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Positioning on a Multiattribute Landscape

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Competitive positioning is a central, yet understudied, topic in strategy. Understanding positioning requires understanding two distinct mappings: how underlying policies are transformed into positions, and how positions are transformed into market performance. A complete treatment of positioning requires incorporating organizational design in the presence of policy interdependence; consumer choice in the presence of trade-offs among multiple product attributes; and competitive interactions among firms. We develop a model that integrates these elements. We show that in a multiattribute setting, trade-offs have critical, nonmonotonic effects on a range of strategy questions including the relationship between positions that are operationally efficient and those that remain viable in the face of competition as well as the concentration of market share in the industry. Of particular interest are implications for firm heterogeneity. We show that increases in business policy interdependence can decrease positioning heterogeneity among firms in an industry, depending on the nature of trade-offs. We also show that the relationship between strategy heterogeneity and positioning heterogeneity is moderated by the extent of policy interdependence.

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1. Introduction

Competitive positioning is a central concern of the strategy literature. At the firm level of analysis, positioning concerns the choice of how to compete in a given market. At an industry level of analysis, a key question is the extent to which a given environment supports heterogeneity in positioning choices (e.g., Nelson 1991). In his influential work on the topic, Porter (1985, 1996) emphasizes that the existence of organizational trade-offs across multiple performance attributes (e.g., cost versus quality or ease of use versus feature richness) is what gives rise to the need for firms to make clear positioning choices. Yet despite being a central topic in the field of strategy, competitive positioning has rarely been the focus of analytic research.

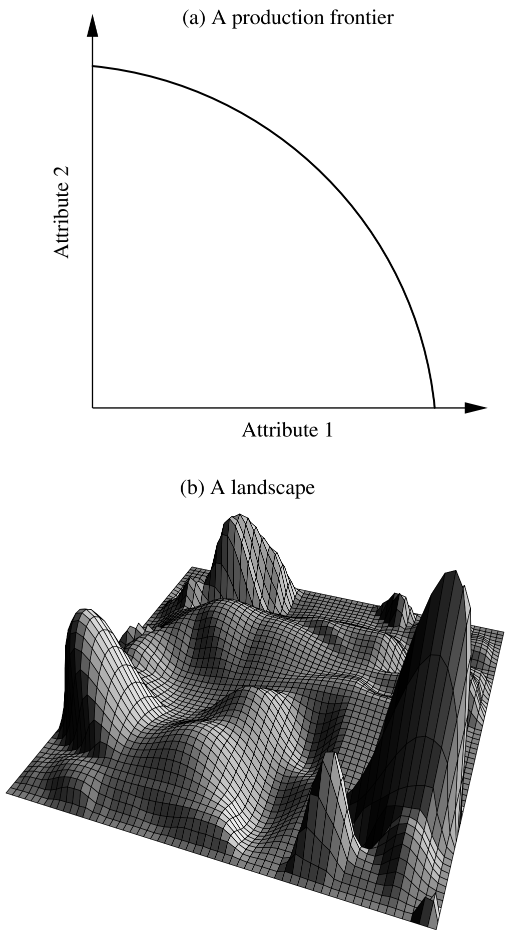
This research gap is likely a result of the interdependencies that underlie competitive positioning. Managers do not choose positions directly—they choose policies. For example, a hotel manager cannot directly control "customer comfort." Rather, the manager controls parameters such as bed size, decor, and staffing levels that give rise to a particular comfort level. Moreover, policy choices impact positioning on multiple attributes (staffing levels affect comfort as well as cost and convenience). Finally, the attractiveness of a given position is determined by the weight that different consumers place on different attributes and on the competition from alternative offers in the market.

For this reason, understanding positioning requires understanding two distinct mappings: how policies are transformed into positions and how positions are transformed into market performance. Thus, complete treatment of competitive positioning needs to incorporate organizational design in the presence of trade-offs, consumer choice in the presence of multiple product attributes, and competitive interactions among firms in the marketplace. In this paper we provide a parsimonious model of competitive positioning that captures all of these key elements. The mechanisms we study—business policy interdependence, attribute correlation, and viability in attribute space—point to an essential set of elements to begin to understand these mappings.

1.1. Current Approaches to Positioning

Two of the most influential representations of firm positions are productivity frontiers, rooted in industrial organization (IO), and rugged landscapes, rooted in evolutionary theory. In a *productivity frontier* (Figure 1(a)), positions are represented as points in a two-dimensional space (see, e.g., Porter 1996, p. 62; Saloner et al. 2001, p. 61). Textbook depictions of the frontier show a smooth trade-off between the two

Figure 1 Examples of a Production Frontier and a Landscape



dimensions. Positions inside the frontier are inefficient because both attributes can be improved by moving to a position on the frontier. Porter (1996, p. 61) asserts that moving to the frontier is an operational matter and that strategy is about the choice of a position on the frontier.

