

The co-evolution of market structure and product architecture

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Industries vary substantially in their evolutionary patterns of market structure and of product architectures. Differences exist in the timing, duration, and severity of the shakeout, and the extent to which architectures evolve towards greater modularity. Existing explanations typically treat these phenomena separately, despite recognizing demand heterogeneity as an important factor in both domains. We develop an evolutionary model that links demand heterogeneity with market and architectural evolution by combining characteristics-based demand with the generalized model of NK landscapes. In our framework, consumer preferences are modeled as weight distributions over product characteristics, while firms compete by searching for better designs through component and architectural innovations. Our results show that the structures of, and changes in, demand heterogeneity jointly shape market structures and product architectures. Under stable preferences, demand shapes market selection, reallocates resources across firms, and constrains the set of viable innovation trajectories. Changing preferences induce path-dependent industry dynamics, affecting the intensity of the shakeout and the speed of architectural change. These findings provide a unified explanation for industry differences in market structure and product architecture, and highlight the central role of demand in shaping both industry lifecycles and technological evolution.

JEL Classification: O32, O33, D21, D40, E14

1. Introduction¹

Industries differ in their evolutionary patterns of market structure and in the technological structure of products. Some industries experience a shakeout relatively early in life, others only at later stages, while others do not show any clear shakeout. Similarly, product architectures change through time and vary from relatively integrated structures to more modular designs. Despite the interdependence between markets and technology, our understanding of the joint determinants of these phenomena remains limited.

Prior studies have largely focused on either of the two facets, proposing complementary perspectives on industry dynamics. Contributions in the *lifecycle* tradition sought to identify the patterns of

¹ The manuscript has been proofread by using ChatGPT (Open AI, GPT-5 class model).

entry, exit, and innovation activities characterizing each phase of industrial evolution (Klepper 1997; Utterback and Abernathy 1975). Existing work has focused on explaining the mechanisms generating the shakeout and the following consolidation phase while industry differences remained secondary or attributed to exogenous factors. The second perspective, instead, focused on organization, strategy and firm performance starting from the inner properties of a product's design (Baldwin and Clark 2000; Henderson and Clark 1990). Works in this tradition identify *modularity* as the architectural form that enables organizational flexibility and quick adaptation to dynamic environments (Baldwin 2023; Simon 1962).

Despite the differences, both research streams recognize demand heterogeneity as an important factor to explain the phenomena at the center of the analyses. Lifecycle models hypothesize that the presence of different types of consumers can underlie the delayed shakeouts and the persistence of submarkets (Malerba et al. 2016; Bhaskarabhatla and Klepper 2014; Windrum and Birchenhall 1998). Works in the product architecture tradition connect demand heterogeneity with firms' incentives to adopt more modular product designs (Sanchez et al. 2023; Schilling 2000). At the same time, the majority of studies in both traditions tend to consider demand heterogeneity and its dynamics without accounting for the underlying determinants.

In this paper, we develop an evolutionary model to study how different distributions of preferences over product characteristics shape industry dynamics and product architecture. Following Lancaster's (1966) theory of characteristics-based demand, consumers evaluate products along multiple dimensions. Preferences are represented as weight distributions over product characteristics. While consumers share the same product characteristics that they value, they differ in both the weight allocation across the characteristics and the minimum performance level required for purchase.

On the technology side, product characteristics are produced by combining a set of components through a product architecture. A product design is the specific combination of components for a given architecture. To improve the fitness of a product with consumer tastes, firms must change single components or the architecture, searching for better designs. The difficulty of this search depends on the complexity of the architecture built over time.

Our framework differs from prior lifecycle models along two dimensions. First, by characterizing preferences as weight distributions, we study how different *types* of heterogeneity in consumer tastes shape industry dynamics. Second, by adopting generalized NK landscapes (Frenken 2006; Altenberg 1994) to represent multi-characteristic products, we endogenize architectural change to study the demand effect on product architecture.

Results reveal that stable consumer preferences over product characteristics exert a dual role. On the one hand, they shape market selection and resource allocation across firms; on the other hand, they constrain the set of viable technological trajectories. The interaction of these forces generates nonlinear relationships between preference distributions and both shakeout dynamics and modularity. When preferences evolve over time, the timing of transitions across demand regimes affects both the intensity of shakeout and the speed of architectural change. Taken together, these results reveal that both the structure and the evolution of demand heterogeneity help explain the variation in industry dynamics and product architectures documented in prior research.

This paper contributes both to the literature on industry lifecycles and to the literature on product architectures. With reference to lifecycle studies, our work provides an explanation not only for cross-industry differences in terms of shakeout timing, duration, and intensity, but also for the branching and persistence of submarkets. In our framework submarkets emerge as the matching between consumer preferences and product characteristics, implying that both demand and technological factors must be jointly considered to understand industry evolution. Regarding the literature on product modularity, our paper disentangles the channels through which demand affects the long-run architectural evolution, providing a clear distinction between static and dynamic environments. In particular, we show that, even in the presence of stable demand regimes, modularity rises due to the need for firms to improve existing product architectures without jeopardizing their inherited benefits. Moreover, the dual role illustrated before indicates that demand represents a strong force selecting current product varieties and constraining future technological variation.

The remainder of the paper unfolds as follows. The next section provides an overview of the background literature connected to our contribution. Section 3 describes the model while section 4 illustrates the results. Finally, section 5 discusses the contributions and the limitations of our work and provides some suggestions for future works.

2. Background literature

Our theory connects three research streams that have largely evolved in parallel: the product lifecycle approach, the research on product modularity, and the tradition of evolutionary models of innovation. The literature on *product lifecycle* (Utterback and Abernathy 1975; Vernon 1966) studies the evolutionary patterns of industries by looking for regularities in their development and investigating the underlying driving forces. The research on *product architecture* (Baldwin et al. 2014; Baldwin and Clark 2000; Langlois and Robertson 1992) focuses instead on the causes of modular designs and the consequences of their adoption for firm's organization and performance. Finally, the tradition of *evolutionary models of innovation* (Querbes and Frenken 2017; Marengo and Valente 2010; Levinthal 1997) adopts models of biological evolution to study innovation as a problem-solving and the consequence of technological complexity for industry dynamics.

By studying the role of preference distribution over product characteristics for the evolution of market structure and product architecture, we provide a unifying framework that sheds light on relevant and underexamined connections between industry dynamics and technological change. The next subsections review the three traditions highlighting the conceptual gaps that motivate our contribution.

2.1 Product lifecycle

The product lifecycle approach conceptualizes the evolution of industries as a sequence of ordered stages characterized by recurring patterns of entry, exit, survival, and innovation, also known as the industry lifecycle (Klepper 1997). The theory of the product lifecycle describes a transition from early product experimentation under demand uncertainty and rising entry to the consolidation of an oligopolistic structure in which process innovation becomes dominant serving a mass market. In early stages, intense product experimentation among a small number of firms reflects unstable demand practices and the absence of a clear technological trajectory. As markets expand, entry accelerates, while product architectures begin to standardize, and process innovations and scale economies become increasingly important. As maturity approaches, declining entry and rising exit generate a *shakeout* and a rise in market concentration. In the mature stage, the number of competitors stabilizes, and process innovation becomes dominant relative to product innovation.

Empirical studies that have tested this pattern reveal substantial heterogeneity in the lifecycle of different industries (Klepper and Simons 2005; Klepper 1997; Agarwal and Gort 1996; Utterback and Suárez 1993). While the product lifecycle captures regularities in early-stage dynamics, its explanatory power is less consistent in accounting for the later-stage consolidation (Fujimoto 2014; Windrum 2005). Studying the evolution of 46 products, Gort and Klepper (1982) show that the *time of arrival*, the *duration*, and the *severity* of the shakeout vary substantially across industries. In some cases, such as the laser industry (Bhaskarabhatla and Klepper 2014), the shakeout is significantly delayed, while in other cases—such as petrochemicals and zippers (Klepper 1997)—shakeouts even appear to be absent. This variation suggests that the mechanisms driving industry consolidation are not uniform across industries and may depend on industry-specific selection environments.

The central role of the shakeout in the product lifecycle has stimulated extensive debate on its underlying mechanism. Existing explanations can be broadly classified into three categories: efficiency-based, product-based, and demand-based explanations. Efficiency-based explanations interpret the shakeout as the outcome of efficiency differentials that allow more productive firms to expand and displace competitors. Differences across contributions lie in the sources of these efficiency gains, including firms' ability to adopt inventions developed outside the industry (Jovanovic and MacDonald 1994); investments in process R&D (Klepper 1996, 2002), and the way interdependent activities are

conducted (Lenox et al. 2007). Despite these differences, efficiency gains are largely associated with improvements in production processes.²

Product-based explanations instead emphasize competition among product varieties. Product variety may result either from market segmentation or from firms' search for superior product designs. In the former case, shakeouts follow from firms' innovation failures and their exit from active submarkets (Uzunca 2018; Malerba et al. 2016; Bhaskarabhatla and Klepper 2014; Tong 2009; Klette and Kortum 2004). In the latter case, shakeouts occur through the emergence of a *dominant design* that firms must adopt to remain competitive (Furr and Kapoor 2018; Christensen et al. 1998; Suárez and Utterback 1995; Utterback and Suárez 1993). Although both interpretations acknowledge the role of demand, they consider product differentiation mainly in terms of quality rather than in terms of the factors steering the technological development along specific characteristics.

Finally, a third stream highlights the role of demand in shaping shakeouts. Compared to efficiency-based and product-based explanations, this perspective remains underdeveloped. Existing studies primarily integrate and extend the other two approaches (Hubbard and Mazzeo 2019; Jaworski and Smyth 2018; Malerba et al. 2016; Argyres et al. 2015; Windrum and Birchenhall 1998). While these contributions differ in scope and methodology, they share the view that the structure of demand can influence industry selection and market segmentation. For example, Windrum and Birchenhall (1998) show that the emergence of a dominant design may depend on the patterns of consumers' preferences over product characteristics. Depending on how consumers *learn* about the available varieties and how firms innovate, markets may fragment into niches or converge towards a single dominant product. Another example is represented by the work of Malerba, Nelson, Orsenigo, and Winter (2016). In the chapter dedicated to the history of the pharmaceutical industry, they propose an interpretation of industry shakeout based on the interaction between the endogenous discovery of latent submarkets and firm's diversification across submarkets. According to this perspective, demand must be activated by firms through the discovery of valuable products—in their case the therapeutic classes to cure specific diseases—while exits are triggered by the inability to conduct successful R&D.

Despite these contributions, existing explanations are often silent regarding the timing, the duration, and the severity of the shakeout. The anomalies documented by the empirical literature often remain in the background of the analysis or attributed to the exogenous dynamics of specific model elements (Uzunca 2018; Bhaskarabhatla and Klepper 2014; Buenstorf and Klepper 2010). At the same time, these interpretations treat the technological trajectory as given (Buenstorf et al. 2022), focusing primarily on improvements linked to firm efficiency or product quality. Furthermore, while demand is increasingly recognized as a determinant of industry evolution, existing explanations rarely examine how different preference distributions over product characteristics affect the timing, duration, and severity of the shakeout. Yet, empirical studies identify heterogeneity in consumer preferences as a defining feature of industry evolution (Wells 2007; Windrum 2005).

2.2 Product architecture

The research on product architecture has its roots in Simon's (1962) study on the properties of hierarchic structures. In his work, Simon illustrates that human artifacts and biological organisms are often structured as *nearly decomposable systems*, i.e. nested hierarchies of subsystems (or modules) in which intra-subsystems links are stronger than inter-subsystems links. To explain this evidence, he argues that nearly decomposable architectures possess the evolutionary advantage of adapting faster to the external environment than highly interdependent systems. Building on this idea, scholars have investigated the factors influencing the shape of product architectures and their tendency to develop modular designs (Baldwin and Clark 1997; Langlois and Robertson 1992; Henderson and Clark 1990). This literature has produced different explanations for modularity that can be broadly grouped into two research traditions.

