 With the exception of Klepper and Sleeper (2005) that was purposefully designed to replicate the characteristics of spinoffs in the laser industry.

7 We thank one anonymous reviewer for pointing this out.

Berchicci, L., A. King and C. L. Tucci (2011), 'Does the apple always fall close to the tree? The geographical proximity choice of spin--outs,' *Strategic Entrepreneurship Journal*, **5**(2), 120–136.

Bhaskarabhatla, A. and S. Klepper (2014), 'Latent submarket dynamics and industry evolution: lessons from the US laser industry,' *Industrial and Corporate Change*, **23**(6), 1381–1415.

Boschma, R. and R. Wenting (2007), 'The spatial evolution of the British automobile industry,' *Industrial and Corporate Change*, **16**(2), 213–238.

Breschi, S., F. Malerba and L. Orsenigo (2000), 'Technological regimes and Schumpeterian patterns of innovation,' *Economic Journal*, **110**(463), 388–410.

Buenstorf, G. (2007), 'Evolution on the shoulders of giants: entrepreneurship and firm survival in the German laser industry,' *Review of Industrial Organization*, **30**(3), 179–202.

Buenstorf, G. and S. Klepper (2009), 'Heritage and agglomeration: the Akron tire cluster revisited,' *Economic Journal*, **119**(537), 705–733.

Capone, G., F. Malerba and L. Orsenigo (2013), 'Are switching costs always effective in creating first-mover advantage? The moderating role of demand and technological regimes,' *Long Range Planning*, **46**(4–5), 348–368.

Cassiman, B. and M. Ueda (2006), 'Optimal project rejection and new firm start-ups,' *Management Science*, **52**(2), 262–275.

Chatterji, A. K. (2009), 'Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry,' *Strategic Management Journal*, **30**(2), 185–206.

Cheyre, C., J. Kowalski and F. M. Veloso (2015), 'Spinoffs and the ascension of Silicon Valley,' *Industrial and Corporate Change*, **24**(4), 837–858.

Christensen, C. M. (1993), 'The rigid disk drive industry: a history of commercial and technological turbulence,' *Business History Review*, **67**(04), 531–588.

Christensen, C. M. (1997), *The Innovator's Dilemma*. Harvard Business School Press: Boston, MA.

Costa, C. and R. Baptista (2012), 'Agglomeration vs. organizational reproduction: the molds cluster in Portugal,' Papers in Evolutionary Economic Geography, 12.22, Utrecht University.

Costa, C. and R. Baptista (2015), 'Organizational heritage and entrepreneurship: Steven Klepper's theories reflected in the emergence and growth of the plastic molds industry in Portugal,' in R. Baptista and J. Leitão (eds), *Entrepreneurship, Human Capital, and Regional Development*. Springer: Cham, CH, 281–293.

Dahl, M. S. and T. Reichstein (2007), 'Are you experienced? Prior experience and the survival of new organizations,' *Industry and Innovation*, **14**(5), 497–511.

De Vaan, M., R. Boschma and K. Frenken (2013), 'Clustering and firm performance in project-based industries: the case of the global video game industry 1972-2007,' *Journal of Economic Geography*, **13**(6), 965–991.

Dick, J. M. H., K. Hussinger, B. Blumberg and J. Hagedoorn (2013), 'Is success hereditary? Evidence on the performance of spawned ventures,' *Small Business Economics*, **40**(4), 911–931.

Dosi, G. (1982), 'Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change,' *Research Policy*, **22**, 147–162.

Elfenbein, D. W., B. H. Hamilton and T. R. Zenger (2010), 'The small firm effect and the entrepreneurial spawning of scientists and engineers,' *Management Science*, **56**(4), 659–681.

Eriksson, T. and J. M. Kuhn (2006), 'Firm spin-offs in Denmark, 1981-2000—patterns of entry and exit,' *International Journal of Industrial Organization*, **24**(5), 1021–1040.

Fagiolo, G., A. Moneta and P. Windrum (2007), 'Empirical validation of agent-based models: alternatives and prospects,' *Journal of Artificial Societies and Social Simulation*, **10**, 8. <http://jasss.soc.surrey.ac.uk/10/2/8.html>.