Although there is an extensive IO literature on product differentiation that is relevant to competitive positioning, this literature is not fully adapted to addressing fundamental strategy questions. For example, there is a vast literature on Hotelling models in which firms position themselves along a line or a circle and then compete. There is even some work that models, as we do, competition in a multiattribute space with heterogeneous consumers (e.g., Lancaster 1966, 1990; de Palma et al. 1985; Canoy and Peitz 1997). However, an important limitation of these models is the lack of a link to the underlying business policies that are required to occupy a given position. Indeed, firms in IO models are typically assumed to face a given and smooth trade-off among positions that is not grounded in any representation of the internal organization of the firm. This is limiting for strategy research on positioning, where a central concern is the fit between a firm's internal organization and its external environment, and where an important dimension of firm heterogeneity is organizational (Milgrom and Roberts 1995, Siggelkow 2002).

In a *rugged landscape* (Figure 1(b)), positions are represented as a vector of business policies that determine an overall fitness level in an NK model (e.g., Levinthal 1997). At the heart of this representation is the degree of interdependence among discrete policy choices within the organization (e.g., policy choices regarding organizational structure, sales incentives, or customer retention programs). The greater the number of interdependencies, the more rugged the landscape (i.e., the greater the number of local peaks). In the strategy literature, this representation has most frequently been used to study search by boundedly rational agents who can become trapped on local peaks. This representation offers a powerful way to formalize policy interdependence within organizations (e.g., Rivkin 2000, Rivkin and Siggelkow 2003).

A limitation of this approach, however, is that the great majority of NK models do not consider issues of competition and hence are silent on the effect of positioning on market share, concentration, and profits (Baumann and Siggelkow 2011). A notable exception is the work by Lenox et al. (2006, 2007), which, by combining an NK model with a Cournot model, has made novel predictions regarding the relationship between industry profits and policy interdependence, as well as offering an alternative causal explanation for industry shakeouts.

A second limitation is that all NK models used in the existing strategy literature measure performance on a unidimensional scale called "fitness," whereas many real-world competitive settings are multidimensional. For example, the car industry competes in terms of price, safety, mileage, etc., and the search engine industry competes in terms of comprehensiveness, usability, response time, etc. In fact, it is the lack of a well-defined ordering relationship in multidimensional spaces that makes the concept of positioning meaningful. More concretely, it is because a product with characteristics $(2, 4)$ is not clearly better than a product with characteristics $(4, 2)$ that it makes sense to ponder questions such as which one of the two to offer, or whether or not it makes sense to come up with product $(3, 3)$.

1.2. Our Approach and Contribution

In this paper we develop a novel approach to positioning that exploits the strengths of both landscape and frontier representations. We characterize the extent of trade-offs according to how changes in business policies that affect performance on one attribute also affect performance on other attributes. Thus we develop an explicit mapping between business policies and product attributes. We introduce a parameter that allows trade-offs among attributes to vary from negative (e.g., increasing the size of a car decreases its fuel efficiency) to zero (e.g., increasing car size does not affect color selection) to positive (e.g., increasing size increases safety). Beyond incorporating business policies and trade-offs among attributes, our model explicitly incorporates consumer choice and competitive interactions such that the attractiveness of a given position depends on how well it serves heterogeneous consumers relative to its competitors.

Our model allows us to characterize three distinct aspects of industry heterogeneity: (i) the number of positions along the frontier that remain viable in the face of competition; (ii) the extent of heterogeneity in business policies among the viable positions, which we call *strategy heterogeneity*; and (iii) the extent of heterogeneity among the product attributes associated with the different viable positions, which we call *positioning heterogeneity*.

A number of results emerge from bringing together the various elements of competitive positioning in a unified analytic framework. First, not all positions on the efficient frontier are viable. Second, increases in business policy interdependence can decrease the number of viable positions. In particular, we qualify the strategy literature on NK models by showing that results derived in a single-attribute setting do not necessarily generalize beyond that setting. Third, the relationship between strategy heterogeneity and positioning heterogeneity is moderated by the extent of policy interdependence. Finally, we find that in a multiattribute setting, the effect of attribute trade-offs on market outcomes (e.g., market share and industry concentration) is larger than the effect of policy interdependence.

