Strategic Search: 
Organizational adaptation with competitive positioning

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ABSTRACT

In this paper, we study how competitive pressures shape organizational adaptation in complex environments with heterogeneous demand. To do so, we combine a standard NK simulation with a differentiated duopoly competition game to model firms simultaneously engaging in an internal search for superior technical proficiency and an external search for horizontally differentiated competitive positions. We show that such 'strategic search' limits innovation in low complexity environments, as firms sacrifice technical proficiency in order to differentiate from each other, but boosts it in high complexity environments, and examine the implications of this pattern for competitive advantage and consumer welfare. We also explore how these findings are moderated by the extent of demand heterogeneity, as well as asymmetric exposure to competition among firms. Our study integrates research on competitive positioning and organizational adaptation, contributing insights to organizational shaping, innovation, and competitive advantage.

Keywords: NK model, search, complexity, competition, differentiation

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INTRODUCTION

How organizations innovate and adapt to changing conditions is a fundamental question in strategy and organizational scholarship. A substantial body of work within the so-called ‘Carnegie School’ tradition has sought to explore that question (see Baumann, Schmidt, and Stiglitz, 2019 for a recent review), conceiving of organizational adaptation as a repeated process in which a limited set of proximate (path-dependent) alternatives are exposed to a selection environment to determine the fittest choice (Levinthal, 2021). As this work acknowledges, the process of organizational adaptation combines two distinct but parallel processes—a process of internal innovation, to discover or create the most effective technologies and production methods, and a process of external positioning to locate the most attractive opportunity in a competitive marketplace—with both external and internal fit being critical to organizational survival and growth (Nelson and Winter, 1978; Levinthal, 2021). Despite this recognition, however, much of the existing work in this tradition has focused primarily on the process of internal search, modeling the firm’s quest for the most efficient or productive technology rather than the most attractive market position. In particular, the classic \( NK \) simulation model that is the canonical representation of organizational adaptation under complexity (Levinthal, 1997) does not account for competitive interactions, taking the search landscape as given, and while some recent work has explored the role of competition using variants of the \( NK \) simulation, the focus has been on understanding how the path-dependent nature of organizational adaptation impacts competitive outcomes such as industry structure and evolution (Lenox, Rockart, and Lewin, 2006; 2007; Knudsen, Levinthal, and Winter, 2014; Adner, Csaszar, and Zemsky, 2014), rather than on the effect of competition on organizational search (Nelson and Winter, 1982). As a result, despite growing empirical evidence that competition impacts where and how firms invest in R&D (Katila and Chen, 2008; Clarkson and Toh, 2010; Katila, Chen, and Piezunka, 2012; Toh and Polidoro, 2013; Giustiziero, Kaul, and Wu, 2019), we know relatively little about how the process of organizational adaptation is shaped by competition (Gavetti et al., 2017; Baumann et al., 2019).

A key reason for this relative neglect is that prior work often assumes that firms offer a homogenous or undifferentiated product or offering (Nelson and Winter, 1982; Lenox et al, 2006; 2007; Knudsen et al,
In other words, it assumes that no matter what technological choices firms make internally to improve their productivity, their market offerings are still seen as identical by customers. Given such homogenous demand, the only way for a firm to improve its profitability is to improve its technical proficiency, so competition has no effect on the firm’s search choices; as Lenox et al. (2006) put it, their “results are identical if firms choose activities that improve cost or quality rather than profits” (Lenox et al., 2006; p. 762). In practice, however, such homogeneity among market offerings is rare: customer and audiences are heterogenous in their preferences and firms can and do choose different technological configurations to target different customer segments (Adner and Levinthal, 2001; Adner, 2002; Adner and Snow, 2010). In fact, such horizontal differentiation among firms is central to the ‘positioning’ view of strategy (Porter, 1980; 1996; Adner, Ruiz-Aliseda, and Zemsky, 2016), which emphasizes that strategy is not simply about maximizing efficiency, but involves making different choices from one’s competitors.

In this study, we relax the assumption of demand homogeneity to study organizational adaptation in a context where firms can differentiate themselves both vertically and horizontally from their rivals, and therefore must consider not only whether their choice of technology (or strategy\(^2\)) increases their internal technical proficiency, but also whether it improves their external competitive position relative to their rivals. More specifically, we build on prior work (Nelson and Winter, 1982; Lenox et al., 2006; 2007; Adner et al., 2014) and distinguish between two distinct selection environments firms face\(^3\): an internal selection environment which determines the technical proficiency or fitness of the organization (Lenox et al., 2006; 2007; Mihm, Sting, and Wang, 2015), which we assume to be exogenously given and model as a standard \(NK\) landscape; and an external selection environment where firms compete against each other to realize profits, which we model as a non-cooperative differentiated duopoly game (Singh and Vives, 1984; Zanchettin, 2006), thus allowing for horizontal differentiation among firms. Our model thus captures \textit{strategic search}—i.e., the quest for the most profitable

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1 Lenox et al., 2006 include an extension that allows for vertical differentiation between firms in quality, but not for horizontal differentiation between offerings, so demand is still assumed to be homogenous.

2 Throughout this paper we use the terms ‘technology’ and ‘strategy’ interchangeably, to mean the configuration of choices made by the firm, reflecting our interest in innovation as any change in the firm’s capabilities rather than simply firm R&D.

3 In this, we follow Nelson and Winter’s precept that “it is important to distinguish between selection on firms and selection on routines” (Nelson and Winter, 1982; p. 143). Thus, the internal selection environment models technology choice within a firm, while the external selection environment captures competition between firms.
market position—rather than technical search—i.e., the quest for the most efficient or productive technology, (as modeled by the standard NK simulation)—and systematically compares the outcomes of the two to see how accounting for demand heterogeneity and thus allowing for competitive positioning alters innovation outcomes.

Baseline results from our model show that strategic search lowers the average technical performance of firms (and thus the overall level of innovation in the market) and increases the competitive advantage of the leading firm under conditions of low complexity, but has the opposite effect under high complexity. The intuition is that in low complexity environments, where there are a limited number of high performing strategies, firms face a trade-off between maximizing technical performance and differentiating themselves from their rivals. Given heterogeneous demand, firms choose to position away from rivals, thus compromising technical proficiency but improving profitability. In doing so, they give rise to a ‘high ground’ advantage, with the first firm to discover a technically superior configuration being protected from competition because its rival may be better off choosing a different though technically inferior position rather than engaging in direct competition by emulating the focal firm. Conversely, in high complexity contexts, where there are many equifinal strategies and the global peak is hard to reach, the pressure to differentiate may complement innovation, driving firms to undertake more distant search in pursuit of heterogeneous preferences and so achieve higher performing strategies than they may otherwise have discovered. Overall, strategic search increases firm profits and the competitive advantage of the leading firm at the expense of innovation and consumer surplus in low complexity environments, but boosts innovation and consumer surplus even as it increases profits in high complexity contexts, though lowering competitive advantage while doing so. Further analysis shows that the trade-off between profitability and innovation in low complexity environments may be moderated by a pre-commercialization period (Moeen and Agarwal, 2017; Moeen, 2017) where firms complete some initial search without facing competition, then continue to search even as they compete.

We explore two key extensions to these baseline results. First, we vary the extent of demand heterogeneity by changing the number of dimensions or organizational choices that are salient to customers, i.e., on which their preferences differ. We show that the trade-off between proficiency and differentiation, and the resulting potential for high ground advantage, has a curvilinear relation with the number of salient
dimensions: when there are only a few dimensions to differentiate on, firms will prioritize differentiation over proficiency, but as the potential bases for differentiation increase they will hold differentiation constant and prioritize proficiency. These results suggest that making new dimensions salient to customers is not always to laggard’s advantage—as prior research has suggested (Vinokurova, 2019)—with the extent and direction of benefit from such shaping depending on technological complexity and demand heterogeneity. Second, we consider the case where one firm prioritizes profits when searching while the other prioritizes technical proficiency, and find, paradoxically, that the technologist ends up earning higher profits than the profit-seeker, with this competitive advantage being greater, the less complex the context. The intuition is that the technologist always ends up claiming the superior technological position, while the profit-seeker ends up accommodating its rival at the cost of its own innovation. We interpret this result as highlighting the potential benefits to an organization from being temporarily buffered from the external selection environment, with firms that have the leeway to ignore profitability in the short-term being better positioned to achieve competitive advantage in the long run.