Ferriani, S., E. Garnsey and G. Lorenzoni (2012), 'Continuity and change in a spin-off venture: the process of reimprinting,' *Industrial and Corporate Change*, **21**(4), 1011–1048.

Fontana, R. and L. Zirulia (2015), 'How far from the tree does the (good) apple fall? Spinout generation and the survival of high-tech firms,' Paper presented at the 37th Druid Society Conference, Rome.

Franco, A. M. and D. Filson (2006), 'Knowledge diffusion through employee mobility,' *The RAND Journal of Economics*, **37**(4), 841–860.

Garnsey, E., G. Lorenzoni and S. Ferriani (2008), 'Speciation through entrepreneurial spin-off: the Acorn-Arm story,' *Research Policy*, **37**(2), 210–224.

Garavaglia, C., F. Malerba, L. Orsenigo and M. Pezzoni (2013), 'A simulation model of the evolution of the Pharmaceutical industry: A history friendly model,' *Journal of Artificial Societies and Social Simulation*, **16**(4), 5–383.

Garvin, D. A. (1983), 'Spin-offs and the new firm formation process,' *California Management Review*, **25**(2), 3–20.

Golman, R. and S. Klepper (2016), 'Spinoffs and clustering,' *RAND Journal of Economics*, **47**(2), 341–365.

Gompers, P., J. Lerner and D. Scharfstein (2005), 'Entrepreneurial spawning: public corporations and the genesis of new ventures, 1986-1999,' *Journal of Finance*, **60**(2), 577–614.

Heebels, B. and R. Boschma (2011), 'Performing in Dutch book publishing 1880-2008: the importance of entrepreneurial experience and the Amsterdam cluster,' *Journal of Economic Geography*, **11**(6), 1007–1029.

Hellman, T. F. (2007), 'When do employees become entrepreneurs?,' *Management Science*, **53**, 919–933.

Hotelling, H. (1929), 'Stability in competition,' *Economic Journal*, **39**(153), 41–57.

Hounshell, D. A. (1984), *From the American System to Mass Production, 1800-1932*. Johns Hopkins University Press: Baltimore, MD.

Hunt, R. A., and D. A. Lerner (2012), 'Reassessing the entrepreneurial spinoff performance advantage: a natural experiment involving a complete population,' *Frontiers of Entrepreneurship Research*, **32**, 2.

Ioannou, I. (2014), 'When do spinouts enhance parent firm performance? Evidence from the U.S. automobile industry, 1890-1986,' *Organization Science*, **25**(2), 529–551.

Klepper, S. (1996), 'Entry, exit, growth, and innovation over the industry life cycle,' *American Economic Review*, **86**, 562–583.

Klepper, S. (1997), 'Industry life cycles,' *Industrial and Corporate Change*, **6**(1), 145–181.

Klepper, S. (2007), 'Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry,' *Management Science*, **53**(4), 616–631.

Klepper, S. (2009a), 'Spinoffs: a review and synthesis,' *European Management Review*, **6**(3), 159–171.

Klepper, S. (2009b), 'Silicon Valley—a chip off the old Detroit bloc,' in D. B. Audretsch and R. Strom (eds), *Entrepreneurship, Growth, and Public Policy*. Cambridge University Press: Cambridge, UK, pp. 79–118.

Klepper, S. (2016), *Experimental Capitalism. The Nanoeconomics of American High-Tech Industries*. Princeton University Press: Princeton, NJ.

Klepper, S. and F. Malerba (2010), 'Demand, innovation and industrial dynamics,' *Industrial and Corporate Change*, **19**(5), 1515–1520.

Klepper, S. and S. D. Sleeper (2005), 'Entry by spinoffs,' *Management Science*, **51**(8), 1291–1306.

Klepper, S. and P. Thompson (2006), 'Submarket and the evolution of market structure,' *The RAND Journal of Economics*, **37**(4), 861–886.

Klepper, S. and P. Thompson (2010), 'Disagreements and intra-industry spinoffs,' *International Journal of Industrial Organization*, **28**(5), 526–538.

Lawless, M. W. and P. Anderson (1996), 'Generational technological change: effects of innovation and local rivalry on performance,' *Academy of Management Journal*, **39**, 1185–1217.