This paper proceeds as follows. Section 2 specifies our model, and §3 illustrates the mechanics of the model by working through an example. Section 4 presents the main results, §5 contrasts our model and results with those in the extant IO and NK literatures, and §6 concludes.

2. Model

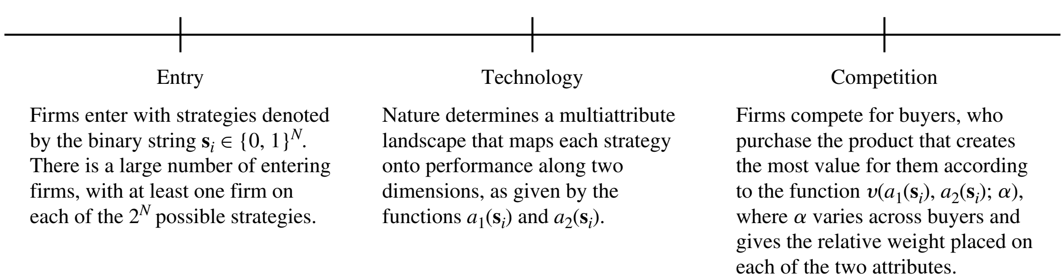
Our model has three stages, as summarized in Figure 2. In the first stage, firms enter the market with heterogeneous business strategies. Building on the NK model, we represent each firm's strategy as a bundle of business policies. Namely, a firm's strategy is represented as N binary business policy choices; we denote the *strategy* of a firm by $\mathbf{s} \in \mathcal{S}$, where $\mathcal{S} = \{0, 1\}^N$. We interpret business policies as encompassing all the choices that affect the firm's performance, such as organization design and product design choices. In other words, a given $\mathbf{s}$ can be understood as a detailed description of the strategy of a firm, akin to the concept of a business model (Casadesus-Masanell and Ricart 2010). We assume that there is entry of a large enough number of heterogeneous firms such that all 2^N possible strategies are represented in the industry.

In the second stage, the firms offer products whose performance on two key attributes a_1 and a_2 varies with a firm's strategy $\mathbf{s}$ according to the functions $a_1(\mathbf{s})$ and $a_2(\mathbf{s})$. The function $a_1(\mathbf{s})$ is modeled as a standard fitness function in an NK model: the relationship between $\mathbf{s}$ and $a_1(\mathbf{s})$ depends on the contributions of each of the N elements of $\mathbf{s}$ toward the value of $a_1(\mathbf{s})$; and each of these contributions is modeled as a *contribution function*, which maps $K+1$ elements of $\mathbf{s}$ into a contribution value. Because K controls how many different elements of $\mathbf{s}$ determine the contribution of each policy, K parameterizes policy interdependence and is said to control the complexity (or ruggedness) of the relationship between $\mathbf{s}$ and $a_1(\mathbf{s})$. Thus, if $K = 0$, a change in one element of $\mathbf{s}$ will only affect one of the contribution functions, whereas if $K = N-1$, the same change would affect all of the contribution functions. The NK part of our model is described in more detail in §2.2. The function $a_2(\mathbf{s})$ is modeled similarly to $a_1(\mathbf{s})$.

Trade-offs are a central element in our model. We introduce trade-offs between the two attributes by allowing for correlation between the underlying contribution functions; this correlation determines the extent (if any) to which a high value of a_1 is associated with a high or low value of a_2.

We call the point $(a_1(\mathbf{s}), a_2(\mathbf{s}))$ the *position* of a firm with strategy $\mathbf{s}$. Note that a strategy corresponds to an N-dimensional point, and a position corresponds to a two-dimensional point. The mappings from $\mathbf{s}$ to a_i ($i \in \{1, 2\}$) capture an essential characteristic of strategic management: that managers must deal with a large number of levers, whereas consumers care

Figure 2 **Stages of the Game**



only about the smaller set of attributes that affect their utility. An important property of our assumptions, as in many business settings, is that managers do not have continuous dials to select their competitive position. Rather, specific competitive positions are determined by a series of underlying organizational and product design choices. Recalling our example above, a hotel manager cannot directly control customer comfort, but he can control such parameters as bed size, decor, and staffing levels.

In the third stage, firms compete for customers who vary in the weight, $\alpha \in [0, 1]$, that they place on the two product attributes. This is the source of demand heterogeneity. Customers purchase the product that creates the most value for them. Value creation is given by the function $v(a_1(\mathbf{s}), a_2(\mathbf{s}); \alpha)$, which depends on the interplay of product attributes ($a_1(\mathbf{s})$ and $a_2(\mathbf{s})$) and customer preferences (α).