² A partial exception is represented by the work of Lenox et al. (2007). Although their model focuses primarily on cost reduction, the authors also provide an appendix extension based on quality improvements. In this sense their contribution can be also connected with the product-based perspective.

The first tradition links adaptability with cost–benefit evaluations and real options (Baldwin 2023; Fujimoto 2012). According to this perspective, product architecture is the outcome of intentional design choices made by firm management to take advantage of the market environment in which the firm operates. Modular designs are chosen because they help the firm to minimize costs and risks, and allow for product customization, quick resource reconfiguration, and diversification (Arrieta et al. 2023; Sanchez et al. 2023; Schilling 2000; Sanchez and Mahoney 1996; Sanchez 1995). The choice of the best architecture is formalized through design rules, while the long-run technological trajectories are largely kept outside the scope of research (Baldwin and Clark 2000).

The second tradition adopts instead an evolutionary perspective and reconnects with historical analyses of technology evolution (Frenken and Nuvolari 2004; Vincenti 1994; Basalla 1988). Works in this research stream emphasize the cumulative and path-dependent nature of architectures (Murmman and Frenken 2006), linking adaptability to firms' *need to survive* rather than to forward-looking decisions to exploit market opportunities. The development of modules is associated with the need to improve product performance without jeopardizing all the benefits of the inherited architecture (Arthur 2009). Technological trajectories are not treated as exogenous but emerge endogenously from the process of architectural improvement.

Despite these differences, the two traditions highlight complementary dimensions of architectural change. The management tradition focuses on product design choices and their connections with industry and firm organization (Murmman and Schuler 2023; Brusoni and Prencipe 2006). This research highlights the benefits of modularity to meet the demand of heterogeneous consumers through product customization. The evolutionary tradition is interested in the long-run forces behind the shape of technological alternatives (Arthur 2009). Works in this second research stream often adopt a complex system perspective to analyze how interdependencies among components influence technological trajectories (Murmman and Frenken 2006; Frenken and Nuvolari 2004).

Market demand is regarded as playing a major role by both traditions (Sanchez et al. 2023; Fujimoto 2014; Schilling 2000). However, the role of heterogeneity in consumers' preferences for architectural evolution remains largely unexplored. When explicitly considered, heterogeneity is typically analyzed over a small number of product characteristics and confined to very extreme cases, while architectures are often assumed either to be modular since the outset or to be easily modularized (Fujimoto 2014; Windrum et al. 2009; Windrum and Birchenhall 1998). This limits our understanding of the mechanisms through which market demand may shape technological trajectories.

2.3 Evolutionary models of innovation

The third research stream relevant to this study is the literature on evolutionary models of innovation. This literature encompasses models inspired by the evolutionary theory of economic change (Nelson and Winter 1982) and the behavioral theory of the firm (Simon 1990; Cyert and March 1963). These models share the view that innovation emerges as the outcome of local problem-solving conducted by boundedly rational heterogeneous agents. However, contributions in this tradition vary substantially in scope and analytical focus: some integrate the behavioral perspective on innovation in traditional industrial organization models, whereas others model industry dynamics as an inherently out-of-equilibrium phenomenon. We focus on contributions that share key features with our approach and highlight how our model differs from them.

Adner and Levinthal (2001) propose a product lifecycle model to study the implications of demand heterogeneity for innovation patterns. In their framework, consumers have different functionality and utility product requirements, while firms compete by choosing profit-maximizing combinations of product and process innovation. Firms are boundedly rational in that their decisions consider only the response of the consumers close to their product offering and treat competitors' strategies as fixed. Despite incorporating demand heterogeneity, Adner and Levinthal (2001) focus exclusively on vertical differentiation, leaving the emergence of submarkets outside the scope of their analysis.

Building on Lancaster's (1966) characteristics-based demand theory, Windrum and Birchenhall (1998) and Malerba, Nelson, Orsenigo, and Winter (2016) depart from this assumption and model products as bundles of characteristics that can address different demand segments. In both works, consumers

evaluate products based on the performance of individual characteristics while firms innovate by changing selected characteristics to increase product attractiveness for targeted consumers. Windrum and Birchenhall (1998) connect the degree of market segmentation and the rise of a dominant design with consumers' learning mechanisms. Malerba, Nelson, Orsenigo, and Winter (2016), instead, propose a history-friendly model on the evolution of the computer industry in which market segments are defined by customers' preferences over computer performance and cheapness. In both models, innovation consists of changes in the performance of product characteristics. However, neither contribution provides an explicit representation of the underlying product architecture. In Windrum and Birchenhall (1998), product architecture is assumed to be fixed and modular, thereby ruling out interdependencies across characteristics. In Malerba et al. (2016), performance improvements are functions of firm strategies and experience, with technology providing only a constraint on the maximum attainable level.

The role of technological complexity is instead central in Marengo and Valente (2010). Building on the complex system perspective (Levinthal 1997; Kauffman 1993; Simon 1962), they model products as systems of interdependent components. Their simulations show that the structure of interdependencies affects industry evolution even when consumers exhibit heterogeneous preferences. At the same time, their product representation requires the number of components to coincide with the number of product characteristics, making the product architecture fixed.

Complexity is also central in Querbes and Frenken's (2017), who study late-mover advantage under evolving user needs. To relax the overlap between components and characteristics, they adopt a product representation in which the number of evaluation dimensions differs from the number of system elements. However, as in Marengo and Valente (2010), product architecture remains exogenous and innovation occurs within a fixed technological trajectory. Moreover, user needs are assumed to coincide with the performance of product characteristics which prevents the rise of mismatches between consumer preferences and firms' technological capabilities.

Our contribution combines elements of these studies while departing from them in key respects. We explicitly model architectural innovation by disentangling product components from product characteristics and allowing interdependencies to evolve over time. In this sense, our work combines the demand-side richness of Windrum and Birchenhall (1998) with a complex product space as in Marengo and Valente (2010) and Querbes and Frenken (2017), providing a more flexible representation of product innovation. Moreover, like Malerba et al. (2016), Adner and Levinthal (2001) and Windrum and Birchenhall (1998), we study the role of heterogeneous consumers in shaping industry dynamics. However, instead of focusing on the degree of heterogeneity, we focus on its *structure* by explicitly characterizing preference distributions. This strategy allows us to identify the channels through which demand shapes industry dynamics and product architecture, and also to investigate the effects of *changes* in preference distributions over time.

Taken together, the literatures on product lifecycle, product architecture, and evolutionary models of innovation shed light on complementary aspects of industry dynamics and innovation. At the same time, few works have proposed a unifying framework tackling the open issues arising from these analyses. In particular, the lifecycle approach fails to explain the cross-industry differences in the maturity stage. The research on product architecture does not study in depth the consequences of preference heterogeneity for architectural evolution. Finally, the literature on evolutionary models of innovation does not provide a structure to different types of demand heterogeneity. For example, although Fujimoto (2014) explicitly connects industry life-cycle with product architecture and demand, the evolutionary search process underlying architectural change remains outside the scope of the analysis.³ Our study contributes in this direction by studying how different types of preference distributions over product characteristics, and changes herein over time, influence industry dynamics and architectural evolution.

³ Our approach differs in three ways. First, we focus on the evolutionary mechanisms shaping architectural change rather than on firm's adoption of alternative architectures. Second, we explicitly consider the interdependencies between market competition and the search for new architectures. Third, we consider more than two product characteristics (price and functional performance).

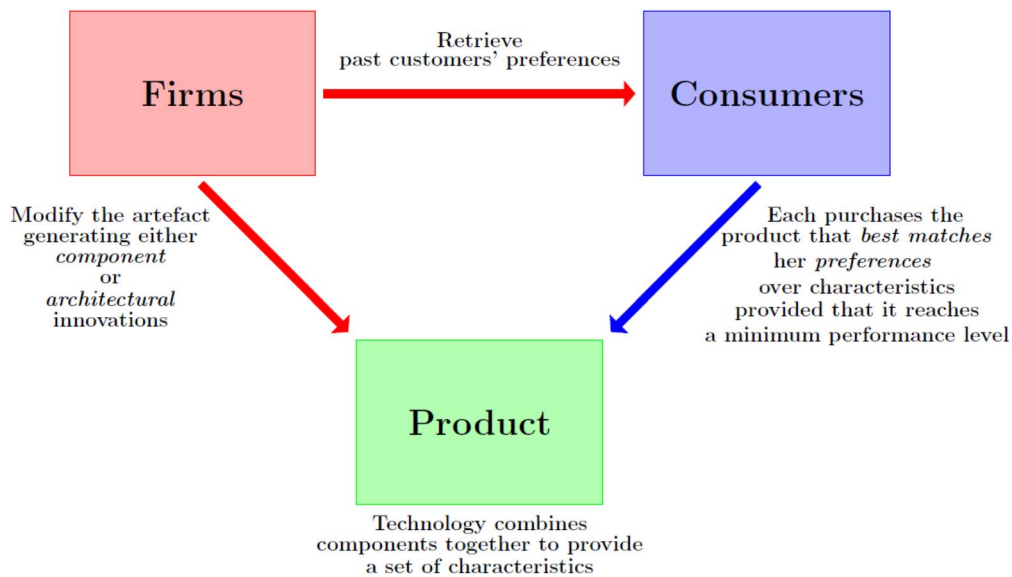


Figure 1 Model framework

3. Model

To investigate *how* the distribution of consumer preferences over product characteristics shapes the industry lifecycle and the evolution of product architecture, we develop a simulation model of market competition with endogenous design and architectural innovation. Building on evolutionary models of economic change (Nelson and Winter 1982) and complex adaptive systems perspectives (Kauffman 1993; Levinthal 1997), the model features three core elements, illustrated in Figure 1: (i) a multi-component, multi-characteristic product; (ii) heterogeneous consumers with preferences over characteristics; and (iii) competing firms that innovate by changing product design.

At the center of our framework lies the multi-characteristic product. Multi-characteristic implies that it is evaluated based on the performance of multiple dimensions. For example, smartphones can be evaluated based on their size, their battery performance or the performance of their calls. The performance level of each characteristic depends upon the underlying design of the corresponding components, while the mapping between components and characteristics delineates the product architecture. From a technology perspective, different mappings are associated with different degrees of complexity. Single components can contribute to the performance of different characteristics in different ways, creating design trade-offs. In the smartphone case, larger batteries can last longer but may require larger phone sizes.

On the demand side, consumers make their purchasing decisions based on their preferences for product characteristics. Preferences are represented as F weights β_f (with $f = 1, \dots, F$) assigned to characteristics and used to evaluate product quality. We generate demand heterogeneity by drawing each consumer's modal characteristic and assigning it weight β^{mode} , distributing the remainder equally across the other $F - 1$ characteristics. The concentration parameter β^{mode} is common across consumers within a demand regime, while heterogeneity arises from the identity of the modal characteristic. Consumers are heterogeneous in their preference weights over the characteristics but share the same underlying preference structure.

On the supply side, firms compete for market share by adapting their product design to consumer preferences. They invest in R&D to improve the performance of the characteristics valued by their customer base, which require changes in product design. Design changes occur either through the substitution of an existing component with an alternative one (*component innovation*) or through the introduction of a new component that modifies the mapping between components and characteristics (*architectural innovation*).

Our approach leans on the fact that industries differ in the ways consumers evaluate products. Different weight distributions correspond to different demand regimes. A highly concentrated distribution indicates that consumers place substantial weight on a limited subset of characteristics. This implies that consumers polarize around specific characteristics overlooking all the remaining ones, consistent with what we observe in the laser industry (Bhaskarabhatla and Klepper 2014) and the US car industry before the advent of Ford Model T (Wells 2007). Instead, a diffuse distribution indicates that weights are more evenly allocated across characteristics and consumers value the overall product quality rather than specific attributes. This second type of industries is characterized by a vertical type of product differentiation, where new product generations exhibit higher average quality. Examples include the hard disks industry (Igami and Uetake 2020) and the tires industry (Klepper and Simons 2000).

