

Strategic Search:
Organizational adaptation with competitive positioning

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March 21, 2022

ABSTRACT

In this paper, we study how demand heterogeneity shapes organizational adaptation in complex environments. 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. We also show 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

*Authors contributed equally and are listed in alphabetical order by last name. We thank Connie Helfat, Thorkjorn Knudsen, Phanish Puranam, Myles Shaver, and Charlie Williams, as well as seminar participants at the DRUID Conference (2021), INSEAD (2022), HEC Paris (2021), SEI Consortium (Barcelona, 2021), and University of Minnesota (2021) for helpful suggestions on earlier versions of this manuscript. All remaining errors are our own.

1. 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 path-dependent process of evolution towards fit (Levinthal, 1997; 2021). This process may be further divided into two parallel but distinct elements: the search for internal fit, i.e., for the internal combination of resources and capabilities that maximize an organization’s technical proficiency; and the search for external fit, i.e., for the market position that maximizes the firm’s appeal to customers, given competition and heterogeneous demand. It is clear that an organization needs both types of fit to survive and prosper (Levinthal, 2021); indeed, it is in this sense that resource-based perspectives of the firm that emphasize the internal proficiency of the organization (Barney, 1991; Peteraf, 1993; Helfat and Peteraf, 2003) and positioning-based perspectives that highlight its competitive position (Porter, 1980; 1996; Adner, Ruiz-Aliseda, and Zemsky, 2016) are correctly seen as two sides of the same coin (Wernerfelt, 1984). Despite this recognition, however, formal theoretical work on organizational innovation remains mostly divided in its focus. On one hand, models of organizational adaptation, building off the *NK* simulation approach (Levinthal, 1997), generally assume homogenous demand, so that an organization’s profitability and survival in these models is determined solely by its technical proficiency, even in a competitive marketplace (Nelson and Winter, 1982; Lenox, Rockart, and Lewin, 2006; 2007; Knudsen, Levinthal, and Winter, 2014; Adner, Csaszar, and Zemsky, 2014). On the other, models of organizational innovation in the face of heterogeneous demand have abstracted away from the experiential nature of evolutionary search, modeling firms making choices between known alternatives with well-specified payoffs (Adner and Levinthal, 2001; Adner, 2002; Adner and Zemsky, 2006).

In this study, we seek to bring these two streams together by developing a model of organizational adaptation under demand heterogeneity, i.e., one where firms engage in a process of experiential search in a context where firms can differentiate themselves both vertically and horizontally from their rivals. The key methodological innovation here is that a firm's payoffs in such a context are determined not only by the technical proficiency of the strategy¹ it chooses (i.e., its internal fit), but by the extent to which this strategy is different from that of its rivals and thus enables it to serve a distinct set of customer needs (i.e., its external fit). 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 face²: 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 study thus models *strategic search*—i.e., the quest for the most profitable market position—and systematically compares the outcomes of such a search to those of technical search—i.e., the quest for the most efficient or productive technology—as modeled by prior work using *NK* simulations.

Baseline results from our model show that strategic search lowers the average technical proficiency of firms while increasing the competitive advantage of one firm over the other under conditions of low complexity, but has the opposite effect under high complexity. The intuition is that

¹ Throughout this paper we use the term ‘strategy’ to mean the configuration of choices made by the firm. As discussed further below, a strategy represents both an internal technology for combining resources and inputs that determines the firm’s proficiency, as well as an external market offering that determines the firm’s position relative to rivals.

² 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.

in low complexity environments, where there are a limited number of high performing strategies, firms face a trade-off between maximizing technical proficiency 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 superior strategy 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 equivalent strategies and the global peak is difficult to find, the pressure to differentiate may boost innovation, driving firms to undertake more distant search and so achieve higher technical proficiency than they might otherwise have discovered.

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 the weaker firm’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 long-term profits than the profit-seeker, with this competitive advantage being greater, the less complex the context. The intuition is that the technologist may end up claiming the superior technological position, while the profit-seeker ends up

accommodating its rival at the cost of its own proficiency. 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. First, we model organizational adaptation under heterogeneous demand, where firms use experiential search to discover not only superior internal configurations of resources and capabilities (Levinthal, 1997; Nelson and Winter, 1982; Lenox et al., 2006; 2007; Knudsen et al., 2014; Baumann et al., 2019) but also superior (horizontally differentiated) positions in a competitive marketplace (Adner, 2002; Adner and Zemsky, 2006). In doing so, we not only integrate the dynamics of internal search with those of competitive positioning (Nelson and Winter, 1978; 1982, Wernerfelt, 1984; Porter, 1980; Adner et al., 2016), we also highlight the critical role of complexity in mediating the relationship between the two, with market differentiation coming at the cost of technical innovation in low complexity settings, but enhancing such innovation in high complexity settings. Second, by modeling an adaptive process where firms search simultaneously and each firm's search choices are endogenously shaped by those of its rivals, we contribute to an emerging literature on organizational shaping (Gavetti et al., 2017; Helfat, 2021). Not only do we show how demand heterogeneity impacts organizational adaptation and competitive advantage, we also model how this effect varies with the extent to which demand is heterogeneous in a non-linear way (Vinokurova, 2019). Third, our study also offers new insights on competitive advantage, 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 heterogeneous customer preferences to differentiate themselves—as well as the long-term benefits to a firm from being temporarily buffered from competitive pressure (Levinthal and Posen, 2007).

2. Organizational adaptation and demand heterogeneity

A long-standing tradition in strategy and management research sees organizational adaptation as an evolutionary process, wherein at each stage boundedly rational actors repeatedly compare between a limited set of (path-dependent) alternatives, choosing the one that best fits the prevailing selection environment (March and Simon, 1958; Nelson and Winter, 1982; Levinthal and March, 1981; 1993; Siggelkow, 2002; Levinthal, 2021). The canonical representation of this process 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).

A key criticism of work in this tradition is that it remains too internally focused, with the outcomes of search being determined by an (exogenous) internal selection environment, leaving little room for competitive dynamics (Baumann et al., 2019) or for the ways in which the selection environment itself may be shaped through interactions with rival firms (Gavetti et al., 2017; Patvardhan and Ramachandran, 2020; Helfat, 2021). Early work in this area largely ignored competition (see Levinthal and Warglien, 1999, for an important exception), focusing instead on how search outcomes were determined by the structure of interdependencies (Ethiraj and Levinthal, 2004a; 2004b; Ethiraj, Levinthal & Roy, 2008), organizational design choices (Siggelkow and Levinthal, 2003; Rivkin and Siggelkow, 2003), or the nature of the search process itself (Gavetti and Levinthal, 2000; Baumann and Siggelkow, 2013). And while more recent studies have incorporated competitive pressures in their analyses, using these to map the results of organizational search to firm profitability

and survival (Lenox et al., 2006; 2007; Adner et al., 2014), the process of search itself remains internally focused. 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).