We say that a position is *efficient* if there is no position that dominates it on both attributes (i.e., it is on the production frontier).[1] We say that a position is *viable* if it has the highest value creation for at least one customer (i.e., the position is able to attract demand even when competing alternatives are located in all other positions). The rest of this section details each part of the model.

2.1. Entry and Firm Strategy

Our focus in this paper is on understanding how the nature of trade-offs and policy interdependence impact industry outcomes. To this end we make the simplifying assumption that there is a large enough number of entrants into the industry such that all the 2^N possible strategies are occupied by at least one firm. We make this assumption for the sake of simplicity, but it is not necessary for our results. In Appendix A we show that our results on efficient and viable strategies are equivalent to formal rational models that involve a large number of potential entrants, no fixed costs to entry, no capacity constraints, and perfect price discrimination. We show this equivalency for both a biform game (Brandenburger and Stuart 2007) and for a traditional two-stage entry game (Tirole 1988). Methodologically, establishing the behavior of a model under high competition is generally useful before turning to small numbers interactions.

2.2. Technology and Trade-Offs

We assume that what matters to consumers is the performance of the product they purchase (e.g., the durability and appearance of a roofing tile), rather than the business policies that give rise to the product (e.g., semiautomated versus fully automated production lines). We focus on the case in which there are two key performance attributes. Textbook examples of two-attribute settings include cost and quality in hotels (Saloner et al. 2001, p. 61) and computing power and battery life in laptop computers (Spulber 2004, p. 218). We characterize the extent of trade-offs between the two attributes by using parameter ρ, which is defined below.

Recall that the level of attribute i is given by $a_i(\mathbf{s})$. In specifying each of these functions, we follow the NK methodology (Levinthal 1997). This methodology, widely adopted in the strategy literature (see, e.g., Rivkin 2000, Gavetti et al. 2005, Rivkin and Siggelkow 2007), creates random landscapes of a size determined by the parameter N and with a degree of interdependence or ruggedness that is determined by the parameter K. Mathematically, each attribute function is defined as

$$a_i(\mathbf{s}) = \frac{1}{N}\sum_{j=1}^{N} c_i^j(s_j; K \text{ other elements of } \mathbf{s}), \qquad (1)$$

where $c_i^j(\cdot)$, called a *contribution function*, determines the contribution of business policy j to attribute i as a function of the value of business policy j and the value of K other business policies. Each of the contribution functions can take values between 0 and 1. Since each attribute is an average of contribution functions, it follows that each attribute takes values between 0 and 1.

In many settings, the value of the attributes may exhibit trade-offs whereby increasing the level of one attribute requires decreasing the other. For example, the size of a car is usually negatively correlated to its fuel efficiency. Porter (1996, p. 69) remarks that "trade-offs are essential to strategy. They create the need for choice and purposefully limit what a company offers."

We can capture strong trade-offs between attribute levels by requiring that the contribution functions for the second attribute are perfectly negatively correlated with the contribution functions for the first attribute:

$$c_2^j(\cdot) = 1 - c_1^j(\cdot) \quad \text{for all } j,$$

so that $a_2(\mathbf{s}) = 1 - a_1(\mathbf{s})$.

Perfect negative correlation is a strong assumption, and in many settings one would expect that attribute levels would only be imperfectly correlated. Indeed, some attributes—such as the interior design and fuel efficiency of a car—might be largely independent. We introduce imperfect correlation by varying the number of contribution functions that are linked across attributes. Let $Q \le N$ be the number of contribution functions for which $c_2^j(\cdot) = 1 - c_1^j(\cdot)$, and let the remaining contribution functions be independent.[2] The case of no trade-offs (and hence no correlation) between attribute levels corresponds to $Q = 0$.

[1] Formally, efficiency requires that there does not exist an $\mathbf{s}' \in \mathcal{S}$ for which $a_1(\mathbf{s}') \ge a_1(\mathbf{s})$ and $a_2(\mathbf{s}') \ge a_2(\mathbf{s})$ with one inequality strict.

[2] Our modeling approach is inspired by Csaszar and Siggelkow (2010), who introduce positive association between contribution functions to

In some settings, it is possible that attributes could be positively correlated. For example, if simpler product designs are easier to use and more reliable, then ease of use and reliability would be positively correlated. We can introduce positive correlation in a similar fashion by equating Q of the contribution functions, so that $c_2^j(\cdot) = c_1^j(\cdot)$, and allowing the rest to be independent. For $Q = N$ we have perfectly positive correlation (i.e., $a_2(\mathbf{s}) = a_1(\mathbf{s})$).