The intuition is that differences in the demand regimes represent different selection environments and generate different innovation trajectories. The degree of preference polarization steers firm innovation efforts, shaping both the technological tradeoffs and the direction of search required to resolve them. Highly polarized preferences provide firms incentives to focus on few characteristics only while innovation trajectories are driven by the necessity to improve their performance, regardless of the remaining ones. This translates into quality competition for single characteristics and not for the product as a whole. On the contrary, dispersed preferences, require firms to account for the average product performance. When multiple dimensions are considered simultaneously, trade-offs become more binding and can increase the likelihood of technological lock-ins. At the same time, quality competition tends to reduce the viability of underperforming products.

To better isolate the channel linking preference distribution with industry dynamics and product architecture, our model makes simplifying assumptions about all those factors connected to alternative interpretations of lifecycle dynamics and modular designs that may interfere with the model results. First, we abstract from cost functions, economies of scale, limits to production capacity and network effects (Arthur 1989; David 1985; Jovanovic 1982; Klepper 1996; Lenox et al. 2007). These mechanisms affect industry structure through cost-side selection and scale economies. Our goal is to isolate the demand-side selection mechanism operating through preference heterogeneity.

Second, we do not explicitly model product prices but consider them as one among the many characteristics considered by consumers. This choice is driven by the fact that the aspect of demand we want to capture is not necessarily driven by price trends, but rather, to the mix of a—more or less narrow—number of dimensions. To be able to do that, we also assume that unitary costs are fully repaid by any unit of product sold.⁴

Our ultimate goal is not to provide an explanation that overtakes the previous ones, but an alternative view that can complement the previous ones in explaining industry lifecycles and technology evolution.

In what follows, we describe each element in detail.

3.1 The multi-functional product

Following the literature on technological evolution (Arthur 2009; Dosi and Nelson 2010), we represent a product as a set of N components whose configuration determines a set of F product characteristics. The quality of each characteristic depends on the design of the interdependent components that contribute to it. Improving product quality, thus, implies finding a superior components' design.

To formalize this structure, we adopt a generalized NK framework (Altenberg 1994; Frenken 2006). The generalized NK extends Kauffman's (1993) original NK formulation by distinguishing the elements that compose the system from the dimensions upon which the system is evaluated. Figure 2 provides a comparison between the structures of the two types of NK. In Altenberg's (1997) original contribution, the distinction between elements and dimensions served to separate the genotypes from the phenotypes on which the fitness is assessed. In our setting, it provides a natural mapping to model product architecture connecting components to the corresponding characteristics. Components define the space over which firms look for new designs while product characteristics are the dimensions evaluated by consumers. This separation allows architectural change to occur through modifications in the component structure

⁴ An alternative interpretation of our supply-side assumption can be that firms operate under constant returns to scale technology while the product price has a mark-up over the unitary costs.

	n_1	n_2	n_3	n_4	n_5					
$f_1 = n_1$	X	X		X						
$f_2 = n_2$		X	X	X						
$f_3 = n_3$			X	X	X					
$f_4 = n_4$	X			X	X					
$f_5 = n_5$		X	X			X				
(A) <i>traditional NK</i>										
	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	
f_1	X	X	X	X	X	X	X			
f_2	X			X	X	X	X	X	X	
f_3	X	X	X	X			X	X	X	
f_4	X	X	X	X	X	X	X			
(B) <i>generalised NK</i>										

Figure 2 Structure comparison of NK models. *Note.* The two panels show the structures of the traditional and the generalized NK. Panel (A) shows the structure for a traditional NK with $N = 5$ and $K = 3$. Panel (B) shows the structure for a generalized NK with $N = 9$, $F = 4$, pleiotropy = 7, and variable pleiotropy.

without altering the evaluation dimensions, a feature that cannot be accommodated with the traditional NK formulation where elements and evaluation dimensions coincide.⁵

As in standard NK, the generalized version defines a landscape over the 2^N combinations of an N -bit string. Each bit can take value zero or one, indicating two alternatives. For example, in the case of a mobile phone, a bit may represent the choice between a plastic chassis (0) and a metallic chassis (1). Unlike traditional NK, however, interdependencies are not summarized by a single parameter K . Instead, they are decomposed into two dimensions: *pleiotropy* and *polygeny*. Pleiotropy denotes the number of characteristics affected by a specific component, capturing interdependencies *across* characteristics. Polygeny denotes the number of components contributing to a given characteristic, capturing the interdependencies *within* that characteristic. In the generalized NK structure reported in Figure 2, the pleiotropy set of a specific component is represented by the “x” symbols in the corresponding column, whereas the polygeny set of a specific characteristic is represented by the “x” symbols in the corresponding row.

The structure of the interdependence between the N components and the F characteristics delineates the product architecture. For each characteristic, a random contribution drawn from a $[0, 1]$ uniform distribution is assigned to every configuration of the components belonging to its polygeny set. This implies that, for a given combination of the N -bit string, the generalized NK associates F performance values w_f (with $f = 1, \dots, F$). The quality of a product depends on the way consumers preferences aggregate these performance values.

⁵ Adner et al. (2014) and Csaszar and Levinthal (2016) propose two NK models in which the same N elements are evaluated over multiple fitness levels. Our approach represents a generalization since we do not impose that all the N components directly influence all the F characteristics.

3.2 Consumers

The demand-side of the market is modeled as a set of I consumers with heterogeneous preferences for the performance of (i) the whole product and of (ii) single characteristics.⁶ Preferences for product performance are represented by minimum quality thresholds W^i (with $i = 1, \dots, I$) drawn from a $[0, 1]$ uniform distribution. In each point in time t , a consumer i considers for purchase only the product varieties with a quality greater or equal to W^i . If no variety satisfies this condition, she does not make any purchase.

The quality of product A for consumer i is measured as a *weighted average* of the performance of A 's characteristics

$$W_A^i = \sum_{f=1}^F \beta_f^i \bullet w_{A,f} \quad \text{with } \sum_{f=1}^F \beta_f^i = 1 \quad (1)$$

where the weight $\beta_f^i \in [0, 1]$ represents consumer i 's preference over product characteristic f . Consumers share the same weight distribution but differ in the allocation of single weights to product characteristics. This implies that consumers have the same preference structure but differ in their preferences over single characteristics.

We assume that each consumer purchases a maximum of one product unit per period by picking the variety with the highest $W^i \geq \bar{W}^i$.

3.3 Firms

Firms compete to increase their customer base by improving product quality. To improve the quality of its product, a firm must change its design. We assume that firms are *heterogeneous* in their technological capabilities and *boundedly rational* (Cyert and March 1963; Gavetti et al. 2012). Heterogeneity implies that each firm is associated with a different generalized NK landscape evaluated over the same F characteristics. This guarantees that they all compete for the same goal but differ in the effectiveness (given the stochastic nature of the landscapes). Bounded rationality implies that firms do not a priori know superior designs within single landscapes, but must engage in a search process. This process requires every firm to decide, at each point in time t , (i) the *search direction* and (ii) the *type* of innovation activity.

We assume that firms rely on the information they gather from their customers to decide for the search direction. They redirect their efforts to improve the performance of the characteristic that is appreciated the most by their customer base. Formally, firm j seeks to improve the performance of the characteristic f^* that had the highest average evaluation

$$\bar{\beta}_f = \frac{1}{I_j} \sum_{i \in I_j} \beta_f^i \quad \text{with } f = 1, \dots, F \quad (2)$$

among its customer base I_j in the preceding period.

In terms of innovation types, firms must decide between (i) *component* and (ii) *architectural* innovations. Component innovation is defined as one-bit mutation in product design and implies a movement *within* a given landscape. This is an incremental change for the structure of interdependencies connecting components and characteristics remains the same. We assume that component innovation is the first type of innovation a firm tries to conduct after the identification of search direction. This process is modeled as a greedy-local search over the bits included in the polygeny set of f^* . If there exist product designs with a strictly higher w_{f^*} compared to the current one, then the firm adopts the one with the highest value. Otherwise, she attempts an architectural innovation.

⁶ This way of modeling heterogeneous preferences is common in the literature following Lancaster's (1966) demand theory (e.g. Malerba et al. 2016; Marengo and Valente 2010; Windrum et al. 2009; Frenken 2006; Windrum and Birchenhall 1998). However, few contributions focus on the shape of preference distribution, and when they do—as, for example, Windrum et al. (2009) and Windrum and Birchenhall (1998)—they use multiple parameters to define the difference between preferences over product characteristics and prices. Instead, we use a different approach, and define the distribution of preferences by defining the mode of the distribution and include product price as one of the many characteristics.

Architectural innovations are more uncertain than component innovations and involve changes in the interdependencies between components and characteristics (Henderson and Clark 1990). Following Altenberg (1994), we model this process through a three-steps *constructional selection mechanism* that adds a new component to current architecture. In the first step, the pleiotropy set of the new component is randomly drawn among the F product characteristics. The only constraint we impose is the presence of f^* in this set. This condition guarantees that the architectural change affects the characteristic of interest. In the second step, all the performance values w_f associated with the characteristics included in the pleiotropy set of the new component are redrawn. Finally, the new component is randomly assigned a value between 0 and 1. The new architecture is accepted only if it increases the appreciation of firm's customer base, i.e. iff $\sum_{f=1}^F \bar{\beta}_f \bullet w_f^{new} > \sum_{f=1}^F \bar{\beta}_f \bullet w_f^{old}$. If otherwise, the firm resorts to the old architecture.

When architectural innovation is successful, the number of product components increases by one and the size of the landscape doubles. By acting on one or more polygeny sets, the constructional selection mechanism is associated with an increase in within-characteristics complexity. However, the stochastic nature of component pleiotropy combined with the decision process mechanism leaves undetermined the cross-characteristics interdependency.

While the search for component innovation is bounded by neighboring designs, the search for architectural innovation is bounded by the resources accumulated in the past. Every product unit sold represents a resource whereas any attempted architectural innovation costs one resource unit. A firm can look for new product architectures as long as the difference between the number of units sold starting from its market entrance and the number of architectural innovation attempts is positive.

4. Analysis

4.1 Simulation settings and experiments

We analyze the properties of the model introduced in the previous section by studying the simulation outcomes under four different types of preference distribution. Each distribution is characterized by a specific value of β^{mode} and represents a different scenario.

The first scenario features $\beta^{mode} = 1$, implying that consumers are interested in one product characteristic only and do not consider the remaining $F - 1$ ones at all. This is the case of maximum demand *polarization* of preferences which creates incentives for market segmentation through horizontal product differentiation.

The second scenario lies at the opposite side of the spectrum and features $\beta^{mode} = \frac{1}{F}$. Under this regime, consumers are indifferent across product characteristics. This makes them homogeneous in weight allocation while remaining heterogeneous in the minimum quality thresholds W^i . In terms of competition, the $\beta^{mode} = \frac{1}{F}$ scenario fosters the rise of vertical product differentiation.

The remaining scenarios represent two intermediate regimes. The first one features $\beta^{mode} = 0.7$. It represents a situation in which consumers have a clear preference for one product characteristic without completely overlooking the remaining $F - 1$ ones. Compared to the $\beta^{mode} = 1$ case, the $\beta^{mode} = 0.7$ regime allows firms to compete along secondary characteristics. At the same time, these latter cannot fully compensate for large gaps in the performance of the main characteristic.

The second intermediate scenario features $\beta^{mode} = 0.5$. This is a further step towards the $\beta^{mode} = \frac{1}{F}$ regime. Under this regime, the modal characteristic receives half of total weight, while the remaining half is distributed across the other dimensions. Performance improvements in non-modal characteristics can partially offset weaknesses in the focal dimension, although the latter remains pivotal for demand.