One reason for this lacuna is that existing models of organizational adaptation generally assume a homogenous product or offering (Nelson and Winter, 1982; Lenox et al., 2006; 2007; Knudsen et al., 2014), meaning that firms can only compete vertically (using superior technical proficiency to achieve higher quality or lower cost) and cannot differentiate from each other horizontally. While this is a useful simplifying assumption for many purposes, it also limits the analysis in meaningful ways. Specifically, it ignores the reality that 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). As several empirical studies have shown, competition impacts not only how aggressively firms search (Chen et al., 2010; Katila, Chen, and Piezunka, 2012) but also where they search (Malerba et al., 2007; Polidoro and Toh, 2011; Giustiziero, Kaul and Wu, 2019), with firms either moving away from their rivals (Clarkson and Toh, 2010; Kaul, 2012; Wang and Shaver, 2016; 2018), or closer to them (Agarwal et al., 2007; Pacheco-de-Almeida and Zemsky, 2012). In fact, such horizontal differentiation among firms is central to the ‘positioning’ view of strategy (Porter, 1980; 1996) which views strategy as not just maximizing efficiency, but making distinct but internally consistent choices in order to differentiate oneself from the competition and serve a distinct market need (Siggelkow, 2001; 2002; Adner et al., 2016). Not only does assuming homogenous offerings mean ignoring the potential for such horizontal positioning, it also implicitly assumes total equifinality across strategic choices in the eyes of the consumer. In other words, it assumes that consumers are indifferent to whatever strategic choices firms make and view offerings from firms that adopt entirely different strategies as perfect substitutes.

In this study, we seek to relax the assumption of homogenous demand when modeling organizational adaptation, 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. In keeping with prior work, we continue to conceive of adaptation as an evolutionary process of local search, with firms choosing different strategic configurations in search of higher performance. Unlike prior work, however, we assume that these choices not only impact the technical proficiency of the firm (i.e., its vertical strength relative to competitors) but also the segment of the market that it targets (i.e., its horizontal position relative to competitors). Thus, the performance impact of each choice is determined not only by whether (and how much) the choice improves the firm's internal proficiency, but also by whether (and how much) it moves the firm away from its rivals. Note that introducing this dimension of horizontal positioning also makes the selection environment fundamentally endogenous, because each firm's choices not only impact its own profitability but also the payoff structure for its rivals (Nelson and Winter, 1982; Helfat, 2021)³. Specifically, the returns to superior technical proficiency change depending on whether rivals move closer together or further apart. We see this as a key feature of our revised model, because it means that the selection environment any individual firm faces (and the search choices it makes) is shaped and determined at each stage by the aggregation of the actions of the firms in that market.

3. Model

3.1. *NK landscape and internal fit*

We develop a modified version of an *NK* simulation to allow for demand heterogeneity. To do so, we build on prior work (Lenox et al., 2006; 2007; Knudsen et al., 2014; Mihm et al., 2015), that uses the

³ As Nelson and Winter 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)

standard *NK* landscape to reflect the internal selection environment of the firm. Fitness on the landscape thus reflects the technical proficiency of the organization rather than its profitability or financial performance, with higher peaks representing strategies that result in superior efficiency and effectiveness. This technical proficiency then becomes the basis on which the focal firm competes with others in a competitive marketplace (as described in more detail below).

Given that our primary interest is in understanding the effect of demand heterogeneity in the external environment, we follow the standard simulation set up in modeling the internal environment represented by the *NK* landscape (Levinthal, 1997; Lenox et al. 2006; 2007). Specifically, as in the standard *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 firms to alter each other’s internal landscapes (Levinthal and Warglien, 1999; Gavetti et al., 2017), such as through the use of patents (Mihm et al., 2015) or nonmarket interventions (Capron and Chatain, 2008; Dorobantu et al., 2017).

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 $K \in \{0, 1, 2, \dots, N - 1\}$. More formally, firm i ’s strategy is an N -dimensional vector $t_i = (t_{i1}, t_{i2}, \dots, t_{iN})$ of binary policy choices $t_{in} \in \{0, 1\}$ for $n \in \{1, \dots, N\}$, yielding a total of 2^N possible combinations of choices⁴. We interpret each element of a strategy t_{in} as a choice to incorporate a component n by firm

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).

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 $c_{in}(t_{in1}, t_{in2} \dots, t_{ink})$ where $in1, in2 \dots, ink$ 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 that each policy choice depends on all other choices, yielding a rugged landscape.

The fitness level of a given technology \mathbf{t}_i is calculated as the arithmetic mean of the N contributions c_{in} according to the function $F(t_i) = N^{-1} \sum_{i=1}^N c_{in}(t_{in}, t_{in1}, t_{in2} \dots, t_{ink})$. A “landscape” represents a mapping of all 2^N possible 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 strategies for which a firm cannot improve its performance through local search alone (Levinthal 1997). The “global peak” is the highest peak in the landscape.

3.2 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 strategies, 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 strategy, retaining that

strategy 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 competition⁵.

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 as well, thus allowing for competitive differentiation and positioning. 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 consumers⁶. 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 addition 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,

⁵ Nelson and Winter model the amount each firm invests in R&D rather than the process of search which is our focus.

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.

2001; Kaul and Luo, 2018)⁷. We limit ourselves to modeling competition between two firms in order to keep the analysis simple; by focusing on 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 our main analysis, though our main findings are robust to using a Bertrand model (as shown in Online Appendix B).

In the standard differentiated duopoly model, the representative consumer's utility, $U = \alpha_1 q_1 + \alpha_2 q_2 - \frac{1}{2}(q_1^2 + q_2^2 + \gamma q_1 q_2)$, 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 $\gamma \in [0,1]$, which is inversely proportional to the degree of differentiation between the two products (with 0 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

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

⁷ We acknowledge the potential inconsistency between the behavioral assumptions of the NK model and the full rationality implied by a Cournot model, though we are not the first to combine the two (Lenox et al., 2006; 2007; Knudsen et al., 2014). Note that our main findings do not strictly require that firms achieve the Cournot equilibrium, only that they move directionally towards it as their strategies change. As discussed later (and shown in Appendix A), we run an alternative analysis where firms face a simple proximity penalty and find results that are relatively robust.