We define an overall measure of trade-offs $\rho = Q/N$ for the case of positive correlation and $\rho = -Q/N$ for the case of negative correlation. Thus, ρ can assume values from -1 to $+1$. For $\rho = -1$ we have $a_2(\mathbf{s}) = 1 - a_1(\mathbf{s})$, for $\rho = 1$ we have $a_2(\mathbf{s}) = a_1(\mathbf{s})$, and for $\rho = 0$ we have that $a_1(\mathbf{s})$ and $a_2(\mathbf{s})$ are independent. The parameter ρ will be useful for presenting our results, as it parameterizes the extent of trade-offs in an industry's technology. Formalizing the notion of positioning trade-offs rooted in organizational considerations is one contribution of our model.

2.3. Competition and Value Creation

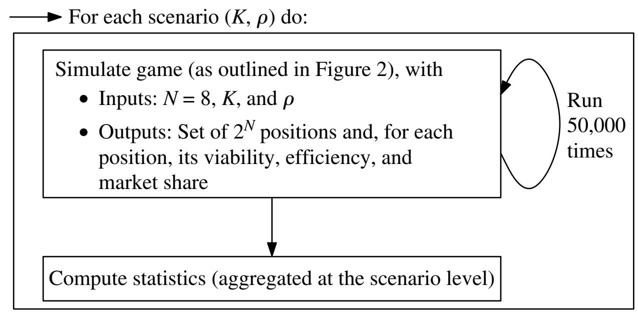
We take a value-based approach to modeling market interactions (Brandenburger and Stuart 1996, 2007); (MacDonald and Ryall 2004). Such an approach starts with a precise statement of the set of actors in the industry and their value creation possibilities. The actors in our model are the set of entrants pursuing strategies $\mathcal{S}$ and a finite number of buyers who vary in their preferences over the two attributes. We parameterize preferences with $\alpha \in [0, 1]$ and denote the set of buyers by $\mathcal{A}$.

Each buyer has demand for one unit of the industry output. Value creation is increasing in both attributes, whose relative importance depends on consumer preferences. In particular, buyer α served by a firm with strategy $\mathbf{s} \in \mathcal{S}$ leads to a value creation of

$$v(\mathbf{s}, \alpha) = v_0 + \alpha \log(1 + a_1(\mathbf{s})) + (1 - \alpha) \log(1 + a_2(\mathbf{s})) - c, \qquad (2)$$

where c is a constant marginal cost of production, v_0 is a constant in the consumer's willingness to pay (WTP), and the term $\alpha \log(1 + a_1(\mathbf{s})) + (1 - \alpha) \cdot \log(1 + a_2(\mathbf{s}))$ captures the effect of attributes and preferences on WTP.[3] We simplify the analysis by assuming that $v_0 \geq c$, so that value creation is always positive.[4]

Figure 3 **Simulation Outline**



Because our primary interest in this paper is the set of viable positions in the industry rather than the profits of individual firms, we do not specify a detailed model of competition. Instead, we assume that competitive rivalry is sufficiently intense to lead customers to be served from the position with the highest value creation for the specific customer. In short, a customer with preferences α is served by a firm with strategy $\mathbf{s}$ if and only if $v(\mathbf{s}; \alpha) \geq v(\mathbf{s}'; \alpha)$ for all $\mathbf{s}' \in \mathcal{S}$. This assumption holds under perfect competition as well as other highly competitive settings. See Appendix A for details.

2.4. Analytic Approach

To explore the model, we set $N = 8$ and numerically analyze the entire parameter space defined by K and ρ. Namely, we vary K from 0 to 7 and vary ρ from -1 to 1 (in increments of 0.125, which, given that $N = 8$, is the minimum increment allowed by the definition of ρ). This leads to 136 ($= 8 \times 17$) scenarios. To avoid interpreting results that are a function of a specific random draw, we generate 50,000 landscapes per scenario and report averages at the scenario level (all the reported results are statistically significant at the 0.01 level at least). Figure 3 outlines the workflow for generating the landscapes and aggregating the results.

In addition to using $N = 8$, we also analyze other values of N (6 and 10). Consistently with the NK literature, in broad terms the results were not sensitive to the choice of N, but rather to the relative size of K with respect to N.

We assume that consumers are uniformly spread over the range $[0, 1]$. Because the model combines simulation (the NK landscape generation) with closed

capture the relatedness of the landscapes for organizations operating in different contexts. We have taken this approach to a multiattribute setting and then introduced the possibility of negative association to capture trade-offs in the attributes.