We study the effect of the four demand regimes through two experiments. In the first experiment, we keep preferences fixed throughout the simulations and compare the outcomes of the four different β^{mode} scenarios. Furthermore, we allow firms only to exit and not to enter the market. If a firm has zero sales for three consecutive periods, it is considered bankrupt. This strategy allows us to isolate the effects of demand regime on market concentration and product architectures abstracting from any entry dynamics. To keep the number of parameters as parsimonious as possible, we set the number of initial firms equal to the number of product characteristics F and the number of consumers equal to

$10 \times F$. This symmetric initialization ensures that, under $\beta^{mode} = 1$, each characteristic can initially be served by at least one firm.

In the second experiment, we depart from the assumption of fixed preferences and examine the *dynamic* effects of changes in demand on market structure and product architecture. To this end, we allow for preferences to change from $\beta^{mode} = 1$ with maximum demand polarization to $\beta^{mode} = \frac{1}{F}$ marked by indifference for characteristics, and passing through the intermediate cases of $\beta^{mode} = 0.7$ and $\beta^{mode} = 0.5$. The sequence from the polarized case to the indifference case resonates the aforementioned empirical studies on the laser, car, hard disks and tire industries (Igami and Uetake 2020; Bhaskarabhatla and Klepper 2014; Wells 2007; Klepper and Simons 2000), with preferences being highly heterogeneous in the early stage of industry evolution giving rise to horizontal product differentiation, and becoming more aligned in later stages giving rise to vertical product differentiation. The manipulated dimension is thus no longer the *type* of preference distribution as in the first experiment, but the *timing* of the transition between regimes. Second, to further analyze the effects of changes in preference distribution on industry dynamics, we allow for market entries and product imitation. Market entries are modeled through a constant rate of three new firms per period. Every new firm imperfectly imitates the product of one of the incumbents. Imitation implies that the entrant adopts the same landscape—i.e. component—characteristic interdependencies and fitness contributions—of the existing firm. Yet, this process is imperfect because the location within the landscape—i.e. the product design and the performance of its characteristics—is randomly drawn among the 2^N possible configurations. Moreover, the imitated firm is stochastically chosen with selection probabilities proportional to incumbents' market share.

To account for all the stochastic elements related to the landscape generating process, the search, and the entry dynamics, each configuration is replicated 10,000 times and we report mean outcomes. Due to the differences in the types of experiments, we also set two different numbers of time steps. The first experiment lasts 30 periods while the second one lasts 120 periods. The larger number of time periods of the second experiment is chosen to provide a direct comparison between the two settings. When the duration of the demand regimes is the same, the four phases of the second experiment can be easily related with the four scenarios in the first experiment. As a final note, the outcomes reported in the next pages have been generated by setting $F = 7$ and every product initially made of one component with a pleiotropy equal to F . This configuration corresponds to a fully integrated initial architecture, allowing modularization to emerge endogenously. Alternative parametrizations produce qualitatively similar patterns, while chosen configuration improves computational tractability.

4.2 Experiment 1: effects with stable demand regimes

Stable preference distributions over product characteristics exert three effects. First, greater preference concentration attenuates firm exits, leading to less pronounced shakeouts. Second, demand regimes influence the length of the shakeout, with intermediate scenarios displaying longer periods of reduction in the number of market participants. Thirdly, architectural evolution responds nonlinearly to demand polarization, with the $\beta^{mode} = 0.5$ regime showing the largest degree of product modularity. Figure 3 illustrates the evolution of the number of surviving firms in each of the four scenarios (Panel A) and the average degree of modularity of surviving firms' products for $\beta^{mode} = \{1, 0.7, 0.5, \frac{1}{F}\}$ in three distinct periods of the simulations (Panel B). Following Frenken (2006), product modularity is measured as the distance between the maximum system pleiotropy (where each component has pleiotropy F) and the *actual* system pleiotropy.⁷

When focusing on surviving firms (Panel A), all demand regimes generate an increase in concentration; however, the magnitude and the duration of the shakeout vary systematically with β^{mode} . On the

⁷ Formally, by indicating as

- P_n the pleiotropy of the n -th component;
- $P = \log_F \left(\prod_{n=1}^N P_n \right)$ the actual system pleiotropy;
- $P_{max} = \log_F F^N = N$ the maximum system's pleiotropy;

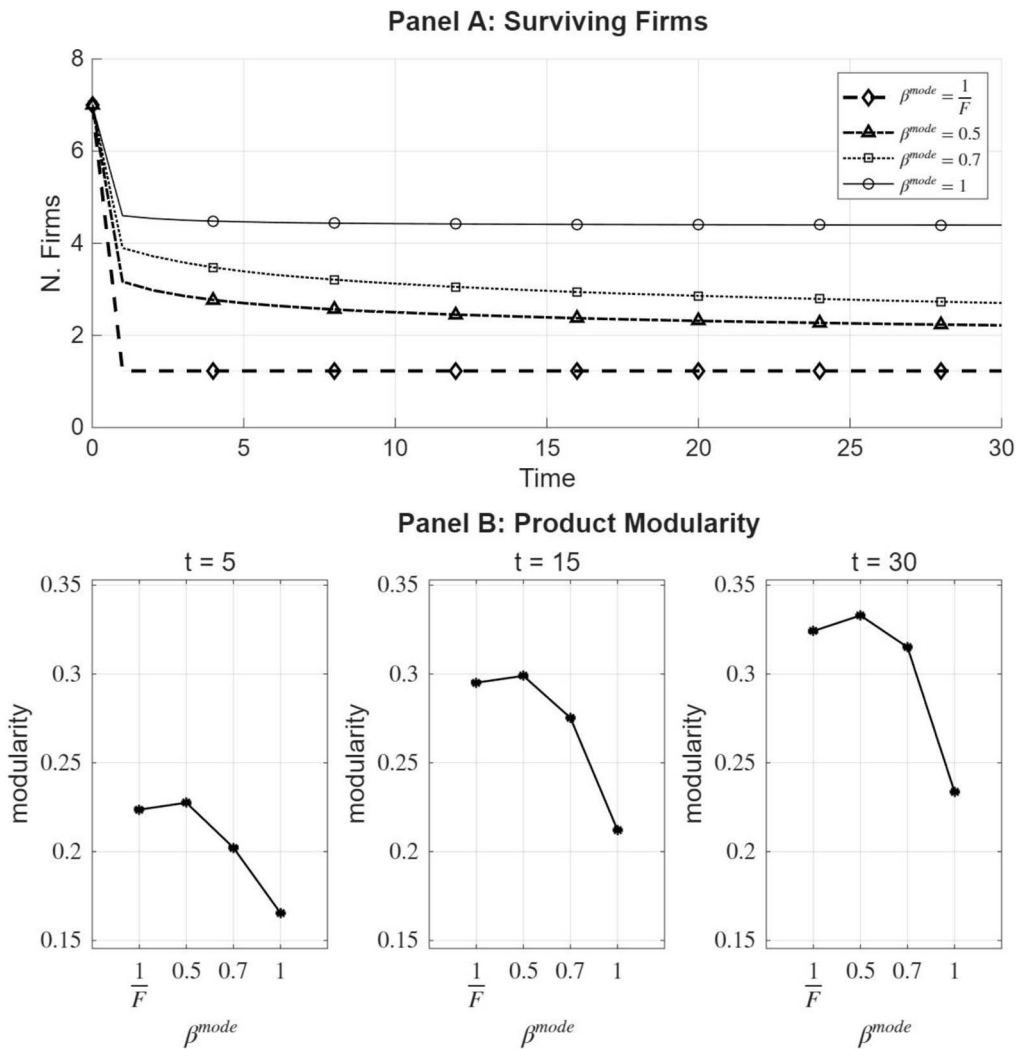


Figure 3 Surviving firms and product modularity—constant preferences. *Note:* The two panels report the averages of 10,000 simulations. Panel A plots the number of surviving firms (y-axis) over time (x-axis) and across scenarios. Panel B compares the average degree of product modularity (y-axis) across the four scenarios (x-axis) in three different periods ($t = 5, 15, 30$). Modularity is computed through the index proposed by [Frenken \(2006\)](#).

one hand, the number of active firms exhibits a reduction in all four demand regimes while, on the other hand, the intensity of this contraction changes based on β^{mode} . The first evidence indicates that submarkets are not determined solely by demand or supply, but by the matching between demand conditions and firms' technological capabilities. Even in the presence of maximum polarization, firms that do not meet consumers' requirements for the focal characteristics fail to survive. This implies that submarkets are not exogenous, but they are endogenously determined. The second evidence, instead, highlights a monotonic relationship between preference distribution and submarkets: higher β^{mode} values are associated with a larger number of surviving firms.

the system modularity index M is computed as

$$M = \frac{\log_F F^N - \log_N \left(\prod_{n=1}^N P_n \right)}{N} = 1 - \frac{P}{N}.$$

At the same time, the length of the reduction phase is also influenced by the type of consumers populating the market. While for $\beta^{mode} = \{1, \frac{1}{F}\}$ the number of surviving firms stabilizes almost immediately, for $\beta^{mode} = \{0.7, 0.5\}$ the reduction of the number of active firms continues even after the initial peak. These differences follow from the possible technological trajectories offered by the degree of preference polarization. Under the $\beta^{mode} = \{1, \frac{1}{F}\}$ regimes, firms reach very quickly the technological frontier, stabilizing the market structure. By contrast, under the $\beta^{mode} = \{0.7, 0.5\}$ regimes, firms have substantial room for developing their products thanks to performance improvements in non-pivotal characteristics. This possibility helps some of them attract new consumers and erode the customer base of weaker competitors.

On the technology side (Panel B), different demand regimes translate into different evolutions of product architectures. Despite the tendency of products to become more modular over time in all scenarios, the relationship between β^{mode} and modularity displays an inverted U-shape. Architectures reach the highest degree of modularity when $\beta^{mode} = 0.5$, whereas the $\beta^{mode} = \{0.7, \frac{1}{F}\}$ regimes exhibit lower and comparable degrees. Finally, under the highly polarized case ($\beta^{mode} = 1$), architecture remains comparatively more integrated.

What drives this evolution? The increase in the degree of modularity highlights two important aspects concerning the relationship between demand regimes and modular architecture. First, in line with [Altenberg \(1994\)](#), increases in modularity emerge endogenously from *evolutionary forces* operating under *stable* selection environments. The need to survive requires firms to adopt strategies that improve the fitness of their products to the corresponding demand regime without jeopardizing the achieved performance level. To minimize this risk, architectural innovations need to avoid creating new tradeoffs among product characteristics that require radical changes in components' design. Thus, new components need to affect a limited number of characteristics through a low degree of pleiotropy. These targeted changes are at the basis of increasing modularity.

Second, the *extent* of this transformation towards modularity depends on the dynamics generated by the specific type of demand faced by firms. This outcome follows from two forces triggered by preferences over product characteristics that vary in *opposite ways* with preference polarization. On the one hand, the influence of the demand regime on market segmentation affects the number of resources at a firm's disposal for attempting architectural innovations. [Figure 4A](#) shows that the number of resources accumulated by surviving firms is inversely proportional to β^{mode} . While increasing survival rates, higher degrees of preference polarization around single characteristics decrease the average number of customers -hence resources- per firm. This translates into a lower number of possible attempts to modify product architecture to overcome technological local optima. Since searching for new architecture is costly and uncertain, the number of resources at a firm's disposal is also connected with the probability of search success. As proof of this, [Figure 4B](#) illustrates that the evolution in the number of components changes across the scenarios. In more polarized regimes, products tend to have fewer components compared to the $\beta^{mode} = 0.5$ and $\beta^{mode} = \frac{1}{F}$ cases.