Mapping this to the *NK* landscape described in the previous sub-section, we set the value created⁸ 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 adopt identical strategies, 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 population⁹. More generally, an inspection of the profit function reveals that profits are increasing in the technical proficiency of the focal firm, i.e., $\frac{\partial \pi_i^C}{\partial (\alpha_i - c_i)} > 0$, decreasing in the technical proficiency of its rival, $\frac{\partial \pi_i^C}{\partial (\alpha_j - c_j)} < 0$, and increasing in the two firms’ differentiation, $\frac{\partial \pi_i^C}{\partial (-\gamma)} > 0$ if $2(\alpha_i - c_i) - \gamma(\alpha_j - c_j) > 0$. As mentioned, we start by assuming that 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.

3.3 Simulation set-up

For our simulation results, we assume that both firms start from the same (randomly determined) point on the landscape¹⁰, 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 π_i^C and determine whether to

⁸ 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).

⁹ 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.

¹⁰ Results are similar if we start the two firms from different (randomly chosen) points on the landscape.

retain the change in firm strategy based on whether it resulted in improved profits (rather than in increased technical fitness).¹¹ We set $N = 12$ and run each simulation for 200 rounds of competitive interactions, 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 fitness¹². 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.

4. Findings

Figure 1 shows the baseline results from our simulation, comparing the outcomes from our model of strategic search to the results from the standard *NK* model, for different levels of complexity (K). Unsurprisingly, 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 profits, whereas in

¹¹ 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.

¹² 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.

the traditional search model they are only trying to maximize technical proficiency. Similarly, Figure 1, Panel (b) shows that firms always 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

4.1 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 innovation¹³ 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 firms face 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 strategy 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

¹³ Consistent with our conceptualization of technical proficiency as reflecting the internal technology of the firm, we use the term 'innovation' throughout the paper to mean improvements in the proficiency of the firm's internal resources and capabilities.

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 (vertical distance) and market power (horizontal distance), 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 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 technically 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 targeted differentiation (Dushnitsky, Piva, and Rossi-Lamastra, 2022).

Next, consider the high complexity case. In highly complex situations, the technically optimal solution is often hard to discover, and there are many ways of achieving moderate proficiency; in NK terms, there are many local peaks, and firms searching on the landscape are likely to end up horizontally differentiated in any case. In such contexts there is therefore no longer a trade-off between technical proficiency and differentiation. 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 levels off 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, under strategic search heterogeneity reaches its zenith for intermediate levels of complexity and 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 simultaneously 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.

4.2 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 better performing firm and its rival. 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 lowers its profits. The rival firm may therefore be motivated to maintain its (horizontal) 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 weaker firm being driven to maintain its distance and search further afield will be that this firm achieves a similar or possibly even stronger technical proficiency than it would have otherwise, closing the (vertical) gap between itself and the stronger firm. 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 stronger firm 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; Ghemawat, 1991; 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 traditional first mover advantage in that it is not that the stronger firm was the first to act, but that it just happened to be the first to stumble upon a superior strategy 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 unable to move past local peaks (Levinthal, 1997). In particular, while the problem of rivals getting stuck at local peaks is more likely to result in competitive advantage as complexity increases, high ground advantage is especially likely in low complexity settings.

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.

4.3 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)). Panel (a) shows that 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 (Panel (b)). 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 (the stronger firm on the global peak and the weaker on a hillside) declines as complexity increases because global peaks, in general, become harder to find and because the weaker firms' 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 Figure 2 approximately here

4.4 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, such as 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 consumers¹⁴. Firms that make different choices only on such non-salient dimensions, while making identical choices on salient dimensions, will therefore still be seen as offering perfect substitutes by consumers, and their different

¹⁴ 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 non-salient dimensions will not serve to differentiate them.

Further, whether a dimension is salient or not 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 create¹⁵ 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. More generally, as customers pay increasing attention to the social and environmental externalities generated by firms’ practices, this increases the heterogeneity of demand in the market and the range of strategies available to firms, as reflected in the rise of B Corps and other hybrid forms (Fosfuri, Giarratana, and Roca, 2016; Kaul and Luo, 2018; Marquis, 2020).

To account for this factor, we modify our simulation to include a parameter $D \in \{0, 1, 2, \dots, N\}$, 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 γ in our duopoly model. In

¹⁵ 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.

other words, we now set $\gamma = D^{-1} \sum_{n=1}^D 1_{\{t_{1n}=t_{2n}\}}$ if $D \in \{1, 2, \dots, N\}$, 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.

Insert Figure 3 approximately here

Figure 3 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 levels off. This progression suggests that firms initially prioritize increasing the level of differentiation (horizontal distance) between them as salient dimensions open up, but beyond a point switch to prioritizing technical proficiency (i.e., reducing vertical distance) while maintaining the level of differentiation they have already achieved. 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 this result is that when D is low, adding more salient dimensions creates room for firms to differentiate themselves from each other, with the returns to such differentiation

being high (because changing just a few choices can maximally differentiate a firm), 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.

In contrast, where D is high, there are many ways in which one firm can differentiate itself from the other, and a firm can more easily find a strategy that both sets it apart from its rival and allows for strong technical proficiency. 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 proficiency¹⁶. 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

¹⁶This 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.

corresponding ruggedness of the landscape, means that with even a few ways in which to differentiate, firms can find differentiated strategies that achieve relatively equal 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 flat relationship between average proficiency and salient dimensions. This is also consistent with empirical work which suggests that firms may be less responsive to diverse customer demands in the face of high complexity (Ethiraj et al., 2012).

Panel (d) in Figure 3 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 stronger firm than to the weaker firm. 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 positions that lead to substantially lower technical proficiency but are profitable anyway because they allow for differentiation. As the weaker firm adopts these strategies, it raises its own profit by horizontally distancing itself from the stronger firm, but it also increases the vertical gap between itself and the stronger firm, so the latter experiences an even greater increase in profits. In other words, increasing demand heterogeneity by introducing a few dimensions of differentiation is initially valuable to the stronger firm because it gives the weaker firm the option to pursue different customer segments rather than try to match the stronger firm's technical proficiency. Beyond a point, however, as D increases firms can be more selective as to the dimensions on which they differentiate, and may choose dimensions that result in limited loss in technical proficiency, leading to less of a competitive advantage for the stronger firm. 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 weaker firms in the market. 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. It is 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 weaker 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.

4.5 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). 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.

Insert Figure 4 approximately here

Figure 4 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 in the long run 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 is more likely to emerge as the stronger firm 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 seen, limiting the number of salient dimensions increases competitive advantage, 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; Nary and Kaul, 2021). The results in Figure 4 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 (Levinthal and Posen, 2007). Finally, these results also offer a potential theoretical rationale for the competitive advantage of business strategies that emphasize social responsibility or sustainability (Fosfuri et al., 2016; Kaul and Luo, 2018). 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 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 (despite the increase in its absolute profits). In sum, the results in Figure 4 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.