[3] As a robustness check, we also analyzed the model under an alternative specification in which we assume consumer preferences have linear trade-offs ($v(\mathbf{s}, \alpha) = v_0 + \alpha a_1(\mathbf{s}) + (1 - \alpha) a_2(\mathbf{s}) - c$), rather than the log formulation. The results are highly consistent with those derived from the main specification. The sole qualitative difference is that, at extremely negative values of ρ, the linear case supports a lower number of viable positions than does the log case.

[4] There is an analogous formulation in which attribute 2 reduces marginal costs instead of increasing WTP; in that case, the frontier maps the trade-off between cost and quality (e.g., Porter 1996). In particular, a model with marginal costs given by $c - \log(1 + a_2(\mathbf{s}))$ and WTP given by $v_0 + (\alpha/(1 - \alpha)) \log(1 + a_1(\mathbf{s}))$ has the same set of viable positions and market shares as the model studied in this paper.

forms (the competition in terms of value creation), it is convenient to use discrete rather than continuous distributions; thus, we assume that there are $M = 1{,}000$ consumers equally spaced in the $[0, 1]$ range. If M is large enough, then, for all practical purposes, the discrete approximation yields the same results as a continuous specification. Consistent with this, we find that results are essentially equivalent in robustness tests where we set $M = 500$ and $M = 2{,}000$.

2.5. Relation to Previous Industrial Organization Models

In this section we point out differences and similarities between our model and how other, traditional IO models have conceptualized demand, supply, and competitive interactions. Our model incorporates features from the extensive literature on product differentiation in IO (see, e.g., Tirole 1988, Chap. 7; Vives 1999, Chap. 6) and combines them with new elements.

2.5.1. Demand. A common way to model demand in the IO literature on differentiation is to have a set of customers who vary in their preferences and who each buy up to one unit of output from among those offered by the firms in the industry. This is precisely our approach.

Although there are notable exceptions (discussed below), IO models of differentiation often represent a firm's position by a single product attribute, which we will here refer to generically as a. In models of horizontal differentiation, shifts in a increase the WTP of some customers and reduce that of others. For example, in Hotelling's (1929) classic linear city model of horizontal differentiation, a is simply the position on the line and customers vary in their ideal point on the line. Therefore, a marginal increase in a increases the WTP of customers to the right of the current position and decreases the WTP of customers to the left.

In the case of vertical differentiation, value is increasing in a for all customers. In these models, customers vary not in their ideal point but rather in their WTP for higher levels of the attribute (e.g., speed or safety). This is usually modeled as a multiplicative term αa, where α varies across customers and parameterizes the WTP for the attribute. An early analysis of competition under vertical differentiation is Shaked and Sutton (1982). The demand side of Shaked and Sutton (1982) is a special case of our model with $a_2 = 0$.

In introducing two distinct product attributes a_1 and a_2 we build on the work of Lancaster (1966), who emphasizes that differentiation in a market is often not unidimensional. Lancaster (1966) and subsequent work such as Ben-Akiva et al. (1989) follow Hotelling (1929) and study a generalized form of horizontal differentiation in which customers vary in their ideal level on each attribute. Instead of modeling an ideal level, we build on the vertical differentiation literature and assume that WTP is monotonically increasing in both attributes. Our model incorporates vertical differentiation to capture the emphasis in the strategy literature on trade-offs between value-creating attributes.