On the other hand, a demand regime is also connected to search costs by delineating the tradeoffs and the opportunities for search activity. [Figure 5A](#) shows that the number of attempts before the discovery of a valid innovation increases through the industry lifecycle but is inversely proportional to β^{mode} . At the initial stage, products are simple and can be developed along different trajectories. It is easy for firms to discover new architectures that enhance product performance. As industry matures, the constraints exerted by the demand regimes become binding, creating different technological trajectories for different distributions of preferences. These trajectories translate into different requirements for changes in architecture. [Figure 5B](#) indicates that the evolution of pleiotropy of the newly added components varies across demand types. The extreme scenarios ($\beta^{mode} = \{1, \frac{1}{F}\}$) exhibit a small reduction in the number of characteristics affected by the last component compared to the intermediate ones ($\beta^{mode} = \{0.7, 0.5\}$).

When preferences are highly polarized, a firm's search activity is constrained only by the characteristic preferred by the corresponding market segment. Any effect on the remaining characteristics is uninfluential, making the degree of pleiotropy of the newly added component less consequential for product performance. This irrelevance keeps search costs low, requiring only few attempts before finding valuable architectural innovations.

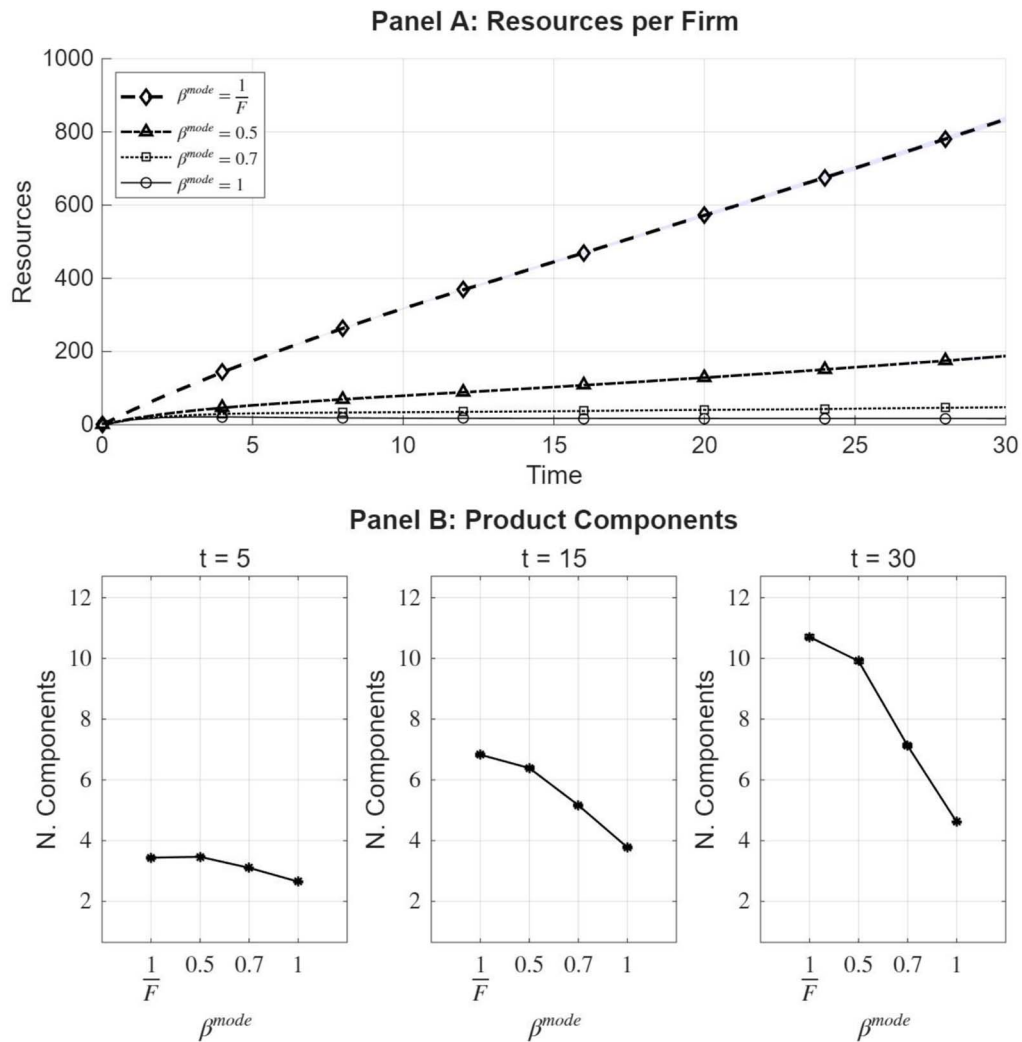


Figure 4 Firm resources and product components—constant preferences. *Note.* The two panels report the averages of 10,000 simulations. Panel A plots the average number of resources per firm (y-axis) over time (x-axis) and across scenarios. Panel B compares the average number of product components (y-axis) across the four scenarios (x-axis) in three different periods ($t = 5, 15, 30$).

When preferences are evenly distributed, instead, the characteristics' average performance becomes more important than a single characteristic performance. Under the $\beta^{mode} = \frac{1}{F}$ regime, changing multiple characteristics may have relevant repercussions on product success and firms must carefully consider the interdependencies generated by product architecture. Search costs are higher because viable architectural innovations must satisfy tighter cross-characteristic constraints. At the same time, the pleiotropy of the new component does not need to be extremely low: if the new component creates complementarities between characteristics, then it will positively contribute to product performance.

In intermediate scenarios, search constraints lie in between the extreme cases. They are less binding than in $\beta^{mode} = \frac{1}{F}$ since one characteristic dominates the others. At the same time, they are higher than in $\beta^{mode} = 1$ because consumers consider more than one dimension to choose their products. While the multiplicity of characteristics may be helpful for design innovations, it nevertheless creates incentives for reducing as much as possible interdependencies across characteristics. Compared to the $\beta^{mode} = \frac{1}{F}$ case, this need is stronger because complementarities can be leveraged only partially due to

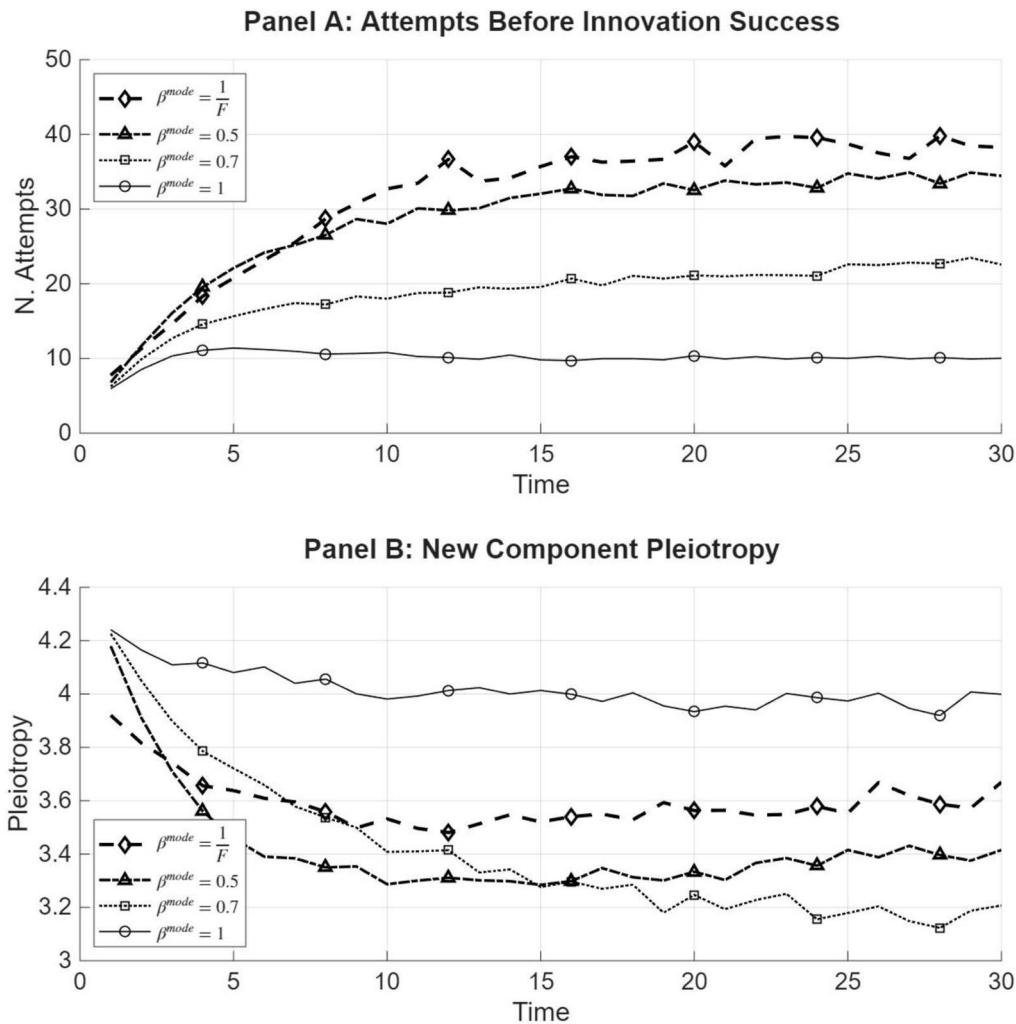


Figure 5 Innovation attempts and new component pleiotropy. *Note.* The two panels report the averages of 10,000 simulations. Panel A plots the average number of trials before finding a valuable architectural innovation (y-axis) over time (x-axis) and across scenarios. Panel B plots the average degree of pleiotropy of the newly added component (y-axis) over time (x-axis) and across scenarios. Data refer to firms that successfully innovate in every period.

asymmetries in preferences. As a result, in the $\beta^{mode} = \{0.7, 0.5\}$ scenarios, the pleiotropy of the newly added component decreases more and faster than in the other two demand regimes.

The tension between the effects on resources and the effects on search costs and tradeoffs generates the inverted-U shape in Figure 3B. Under the $\beta^{mode} = 1$ regime, modularity remains low because resource scarcity limits architectural experimentation and performance evaluation focuses narrowly on a single dimension. Under the $\beta^{mode} = \frac{1}{F}$ regime, modularity is not at its highest because search is costly and medium pleiotropy components can nevertheless help firm performance. Finally, under the intermediate regimes, the degree of modularity depends on resource constraints while the need for low pleiotropy components is high. When $\beta^{mode} = 0.5$, modularity peaks because the incentive to reduce interdependencies is strong while resource availability remains sufficient to explore alternative architectures.

These findings suggest that, under stable preferences, demand regimes are not merely passive selection environments but active determinants of product architecture, shaping both the pace of industry concentration and the degree of modularization.