Our study contributes to the existing literature in several ways. By modeling how competitive positioning influences organizational innovation we move beyond both models of organizational adaptation with homogenous demand (Nelson and Winter, 1982; Lenox et al., 2006; 2007; Knudsen et al., 2014; Baumann et al., 2019) and models of heterogenous demand with simple linear innovation functions (Adner and Levinthal, 2001; Adner, 2002; Adner and Zemsky, 2006) to develop a model that simultaneously captures the vertical gains from internal adaptation and the horizontal benefits of external positioning, thus re-integrating the dynamics of internal search under complexity with those of competitive positioning (Nelson and Winter, 1978; 1982, Wernerfelt, 1984; Porter, 1980; Adner et al., 2016). In doing so, we also contribute to an emerging literature on organizational shaping (Gavetti et al., 2017; Helfat, 2021), showing how competitive pressures impact organizational innovation and how changing the dimensions that are salient to customers impacts firms’ profits. Further, we highlight the moderating role of complexity, with firms’ attempts to differentiate coming at the cost of innovation (and consumer surplus) in low complexity environments, but boosting innovation and consumer welfare in high complexity settings. Our study also offers new insights on competitive advantage in
the face of heterogeneous demand (Adner and Zemsky, 2006), highlighting the case of high ground advantage wherein the fact of being the first to stumble on a discovery itself forms a barrier to imitation, driving rivals to seek out heterogenous customer preferences to differentiate themselves, as well as the long-term benefits to a firm from being temporarily buffered from competitive pressure.

THEORETICAL BACKGROUND

Organizational innovation and search

Innovation—broadly defined as the development of new capabilities, including new technologies, products, processes, or business models—is a topic of fundamental interest to scholars in both strategy and economics, being both the means by which firms can create and sustain competitive advantage and the engine driving increasing productivity and growth in the economy (Schumpeter, 1942; Solow, 1957; Levin, Cohen, and Mowery, 1985; Aghion and Howitt, 1992; Nelson and Winter, 1982). While economic theorists often model innovation as the choice between known alternatives with well-understood (albeit risky) payoffs—e.g., in the literature on patent races (Harris and Vickers, 1985; Denicolo, 2000) and other types of resource development contests (Pacheco-de-Almeida and Zemsky, 2003; 2007)—organizational scholars have long recognized that organizational innovation is more accurately represented as an evolutionary process of search over uncertain and ill-defined alternatives by boundedly rational actors (March and Simon, 1958; Nelson and Winter, 1982; Levinthal and March, 1981; 1993; Mihm et al., 2015).

More specifically, organizational innovation may be characterized as a process of path-dependent search with selection (Nelson and Winter, 1982; Levinthal, 2021). Being boundedly rational, firms cannot know the full range of potential resource configurations available to them and their (probabilistic) payoffs; instead, faced with a complex and uncertain environment (Sommer and Loch, 2004), they engage in a process of sequential search, assessing a few alternatives at a time, often choosing those that are proximate to their current position (March and Simon, 1958). The localness of this search process means that organizational innovation is fundamentally path-dependent, since the alternatives assessed by the organization are defined and constrained by its existing capabilities and beliefs (Nelson and Winter, 1982; Levinthal and March, 1993). These assessed
alternatives are then subject to a selection environment, that determines the proficiency or ‘fitness’ of each alternative, allowing organizations to use this feedback to decide which alternative they wish to retain (Nelson and Winter, 1982; Levinthal, 2021). The canonical representation of this process of organizational adaptation in the literature is the NK simulation model (Levinthal, 1997) which captures both the path-dependent nature of the search process as well as the idea of a selection environment where, importantly, the fitness of a given resource configuration is not simply the sum of the performance of its individual parts, but is determined by the potential interdependencies between these different components. As a model of organizational search, the NK simulation has been widely used to examine how organizations innovate and adapt over time, the role of this evolutionary process in producing heterogeneity of resource positions among actors, and the resulting implications for competitive advantage (see Baumann et al., 2019 for a review).

Selection in NK models: Two critiques

Useful as the NK simulation has proven—with work based on the NK simulation framework making substantial contributions to our understanding of the process of organizational innovation—its conceptualization of a selection environment is subject to at least two key critiques. First, much of this work models the selection environment as entirely exogenous; organizations have no ability to change the landscape through their actions. Yet organizations can and do play a key role in shaping the selection environment in which they compete, and such shaping activities represent an important dimension of both the market and nonmarket strategies through which firms strive to achieve competitive advantage (Gavetti et al. 2017; Helfat, 2021; Patvardhan and Ramachandran, 2020). There are many ways in which a firm may alter the payoff structure and therefore the selection environment faced by firms in its market (Gavetti et al., 2017; Helfat, 2021). It may limit the choices available to its rivals through the use of patents that give it exclusive rights over certain technologies or resource configurations (Mihm et al., 2015), or increase the choices available by making new dimensions of the product or service salient in the mind of consumers (Vinokurova, 2019). It may use a variety of nonmarket strategies to transform or supplement the existing institutional environment, effectively changing the ‘rules of the game’ under which it operates (Dorobantu, Kaul, and Zelner, 2017; Oberholzer-Gee and Yao, 2018). Or it may introduce new product or process innovations that shift not only its own demand and supply
curves, but those for the entire market, thus changing the payoff structure for all its rivals (Nelson and Winter, 1982; Helfat, 2021). The key point is that the selection environment that organizations in a market face is rarely, if ever, exogenous to their actions, as the standard $NK$ model would have it. On the contrary, consistent with the notion of external fit, it may be more accurate to think of a market as a selection environment that is shaped and determined by the aggregation of the actions of the firms in that market, and is thus fundamentally endogenous to organizational innovation and search. As Nelson and Winter (1982) put it:

“the routines of extant firms determine, to some degree at least, the environment that selects on routines”... “therefore, no theory of long-run evolutionary change logically can take the environment of the individual species (collection of firms) as exogenous.” (Nelson and Winter, 1982; pp. 160-161)

A second critique of traditional NK simulations is their unidimensional focus: because fitness in the NK simulation is modeled as a single dimension, all firms are assumed to be maximizing on that dimension. In early simulations this ‘fitness’ was equated to firm performance (Levinthal, 1997), with this work thus making no distinction between technical proficiency and profit, despite the centrality of that distinction to strategy scholarship (Helfat, 2000; Helfat and Winter, 2011). More recent work does make such a distinction—conceptualizing fitness on the NK landscape as reflecting an organization’s technical proficiency or productivity, and then taking this proficiency level to be the basis on which an organization competes with others in the market (Lenox et al., 2006; 2007; Adner et al., 2014; Knudsen et al, 2014)—but, as previously discussed, this work continues to model undifferentiated competition between firms making a homogenous product. It thus remains the case that the only way for a firm to improve its profitability is by improving its fitness, and competition does not impact the adaptation process itself (Lenox et al., 2006; 2007). Such a set-up is at odds with the recognition that firms face heterogeneous demand and may choose to serve different customer preferences when making technology choices (Adner and Levinthal, 2001; Adner, 2002). It is also inconsistent with the ‘positioning’ school within strategy, which has long emphasized that strategy is not simply about maximizing efficiency or technical proficiency, it is about doing things differently from one’s rivals (Porter, 1980; 1996). Indeed, a key insight from this work is that firms make distinct but internally consistent choices in order to serve different customer segments and differentiate themselves from each other (Siggelkow, 2001;
2002; Adner et al., 2016). It thus seems important to incorporate this potential for horizontal differentiation into our models of organizational adaptation.

**Organizational search with competitive positioning**

In this paper, we try to address both these critiques of the way selection environments are modeled in NK simulations, by developing a model of organizational adaptation that allows firms to compete both vertically on the basis of technical proficiency and horizontally on the basis of the heterogeneous preferences they serve, and considers not only how firms adapt towards the best competitive position, but how competition itself impacts adaptation. Such a model seems called for by existing work, both conceptual and empirical. Conceptually, prior studies have shown that heterogenous customer preferences may impact firms’ innovation choices, influencing the choice between product and process innovation (Adner and Levinthal, 2001) and creating the potential for disruption by enabling firms to pursue different technological trajectories (Adner, 2002; Malerba, Nelson, Orsenigo, and Winter, 2007). Relatedly, prior work has theorized that firms’ competitive actions in the product market shape their rival’s resource investments (Capron and Chatain, 2008) and factor market conditions more generally (Chatain, 2014). These studies suggest that organizational innovation is co-determined between rivals (Pacheco-de-Almeida and Zemsky, 2003; 2007), with every organizational innovation impacting the prevailing demand and supply conditions in the market and thus changing the (external) selection environment, or pay-off structure (Gavetti et al., 2017; Helfat, 2021) that firms in the market face (Nelson and Winter, 1982). While this work thus highlights the influence of competitive positioning on organizational innovation, it continues to conceive of innovation in relatively simple and deterministic ways. It is thus interesting to consider how these factors may influence a more adaptive version of internal search (Adner et al., 2016).