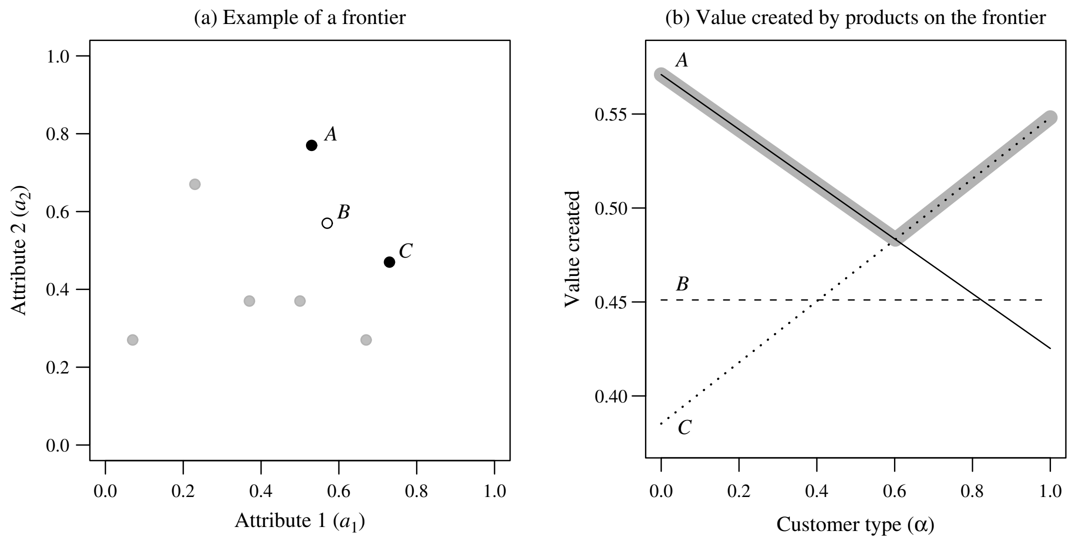
We are also able to incorporate horizontal differentiation by allowing the relative weight placed on a_1 and a_2 to vary across customers. Recall that in our model WTP is given by Equation (2). Consider two products, one with attributes (a_1, a_2) and the other with attributes (a'_1, a'_2). If $a_1 > a'_1$ and $a_2 > a'_2$, then all customers have a higher WTP for the first product. Yet if $a_1 > a'_1$ but $a'_2 > a_2$, then some customers (depending on their value of α) will have a higher WTP for the first product and others for the second—this corresponds to horizontal differentiation.

Finally, a number of IO models on differentiation have incorporated stochastic elements on the demand side. For example, de Palma et al. (1987) take a standard Hotelling model and add an independent random shock to the value that a customer gets from consuming the product of a given firm; Rhee (1996) extends Shaked and Sutton (1982) along the same lines. The stochastic element of consumer WTP serves to lessen competitive pressures because firms with similar positions are less perfect substitutes. In contrast, we add a stochastic component on the supply side, which allows us to link positions directly to policy choices and to identify two key parameters of the underlying supply side stochastic process—K (policy interdependence) and ρ (attribute trade-offs)—that have clear managerial interpretations.

2.5.2. Supply. The demand side of our model draws on elements from the existing IO literature on differentiation, whereas the supply side is a significant departure. In terms of technology, it is common in IO to assume that firms choose their positions directly and face smooth exogenous trade-offs. For example, the firms in Hotelling models can directly choose their location a and, as discussed previously, smoothly increase the WTP of some customers while smoothly reducing it for others. Similarly, in the vertical differentiation literature, when Motta (1993) extends Shaked and Sutton (1982) to include cost asymmetries, he assumes that costs are a smooth increasing function of quality. These modeling assumptions are consistent with the emphasis on trade-offs and a smooth frontier in Porter (1996) and Saloner et al. (2001).

In contrast, we assume that firms do not directly choose their position but do choose their business policies. The frontier in our model is not necessarily smooth but rather the result of complex interactions among the set of business policies, which we model using the NK landscape methodology. This aspect of our model offers a novel approach to "unpacking" the black box of organizations while maintaining the benefits of a formal approach.

Figure 4 Example of a Frontier and How It Relates to Consumer Valuations



Note. In panel (a), the dots represent viable (•), efficient but not viable (○), and dominated (●) positions.

2.5.3. Competitive Interactions. Finally, most IO models of differentiation involve price competition in which firms simultaneously commit to a single price for all customers. This often leads to involved game-theoretic analyses where positions are more determined byvalue capture concerns (i.e., the desire to reduce price competition) than by issues of value creation. In contrast, we consider a setting where outcomes are driven purely by value creation, which in IO terms is most naturally interpreted as an assumption of perfect competition (see Appendix A).

3. Understanding Positioning on a Multiattribute Landscape

In this section we illustrate our analysis of positioning on a multiattribute landscape. We start with a given set of possible positions and then identify the efficient and viable positions. For each of the viable positions, we identify their market share. These mechanics are important for understanding the paper's main results, which characterize patterns in these variables over a large number of such landscapes.

We illustrate the analysis for the multiattribute landscape given in Figure 4(a), which is for the simplified case of $N = 3$ business policies. In this case there are $2^3 = 8$ possible positions, and the figure shows the level of attribute 1 and attribute 2 for each of the positions.

Value creation is increasing in both attributes. In Figure 4(a), the points A, B, and C are the set of efficient positions and constitute the efficient frontier in this example (i.e., these are the only three points in the plot for which there are no points located to their "northeast"). All remaining points are inefficient because they offer less of attribute 1 and attribute 2 than one of the points on the frontier and therefore create less value. Firms located at these inefficient positions never have maximum value creation for a customer once the positions on the frontier are occupied.