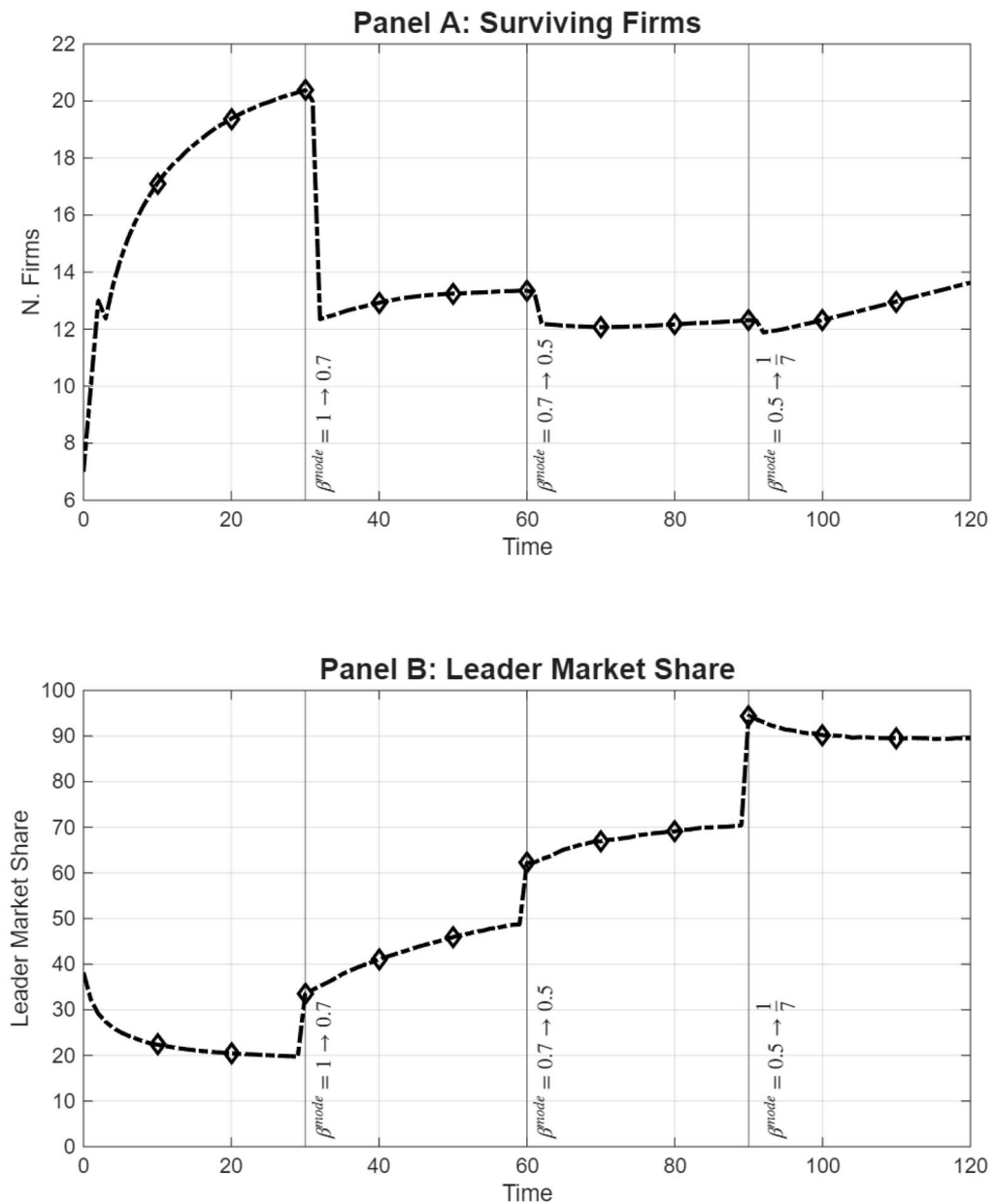


Figure 6 Surviving firms and leader market share—evolving preference. *Note.* The two panels report the averages of 10,000 simulations. Panel A plots the number of surviving firms (y-axis) over time (x-axis) with transitions occurring in $t = 30, 60, 90$. Panel B plots the market share of the market leader (y-axis) over time (x-axis) with transitions occurring in $t = 30, 60, 90$.

4.3 Experiment 2: effects with evolving demand regimes

Allowing demand regimes to change over time reveals two additional mechanisms. First, preference shifts trigger endogenous shakeouts even in the presence of ongoing entries. Second, the timing of these transitions generates path dependent differences in architectural evolution.

Figure 6 illustrates the first effect by showing the evolution of industry when preference distribution changes in periods $t = \{30, 60, 90\}$. Panel A displays the number of surviving firms over time, whereas Panel B displays the market share of the firm with the largest customer base.

The shift in preferences reorders the relative fitness of existing product varieties. This leads to a reallocation of consumers across competing firms. Some firms gain attractiveness thanks to architectural complementarities, while others lose alignment with the new evaluation criteria. This reallocation triggers firm exits and an increase in the leader's market share. The extent of this reduction depends on the transition. The strongest reduction occurs when passing from $\beta^{mode} = 1$ to $\beta^{mode} = 0.7$. This transition activates the evaluation of previously irrelevant characteristics, rewarding product architectures that had built complementarities across characteristics. On the contrary, the severity of the shakeout in the remaining transitions is lower. Because consumers already evaluate the performance of all the characteristics, most surviving products already satisfy the new criteria. As a result, there are fewer inefficient firms—hence fewer exits—than before. In the latest stage, when $\beta^{mode} = \frac{1}{F}$, the number of surviving firms increases. This is due to the constant entry rate assumed by the model. Although this increase suggests a rebound in the degree of market competition, many of the surviving firms remain on the fringe of the market because the leader owns more than 80% of customers.

A second determinant of the shape of the shakeout is the *timing* of the transitions. Figure 7A reports the number of surviving firms under three different transition patterns. The baseline scenario is the case in which every demand regime lasts for 30 periods and changes occur in $t = \{30, 60, 90\}$. A first alternative scenario sees the intermediate regimes $\beta^{mode} = \{0.7, 0.5\}$ lasting longer than the extreme regimes $\beta^{mode} = \{1, \frac{1}{F}\}$, with transitions occurring in $t = \{15, 60, 105\}$. In the second alternative scenario, instead, the extreme regimes last longer and transitions occur in $t = \{45, 60, 75\}$.

From an industry dynamics point of view, the speed of transition influences both the *timing* and the *severity* of the shakeout. An earlier transition from the polarized regime to the $\beta^{mode} = 0.7$ regime anticipates the arrival of the shakeout compared to the baseline case by anticipating the reorder of product varieties. At the same time, the reduction in the number of firms is milder: industries that experience an early change in consumers' preferences are populated by few competitors and reallocation affects a small number of firms. This translates into a smaller number of exits and a milder shakeout. The opposite dynamics occur when the initial and final phases last longer. When the polarized regime persists longer, firms develop architectures specialized along a narrow evaluation criterion. The expansion of evaluation dimension brought about by the transition therefore generates larger misalignment between inherited designs and the new demand regime. Constructional selection implies path dependence in architecture evolution and structural rigidity in the face of environmental changes. When consumers start evaluating a larger number of product characteristics, only few firms are endowed with the necessary technical capabilities.

By changing the evaluation criteria on markets and technologies, the timing of the transition also affects the *speed* and *evolutionary pattern* of increases in modularity. Figure 7B displays the degree of modularity in the three alternative scenarios. Early transitions induce earlier but gradual modularization, whereas late transitions generate sharper post-transition modularization due to a greater resource concentration among survivors. This evidence reconnects with the findings of the model under stable distributions of preferences. When consumers start appreciating multiple characteristics, firms start having higher pressure to find new components with a lower degree of pleiotropy. At the same time, by reshuffling market shares, transition redistributes resources for architectural innovation. As early transitions are associated with milder shakeouts than later ones, surviving firms gain lower resources for their search activity. The change in speed of product modularization when transition is in $t = 15$ is lower than when transition is in $t = 45$. In this second case, surviving firms have more resources and can find valuable architectural innovations faster than in the first case. Early transitions, then, limit resource accumulation before modular pressure intensifies.

Together, these findings show that demand transitions reshape industry structure not only through immediate selection effects but also by interacting with inherited architectures. The timing of demand regime change determines whether industries modularize gradually or through abrupt structural reconfiguration.

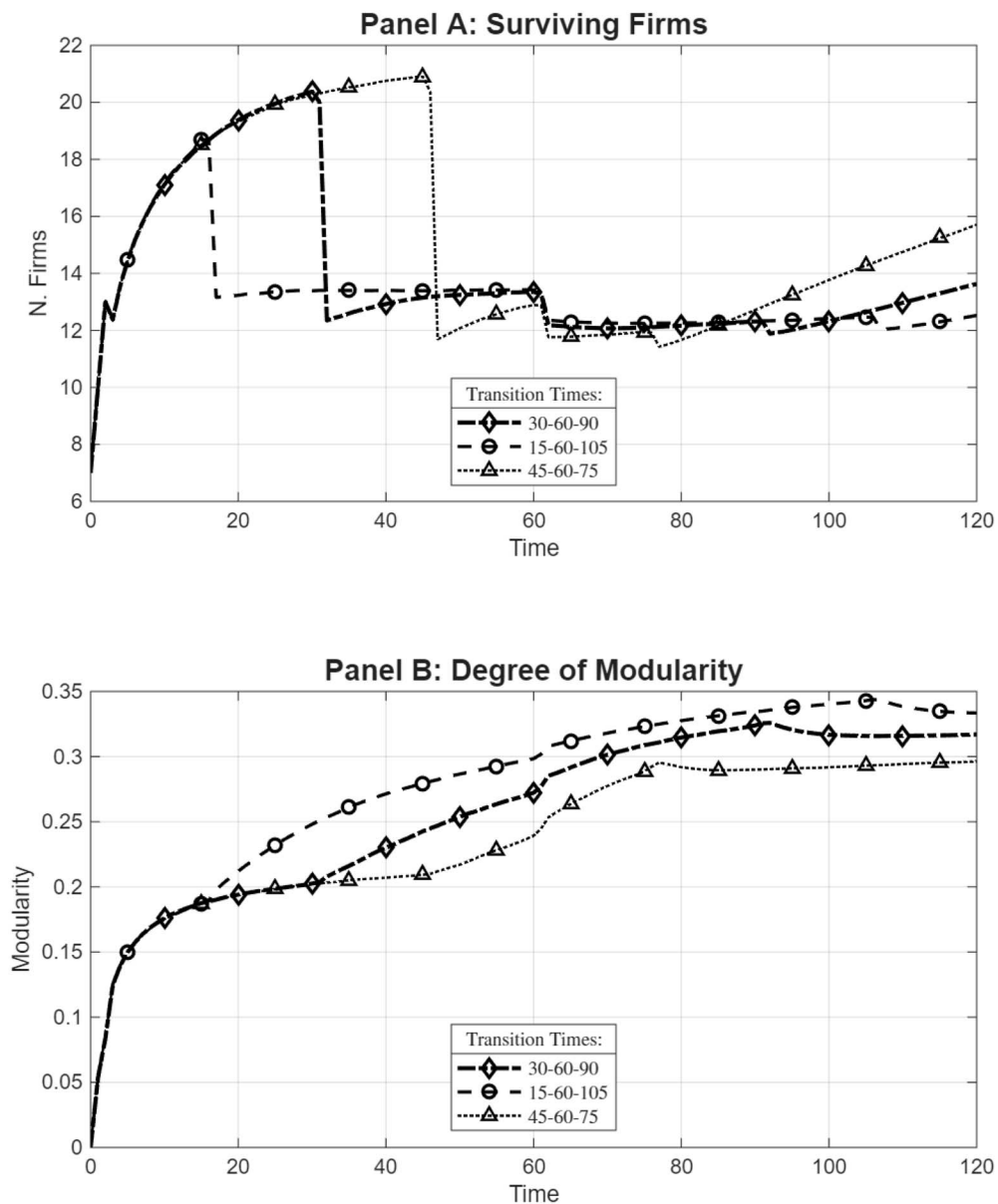


Figure 7 Surviving firms and degree of modularity under different preference evolution patterns. *Note.* The two panels report the averages of 10,000 simulations. Panel A plots the number of surviving firms (y-axis) over time (x-axis) comparing three different transition patterns. Panel B plots the average degree of product modularity (y-axis) over time (x-axis) comparing three different transition patterns. Modularity is computed through the index proposed by Frenken (2006).

5. Discussion and conclusions

This work develops an evolutionary model to study how the distribution of preferences over product characteristics shapes industry dynamics and product architecture. Our findings highlight distinct mechanisms depending on the structure of preferences and changes herein over time. Under *stable* preferences, demand regimes affect both the extent and the duration of industry shakeouts by shaping the direction and feasibility of product innovation. On the technological side, demand regimes influence

the degree of product modularity by jointly determining the resources available for the search of new components and the costs of discovering valuable architectures.