Lerner, J. (1997), 'An empirical exploration of a technology race,' *RAND Journal of Economics*, **28**(2), 228–247.

Li, D., G. Capone and F. Malerba (2018), 'The long march to catch-up: a history-friendly model of China's mobile communications industry,' *Research Policy*, doi: 10.1016/j.respol.2018.10.019.

Malerba, F., R. R. Nelson, L. Orsenigo and S. G. Winter (1999), 'History-friendly models of industry evolution: the computer industry,' *Industrial and Corporate Change*, **8**(1), 3–41.

Malerba, F., R. R. Nelson, L. Orsenigo and S. G. Winter (2016), *Innovation and the Evolution of Industries: History-Friendly Models*. Cambridge University Press: Cambridge, UK.

Malerba, F. and L. Orsenigo (1999), 'Technological entry, exit and survival: an empirical analysis of patent data,' *Research Policy*, **28**(6), 643–660.

Marsili, O. (2001), *The Anatomy and Evolution of Industries*. Edward Elgar: Cheltenham, UK.

McKendrick, D. G., J. B. Wade and J. Jaffee (2009), 'A good riddance? Spin-offs and the technological performance of parent firms,' *Organization Science*, **20**(6), 979–992.

Morrison A. and R., Boschma (2018), 'The spatial evolution of the Italian motorcycle industry (1893-1993): Klepper's heritage theory revisited,' *Industrial and Corporate Change*, doi: 10.1093/icc/dty019.

Muendler, M., J. E. Rauch and O. Tocoian (2012), 'Employee spinoffs and other entrants: stylized facts from Brazil,' *International Journal of Industrial Organization*, **30**(5), 447–458.

Nelson, R. R. and S. G. Winter (1982), *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge, MA.

Philips, D. J. (2002), 'A genealogical approach to organizational life chances: the parent-progeny transfer among Silicon Valley law firms, 1946–1996,' *Administrative Science Quarterly*, **47**, 474–506.

Roberts, P. W., S. Klepper and S. Hayward (2011), 'Founder backgrounds and the evolution of firm size,' *Industrial and Corporate Change*, **20**(6), 1515–1538.

Stuart, T. E. and O. Sorenson (2003), 'Liquidity events and the geographic distribution of entrepreneurial activity,' *Administrative Science Quarterly*, **48**(2), 175–201.

Thompson, P. and J. Chen (2011), 'Disagreements, employee spinoffs and the choice of technology,' *Review of Economic Dynamics*, **14**(3), 455–474.

Tushman, M. L. and P. Anderson (1986), 'Technological discontinuities and organizational environments,' *Administrative Science Quarterly*, **31**(3), 439–465.

von Rhein, K. (2008), 'Heritage and firm survival—an analysis of German automobile spinoffs 1886-1939,' *Economics Bulletin*, **12**, 1–8.

Wenting, R. (2008), 'Spinoff dynamics and the spatial formation of the fashion design industry, 1858–2005,' *Journal of Economic Geography*, **8**(5), 593–614.

Wezel, F. C., G. Cattani and J. M. Pennings (2006), 'Competitive implications of interfirm mobility,' *Organization Science*, **19**, 56–68.

Winter, S. G. (1984), 'Schumpeterian competition in alternative technological regimes,' *Journal of Economic Behavior and Organization*, **5**(3–4), 287–320.

Winter, S. G., Y. Kaniovski and G. Dosi (2003), 'A baseline model of industry evolution,' *Journal of Evolutionary Economics*, **13**(4), 355–383.

Appendix

Demand

Consumers purchasing decisions depend on their preferences and the characteristics of products—quality and price. Consumers are grouped in S submarkets. Let the consumers in any submarket be uniformly distributed along the real unit segment: we define the propensity for the product j ($j \in \{1, \dots, J\}$) to be sold to a consumer i ($i \in [0,\ 1]$) in the submarket s ($s \in \{1, \dots, S\}$) at time t ($t \in \{1, \dots, T\}$) as

$$U(i)_{j,s,t} = \begin{cases} 0, & q_{j,s,t} < F(i) \\ \dfrac{q_{j,t} \cdot v_{s,j}}{p_{j,t}}, & q_{j,s,t} \geq F(i) \end{cases} \tag{1}$$