4.6 Some extensions

We run two additional extensions to our main analyses to investigate the boundary conditions for our findings. First, while our analyses thus far assume that firms engage in market competition

from the very start of the simulation, this may not always be the case. Firms may need to achieve some minimal level of technical proficiency before they can compete in the market (Adner, 2002; Adner and Zemsky, 2006) and many industries go through a pre-commercialization phase where firms are working to develop commercially viable technologies and not competing directly in the market (Moeen, 2017; Moeen and Agarwal, 2017). We therefore run a robustness check on our main analysis where we allow for a pre-commercialization period, i.e., we let the two firms in our simulation engage in technical search for some initial period, and then switch them to strategic search. The results of this analysis are shown in Online Appendix C. Unsurprisingly, the longer this pre-commercialization period, the closer the long-term outcomes are to those achieved through pure technical search. However, we also see that the introduction of a pre-commercialization period has a stronger positive effect on average technical proficiency than its negative effect on average profitability. Thus, temporarily buffering firms from an external selection environment early in their lifecycle may allow for substantial differentiation between firms without compromising innovation.

Second, we also rerun our main analyses imposing a simple proximity penalty on firms (i.e., penalizing them for every choice they make in common with a rival) but otherwise allowing them to engage in technical search. We do so in part to avoid having to assume that firms arrive at a Cournot equilibrium, which seems inconsistent with the boundedly rational nature of our simulation, and partly to separate the pure effect of horizontal distance in our model from the effect of vertical distance. As shown in Online Appendix A, this proximity penalty works in exactly the same way as a Cournot model in low complexity contexts: firms sacrifice technical proficiency for greater differentiation, increasing average profits but lowering average innovation relative to the technical search case. In high complexity contexts, however, we no longer see the same increase in average technical proficiency as we saw in our main analysis. The intuition is that while imposing a simple penalty for making common choices incentivizes firms to pursue horizontal distance, it does not create the same incentives for the

weaker firm to try and close the vertical distance between itself and the stronger firm as the Cournot model does, so we do not see the same benefits of distant search.

5. 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 bring together work on organizational adaptation that emphasizes the evolutionary and boundedly rational nature of search but focuses on homogenous offerings (Nelson and Winter, 1982; Levingthal, 1997; Lenox et al., 2006; 2007) and work on market positioning that accounts for heterogenous demand but models search as a rational choice between known alternatives (Adner and Levingthal, 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 formally 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 extend our understanding of firm adaptation and 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 are better off focusing on a different niche segment that trying 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 (Levinthal and Posen, 2007). 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 promising strategies. 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. 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 hand, 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.

Our findings also speak to a growing literature on organizational shaping (Gavetti et al., 2017; Helfat, 2021). 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; Patwardhan 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.

Finally, our findings also offer new insight for the innovation literature, suggesting that the effect of competition on innovation is likely to be moderated by both the complexity of the task environment and the heterogeneity of market demand. When complexity is low, and the number of high performing strategies available are limited, competitive pressure may push firms to compromise on technological innovation for the sake of differentiation. In other words, in such contexts firms prioritize value capture over value creation, increasing their market power at the cost of lower average proficiency (and therefore lower consumer surplus). 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 value creation, 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, albeit in non-linear ways.

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, and we believe the general intuition for our results would hold even in contexts with multiple firms (as reflected in our examples), 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 NK 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, 2004a; 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 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 strategy 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 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.

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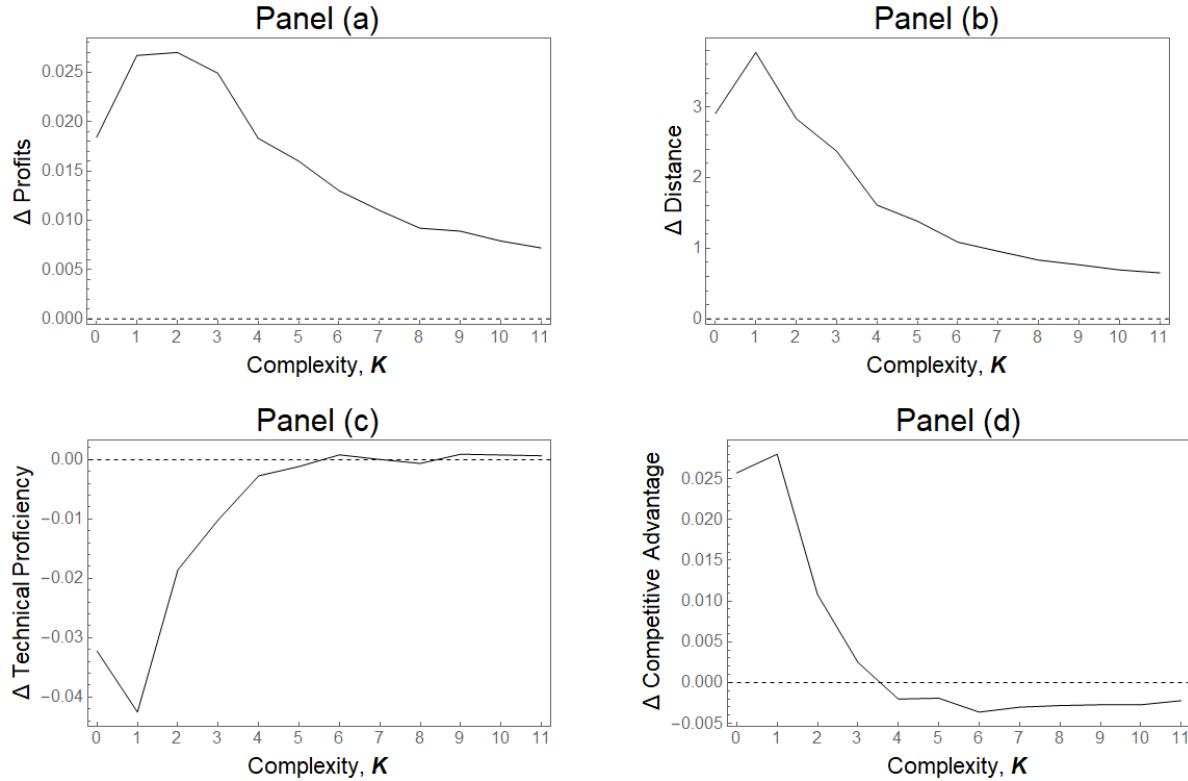
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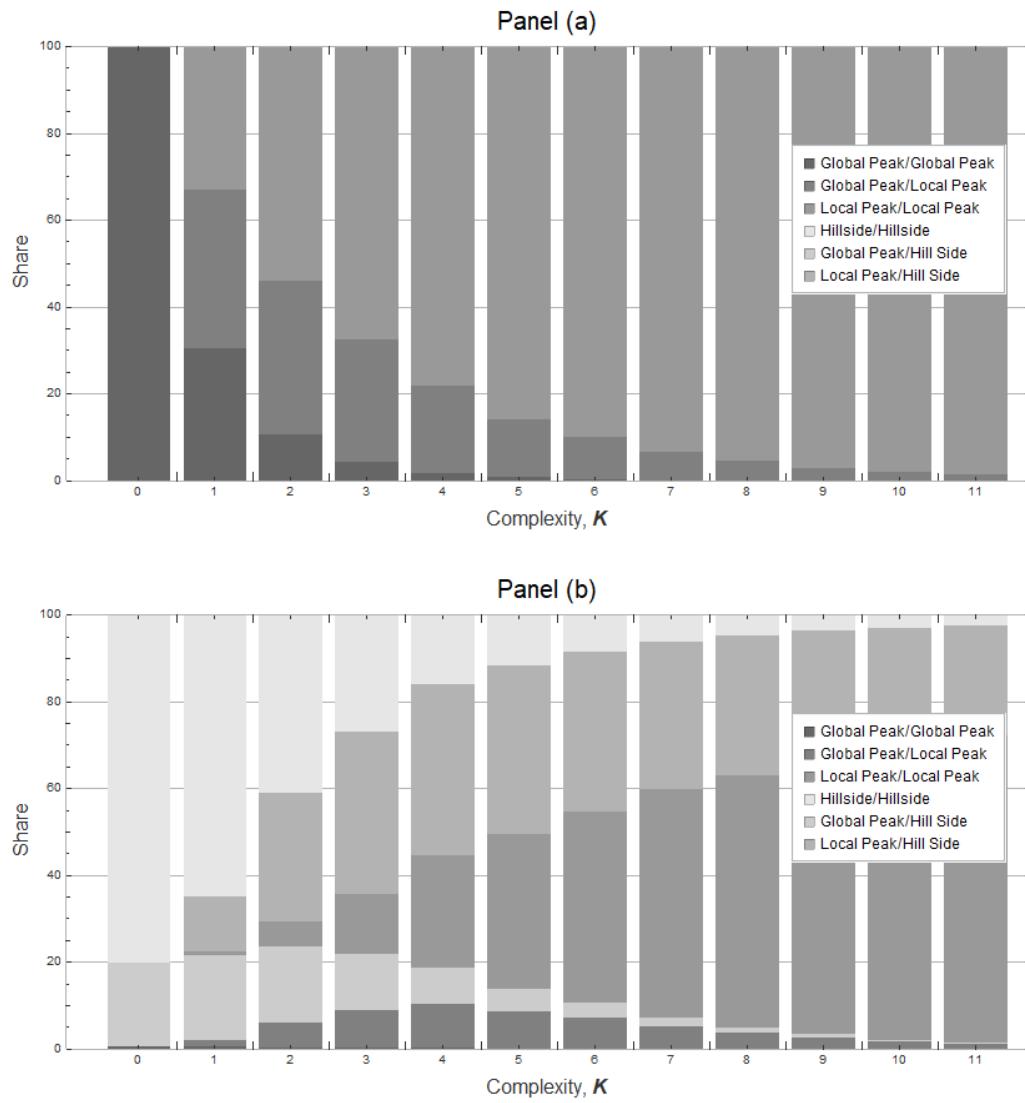
FIGURES