Empirically, we have substantial evidence of competition shaping innovation (Aghion et al., 2005). As several studies have shown, innovation by rivals not only impacts the value of firm’s own capabilities (McGahan and Silverman, 2006) but also where and how it chooses to search (Polidoro and Toh, 2011; Giustiziero et al., 2019). While in some cases, firms may choose (or be forced) to steer away from positions already staked by
their rivals (Clarkson and Toh, 2010; Mihm et al., 2015; Wang and Shaver, 2016), in other cases they may be
drawn to their rival’s innovations in the hope of imitating and building on them (Nelson and Winter, 1978;
Pacheco-de-Almeida and Zemsky, 2012, Agarwal et al., 2007), with the choice between these two alternatives
depending on several factors including the strength of IP regimes (Levin et al., 1985, Hall and Ziedonis, 2001;
McGahan and Silverman, 2006), the comparative strength of the players (Giustiziero et al., 2019) and whether
the rival innovations are complementary or substitutive (Kaul, 2012). Relatedly, scholars have shown that rival
innovation impacts how firms search, with successful innovations by rivals prompting firms to search more
aggressively (Chen et al., 2010; Katila et al., 2012), more narrowly (Kim and Toh, 2013), and with less internal
collaboration (Toh and Polidoro, 2013). It is hard to reconcile this plethora of evidence for an organization’s
innovation efforts being shaped by those of its rivals with the process of organizational search in isolation as
depicted in the standard \textit{NK} model.

**MODEL**

\textit{NK} landscape and internal fit

In order to study how competitive positioning in the face of heterogenous demand shapes the organizational
search process, we develop a modified version of an \textit{NK} simulation. To do so, we build on prior work that has
studied how organizational search (and the resulting heterogeneity) impacts industry competition (Lenox et al.,
2006; 2007; Knudsen et al., 2014). In common with this work, as well as with studies that use the \textit{NK} model to
think specifically about innovation (Mihm et al., 2015), we take the standard \textit{NK} landscape to reflect the internal
selection environment of the firm. Fitness on the landscape thus reflects the technical proficiency or
productivity of the organization rather than its profitability or financial performance, with higher peaks
representing strategies that result in superior efficiency and effectiveness.

Given that our primary interest is in understanding the effect of the external selection environment
resulting from competition between firms, we follow the standard simulation set up in modeling the internal
environment represented by the \textit{NK} landscape (Levinthal, 1997; Lenox et al. 2006; 2007). Specifically, as in the
standard \textit{NK} set up, we model innovation as a search process that is both local and experiential: organizations
innovate by changing one choice at a time and either retain or reverse that change based on its observed outcome. We thus do not consider the potential for cognitive search or ‘long leaps’ (Gavetti and Levinthal, 2000) nor do we model learning through imitation across firms. Moreover, in order to focus on the endogeneity of the external selection environment, we hold the internal selection environment fixed and exogenous, i.e., we do not consider exogenous changes to the internal environment (Siggelkow and Levinthal, 2003), nor do we allow for endogenous actions by which firms could alter each other’s internal landscapes (Levinthal and Warglien, 1999; Gavetti et al., 2017). This is not to imply that firms cannot shape each other’s internal selection environment: such shaping could take the form of a firm blocking others from pursuing specific technologies or innovation through the use of patents (Mihm et al., 2015) or influencing regulation to make some choices unavailable (Dorobantu et al., 2017). That is not, however, the type of shaping we are focused on in this study; instead, our interest is in understanding how, given, a static and exogenous internal landscape, the endogenous external pressure exerted by competition influences firm search.

In brief, the internal landscape is modeled as a standard NK simulation, where each firm’s technical proficiency depends on $N$ activities, each of which interacts with $K$ other activities, with $K \in \{0, 1, 2, ..., N - 1\}$. More formally, firm $i$’s technology (or strategy) is an $N$-dimensional vector $t_i = (t_{i1}, t_{i2}, ..., t_{iN})$ of binary policy choices $t_{in} \in \{0, 1\}$ for $n \in \{1, .., N\}$, yielding a total of $2^N$ possible combinations of choices. We interpret each element of a technology $t_{in}$ as a choice to incorporate a component $n$ by firm $i$. The degree of interdependence among components is determined by the parameter $K$, a measure of complexity, which describes the number of choices $t_{ink}$ that (co-)determine the performance effect of activity $in$. This effect is characterized by the contribution function $c_{in}(t_{in1}, t_{in2} ..., t_{ink})$ where $in1, in2 ... ink$ are $K$ distinct activities other than $in$, with the realizations of the contribution function being drawn from a uniform distribution over the unit interval, i.e., $c_{in} \sim U[0; 1]$. The lowest value, $K = 0$, implies the policy choices do not depend on each other, yielding a smooth performance landscape with a single (global) peak; the highest value $K = N - 1$ implies

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4 If we interpret the overall combination as the firm’s strategy, then each individual decision may be thought of as an element in the firm’s overall value chain (Porter, 1980).
that each policy choice depends on all other choices, yielding a rugged landscape.

The fitness level of a given technology $t_i$ is calculated as the arithmetic mean of the $N$ contributions $c_{in}$ according to the function $F(t_i) = N^{-1} \sum_{i=1}^{N} c_{in}(t_{in}, t_{in1}, t_{in2}, \ldots, t_{ink})$. A “landscape” represents a mapping of all $2^N$ possible technologies (or strategies) onto performance values. We normalize each landscape to the unit interval such that the mean value of the normalized landscape equals 0.5 and the global maximum equals 1.0. The “local peaks” on the performance landscape represent technologies for which a firm cannot improve its performance through local search alone (Levinthal 1997). The “global peak” is the highest peak in the landscape.

**External selection as a differentiated duopoly**

As in prior work (Lenox et al, 2006; 2007; Knudsen et al., 2014), the technical proficiency or productivity achieved by a firm on this internal landscape forms the basis on which it competes with other firms in the market. As in this work, we assume that firms engage in quantity competition based on their technical proficiency, while simultaneously continuing to adapt their internal configurations, with the choice of which innovations to keep or discard being based on whether they increase profit or not (Lenox et al, 2006; 2007). Specifically, in each period, each firm in the market changes one of its $N$ choices (at random), and then competes with all the other firms using its new configuration, retaining that configuration if and only if the resulting profits in the period are greater than or equal to those in the previous period. Both internal and external selection forces thus operate simultaneously to determine which innovations are chosen in our model. In this way, our model is also consistent with the model of competition and technological progress developed by Nelson and Winter (1982; Chapter 12), in that both simulations model the trajectory of technological progress as being shaped by competition.

Where we depart from prior work is that while this work deals with a homogenous or undifferentiated product, only allowing for vertical differences between firms in terms of their quality or productivity (Nelson and Winter, 1982; Lenox et al., 2007; Knudsen et al., 2014), we consider the horizontal distance between firms

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5 Nelson and Winter model the amount each firm invests in R&D rather than the process of search which is our focus.
as well, thus allowing for competitive differentiation and positioning. The underlying rationale is that different configurations of choices (or positions on the landscape) represent distinct strategies, which differentiate firms from each other (Adner et al., 2014). More specifically, we assume that consumers are heterogenous in their preferences (Adner and Levinthal, 2001; Adner, 2002) and that by making different choices on the N dimensions firms are able to offer distinct products or services in the market, thus differentiating themselves in the minds of their consumers. As different segments of consumers prefer the offerings of different firms, this reduces the competitive pressure that each firm faces and allows it to realize some level of market power, with the extent of this market power being greater, the less the overlap between a firm’s strategy and that of its rivals, reflecting its greater ability to produce a unique offering or, equivalently, to serve a unique customer segment (Adner, 2002). Incorporating the potential for horizontal differentiation in additional to vertical capability differences in this way is consistent with the idea of market positioning as “performing different activities from rivals” (Porter, 1996).

Specifically, we model competition among firms using a model of differentiated duopoly developed by Singh and Vives (1984) and Zanchettin (2006) and used in prior strategy research (Baron, 2001; Kaul and Luo, 2018; Jansen, 2011). We limit ourselves to modeling competition between two firms in order to keep the analysis simple; by focusing on just two players we are better able to delineate the underlying mechanisms at play and capture the essence of how competitive pressures change search behavior (Knudsen et al., 2019). In line with prior work, we model quantity competition using a Cournot model (Nelson and Winter, 1982; Lenox et al., 2006; 2007; Knudsen et al., 2014) in the main analysis reported below.