where $q_{j,\ t}$ is the quality of product j at time t, $v_{s,\ j}$ is the extent to which product j is ideal for consumers belonging to submarket s, $q_{j,\ s,\ t}$ is the quality of product j as perceived at time t by consumers in the submarket s ($q_{j,s,t} = q_{j,t} \cdot v_{s,j}$), $p_{j,\ t}$ is the price of product j at time t, and F(.) is a function that assigns a minimum quality threshold to each consumer. Condition (1) says that consumers never consider a product for purchase if it does not meet their minimum quality requirements, and in their purchasing decision they consider both subjective (preferences for variety) and objective (quality and price) elements.

Horizontal fragmentation

The preferences of consumers for variety are represented by grouping them in a set of S submarkets. Each submarket s is characterized by a vector $\boldsymbol{v}_s$ of real values in the set [0, 1] of dimensions equal to the number of potential products (J). Each element of $\boldsymbol{v}_s$ ($v_{s,\ j}$) represents the degree to which product j is "ideal" for the consumers in submarket s: one of the elements of $\boldsymbol{v}_s$ must be equal to 1, so that for each submarket there is at least one "ideal" product. All other elements of $\boldsymbol{v}_s$ are independently extracted from a beta probability distribution[8]: the mean of this distribution (μ_R) represents the extent to which consumers' preferences are homogeneous. Thus, the degree of horizontal fragmentation is $\mu_H = 1 - \mu_R$: when the parameter μ_H takes its maximum value (1), the fragmentation is so high that consumers will not consider any product for purchasing, unless it is "ideal"; when it takes its minimum value (0), consumers consider all the products as perfect substitutes for each other.

Vertical fragmentation

To model heterogeneity in the minimum quality requirements, we assume that consumers are distributed along the unit segment so that their thresholds are in a nondecreasing order. Moreover, we also assume that quality is bounded between 0 and 1. Then, the function $F(\cdot)$ that assigns to each consumer i its minimum quality requirement $F(i)$ can be represented through a cumulative distribution function: we use the beta cumulative distribution function.[9] The degree of vertical fragmentation (μ_V) is the reciprocal of one of the shape parameters of this distribution: when the

8 The beta probability distribution has two shape parameters, usually denoted as α and β. An intermediate level of fragmentation is obtained by setting both the shape parameters as equal to 1, which yields a uniform distribution between 0 and 1. To get higher values of fragmentation, we reduce the value of β keeping α constant at 1; symmetrically, to get lower values of fragmentation, we reduce the value of α keeping β constant at 1.

9 The highest level of vertical fragmentation is obtained when both the shape parameters are equal to 1, so that *F(·)* is the standard uniform distribution. To get lower values of vertical fragmentation, we increase the value of β keeping constant $\alpha = 1$; the value of vertical fragmentation (μ_V) is the reciprocal of β.

parameter μ_V takes its maximum value (1), consumers' minimum thresholds are uniformly distributed along the quality dimension; when it takes its minimum value (0), all consumers will consider purchasing a product with a strictly positive quality.

Price

All consumers prefer lower prices. Firms set the price of each product according to a mark-up rule, as follows:

$$p_{j,t} = C \cdot (1 + w_{j,t}) \tag{2}$$

where C is the marginal cost, that we assume equal across all products and constant over time. At time *t*, a firm chooses the mark-up $w_{j,\,t}$ for product *j* to maximize profits, given the price elasticity of demand η and a proxy for the general competitive pressure at time *t-1*:

$$w_{j,t} = \frac{m^*_{j,t-1}}{\eta - m^*_{j,t-1}} \tag{3}$$

We assume that the price elasticity of demand is the same for all consumers in all submarkets and it is constant over time. The general competitive pressure proxy ($m^*_{j,\,t}$) is analogous to a market share, but it refers to the whole industry and it takes into account the fact that horizontal and vertical fragmentations affect the boundaries of the "relevant market." More specifically, the variable $m^*_{\mathrm{j,t}}$ is the ratio between the number of consumers actually purchasing the product in all submarkets and the number of potential consumers in the industry. The latter is obtained by subtracting to the total number of consumers in the industry both the consumers whose minimum quality requirements are higher than the current quality of the product (as a change in the price would not affect their purchasing behavior) and the consumers who are currently buying other products of the firm (so as to avoid internal price competition).