Figure 1
Strategic search vs. technical search



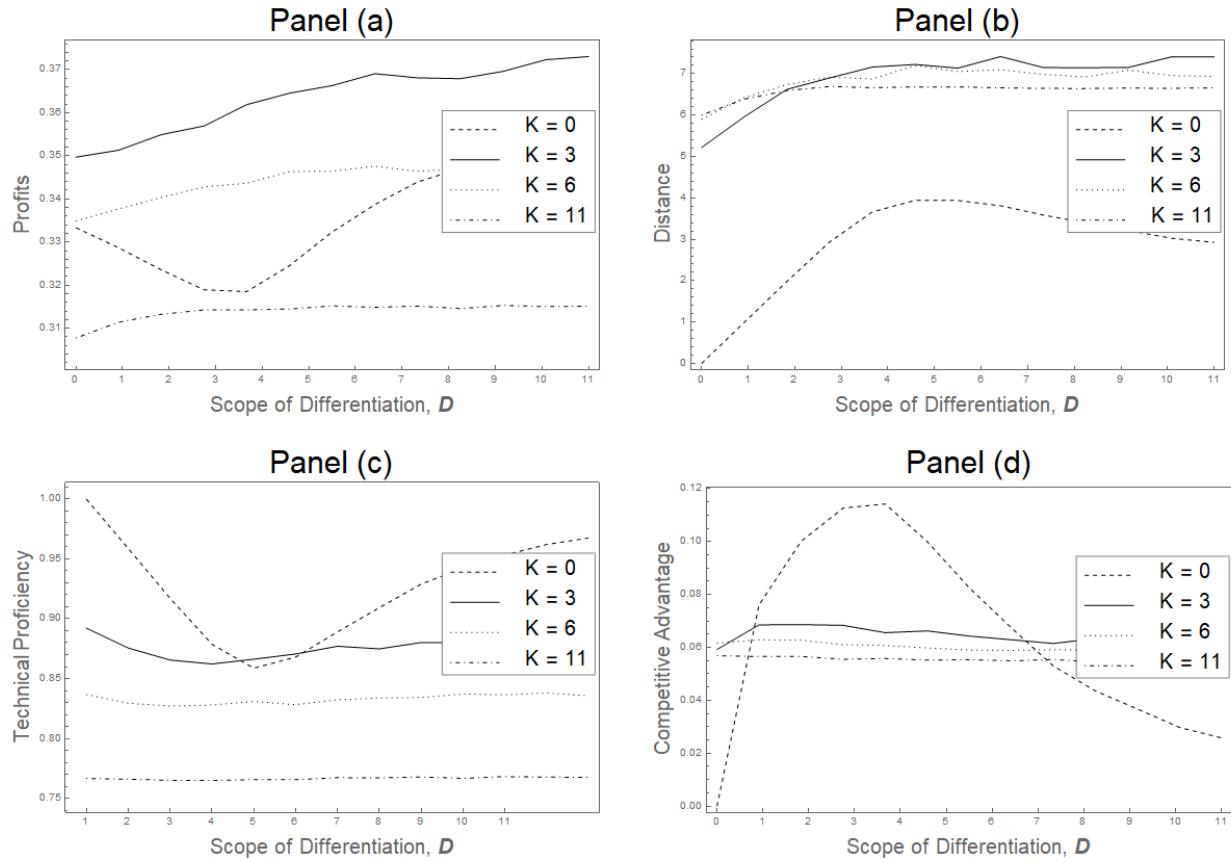
Notes: Figure 1 graphs the difference in average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)) between firms engaging in *strategic search* and those engaging in the standard *technical search*. Firms engaging in *strategic search* 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