In the standard differentiated duopoly model, the representative consumer’s utility, \( U = \alpha_1 q_1 + \alpha_2 q_1 - \frac{1}{2} (q_1^2 + q_2^2 + y q_1 q_2) \), is a function of the quantities \( q_1 \) and \( q_2 \) of the goods produced by firm 1 and 2; of the parameters \( \alpha_1, \alpha_2 \in \mathbb{R}_{>0} \) corresponding to the baseline willingness to pay for products 1 and 2; and of \( y \in [0,1] \), which is inversely proportional to the degree of differentiation between the two products (with 0

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6 More specifically, we assume that consumer preferences are evenly and symmetrically distributed across all N dimensions of strategic choice; an assumption we maintain for our baseline analysis but relax and explore in supplementary analyses.
corresponding to independent products and 1 to perfect substitutes). This utility function generates the linear system of inverse demand functions

\[ p_i = \alpha_i - q_i - \gamma q_j \quad [i, j = 1, 2; i \neq j]. \]

On the supply side, both firms face linear cost functions, with firm 1’s marginal cost set at \( c_1 \geq 0 \) and firm 2’s at \( c_2 \geq 0 \). In equilibrium, both firms set quantities equal to

\[ q_i^C = p_i^C - c_i = (4 - \gamma^2)^{-1} \left( 2(\alpha_i - c_i) - \gamma(\alpha_j - c_j) \right) \text{ if } 2(\alpha_i - c_i) - \gamma(\alpha_j - c_j) > 0, \text{ else } q_i^C = 0 \]

and generate profits

\[ \pi_i = q_i^C(p_i^C - c_i) = \left( (4 - \gamma^2)^{-1} \left( 2(\alpha_i - c_i) - \gamma(\alpha_j - c_j) \right) \right)^2 = q_i^C \pi_i^2. \]

Mapping this to the NK landscape described in the previous sub-section, we set the value created\(^7\) by firm \( i \)—i.e., \((\alpha_i - c_i)\)—equal to the firm’s technical proficiency as reflected by its fitness on the NK landscape \( F(t_i) \), and set \( \gamma = N^{-1} \sum_{n=1}^{N} 1_{\{t_{1n} = t_{2n}\}} \) where \( 1_{\{t_{1n} = t_{2n}\}} \) is an indicator function equal to 1 if \( t_{1n} = t_{2n} \). Thus, if the two firms make identical choices, meaning they occupy the same position on the landscape, then their offerings are perfect substitutes for each other and the competition between them plays out as in a standard Cournot model. On the other extreme, if the two firms make entirely different choices and thus occupy diametrically opposite positions on the landscape, then \( \gamma = 0 \) and the two firms are effectively monopolists, each catering to a different segment of the population represented by the average consumer\(^8\). More generally, an inspection of the profit function reveals that profits are increasing in the technical proficiency of the focal firm, i.e., \( \frac{\partial \pi_i}{\partial(\alpha_i - c_i)} > 0 \), decreasing in the technical proficiency of its rival, \( \frac{\partial \pi_i}{\partial(\alpha_j - c_j)} < 0 \), and increasing in the two firms’ differentiation, \( \frac{\partial \pi_i}{\partial(-\gamma)} > 0 \) if \( 2(\alpha_i - c_i) - \gamma(\alpha_j - c_j) > 0 \). As mentioned, we start by assuming that

\(^7\) The value created by the firm is equal to the difference between the willingness to pay and its costs, i.e., \( \alpha_i - c_i \) (Brandenburger and Stuart, 1996; Adner and Zemsky, 2006). An improvement in fitness level (or technical performance) can thus be interpreted as the extent to which a firm may reduce costs for a given level of quality or achieve superior quality while keeping costs constant (Porter, 1996; Lenox et al, 2006).

\(^8\) These two extreme cases map to the two-segment analysis in Adner (2002), where a firm may either choose to isolate itself by choosing a different customer segment than its rival or compete head to head for the same customer segment.
demand is heterogeneous across the full set of N activities, meaning that all choices are relevant in determining the firms’ degree of differentiation, though we later relax this assumption.

**Simulation set-up**

For our simulation results, we assume that both firms start from the same (randomly determined) point on the landscape\(^9\), and engage in local experiential search as in the standard NK model, except that, as described above, in each period we calculate each firm’s profit \(\pi_i\) and determine whether to retain the change in firm strategy based on whether it resulted in improved profits (rather than in increased technical fitness).\(^{10}\) We run each simulation for 200 rounds of competitive interaction, reaching a steady state where there is no further potential for improvement for either firm. Each outcome represents the average of 250,000 simulations.

Since we are interested in understanding how competition shapes the search process, we compare the outcomes from our modified model of *strategic search* to the results from a standard *NK* model, which we label *technical search*. In the latter case, the two firms focus on improving technical proficiency rather than profits, thus achieving the same technical proficiency as in the standard NK model. Profits in this case are calculated ex post based on the firms’ relative fitness and differentiation, and do not factor into the firms’ adaptation decisions, which are based purely on improving fitness \(^{11}\). Note that profits under technical search are thus greater than what the two firms would achieve assuming undifferentiated Cournot competition as in Lenox et al. (2006; 2007) (equivalent to setting \(\gamma = 1\) in our model), which makes our estimate of how much strategic search outperforms technical search in terms of realized profits conservative.

**FINDINGS**

Figure 1 shows the baseline results from our simulation, comparing the outcomes from our modified simulations to the results from the standard NK model, for different levels of complexity (\(K\)). Unsurprisingly,

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\(^9\) Results are similar if we start the two firms from different (randomly chosen) points on the landscape.

\(^{10}\) For simplicity, we examine (and report) the square root of the two firms’ profits. Because the square root of profits is a monotonic transformation of the objective function, the two are equivalent and lead to the exact same results.

\(^{11}\) In this sense, the technical search is identical to the case modeled by Lenox et al. (2006; 2007). While they do model firms basing adaptation decision on profit, the lack of horizontal differentiation in their model means that their results are identical to those achieved by maximizing fitness.
Figure 1, Panel (a) shows that average profits across the two firms are always equal or higher under strategic search than under technical search; this follows logically from the fact that under strategic search firms are seeking the best competitive position so as to maximize profit, whereas in the traditional search model they are only trying to maximize technical proficiency. Similarly, Figure 1, Panel (b) shows that firms always choose to locate at a greater distance from each other under strategic search, which is a natural consequence of our rewarding firms for horizontally differentiating themselves.

***Insert Figure 1 about here***

**The moderating role of complexity**

A more interesting finding from our simulation can be seen in Figure 1, Panel (c), which compares the average technical proficiency of the two firms, and thus the overall level of innovation in the market, with and without competition. It shows that the effect of strategic search on the level of innovation is contingent on complexity: in low complexity environments, firms innovate less when they take competition into account than they would have otherwise, but in high complexity environments they innovate more.

To understand the mechanisms underlying this result, consider first the low complexity case. Where complexity is low and the choices a firm faces are largely independent, there are relatively few ways of achieving superior technical proficiency and the technically optimal solution is easily discovered. In such a market, firms searching on their own will tend to converge on an identical strategy. In $NK$ landscape terms, both firms will tend to find their way to the global peak, so long as they ignore each other. Once the firms start to take each other’s presence into account, however, converging on the same (global) peak may no longer be the best solution because it means both firms will face intense competition from each other. Firms may therefore be better off choosing to differentiate from each other, even if doing so means making choices that compromise proficiency. In $NK$ terms, firms may be better off staying on the hillside of a technological peak and maintaining distance between each other—as shown in Figure 1, Panel (b)—for the sake of maintaining differentiation. Low complexity environments thus present a trade-off between technical proficiency and market power, with firms choosing positions that balance the two.
As an example of such behavior, consider the case of craft beer. While organizational theorists have sought to explain the emergence of microbreweries producing craft beer using perspectives from resource partitioning (Carroll and Swaminathan, 2000), authenticity (Frake, 2017), and categorical identity (Mathias et al., 2018), our model suggests a simple, though complementary explanation. Given that brewing is a relatively simple task, it is generally the case that beer production is most efficiently undertaken at scale, as reflected in the pattern of brewer consolidation observed in several markets (McGahan, 1991; Kaul and Wu, 2016). As more and more firms converge on the same technically optimal solution, however, it becomes profitable from some players to choose to deliberately adopt a less efficient solution (microbrewing) in order to differentiate themselves from the dominant players in the market, and achieve market power over a segment of customers who value a different offering (craft beer). Craft brewing is thus consistent with the low complexity case in Figure 1: a strategic innovation that leads to greater differentiation in the market, even at the cost of technical proficiency, and thus raises industry profits overall. Similarly, recent work on competition in crowdfunding platforms shows that some players in this market choose more specialized offerings, sacrificing broad network economies in favor of more targeted differentiation (Dushnitsky, Piva, and Rossi-Lamastra, 2020).