When preferences *change*, the timing of demand regime transitions further shapes industry trajectories. Early versus delayed transitions affect the onset and intensity of the shakeout, as well as the speed of product modularization. Path dependence in architectural evolution generates structural rigidity that amplifies firm exits after a demand shift, while resource redistribution after the shakeout affects the possibility for firms to generate valuable architectural innovations.⁸

These findings contribute to the literature on lifecycle (Klepper 1997; Utterback and Abernathy 1975) by providing a demand-led mechanism for the cross-industry heterogeneity in the maturity stage. Differences in shakeout timing, duration, and intensity emerge from the variation and transitions in demand regimes, providing a unifying explanation for the empirical heterogeneity documented in prior studies. Moreover, our framework provides a new mechanism for market segmentation: submarkets emerge endogenously from the interaction between product characteristics and consumer preferences, and evolve through the joint effects of architectural innovation and changes in demand. This perspective differs from existing accounts which either assume submarkets as exogenous (Buenstorf et al. 2022; Bhaskarabhatla and Klepper 2014) or abstract from the role of product architecture (Uzunca 2018; Malerba et al. 2016; Windrum et al. 2009; Windrum and Birchenhall 1998).

From a product architecture perspective, our results characterize the forces underlying the evolution of modular designs. In particular, by disentangling the effects under stable preferences from those under changing preferences, we show that modularity does not need demand changes to arise. In our framework, increases in modularity follow from the need to improve product performance under survival pressure. On the contrary, demand changes primarily affect the speed rather than the direction of architectural innovation. This perspective differs from the management-based view that sees changes in system modularity as consequential to changes in the environment (Sanchez et al. 2023; Fujimoto 2014; Schilling 2000). At the same time, our results are not in contrast but complementary to the management-based view (Arrieta et al. 2023). Our model explains how different demand regimes affect the *difficulty of discovering*—rather than the incentives to adopt—architectures with a higher degree of modularity. By focusing on the long run, we keep the adoption mechanism as simple as possible, leaving strategic choices outside the scope of our analysis.

More broadly, from an evolutionary perspective, the mechanism underlying the endogenous change in product architecture characterizes technological evolution as the outcome of a search process in a multidimensional space that combines random events with intentional decision making. This is an important departure from the established traditions in the evolutionary economics literature that conceive technological change either as the outcome of random events and learning abstracting from any structure (Dosi et al. 2022; Malerba et al. 2016; Almudi et al. 2013), or as a search process within technological landscapes whose structure is not intentionally shaped by agents (Querbes and Frenken 2017; Marengo and Valente 2010). Our framework is consistent with what Levinthal (2017) characterizes as the “Mendelian executive”, in which firms exercise limited intentionality in shaping technological evolution. However, unlike many previous landscape models, our framework allows architectural innovation to reshape the technological landscape itself.⁹ Selection, therefore, operates at two different distinct levels. The first is conducted by the same boundedly rational firms when choosing architectural innovations. The second is conducted by market demand through competition among products. This double selection mechanism allows to relocate technological path dependence from accumulated

⁸ Key to our contribution is the characterization and the combination of these effects. For example, while studying the role of demand for the pharmaceutical industry, Malerba et al. (2016) already highlight that the success-breed-success dynamic depends on the value of the market rather than on market fragmentation. However, their model does not consider the architecture underlying the therapeutic classes (i.e., the products). In this way, they do not connect a firm's ability to increase/decrease its customer base with the technological architecture of its product that and the implied innovation difficulties.

⁹ An exception is represented by Gavetti et al. (2017) who study the effect of landscape shaping on competition. However, our model departs from theirs from at least two relevant perspectives. First, in their model there exists one landscape only and shaping affects all the firms. Instead, in our case, every firm is associated with its own landscape. Second, Gavetti et al. (2017) model shaping as a change in the fitness values of a landscape, with a given size. In our model, technological shaping implies changing the size and structure of the landscape itself.

knowledge to evolving architectural structures, making technological complexity itself an endogenous outcome of the innovation process.

Taken together, our findings show that the distribution of preferences over product characteristics shapes both competitive dynamics and architectural evolution. By defining product evaluation criteria, they exert a selective force both over existing product varieties and over the possible innovation trajectories, operating both on current selection *and* on future variation of products. The model results for different demand parameters provide a list of predictions that we hope will motivate empirical studies on the effects of demand heterogeneity on market structures and product architectures over time across industries.

In addition to that, the mechanisms underlying the increases in modularity also contribute to the debate on the decreasing returns in R&D. Over the last decades, a vast empirical literature has been revealing a declining trend in R&D productivity (Scannell et al. 2012; Pammolli et al. 2011; Griliches 1994; Kortum 1993). This evidence has been interpreted as the sign that ideas have become harder to find (Bloom et al. 2020), generating decreasing returns in research and development activities. In this context, our results identify a mechanism based on demand heterogeneity and architectural evolution that can contribute to declining research productivity. In our framework, the decreasing returns—represented by the increasing number of attempts needed before finding a valuable architectural innovation—depend on the interaction between demand conditions and technological architecture. Innovations are harder to find because technological trajectories call for novelties that build upon existing architectures without endangering firm survival. When technologies are evaluated over multiple characteristics, this translates into finding solutions that deal with multiple tradeoffs, which may require a large number of attempts as time goes by.

The model is subject to limitations. As indicated in the description, we abstract from any element related to costs and prices. To this extent, we do not analyze process innovation and its relationship with product innovations over the course of the lifecycle. Future works can extend our framework by introducing an evolution of production costs that mirrors product innovation. A possible strategy could be the adoption of an NK landscape for efficiency as done in the study by Lenox et al. (2007). Another limitation is the absence of any strategic consideration regarding the competitive environment. In our model, firms do not consider competitors nor evaluate the environment except for their customer base. Future works may study whether our results are still valid when more elaborated adoption decisions are incorporated into the model. Finally, some works started to question the tendency of increase in modular architectures, providing examples of an increase in complexity and a decrease in modularity (Lim and Fujimoto 2019; Fixson and Park 2008). Even if our theory predicts that modularity tends to increase, it should be noted that complexity within single characteristics (polygeny) increases. What is more, when preference distributions are changing, modularity may even decline (Figure 7B). Furthermore, our work has explored only one way—adding new components—through which product architecture can change. Future works can explore mechanisms in which components can be removed, instead of being added. Moreover, future empirical studies may focus on gathering more information on product architecture and conducting large sample analysis on architectural change.

As a final note, the model proposed in this work has some implications for innovation policies. Our findings suggest that policies that reshape the type of preference structure for technological characteristics should consider the double effects on markets and innovation activities. For example, pushing demand towards a specific mix of product characteristics may increase market concentration and accelerate modularity designs. Policy makers should then evaluate the trade-offs of too stringent standards.

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Conflict of interest

The authors declare that they have no conflict of interest.

References

- Adner, R. and D. Levinthal (2001), 'Demand heterogeneity and technology evolution: implications for product and process innovation,' *Management Science*, **47**(5), 611–628. <https://doi.org/10.1287/mnsc.47.5.611.10482>.
- Adner, R., F. A. Csaszar and P. B. Zemsky (2014), 'Positioning on a multiattribute landscape,' *Management Science*, **60**(11), 2794–2815.
- Agarwal, R. and M. Gort (1996), 'The evolution of markets and entry, exit and survival of firms,' *The Review of Economics and Statistics*, **78**(3), 489. <https://doi.org/10.2307/2109796>.
- Almudi, I., F. Fatas-Villafranca and L. R. Izquierdo (2013), 'Industry dynamics, technological regimes and the role of demand,' *Journal of Evolutionary Economics*, **23**(5), 1073–1098. <https://doi.org/10.1007/s00191-013-0303-y>.
- Altenberg, LEE. 1994. "Evolving better representations through selective genome growth." *Proceedings of the First IEEE Conference on Evolutionary Computation IEEE World Congress on Computational Intelligence ICEC-94*, 182–87 vol. 1, Orlando, FL, USA. <https://doi.org/10.1109/ICEC.1994.350019>.
- Altenberg, L. (1997), 'Fitness landscapes: NK landscapes,' in Back and Fogel. (ed), *Handbook of Evolutionary Computation*. Oxford University Press: New York, NY.
- Argyres, N., L. B. Bigelow and J. Nickerson (2015), 'Dominant designs, innovation shocks, and the Follower's dilemma,' *Strategic Management Journal* **36**(2), 216–234.
- Arrieta, J. P., R. Fontana and S. Brusoni (2023), 'On the strategic use of product modularity for market entry,' *Industrial and Corporate Change*, **32**(1), 155–180. <https://doi.org/10.1093/icc/dtac053>.
- Arthur, W. B. (1989), 'Competing technologies, increasing returns, and lock-in by historical events,' *The Economic Journal*, **99**(394), 116–131. <https://doi.org/10.2307/2234208>.
- Arthur, W. (2009), *The nature of technology: What it is and how it evolves*. Free Press: New York, NY.
- Baldwin, C. (2023), 'Design rules: past and future,' *Industrial and Corporate Change*, **32**(1), 11–27. <https://doi.org/10.1093/icc/dtac055>.
- Baldwin, C. and K. Clark (1997), 'Managing in an age of modularity,' *Harvard Business Review*, **75**(5), 84–93.
- Baldwin, C. and K. B. Clark (2000), *Design Rules, Volume 1: The Power of Modularity*. MIT Press: Cambridge, MA.
- Baldwin, C., A. MacCormack and J. Rusnak (2014), 'Hidden structure: using network methods to map system architecture,' *Research Policy*, **43**(8), 1381–1397.
- Basalla, G. (1988), *The Evolution of Technology*. Cambridge University Press: Cambridge, UK.
- 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. <https://doi.org/10.1093/icc/dtt060>.
- Bloom, N., C. I. Jones, J. Van Reenen and M. Webb (2020), 'Are ideas getting harder to find?' *American Economic Review*, **110**(4), 1104–1144. <https://doi.org/10.1257/aer.20180338>.
- Brusoni, S. and A. Prencipe (2006), 'Making design rules: a multidomain perspective,' *Organization Science*, **17**(2), 179–189. <https://pubsonline.informs.org/doi/abs/10.1287/orsc.1060.0180>.
- Buenstorf, G. and S. Klepper (2010), 'Submarket dynamics and innovation: the case of the US tire industry,' *Industrial and Corporate Change*, **19**(5), 1563–1587. <https://doi.org/10.1093/icc/dtq044>.