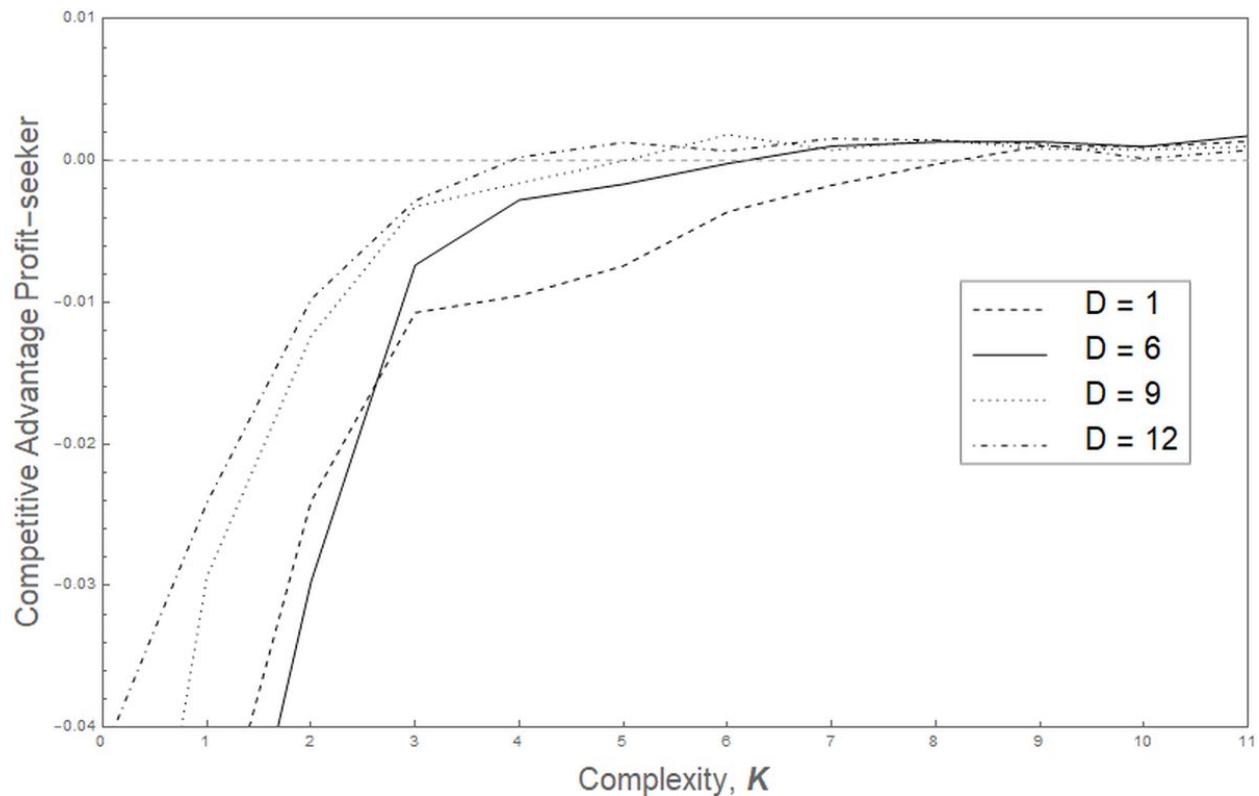
Notes: Figure 2 demonstrates differences in firms' locations between the standard case with *technical search* (Panel (a)) and the case with *strategic search* (Panel (b)). With *strategic search*, firms tend to gravitate towards the hillside of peaks, especially for low levels of complexity.

Figure 3
Effects of strategic search with $D \leq N$ dimensions for differentiation



Notes: Figure 3 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 4
Competition against technologists



Notes: Figure 4 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.

ONLINE APPENDICES

Appendix A: Proximity Penalty

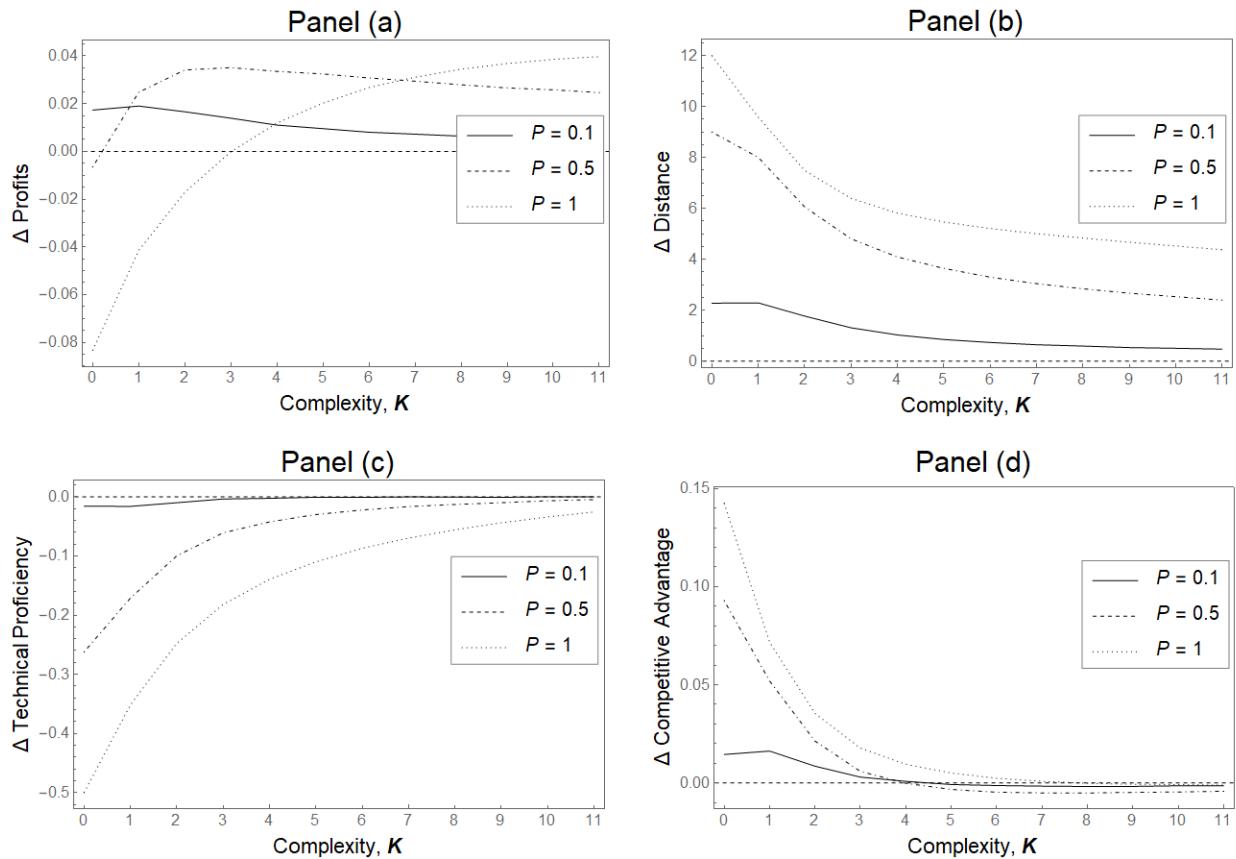
In this appendix, we explore whether a simple behavioral model, wherein firms try to avoid coming close to each other, would lead to results similar to those in our main analyses. We consider a scenario in which firms are assumed to have a partial understanding of the consequences of their positioning strategies on equilibrium prices and quantities, and would therefore prefer not to emulate the choices of the rival, even if doing so comes at some cost to their internal fitness. We model this case by assuming firm i 's search is directed by the objective function $\pi_i^P = F(t_i) - \gamma P$, where P corresponds to an exogenously determined *proximity penalty*, while $F(t_i)$ to the fitness of strategy t_i and γ to the proximity of the two firms on the landscape.