Next, consider the high complexity case. In highly complex situations, the technically optimal solution is often hard to discover, and there are many equifinal ways of achieving moderate proficiency; in $NK$ terms, there are many local peaks, and firms searching on the landscape are likely to end up on different local peaks in any case. In such contexts there is therefore no longer a trade-off between technical proficiency and differentiation, because firms can (and generally do) end up being differentiated from each other even when they only seek to maximize technical proficiency. On the contrary, by incentivizing firms to distance from each other, competition may actually boost their innovative performance. The intuition is that taking competition into account will drive firms to undertake more distant search, and in doing so, increase the chance that the firms will explore new combinations and discover technological opportunities they might not have considered otherwise. In terms of the $NK$ landscape, strategic search may help firms escape the ‘basin of attraction’ of a lower peak, allowing them to end up at a higher local peak than they might otherwise have found. As Figure 1, Panel (c) shows, this beneficial effect of strategic search asymptotes and may even decline slightly with extreme
complexity, because beyond a point the firms are already so distant, and the landscape is so rugged, that competition has little additional effect. In line with this, Figure 1, Panel (b) shows that the distance between the two firms on the landscape converges towards the technical search case as complexity increases. Thus, unlike the traditional NK model, where heterogeneity increases with complexity, once we allow for strategic search, heterogeneity reaches its zenith for intermediate levels of complexity, but then decreases.

As an example of this case, consider Tesla. By making multiple value chain choices—on design, manufacturing, retail and distribution, after sales service, etc.—that are very different from those of other automobile manufacturers (including those developing electric vehicles), Tesla has been able to both substantially differentiate itself from its competitors and achieve superior technical performance. Tesla’s success thus represents the right-hand side of Figure 1: a case of a high complexity environment where a firm achieves stronger innovation and superior technical proficiency while also setting itself clearly apart from its rivals.

**High ground advantage**

Not only does the level of complexity in the market determine whether firms’ attempts to differentiate from each other cause them to sacrifice or bolster their technical proficiency (as shown in Figure 1, Panel (c)), it also impacts the extent to which one firm is able to enjoy a competitive advantage over the other. This is shown in Figure 1, Panel (d), which shows the difference in profitability between the best performing firm (the leader) and its rival (the laggard). It shows that competitive advantage is higher under strategic search in the low complexity case, but lower in the high complexity case.

To understand why this pattern occurs, consider the case where one of the searching firms discovers an especially valuable technology, i.e., it discovers a (local or global) peak. In the standard $NK$ model, any other firm in the same basin of attraction as this focal firm would also eventually make its way to the same peak. When firms search strategically however, they learn that choosing the same position as a rival comes at a cost. Under strategic search, the rival firm may be loath to approach too close to the focal firm because when it tries to do so it may find that the improvement in its technical proficiency is more than offset by the reduction in its differentiation, so that moving closer to the focal firm causes its profits to decline. The rival firm may
therefore be motivated to maintain its distance from the focal firm, and potentially to move further away from it. This is the underlying dynamic beneath the increase in final distance between the two firms shown in Figure 1, Panel (b).

In the case of high complexity, as already discussed, the result of the laggard firm being driven to maintain its distance and search further afield will be that the laggard achieves a similar or possibly even stronger technical proficiency than it would have otherwise, closing the gap between itself and the leader. In the case of low complexity, however, it means that once a firm has discovered an innovation that gives it a performance advantage, it may be able to sustain this competitive advantage purely through competitive pressure. We term this effect the high ground advantage, reflecting the idea that once a player captures a higher position on the landscape it is able to defend this position against rivals. Such a competitive advantage is analogous to a first mover advantage (Lieberman and Montgomery, 1988), in that it accrues to the leader not because it has a patent (Mihm et al., 2015), tacit knowledge (Nelson and Winter, 1982), or any other barrier to imitation (Lippman and Rumelt, 1982; Rivkin, 2000; Ryall, 2009), but because once it has established a position, its rivals no longer have sufficient incentive to try to imitate its position. It is different from first mover advantage in that it is not that the leader was the first to act, but that it just happened to be the first to stumble upon a superior technology while searching. This finding of a high ground advantage is important because it suggests a further source of long-term heterogeneity and sustained competitive advantage between firms, one that is distinct from traditional explanations based on rivals being stuck on local peaks (Levinthal, 1997) or being constrained by patents (Mihm et al., 2015).

Our notion of a high ground advantage is consistent with prior work that argues and shows that in the presence of demand heterogeneity incumbent firms may choose to respond to the emergence of a new technology by continuing to focus on their existing technology, finding it more profitable to serve consumers who still prefer the old technology effectively than to imitate and compete with the leaders in the new technology (Adner, 2002; Adner and Snow, 2010). It is also consistent with studies that have emphasized the importance of niche markets and experimental customers as a space for the development of (initially inferior) new technologies (Malerba et al., 2007). In fact, the model suggests that firms may systematically seek out such
distinct customer preferences even if serving them initially results in lower technical proficiency, as a way of differentiating themselves from an established competitor, and shows how, at least in highly complex markets, the pursuit of these distinct customer segments may eventually lead to superior innovations than would otherwise be achieved. Indeed, while the model does not show this directly, in some cases the firm driven away may end up at a higher peak than the original leader, thus proving disruptive (Christensen, 1997; Adner, 2002). The idea of high ground advantage is also consistent with discussions of ‘kill zones’ in start-up venture financing (Kamepalli, Rajan, and Zingales, 2021; Rizzo, 2021), where start-ups may be deterred from entering a technology space because the presence of an existing player in that space makes proximate technology positions potentially unprofitable.

**Distribution of outcomes**

While the results in Figure 1 show the average outcomes across simulations both with and without competition, Figure 2 sheds further light on these mechanisms by graphing the distribution of outcomes for the two firms on the landscape for different levels of complexity in the technical search case (Figure 2, Panel (a)) and in the strategic search case (Figure 2, Panel (b)). Firms pursuing technical search always reach a peak, whether local or global. When $K$ equals zero, they both reach the global peak, but each becomes less likely to do so as complexity increases, until at $K = 11$ it is almost always the case that both end up at a local peak.

The picture looks very different under strategic search. With zero complexity, competitive tension keeps both firms on the hillside of the global peak in approximately 80% of cases. In other words, competition can induce firms to sell products that are technically sub-optimal, but distinctive, because the cost of lower technical proficiency is more than offset by the increase in market power as a result of differentiation. In the remaining 20% of cases, the global peak is reached by just one firm while the other is forced onto the hillside. The frequency of this positioning configuration (leader on a global peak vs. laggard on the hillside) declines as complexity increases because global peaks, in general, become harder to find and because the laggard’s impulse towards differentiation leads towards new local peaks. As complexity increases, the behavior of firms tends to converge towards the standard (technical search) case, with both firms becoming more likely to position on
local peaks, though it remains the case, even with $K = 11$, that a substantial proportion of simulations end with at least one firm stalled on a hillside.

***Insert Figures 2 & 3 approximately here***

**Welfare implications**

Figure 3 shows the welfare implications of strategic search, based on the results shown so far; specifically, it shows the level of consumer surplus, firms’ combined profits, and total welfare in our baseline model relative to the technical search case. As we have already seen, searching strategically allows firms to increase their profits. Figure 3 shows that in low complexity environments this increase comes at the cost of consumer surplus; as firms differentiate, they set higher prices and reduce quantities, thus capturing more of the value created at the expense of consumers. Moreover, because the net effect of strategic search under low complexity is to reduce innovation and lower average technical proficiency, consumer surplus is further reduced and overall welfare suffers because there is less total value creation in the market. In contrast, in high complexity environments, strategic search enhances technical proficiency, boosting overall value creation and welfare. Further, at high complexity levels the improvement in technical proficiency resulting from strategic search largely or entirely compensates for the increase in market power from the increase in differentiation relative to the technical search case, so that consumer surplus is largely unchanged and potentially somewhat enhanced. In other words, while firms’ increased profits under strategic search come from their exercise of market power in the low complexity case, they come from greater innovation and value creation by firms in the high complexity case.

**Nascent technologies and pre-commercial search**

Thus far, we have assumed that firms start to take their market rivals into account as soon as they start searching. This may not always be the case however. As a growing body of literature has pointed out, new industries tend to go through a pre-commercialization phase, during which technologies are still developing and market competition is yet to develop (Moeen, 2017; Moeen and Agarwal 2017; Eggers and Moeen, 2018). In such a case, organizational adaptation may initially be subject only to an internal selection environment, i.e., firms may search for viable strategies to bring the technology to market without considering or being aware of any rivals.
Only after some minimum level of technical proficiency has been achieved may firms be able to commercialize their offerings (Adner, 2002; Adner and Zemsky, 2006), from which point onward they will be subject to an external selection environment, with subsequent search being shaped by competition.