- Buenstorf, G., C. Guenther and S. Wilfling (2022), 'Submarket emergence, customer base expansion and strategic entry timing in the evolution of the German farm tractor industry,' *Industrial and Corporate Change*, **31**(4), 1086–1112.
- Christensen, C. M., F. F. Suárez and J. M. Utterback (1998), 'Strategies for survival in fast-changing industries,' *Management Science*, **44**(12-part-2), S207–S220. <https://doi.org/10.1287/mnsc.44.12.S207>.
- Csaszar, F. A. and D. A. Levinthal (2016), 'Mental representation and the discovery of new strategies,' *Strategic Management Journal*, **37**(10), 2031–2049. <https://doi.org/10.1002/smj.2440>.
- Cyert, R. M. and J. G. March (1963), *A Behavioral Theory of the Firm*. Prentice Hall: Englewood Cliffs, NJ.
- David, P. A. (1985), 'Clio and the economics of QWERTY,' *The American Economic Review*, **75**(2), 332–337.
- Dosi, GIOVANNI, and RICHARD R. Nelson. (2010), 'Technical change and industrial dynamics as evolutionary processes,' in B. H. Hall and N. Rosenberg (eds), *Handbook of the Economics of Innovation*, vol. **1**. North-Holland: Amsterdam. [https://doi.org/10.1016/S0169-7218\(10\)01003-8](https://doi.org/10.1016/S0169-7218(10)01003-8).
- Dosi, G., M. C. Pereira, A. Roventini and M. E. Virgillito (2022), 'Technological paradigms, labour creation and destruction in a multi-sector agent-based model,' *Research Policy*, **51**(10), 104565. <https://doi.org/10.1016/j.respol.2022.104565>.
- Fixson, S. K. and J.-K. Park (2008), 'The power of Integrality: linkages between product architecture, innovation, and industry structure,' *Research Policy, Special Section on University-Industry Linkages: The Significance of Tacit Knowledge and the Role of Intermediaries*, **37**(8), 1296–1316. <https://doi.org/10.1016/j.respol.2008.04.026>.
- Frenken, K. (2006), 'A fitness landscape approach to technological complexity, modularity, and vertical disintegration,' *Structural Change and Economic Dynamics*, **17**(3), 288–305. <https://doi.org/10.1016/j.strueco.2006.01.001>.
- Frenken, K. and A. Nuvolari (2004), 'The early development of the steam engine: an evolutionary interpretation using complexity theory,' *Industrial and Corporate Change*, **13**(2), 419–450. <https://doi.org/10.1093/icc/dth017>.
- Fujimoto, T. (2012), 'An economic analysis of architecture and coordination: applying Ricardian comparative advantage to design costs and locations,' *Evolutionary and Institutional Economics Review*, **9**(1), 51–124. [10.14441/eier.A2012004](https://doi.org/10.14441/eier.A2012004).
- Fujimoto, T. (2014), 'The long tail of the auto industry life cycle,' *Journal of Product Innovation Management*, **31**(1), 8–16.
- Furr, N. and R. Kapoor (2018), 'Capabilities, technologies, and firm exit during industry shakeout: evidence from the global solar photovoltaic industry,' *Strategic Management Journal*, **39**(1), 33–61. <https://doi.org/10.1002/smj.2709>.
- Gavetti, G., H. R. Greve, D. A. Levinthal and W. Ocasio (2012), 'The Behavioral theory of the firm: assessment and prospects,' *Academy of Management Annals*, **6**(1), 1–40. <https://doi.org/10.5465/19416520.2012.656841>.
- Gavetti, G., C. E. Helfat and L. Marengo (2017), 'Searching, shaping, and the quest for superior performance,' *Strategy Science*, **2**(3), 194–209. <https://doi.org/10.1287/stsc.2017.0036>.
- Gort, M. and S. Klepper (1982), 'Time paths in the diffusion of product innovations,' *The Economic Journal*, **92**(367), 630–653. <https://doi.org/10.2307/2232554>.
- Griliches, Z. (1994), 'Productivity, R&D, and the data constraint,' *The American Economic Review*, **84**(1), 1–23.
- Henderson, R. M. and K. B. Clark (1990), 'Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms,' *Administrative Science Quarterly*, **35**(1), 9–30. <https://doi.org/10.2307/2393549>.
- Hubbard, T. N. and M. J. Mazzeo (2019), 'When demand increases cause shakeouts,' *American Economic Journal: Microeconomics*, **11**(4), 216–249. <https://doi.org/10.1257/mic.20180040>.
- Igami, M. and K. Uetake (2020), 'Mergers, innovation, and entry-exit dynamics: consolidation of the hard disk drive industry, 1996–2016,' *The Review of Economic Studies*, **87**(6), 2672–2702. <https://doi.org/10.1093/restud/rdz044>.
- Jaworski, T. and A. Smyth (2018), 'Shakeout in the early commercial airframe industry,' *The Economic History Review*, **71**(2), 617–638.

- Jovanovic, B. (1982), 'Selection and the evolution of industry,' *Econometrica*, **50**(3), 649–670. <https://doi.org/10.2307/1912606>.
- Jovanovic, B. and G. M. MacDonald (1994), 'The life cycle of a competitive industry,' *Journal of Political Economy*, **102**(2), 322–347. <https://doi.org/10.1086/261934>.
- Kauffman, S. (1993), *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press: New York, NY.
- Klepper, S. (1996), 'Entry, exit, growth, and innovation over the product life cycle,' *The American Economic Review*, **86**(3), 562–583.
- Klepper, S. (1997), 'Industry life cycles,' *Industrial and Corporate Change*, **6**(1), 145–182. <https://doi.org/10.1093/icc/6.1.145>.
- Klepper, S. (2002), 'Firm survival and the evolution of oligopoly,' *The Rand Journal of Economics*, **33**(1), 37–61. <https://doi.org/10.2307/2696374>.
- Klepper, S. and K. L. Simons (2000), 'The making of an oligopoly: firm survival and technological change in the evolution of the U.S. tire industry,' *Journal of Political Economy*, **108**(4), 728–760. <https://doi.org/10.1086/316100>.
- Klepper, S. and K. L. Simons (2005), 'Industry shakeouts and technological change,' *International Journal of Industrial Organization*, **23**(1–2), 23–43. <https://doi.org/10.1016/j.ijindorg.2004.11.003>.
- Klette, J. and S. Kortum (2004), 'Innovating firms and aggregate innovation,' *Journal of Political Economy*, **112**(5), 986–1018. <https://www.journals.uchicago.edu/doi/full/10.1086/422563>.
- Kortum, S. (1993), 'Equilibrium R&D and the Patent–R&D Ratio: U.S. evidence,' *The American Economic Review*, **83**(2), 450–457.
- Lancaster, K. (1966), 'A new approach to consumer theory | journal of political economy: vol 74, No 2,' *Journal of Political Economy*, <https://www.journals.uchicago.edu/doi/10.1086/259131>.
- Langlois, R. N. and P. L. Robertson (1992), 'Networks and innovation in a modular system: lessons from the microcomputer and stereo component industries,' *Research Policy*, **21**(4), 297–313. [https://doi.org/10.1016/0048-7333\(92\)90030-8](https://doi.org/10.1016/0048-7333(92)90030-8).
- Lenox, M. J., S. F. Rockart and A. Y. Lewin (2007), 'Interdependency, competition, and industry dynamics,' *Management Science*, **53**(4), 599–615. <https://doi.org/10.1287/mnsc.1060.0679>.
- Levinthal, D. A. (1997), 'Adaptation on rugged landscapes,' *Management Science*, **43**(7), 934–950. <https://doi.org/10.1287/mnsc.43.7.934>.
- Levinthal, D. A. (2017), 'Mendel in the C-suite: design and the evolution of strategies,' *Strategy Science*, **2**(4), 282–287. <https://doi.org/10.1287/stsc.2017.0047>.
- Lim, C. and T. Fujimoto (2019), 'Frugal innovation and design changes expanding the cost-performance frontier: a Schumpeterian approach,' *Research Policy*, **48**(4), 1016–1029. <https://doi.org/10.1016/j.respol.2018.10.014>.
- Malerba, F., Nelson, R. R., Orsenigo, L., and Winter, S. G. (2016), *Innovation and the Evolution of Industries: History-Friendly Models*. Cambridge University Press: Cambridge, UK. <https://doi.org/10.1017/CBO9781107280120>.
- Marengo, L. and M. Valente (2010), 'Industry dynamics in complex product spaces: an evolutionary model,' *Structural Change and Economic Dynamics, Innovation, Qualitative Change and Economic Development. Special Issue in Honour of Pier-Paolo Saviotti*, **21**(1), 5–16. <https://doi.org/10.1016/j.strueco.2009.11.004>.
- Murmann, J. P. and K. Frenken (2006), 'Toward a systematic framework for research on dominant designs, technological innovations, and industrial change,' *Research Policy*, **35**(7), 925–952. <https://doi.org/10.1016/j.respol.2006.04.011>.
- Murmann, J. P. and B. A. Schuler (2023), 'Exploring the structure of internal combustion engine and battery electric vehicles: Implications for the architecture of the automotive industry,' *Industrial and Corporate Change*, **32**(1), 129–154. <https://academic.oup.com/icc/article/32/1/129/6855272?guestAccessKey=>.
- Nelson, R. R. and S. G. Winter (1982), *An Evolutionary Theory of Economic Change*. Belknap Press of Harvard University Press: Cambridge, MA.
- Pammolli, F., L. Magazzini and M. Riccaboni (2011), 'The productivity crisis in Pharmaceutical R&D,' *Nature Reviews Drug Discovery*, **10**(6), 428–438. <https://doi.org/10.1038/nrd3405>.

- Querbes, A. and K. Frenken (2017), 'Evolving user needs and late-mover advantage,' *Strategic Organization*, **15**(1), 67–90. <https://doi.org/10.1177/1476127016648498>.
- Sanchez, R. (1995), 'Strategic flexibility in product competition,' *Strategic Management Journal*, **16**(S1), 135–159. <https://doi.org/10.1002/smj.4250160921>.
- Sanchez, R. and J. T. Mahoney (1996), 'Modularity, flexibility, and knowledge Management in Product and Organization Design,' *Strategic Management Journal*, **17**(S2), 63–76. <https://doi.org/10.1002/smj.4250171107>.
- Sanchez, R., P. Galvin and N. Bach (2023), 'How design rules emerge and evolve: a coevolutionary architectural perspective on firm and industry organization,' *Industrial and Corporate Change*, **32**(1), 28–46. <https://doi.org/10.1093/icc/dtac052>.
- Scannell, J. W., A. Blanckley, H. Boldon and B. Warrington (2012), 'Diagnosing the decline in Pharmaceutical R&D Efficiency,' *Nature Reviews Drug Discovery*, **11**(3), 191–200. <https://doi.org/10.1038/nrd3681>.
- Schilling, M. A. (2000), 'Toward a general modular systems theory and its application to interfirm product modularity,' *Academy of Management Review*, **25**(2), 312–334. <https://doi.org/10.5465/amr.2000.3312918>.
- Simon, H. A. (1962), 'The architecture of complexity,' *Proceedings of the American Philosophical Society*, **106**(6), 467–482.
- Simon, HERBERT A. 1990. "Bounded Rationality." In *Utility and Probability*. Palgrave Macmillan, London. https://doi.org/10.1007/978-1-349-20568-4_5.
- Suárez, F. F. and J. M. Utterback (1995), 'Dominant designs and the survival of firms,' *Strategic Management Journal*, **16**(6), 415–430. <https://doi.org/10.1002/smj.4250160602>.
- Tong, J. (2009), 'Explaining the shakeout process: a 'successive submarkets' model,' *The Economic Journal*, **119**(537), 950–975. <https://doi.org/10.1111/j.1468-0297.2009.02252.x>.
- Utterback, J. and W. Abernathy (1975), 'A dynamic model of process and product innovation,' *Omega*, **3**(6), 639–656.
- Utterback, J. and F. Suárez (1993), 'Innovation, competition, and industry structure,' *Research Policy*, **22**(1), 1–21. [https://doi.org/10.1016/0048-7333\(93\)90030-L](https://doi.org/10.1016/0048-7333(93)90030-L).
- Uzunca, B. (2018), 'A competence-based view of industry evolution: the impact of submarket convergence on incumbent–entrant dynamics,' *The Academy of Management Journal*, **61**(2), 738–768.
- Vernon, R. (1966), 'International investment and international trade in the product life cycle,' *Quarterly Journal of Economics*, **80**(2), 190–207.
- Vincenti, W. G. (1994), 'The retractable airplane landing gear and the Northrop 'anomaly': variation-selection and the shaping of technology,' *Technology and Culture*, **35**(1), 1–33.
- Wells, C. W. (2007), 'The road to the model T: culture, road conditions, and innovation at the Dawn of the American motor age,' *Technology and Culture*, **48**(3), 497–523.
- Windrum, P. (2005), 'Heterogeneous preferences and new innovation cycles in mature industries: the amateur camera industry 1955–1974,' *Industrial and Corporate Change*, **14**(6), 1043–1074. <https://doi.org/10.1093/icc/dth069>.
- Windrum, P. and C. Birchenhall (1998), 'Is product life cycle theory a special case? Dominant designs and the emergence of market niches through coevolutionary-learning,' *Structural Change and Economic Dynamics*, **9**(1), 109–134. [https://doi.org/10.1016/S0954-349X\(97\)00039-8](https://doi.org/10.1016/S0954-349X(97)00039-8).
- Windrum, P., T. Ciarli and C. Birchenhall (2009), 'Consumer heterogeneity and the development of Environmentallyfriendly technologies,' *Technological Forecasting and Social Change*, *Evolutionary Methodologies for Analyzing Environmental Innovations and the Implications for Environmental Policy*, **76**(4), 533–551. <https://doi.org/10.1016/j.techfore.2008.04.011>.