Figure A1 demonstrates the implications of different levels of the *proximity penalty* parameter, P , on outcomes such as differences in average profits¹ (Panel (a)), distance (Panel (b)), technical proficiency (Panel (c)), and competitive advantage (Panel (d)) compared to *technical search*. The general pattern of results with a *proximity penalty* is similar to that of *strategic search*. In particular, in low-complexity settings, we see the same pattern of firms trading off technical proficiency for differentiation as in our main results. Interestingly, though, the results diverge in high complexity environments. While firms under *strategic search* firms tend to outperform those engaging in *technical search* in such environments, firms engaging in search with a *proximity penalty* tend to gravitate towards inferior technical solutions even where complexity is high. These diverging outcomes reflect a key distinction between the two types of search. With *strategic search*, profits do not depend only on the degree of differentiation between the two firms, but also on their relative performance. With a *proximity penalty*, however, only differentiation matters. For this reason, a firm may find it optimal to locate on

¹ To allow for a direct comparison with the results of the main analyses, we report the profits computed by plugging the steady state values of $F(t_i), F(t_{j\neq i})$, and γ of the firms engaging in search with a *proximity penalty* into the Cournot profit function, π_i^C . Note that under search with proximity penalty, these profits no longer drive firm search.

the hillside of a peak already claimed by its rival, even though doing so would imply adopting an inferior technology. With *strategic search*, however, such a strategy would not be sustainable. The performance gap with the rival would hurt profits and therefore incentivize firms to search further afield and to discover new peaks.

Figure A1
Search with proximity penalty vs. technical search



Notes: Figure A1 graphs the difference between *search with proximity penalty* and *technical search* in average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)). Interestingly, firms engaging in search with proximity penalty tend not to discover higher peaks than in the classic *technical search* case.

Appendix B: Differentiated Bertrand Competition

In this appendix, we demonstrate the robustness of our results to a differentiated Bertrand duopoly model. In Bertrand competition, firms compete by setting prices simultaneously rather than quantities. If $\gamma < 1$ and $(2 - \gamma^2)(\alpha_i - c_i) - \gamma(\alpha_j - c_j) > 0$ for $i, j = 1, 2$ and $j \neq i$, equilibrium prices are

$$p_i^B = \frac{(2-\gamma^2)(\alpha_i-c_i)-\gamma(\alpha_j-c_j)}{(4-\gamma^2)} + c_i \text{ and profits are } \pi_i^B = \frac{1}{1-\gamma^2} \left(\frac{(2-\gamma^2)(\alpha_i-c_i)-\gamma(\alpha_j-c_j)}{4-\gamma^2} \right)^2.$$

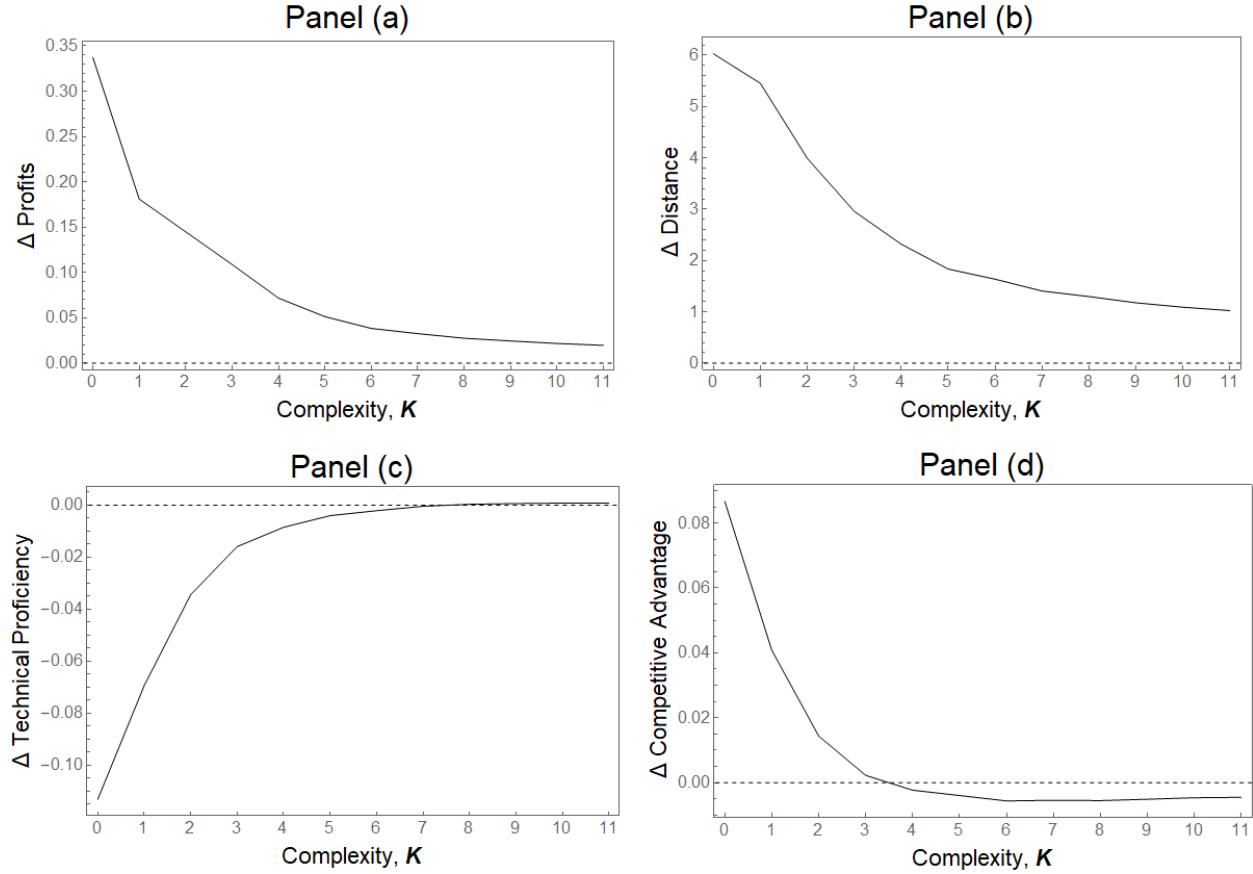
Thus, as in the Cournot case, profits are increasing in the firms' technical proficiency, i.e., $\frac{\partial \pi_i^B}{\partial (\alpha_i - c_i)} > 0$, decreasing