To incorporate this possibility, we run variations on our main model where we allow our two firms to pursue technical search (i.e., search the internal landscape while maximizing technical proficiency rather than profitability) for an initial pre-commercialization phase (varying in lengths of 20 and 100 periods), and then have them switch to strategic search. Figure 4 illustrates the results of these experiments. It shows that the presence of a pre-commercialization phase tends to raise average technical proficiency without substantially sacrificing long run profitability under strategic search.

In particular, Panel (a) shows the effect of pre-commercialization phase on profits, and while average profits do fall, the decline is relatively small (note that the vertical axis of Panel (a) has a much higher resolution than other graphs). Part of this reduction in profits is due to the firms ending up being closer in the experiments with a pre-commercialization phase (shown in Panel (b)). Panel (c) reports the average technical proficiency with and without pre-commercialization and compare these outcomes to the technical search case (normalized to zero). It shows that the introduction of a pre-commercialization phase always boosts technical proficiency, with the extent of increase being greater, the longer the pre-commercialization phase lasts. With a lengthy pre-commercialization phase, technical proficiency is almost as high as in the pure technical search case with low complexity, and substantially higher with high complexity. The intuition is that by the end of a long pre-commercialization phase firms have often achieved a technological peak, just as they would have in the standard NK model. In high complexity cases, the introduction of competitive concerns after this point pushes them to try even more distant search, producing yet higher proficiency; in low complexity cases, firms are content to stay on the peaks they have achieved. Interestingly, then, a pre-commercialization phase can lead to a best-of-both-worlds outcome by increasing average proficiency without substantially compromising average profits, especially for higher levels of complexity.

Panel (d) shows the underlying mechanism that separates the pre-commercialization case from the case
without pre-commercialization. The addition of the pre-commercialization phase undermines the potential for high ground advantage. With pre-commercialization each firm can arrive at a superior technological solution while searching on its own, then adjusts its position to maximize profits once the technology is brought to the market and competitive considerations start shaping the search process.

***Insert Figure 4 approximately here***

**Scope of demand heterogeneity**

As mentioned, our baseline model assumes that consumers have heterogeneous preferences across all $N$ dimensions of organization choice, so that a lack of overlap on any choice can be a basis for differentiation in the eyes of the customer. In practice, however, the heterogeneity in consumer preferences may be more limited, with consumers differing in their preference on only a handful of dimensions that are directly salient or visible to them. Consider, for instance, the case of car manufacturers. Some of the choices a car manufacturer makes, for instance, the car’s fuel efficiency or its safety features, are clearly important factors that customers will consider when choosing a car, and on which their preferences may vary. There are other choices, however, such as where the car is manufactured or which supplier the components come from, that may have substantial bearing on the cost of car production, but that are unlikely to be salient to customers, i.e., consumers are not likely to differ on which supplier they prefer, and may be homogenous in their preference for the lower cost option. Similarly, closer to home, MBA candidates deciding where to apply may consider a school’s placement record or the electives it offers (or even the reputation of the University’s sports teams!) but are largely indifferent to its tenure standards or its faculty’s research record. We can thus distinguish between salient dimensions, on which consumers have heterogeneous preferences and that may thus serve as a basis for differentiation, and non-salient dimensions on which consumer preferences are homogeneous. This is not to say that non-salient dimensions do not impact performance; only that they are not heterogeneously preferred by consumers$^{12}$. Firms that make different choices only on such non-salient dimensions, while making identical

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$^{12}$ Equivalently, we can think of innovations on salient dimensions being product innovations, the returns to which depend on consumer reactions, and innovations on non-salient dimensions being process innovations, the returns to which come from their effect on costs (Nelson and Winter, 1982).
choices on salient dimensions, will therefore still be seen as offering perfect substitutes by consumers, and their different choices on non-salient dimensions will not serve to differentiate them.

Further, whether a dimension is salient or not is not fixed, but may be susceptible to change. Firms may be able to increase the salience of a hitherto non-salient dimension, drawing consumer attention to it and convincing them of the importance of taking it into account when evaluating market offerings. By doing so, firms can endogenously create\textsuperscript{13} a basis of differentiation, inducing heterogeneous demand by highlighting hitherto ignored aspects of their offerings that may help make them distinctive (Vinokurova 2019). As an example, consider the case of fair trade coffee. Where coffee beans are sourced from, and under what terms they are purchased, has always been a key determinant of performance in the coffee industry, but historically this was not something that customers knew or cared about. By making ‘fair trade’ salient to consumers, a set of coffee providers have given rise to heterogeneity in consumer preferences— with some customers valuing ‘fair trade’ coffee while others do not—and thus created a new basis of differentiation in the market. Similarly, the growing B Corp movement (Marquis, 2020) is a means of making hitherto overlooked dimensions of organizational choice— specifically those linked to social or environmental externalities—salient to consumers.

To account for this factor, we modify our simulation to include a parameter $D \in \{0, 1, 2, \ldots, N\}$, which is the number of salient dimensions. In every simulation, we randomly choose $D$ of the $N$ dimensions to be salient, and only if the firms make different choices on these dimensions do we consider them as being differentiated from each other; differences on other dimensions no longer count towards differentiation, i.e., they do not enter the parameter $\gamma$ in our duopoly model. In other words, we now set $\gamma = D^{-1} \sum_{n=1}^{D} \sum_{t_{1n} = t_{2n}} \mathbf{1} \text{ if } D \in \{1, 2, \ldots, N\}$, and $\gamma = 1$ if $D = 0$. Our baseline results thus reflect the special case where all dimensions are salient, i.e., $D = N$. Similarly, we can think of prior work (Lenox et al., 2006; 2007) as capturing the special case where $D = 0 \rightarrow \gamma = 1$, in which there is no demand heterogeneity and therefore no scope for horizontal differentiation, and firms compete purely on vertical differences in cost or quality.

\textsuperscript{13}We do not distinguish here between the creation or discovery of demand heterogeneity (Alvarez and Barney, 2007), i.e., between firms shaping customer preferences to make them heterogeneous or simply realizing that there are customer preferences that remain untapped, using the term ‘creation’ to cover both.
Figure 5 shows how the outcomes of strategic search change as we change the number of salient dimensions ($D$) for various levels of complexity. As noted, the $D = 0$ case in these figures represents the technical search case, because in the absence of any basis of horizontal differentiation, the profit-maximizing strategy is the one with the strongest technical proficiency. Panel (a) shows a U-shaped relationship between average profits and the number of salient dimensions when $K = 0$, but the relationship morphs into an upward sloping curve for higher levels of complexity. Panel (b) shows that such variation in profits is in part explained by the distance between the two firms. As $D$ increases the distance between firms increases sharply at first, then asymptotes. This progression suggests that firms initially prioritize increasing the level of differentiation as salient dimensions open up, but beyond a point, start to care more about the way in which they differentiate, searching for the least costly way (in terms of lost technical proficiency) to achieve the same level of distance from each other. Panel (c) corroborates these dynamics, showing a U-shaped relationship between average technical proficiency and the number of salient dimensions, with average proficiency first declining and then increasing as the number of dimensions on which firms can differentiate themselves increases.

The intuition for these result is that initially as more dimensions become salient they create room for firms to differentiate themselves from each other, with the returns to such differentiation being high, so that firms are strongly motivated to make different choices to enhance their market power. However, because there are only a limited number of ways to differentiate it is likely that such differentiation comes at the cost of a substantial technological penalty. In terms of the landscape, it is hard for firms to find an alternative peak (even a local one) within the realm of strategies that differ in the $D$ elements. So with only a limited number of salient dimensions, the trade-off between differentiation and technical proficiency is most pronounced.

As $D$ increases further, the number of ways in which one firm can differentiate itself from the other increases, and the chances that a firm can find a strategy that both sets it apart from its rival and allows for strong technical proficiency increase. Beyond a point, therefore, further increases in $D$ are associated with
increasing proficiency, as firms no longer feel the pressure to distance themselves further from each other, and instead use the flexibility offered by the many ways to differentiate to improve their technical proficiency\(^{14}\). In terms of the landscape, the greater the value of \(D\), the higher the next best local peak that lies within the range of changes in \(D\) dimensions. In the extreme, when \(D = N\) we are back to the level of performance drop (or increase) we saw in our baseline model, with firms having full flexibility in how they choose to differentiate from each other, allowing them to effectively manage that trade-off.