Technology and innovation

To provide more quality to consumers, firms must either find a new product with higher quality or increase the knowledge base of their current products. The relationship between knowledge and quality is product-specific and is represented by its technological trajectory. Let k_j be the knowledge base of product *j*, the resulting quality q_j is given by the following generalized logistic function:

$$q_j(k_j) = \frac{A_j}{\left[1 + X_j e^{-Y_j \cdot k_j}\right]^{\frac{1}{Z_j}}} \tag{4}$$

The maximum quality that can be reached by any product is equal to the numerator (A_j) that can take any value between 0 and 1. Three parameters, which differ across products, determine the exact shape of the technological trajectory. The parameter X_j determines the level of quality when knowledge is at the minimum level, that is, $q_j(0)$: the only constraint we impose to its value guarantees that quality has a strictly positive value even for $k_j = 0$. The parameter Z_j determines the symmetry of the function and in particular the distance of the maximum growth rate from the asymptotes. Z_j takes any value in the range of real numbers[10] with the same probability. The parameter Y_j represents the average growth rate of quality with respect to knowledge. Its value is partially constrained by the previous parameters. We also restrict the range of possible values so that the growth of quality is not too fast.

Allocation of financial resources

All firms finance their innovation activities by investing all profits earned in the previous period—but only if they have already repaid the investors the loan that was necessary to set up the firm (which is equal to L_f). The profits of firm *f* at time *t* ($\Pi_{f,\,t}$) are the sum of the profits obtained from all its products ($\Pi_{j,\,t}$). Available financial resources must be allocated between different teams. Let $q'_{j,t}$ be the increase in the quality of product *j* that has occurred from

10 To the extent this is possible in a simulation model.

the previous period. Then, the budget of team j for its innovative activities in period t ($b_{j,\ t}$) is determined according to the following rule:

$$b_{j,t} = \left[\lambda_{f,t} \cdot \frac{q'_{j,t-1}}{\sum_{j=1}^{J_f} q'_{j,t-1}} + (1 - \lambda_{f,t}) \cdot \frac{\Pi_{j,t-1}}{\sum_{j=1}^{J_f} \Pi_{\mathrm{j},\ \mathrm{t}-1}} \right] \cdot \Pi_{f,t-1} \tag{5}$$

which means that the share of resources that can be used by team j depends on both the share of profits earned by the associated product and the team innovative performance in the last period *vis-à-vis* the other teams of the firm. Moreover, the weight that is assigned to earned profits and innovation performance varies over time, according to the overall innovative performance obtained by the firm:

$$\lambda_{f,t} = 1 - \frac{1}{1 + \sum_{j=1}^{J_f} q'_{j,t-1}} \tag{6}$$

Team innovation activities

A team can use its resources either to improve the quality of its product or to search for new products. The probability that a team will use its resources at any time to improve its product is z and is set exogenously at the same value for all teams and firms; the probability that a team will use its resources to search for new products is $1 - z$.

Search for new products

If a team chooses to search for new products, it will continue to search until it is successful or it exhausts its financial resources for the current period. The number of tries that are available for a team j with financial resources $b_{j,\ t}$ is equal to $floor\left(\frac{b_{j,t}}{C^N_{j,t}}\right)$, where $C^N_{j,t}$ is the unit cost of search for new products for team j at time t.

The probability of success is a nonlinear function of the level of innovative opportunities (ξ) and the appropriability of innovations (χ). The former determines the fraction of products with strictly positive quality: when the parameter ξ takes a low value, teams have a limited amount of innovative opportunities; when it takes its maximum value (1), it becomes much easier for them to discover new products. The latter determines the probability of imitating a product that has been already discovered by another firm: when the parameter χ takes its minimum value (0), imitation is always possible; when it takes its maximum value (1), imitation is never possible.