in their rivals' technical proficiency, $\frac{\partial \pi_i^B}{\partial (\alpha_j - c_j)} < 0$, and increasing in their differentiation, $\frac{\partial \pi_i^B}{\partial (-\gamma)} > 0$. If

$(2 - \gamma^2)(\alpha_i - c_i) - \gamma(\alpha_j - c_j) \leq 0$, firm i makes zero profits, while firm $j \neq i$ attains monopoly profits $\pi_j^B = 4^{-1}(\alpha_j - c_j)^2$. If $\gamma = 1$, the model transposes into a classic Bertrand model with two identical firms selling an undifferentiated product or service, with both firms making zero profits. Consistent with our treatment of Cournot competition, the Bertrand model maps onto the NK simulation by linking value created to the firms' fitness and differentiation to their distance on the landscape. Specifically, we set $(\alpha_i - c_i)$ equal to $F(t_i)$, and $\gamma = N^{-1} \sum_{n=1}^N 1_{\{t_{1n}=t_{2n}\}}$ where $1_{\{t_{1n}=t_{2n}\}}$ is an indicator function equal to 1 if $t_{1n} = t_{2n}$.

Figure A2 reports the results for Bertrand competition, graphing the differences between *strategic search* and *technical search* in terms of average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)). Overall, Figure A2 paints a consistent picture with Figure 1 from the main analyses. As with Cournot competition, firms engaging in *strategic search* in the Bertrand model achieve higher profits, are further apart on the landscape, and attain superior technical proficiency in high-complexity task environments.

Figure A2
Strategic search vs. technical search with Bertrand Competition



Notes: Figure A2 graphs the difference between *strategic search* and *technical search* in average profits (Panel (a)), distance (Panel (b)), technological proficiency (Panel (c)), and competitive advantage (Panel (d)) when firms engage in a differentiated Bertrand model. The results are qualitatively similar to those of the Cournot model of Figure 1.

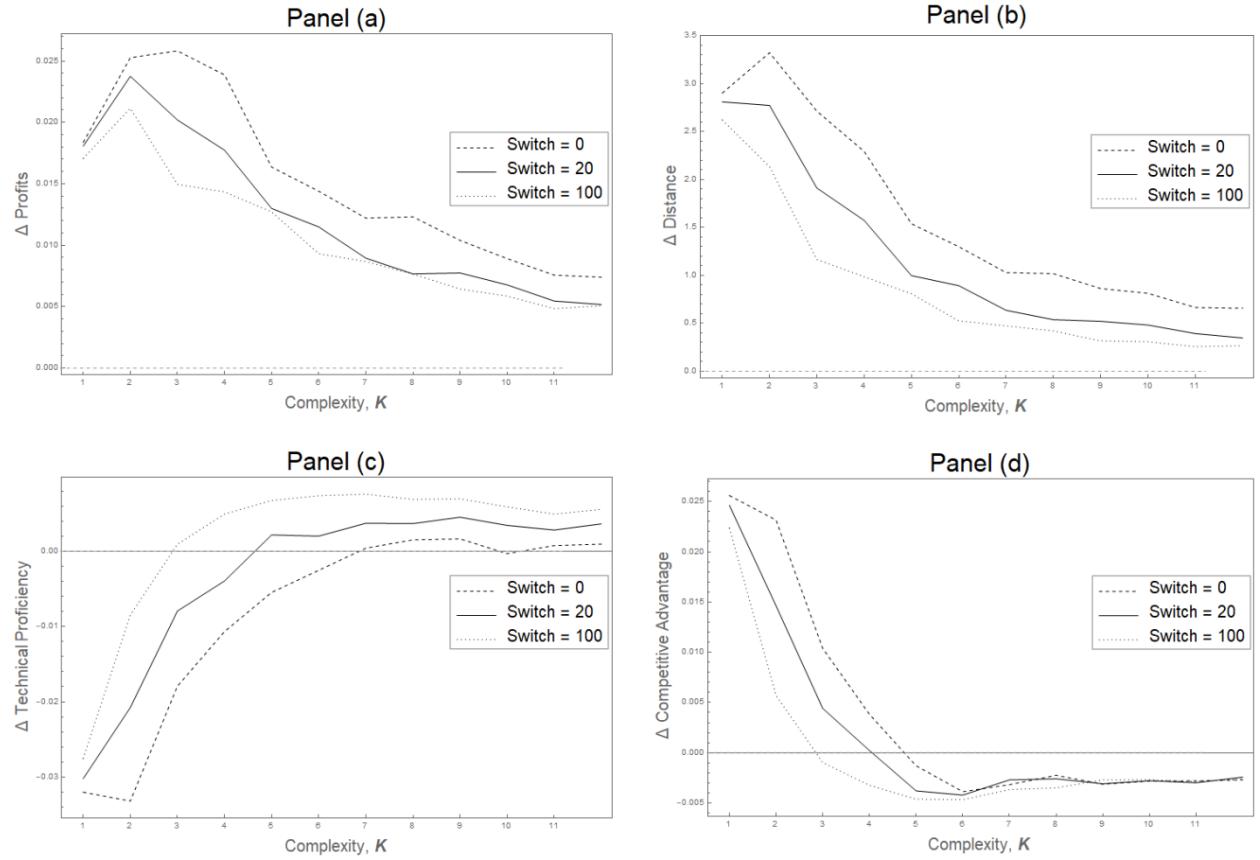
Appendix C: Pre-commercialization Phase

In this Appendix, 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 A3 illustrates the results of these analyses. 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 with a pre-commercialization phase (shown in Panel (b)). Panel (c) reports the average technical proficiency with and without pre-commercialization and compares 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.

Figure A3
Pre-commercialization phase



Notes: Figure A3 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 $t = 100$.