Note that the U-shaped relationship between proficiency and salient dimensions holds mostly for low levels of complexity; as complexity increases, the relationship flattens out. This follows logically from our previous discussion of the lack of a trade-off between technical proficiency and differentiation in high complexity environments. On one hand, high complexity, and the corresponding ruggedness of the landscape, means that with even a few ways in which to differentiate, firms can find differentiated strategies that achieve relatively equifinal proficiency. On the other hand, high complexity also means that changing one or two choices purely for the sake of being different is likely to lead to a substantial drop in technical proficiency; large enough to overcome any benefits from differentiation. Thus firms in high complexity environments are neither likely to be tempted to make technically suboptimal choices purely for the sake of differentiation when the number of salient dimensions are low, nor likely to benefit much from the greater flexibility offered by a larger number of salient dimensions, resulting in a more or less flatch relationship between average proficiency and salient dimensions.

Panel (d) in Figure 5 further supports this explanation. It shows that competitive advantage has an inverted-U relationship with the number of salient dimensions. This means that creating room for differentiation is initially more beneficial to the leader than to the laggard. In a sense, this follows from our discussion of the effect of salient dimensions on proficiency: as \(D\) increases, the initial effect is to make available strategies that lead to substantially lower technical proficiency but are profitable anyway because they allow for differentiation. As the laggard firm adopts these strategies, it raises its own profit by distancing itself from the

\(^{14}\) This is not unlike the result in Adner and Levinthal (2001), where firms that are sufficiently distanced from each other in terms of customer preferences focus on improving technical performance rather than on direct market competition.
leader, but it raises the leader’s profits even more. In other words, increasing demand heterogeneity by opening up a few dimensions of differentiation is initially valuable to the market leader because it gives laggards the option to pursue different customer segments rather than try to match the leader’s technical proficiency. Beyond a point, however, opening up further dimensions creates ways for the laggard to differentiate itself more efficiently, which reduces the leader’s competitive advantage. This inverted-U relationship is important because it means that, contrary to the argument in Vinokurova (2019), introducing new dimensions of competition is not always to the (relative) advantage of market laggards. Rather, our findings suggest that up to a point, all firms in the market will want to increase the number of salient dimensions on which they compete, since doing so will raise the laggard’s absolute profitability and the leader’s competitive advantage. It’s only after a certain level of $D$ that the dominant firm will want to limit the introduction of additional dimensions of salience, even as the laggard firm is highly motivated to introduce them.

Further, the results in Panels (c) and (d) also suggest that demand heterogeneity is mostly beneficial for either firm in low complexity environments. In high complexity environments, the potential for horizontal differentiation given heterogeneous demand serves little purpose. The intuition is that while we might expect an increase in salient dimensions to drive firms to differentiate themselves more extensively in order to reduce competitive intensity (Vinokurova, 2019), this is not necessarily the case once we consider the potential negative impact of changing one aspect of a firm’s strategy on technical proficiency. Our model thus underscores the dual nature of differentiation, and the need to account for both demand-side and supply-side considerations.

**Competition with asymmetric selection**

Our assumption thus far has been that both organizations in the market are seeking to maximize profits rather than technical proficiency. This may not always be the case, however. First, in many contexts, for-profit firms face competition from non-profits, member cooperatives, government providers, or other organizations that may be concerned with maximizing welfare (and therefore technical proficiency) rather than profit (Hansmann, 1996; Kaul and Luo, 2018; Luo and Kaul, 2019). Second, even among for-profits, some firms may be temporarily buffered from the external selection environment, and may therefore choose to focus on
maximizing technical proficiency instead. For instance, new start-ups, especially those with venture backing, may often be willing to bear immediate losses in the hope of establishing themselves in the market and achieving superior technical proficiency. Similarly, large firms may invest in skunk works or other internal ventures, whose purpose is to explore potential new innovations, even if the immediate payoffs from their activity are negative.

If both firms in our simulation were buffered from external selection and subject only to internal selection, i.e., if both were seeking to maximize technical proficiency rather than profit, then we would be back to the familiar NK simulation case in prior work (Levinthal, 1997). What remains to be explored is the case where one firm—hereafter called the profit-seeker—bases its choices on whether they yield improvements in its profits, while the other—hereafter the technologist—bases its choices on whether they improve its technical proficiency.

Figure 6 shows the results of such a competition; specifically it shows how the comparative (dis)advantage of the profit-seeker vs. the technologist changes under different levels of complexity and scope of differentiation. We find that the technologist generally outperforms the profit-seeking firm, except when complexity is high and there is substantial room for differentiation—in which case, both firms’ profits are roughly equal. At first glance, this might seem counter-intuitive: why would the firm that was trying to maximize profits end up being less profitable than the one that was just pursuing innovation for innovation’s sake? The intuition behind this result is that its focus on technical proficiency means that the technologist always emerges as the leader in the simulation. To see why, consider the case where the profit-seeker happens to discover a dominant strategy (i.e., reach the global peak) first. If the firm were competing with another profit-seeker, this discovery would have translated into a high ground advantage, as we have seen previously. However, the fact that the profit-seeker is already occupying a dominant position will not deter the technologist from trying to reach that position; it will keep moving towards the same global peak. Further, as the technologist draws nearer, the profit-seeker will find its profits declining, and may eventually discover that it can improve its profits by moving away from that position, because the loss in technical proficiency from doing so will be more than compensated by the increase in differentiation. The profit-seeker may thus end up climbing down from the global peak, despite having been the first to reach it, and instead settle on a position on the hillside where its profits are maximized. More generally, by ignoring short-term profits, and focusing purely on improving its
technical proficiency, the technologist is able to force the profit seeker to accommodate its presence, even at the cost of the latter’s own performance. In the process, the technologist ends up earning higher profits in the long run than the profit-seeker. This dynamic is stronger when only a limited number of dimensions are salient because, as we have already seen, limiting the number of salient dimensions increases the gap between the leader and the laggard, which in this case is the gap between the technologist and the profit-seeker, respectively.

The long-term advantage of the technologist has several real-world implications. First, it suggests an alternative explanation for why entrants may end up outperforming incumbents in some markets. While prior explanations of incumbent disruption have focused on the role of organizational inertia or managerial cognition (Levinthal and March, 1993; Tripsas and Gavetti, 2000), our model suggests an additional, though complementary mechanism: to the extent that entrants may be (temporarily) buffered from external selection forces because of their experimental nature, they may have a natural advantage over incumbents that are expected to report regular profits. So, for instance, many platform businesses—Amazon, Uber, etc.—may owe their success to being able to experiment and develop their business models against competitors (Barnes and Noble, cab companies) that could not afford to lose money at the same rate. Second, it highlights the limits to public equity markets in supporting innovation. Several scholars have expressed concern about the growing short-termism of public markets (Sampson and Shi, 2020), with their emphasis on quarterly returns, arguing that such myopia comes at the cost of long-term investments in R&D (Manso, 2011) and capital assets (Souder and Shaver, 2010), leaving innovative, long-term strategies to be pursued by privately held firms with relatively patient capital (Benner and Zenger, 2016; Kaul, Nary, and Singh, 2018). The results in Figure 6 are consistent with these arguments, showing that being constantly subject to an aggressive external selection environment may prove harmful to the long-term adaptation and eventual competitive advantage of an organization. Finally, these results also offer a potential theoretical rationale for the competitive advantage of business strategies that emphasize social responsibility or sustainability. By focusing on maximizing overall value creation rather than profits (Mahoney and McGahan, 2007), such strategies, while costly in the short-run, may inadvertently boost innovation, allowing firms focused on sustainability to discover high value strategies their more profit-seeking rivals may be unable to discover and loath to imitate, resulting in long run competitive advantage.
It is also worth noting that this result suggests something of a game-theoretic dilemma for each firm, at least in low complexity environments. On one hand, if both firms choose to focus on maximizing profits (or, equivalently, if both firms face a strong external selection environment) then both will realize higher profits than if they had both chosen to focus on maximizing technical proficiency. On the other hand, if only one firm focuses on maximizing profits, while its rival focuses on maximizing technical proficiency, then it risks being placed at a serious competitive disadvantage (though it would still achieve higher absolute profits than if it too focused on maximizing technical proficiency). In sum, the results in Figure 6 suggest that a firm is best served if it can ensure that its rival focuses on profits while it focuses on technical proficiency. Of course, with high complexity and high demand heterogeneity, this tension goes away, because in such a context profit-seeking is the dominant approach, allowing the firm to realize both superior profits and superior technical proficiency.