Improvement of existing products

Alternatively, the team can improve the quality of its associated product by increasing the knowledge base of the product. The probability of generating a new piece of knowledge ($n_{j,\ t}$) depends on the amount of resources invested in this activity: if a new piece of knowledge is generated, its value is a positive function of the technological capabilities of the firm (θ_{f}). This is formally expressed by the following condition:

$$n_{j,t} = \begin{cases} 0, & if \;\; U(0,\ 1) < \dfrac{1}{1 + \sqrt{b_{j,t}/C^L_{j,t}}}; \\ \exp(\theta_{\mathrm{f}}), & otherwise \end{cases} \tag{7}$$

where $C^L_{j,t}$ is the unit cost of improving the existing product j at time t. The extent to which the new piece of knowledge can be added to the existing knowledge depends on the degree of cumulativeness (γ): when the parameter γ takes its minimum value (0), the increase of knowledge depends only on luck and financial resources; when it takes its maximum value (1), the starting point for the generation of new knowledge is the existing level of knowledge. The new level of knowledge ($k_{n,\ t}$) is given by the combination of the new piece of knowledge and the existing knowledge and can be expressed formally as:

$$k_{n,t} = \gamma \cdot k_{j,t-1} + n_{j,t} \tag{8}$$

Finally, the firm uses the new knowledge only if this allows the firm to increase the quality of the product, that is, if the level of the new knowledge is higher than the previous level of knowledge.

Submarkets dynamics

An industry is composed by several submarkets that appear, grow, and disappear. A simulation run represents the evolution of the industry over time: it goes on for a fixed number of periods (T) after the last submarket has appeared. The appearance of submarkets changes according to the type of discontinuity prevailing in the industry: (i) "regular": in each period a new submarket appears with probability ζ; (ii) "endogenous": a new submarket appears when a firm discovers it; (iii) "disruptive": the new submarkets absorb the old ones; and (iv) "generational": the new submarkets appear in bundles at regular intervals. Existing submarkets are subject to a temporary negative shock that sets its size to zero, with probability ψ. Submarket size is extracted from a normal distribution with mean μ^S and standard deviation σ^S, and grows at rate g.

Entry and exit of firms

At the beginning of the simulation, a *de novo* firm develops a new product and starts its activities in the industry. In the following periods, other *de novo* firms (up to N) search for new products: if they are successful, they also enter and start producing and selling their products on the market. At any time, further *de novo* entry is driven by the profits of past *de novo* entrants: in each period, the number of *de novo* entrants is given by a Poisson process whose mean is a function of the average profits earned by *de novo* firms that have recently entered the industry. If there are no recent entrants, the number of *de novo* entrants is determined by a Poisson process with mean equal to the number of consecutive periods in which entry does not occur.

Entry of spinoffs is strictly linked to the innovation activities of existing firms. Whenever a firm discovers a new product, a new firm might actually spin off. The probability that this happens is:

$$\Pr(Spinoff) = \rho \cdot D_{j,h} \cdot M_{s,t} \cdot R_{f,t} \tag{9}$$

where ρ is the exogenous spinoff rate of the industry, $D_{j,h}$is the dissimilarity between product j (the new product discovered) and product h (the nearest product the firm is currently producing), $M_{s,\,t}$ is a negative function of the time since the submarket s to which product j is related has appeared, and $R_{f,\,t}$ is a negative function of the number of submarkets explored by firm f in its innovation activities. Therefore, the farther the new product is from the current productive profile of the existing firm, the higher the probability that the firm will not exploit that innovation and a spinoff will come out pursuing it.

To reduce the parameter space of the model, we exploit the link between products and submarkets to characterize the dissimilarity between products:

$$D_{j,h} = \sum\nolimits_s |v_{s,j} - v_{s,h}| \tag{10}$$

where $v_{s,\,j}$ ($v_{s,\,h}$) is the extent to which product j (h) is ideal for consumers belonging to submarket s. The natural minimum of this measure is 0, and the values are rescaled so that the maximum is actually 1.

The new spinoff firm will also inherit the knowledge of the parent firm, more specifically of the research team in which the innovation originated. The capabilities of both spinoffs and *de novo* firms are extracted from a uniform distribution within a meaningful range.

Market shares are computed as the ratio between actual consumers buying the product and all consumers in the submarket such that there is at least one product that satisfies their minimum quality requirements. The market share determines the withdrawal of products from the market: a product is not produced anymore if it does not reach a minimum market share (E) in at least one submarket. A firm exits if it does not have any product to sell on the market.