***Insert Figure 6 approximately here***

**DISCUSSION AND CONCLUSIONS**

We develop a model of organizational adaptation in the face of both technical complexity and heterogeneous demand, where firms are able to differentiate from their rivals both vertically and horizontally, and therefore search for the best competitive position rather than the most efficient technology. In doing so, we address a long-standing gap in theories of organizational adaptation (Baumann et al., 2019) moving beyond models of industry structure and evolution with homogenous offerings (Lenox et al., 2006; 2007; Knudsen et al., 2014) to introduce heterogeneous demand conditions and examine how competitive pressures influence the process of organizational search (Nelson and Winter, 1982). We also contribute to work on demand-side heterogeneity and its effect on innovation by modeling a richer process of internal adaptation than the simple linear models generally assumed in this literature (Adner and Levinthal, 2001; Adner, 2002; Adner and Zemsky, 2006). More generally, by incorporating both supply-side technological complexity and demand-side preference heterogeneity, our model combines the internal search for superior technologies with the external quest for superior market position, thus integrating two streams of the literature that have long been acknowledged to be inherently connected (Wernerfelt, 1984; Porter, 1980; 1996; Adner et al., 2016).
Our findings also offer new insight for the innovation literature more broadly, suggesting that the effect of competition on innovation is likely to be moderated by the complexity of the task environment. When complexity is low, and the number of equifinal technologies available are limited, competitive pressure may push firms to compromise on innovation for the sake of differentiation. In such conditions, firms’ strategic actions to differentiate themselves and increase market power thus come at the cost of consumer surplus and social welfare, consistent with a traditional neo-classical economics perspective. Conversely, when complexity is high, competitive pressure may facilitate organizational innovation by getting firms out of their current rut, and driving them to explore more broadly. In such conditions, firms’ quest for differentiation actually boosts innovation and welfare, in line with work in Austrian economics which sees market power as essential for dynamic efficiency (Schumpeter, 1942; Nelson and Winter, 1982). We further demonstrate that these mechanisms depend on the extent of demand heterogeneity, as captured by the number of salient dimensions on which firms may differentiate.

Our findings also extend our understanding of competitive advantage in several ways. First, we contribute to demand-side perspectives on competitive advantage (Adner and Zemsky, 2006) by introducing the case of high ground advantage, in which a firm maintains a superior technological position not because it has patent protection, unique competences, or other barriers to imitation to protect it, but simply because it discovered a superior configuration first, and its rivals had little incentive to imitate it. Our findings are also consistent with prior work that has emphasized the importance of niche markets for the development of (initially) inferior technologies (Adner, 2002; Malerba et al., 2007), and suggest that firms seeking to improve their competitive position may systematically seek out such heterogeneous customer preferences even if serving them requires the adoption of less efficient technologies. Second, consistent with work on slack-driven search (Cyert and March, 1963), our findings demonstrate how being temporarily buffered from external selection may prove beneficial for a firm’s long-run competitive advantage. We show that firms with a technological focus can credibly commit to achieving a superior technological position, forcing their short-term oriented rivals to accommodate them and choose less desirable technologies. As such, our findings speak to work on the perils of short-termism (Souder and Shaver, 2010; Benner and Zenger, 2016; Kaul et al., 2019; Nary and
Kaul, 2021) while offering a novel explanation for the disruption of incumbents by new entrants, based on their differential sensitivity to short-term losses. Moreover, our analyses suggest that the benefits of such buffering are not uniform: not only is being protected from the selection environment only valuable in low complexity environments, but it is also only valuable when such protection is exclusive. If all firms are protected from external selection, as during a pre-commercialization phase (Moeen, 2017; Moeen and Agarwal, 2017), the result is stronger innovation but a lower competitive advantage for the leader. Third, our findings also have potential implications for the literature on sustainability and social enterprises, suggesting two ways in which combining a social mission with commercial objectives may prove beneficial. On one hand, such a combination may open up additional room for differentiation, which may allow a firm pursuing a social mission to raise its profitability, though its implications for competitive advantage are less clear. On the other, its embrace of a combined mission may buffer the firm from external selection pressures, enabling it to discover technologies and strategies that its more profit-focused rivals may overlook.

Finally, our findings speak to a growing literature on organizational shaping (Gavetti et al., 2017; Helfat, 2021). In particular, we break the overall construct of a pay-off structure (or selection environment) down into two parts—an internal payoff structure that guides which innovations are retained within a firm, and an external payoff structure that determines how profits are distributed across firms (Nelson and Winter, 1982)—thus incorporating the crucial difference between capability (or value creation) and profit (or value capture). Further, we focus on one particular type of shaping: the effect of competitive interactions on the firm’s payoff structure. While prior work on shaping has largely focused on deliberate efforts by firms to reshape the payoff structures of their rivals (Gavetti et al., 2017; Patvardhan and Ramachandran, 2020), our findings highlight that the very process of organizational innovation will automatically reshape the market for its rivals by changing the structure of demand and supply they face (Nelson and Winter, 1982; Helfat, 2021). Our findings also extend research on the potential for firms to reshape demand conditions by making certain dimensions of their offerings more (or less) salient (Vinokurova, 2019), delineating the conditions under which such reshaping is likely to be successful, and its implication for competitive advantage.

As with any study, our work has its limitations, which offer avenues for further research. First, our
model is limited to considering competitive interactions between only two firms. Although this setup allows us to parsimoniously explore the competitive mechanisms at play, future research could examine more complex industry structures and patterns of on-going competitive interaction among several firms. Second, because we are interested in the effect of competitive interactions, we have deliberately chosen to keep the internal landscape fixed and exogenous to firm action. Future work could relax this assumption, allowing firms to influence each other’s selection environments, e.g., by incorporating patent protection (Mihm et al., 2015) or allowing firms to modify the $N K$ landscape in other ways (Gavetti et al., 2017); it could also model turbulence in the internal selection environment (Siggelkow and Levinthal, 2003). Third, given our focus on external selection environments, we have chosen to model internal organizational search in line with existing models of adaptation, assuming it to be local, experiential, and costless. Future work could relax these assumptions, e.g., by allowing for cognitive search or imitation (Nelson and Winter, 1982; Martignoni et al., 2016; Posen and Martignoni, 2018), including search costs, or modeling various types of internal decision making structures (Ethiraj and Levinthal, 2004; Mihm et al., 2010; Baumann et al., 2019). Future work could also modify how we model demand heterogeneity by allowing for asymmetric preferences (Adner, 2002) so that demand may be unevenly distributed even within the salient dimensions. Finally, as a model, our theory is meant to provide a simple representation of the mechanisms connecting competitive dynamics to adaptation; as such there are many aspects of innovation that we do not consider for the sake of parsimony (Knudsen et al., 2019).

In conclusion, our study offers fresh insights into the way that competitive positioning in the face of heterogeneous demand shapes the process of organizational adaptation, using a simulation model that combines the internal search for technical proficiency with the external quest for a differentiated market position. We show that searching strategically—i.e., seeking the best competitive position—limits innovation in low complexity environments, but boosts it in high complexity environments, with these effects being moderated by the extent to which the market has a pre-commercialization phase, the extent of demand heterogeneity, and whether both firms are equally susceptible to external competitive pressure. Our findings integrate demand heterogeneity and competitive dynamics into models of organizational adaptation, while contributing to work on organizational shaping, innovation, and competitive advantage.
REFERENCES


FIGURES

Figure 1
Strategic search vs. technical search

Notes: Figure 1 graphs the difference in average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)) between firms engaging in strategic search and those engaging in the standard technical search. Firms engaging in strategic search achieve higher profits, are further apart on the landscape, and achieve superior technical proficiency in high-complexity task environments.
Figure 2
Effects of strategic search on firms’ positions and performance

Notes: Figure 2 demonstrates differences in firms’ locations between the standard case with technical search (Panel (a)) and the case with strategic search (Panel (b)). The most salient difference between the two cases is that, with strategic search, firms tend to gravitate towards the hillside of peaks, especially for low levels of complexity.
Figure 3
Welfare implications of strategic search

Notes: Competition increases profits and decreases consumer surplus along the complexity spectrum. Both effects are driven by market power: as firms differentiate, they can set higher prices and reduce quantities, increasing the firms’ ability to capture value at the expenses of the consumers. Interestingly, however, while for low levels of complexity, the decrease in consumer surplus outweighs the increase in profits, for high levels of complexity, the opposite holds true, leading to value creation overall.
Notes: Figure 4 graphs the difference in average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)) between firms in the standard technical search case and firms engaging in strategic search starting at $t = 0$, those that engage in technical search then switch to strategic search at $t = 20$, and those that engage in technical search then switch to strategic search at $t = 100$. Engaging in technical search before switching to strategic search can increase technical proficiency while only marginally reducing profits.
Figure 5
Effects of strategic search with $D \leq N$ dimensions for differentiation

Notes: Figure 5 graphs the average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)) for firms engaging strategic search for different levels of complexity and dimensions salient for differentiation. Increasing the number of dimensions salient for differentiation can lead to less differentiation in equilibrium, especially at low levels of complexity.
Figure 6

Competition against technologists

Notes: Figure 6 plots the average difference in profits between the profit-seeker and technologist firm. The technologist has a competitive advantage for low and moderate levels of complexity, especially when the number of dimensions relevant for differentiation is small.