Table A1. Index of symbols

Symbol	Meaning	Type	Level (indicator)	Value/range
A	Maximum point of technological trajectory	Parameter	Product (j)	[0, 1]
B	Financial resources for innovation	Variable	Team (j)	$\mathbb{R}_{+}$
C	Marginal cost of production	Parameter	Industry	1
C^N	Unit cost of search for new products	Parameter	Team (j)	[1, 100]
C^L	Unit cost of improving existing product	Parameter	Team (j)	[1, 100]
D	Dissimilarity between products	Parameter	Product (j, h)	[0, 1]
E	Market share threshold for exit	Parameter	Industry	0.02
$F(\cdot)$	Minimum quality requirements	Function	Consumers (i)	[0, 1]
f	Indicator	Indicator	Firm	$\mathbb{N}_{++}$
g	Growth rate of submarket size	Parameter	Industry	0.01
h	Indicator	Indicator	Products, Teams	$\mathbb{N}_{++}$
i	Indicator	Indicator	Consumers	[0, 1]
J	Number of potential products	Parameter	Industry	1000
j	Indicator	Indicator	Products, Teams	$\mathbb{N}_{++}$
k	Knowledge	Variable	Product (j)	$\mathbb{R}_{+}$
L	Amount to payback to investors	Parameter	Firm (f)	[1, 100]
M	Newness of a submarket	Variable	Submarket (s)	[0, 1]
m^*	Global competitive pressure proxy	Variable	Product (j)	[0, 1]
N	Number of exogenous *de novo* entrants	Parameter	Industry	10
n	New piece of knowledge	Variable	Product (j)	$\mathbb{R}_{+}$
p	Price of a product	Variable	Product (j)	$\mathbb{R}_{++}$
q	Quality of a product	Variable	Product (j)	[0, 1]
q'	Increase in quality	Variable	Product (j)	[0, 1]
R	Innovative experience of a firm	Variable	Firm (f)	[0, 1]
S	Number of submarkets	Parameter	Industry	50
s	Indicator	Indicator	Submarkets	{1,. . ., S}
T	Time horizon after entry of last submarket	Parameter	Industry	20
t	Indicator	Indicator	Time	{1,. . ., T}
$U(\cdot)$	Propensity to purchase	Function	Consumers (i)	[0, 1]
v	Relatedness vector	Parameter	Submarket (s)	[0, 1]
w	Markup	Variable	Product (j)	$\mathbb{R}_{+}$
X	Intercept of technological trajectory	Parameter	Product (j)	$\mathbb{R}$
Y	Growth of technological trajectory	Parameter	Product (j)	$\mathbb{R}_{++}$
Z	Symmetry of technological trajectory	Parameter	Product (j)	$\mathbb{R}$
z	Probability of improving existing product	Parameter	Industry	[0, 1]
α	Shape parameter of beta distribution	–	–	$\mathbb{R}_{+}$
β	Shape parameter of beta distribution	–	–	$\mathbb{R}_{+}$
γ	Cumulativeness of knowledge	Parameter	Industry	[0, 1]
ζ	Probability that a submarket appears at t	Parameter	Industry	0.5
η	Price elasticity of demand	Parameter	Industry	1.5
θ	Firms exploration capabilities	Parameter	Firm (f)	$\mathbb{R}_{+}$
λ	Weight of innovation in resources allocation	Variable	Firm (f)	[0, 1]
μ^H	Horizontal fragmentation	Parameter	Industry	[0, 1]
μ^S	Mean of submarket size	Parameter	Industry	300
μ^V	Vertical fragmentation	Parameter	Industry	[0, 1]
ξ	Level of opportunities	Parameter	Industry	[0, 1]
Π	Profits	Variable	Product (j), Firm (f)	$\mathbb{R}_{+}$
ρ	Spinoff rate	Parameter	Industry	0.5
σ^S	Standard deviation of submarket size	Parameter	Industry	100
χ	Appropriability of innovations	Parameter	Industry	[0, 1]
ψ	Probability that a submarket has a shock	Parameter	Industry	1/S