An efficient position is not necessarily viable. Viability requires that a position have the highest value creation for at least one customer (i.e., the position is able to attract demand even when competing alternatives are located in all other positions). A position with only marginally more of attribute 1 or attribute 2 than other positions might be efficient but need not be viable. To identify the viable positions, Figure 4(b) plots the value creation of the three efficient positions. Because value creation varies across buyers, the horizontal axis represents the consumer type, α. A position has added value if there are some buyer types for which it has the highest value creation.

In Figure 4, positions A and C are viable, but not position B. Position A has added value for customers with $\alpha < 0.6$ and position C has added value for customers with $\alpha > 0.6$, so firms can occupy these positions and capture demand. In contrast, position B does not have added value for any buyer type: either A or B creates more value for each buyer type. For this reason, despite being on the frontier, position B is not viable and cannot be occupied profitably in the face of rivals in positions A and C.[5]

The market share of each viable position corresponds to the proportion of buyers for which it has added value. If buyers are uniformly distributed over the range $[0, 1]$, then the market share of position A is 60% and of position C is 40%.

[5] It is certainly possible for intermediate positions like B to be viable; for example, if the B line in Figure 4(b) were shifted upward by 0.1, then B would have added value for consumers with intermediate levels of α.

4. Results

We use our model to explore how attribute trade-offs (ρ) and policy interdependence (K) affect key strategic variables in a multiattribute world. We start by characterizing the topography of the competitive landscape in terms of both efficient and viable positions. We then examine relative market shares associated with different positions, the extent of strategy heterogeneity, and the extent of positioning heterogeneity.

4.1. Efficient Positions

The variety of strategies in the industry is limited by the number of efficient positions. Figure 5 shows the expected number of efficient positions in an industry as a function of trade-offs (ρ) and policy interdependencies (K).

A first observation from this figure is that attribute trade-offs (ρ) are a significant driver of heterogeneity. If attributes are perfectly correlated ($\rho = 1$), then effectively there is only one attribute and only one position on the efficient frontier (i.e., $\rho = 1$ is the special case of a single-attribute landscape). This is because, regardless of customer preferences (α), every position that offers less value than the single maximum is inefficient. In contrast, if attribute trade-offs are extreme ($\rho = -1$) such that increasing the performance of one attribute requires a corresponding decrease in performance of the other attribute, then each of the 256 possible positions lies along the efficiency frontier.[6] Note that, as attribute correlation is reduced from $+1$, we depart from the single-attribute landscape. Conversely, as the correlation is increased from -1, we depart from the strongest form of trade-offs.

Figure 6 offers a graphical intuition for the effect of ρ on the number of efficient positions. It plots all 256 positions for a representative landscape for different values of ρ. Recall from §3 that the efficient positions are those for which no positions lie to their northeast. If $\rho = 1$ and so all positions lie along the line that extends upward from the origin at a 45° angle, then the only efficient position is the single one farthest from the origin. In contrast, if $\rho = -1$, then the positions extend downward at a $-45°$ angle, so there is no single position located northeast of another. As ρ values approach 0 from both directions, such that there is less and less correlation between the attributes, we find a shift from the linear distributions at the extremes toward an increasingly cloudlike distribution. Positions that lie within this "cloud" are dominated by a few positions on its upper right edge. These positions on the upper right edge define the efficiency frontier (these are the solid and the hollow black points in Figure 6).

[6] There are 256 ($= 2^8$) positions because $N = 8$ in the simulations and each policy can take one of two values.

Figure 5 **Number of Efficient Positions as a Function of Attribute Correlation ρ and Policy Interdependence K**

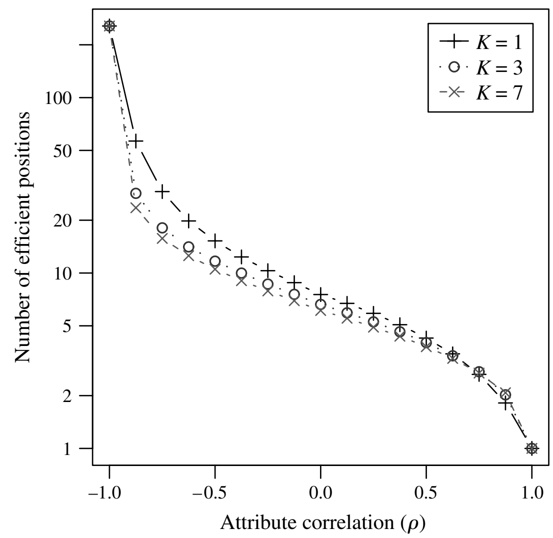
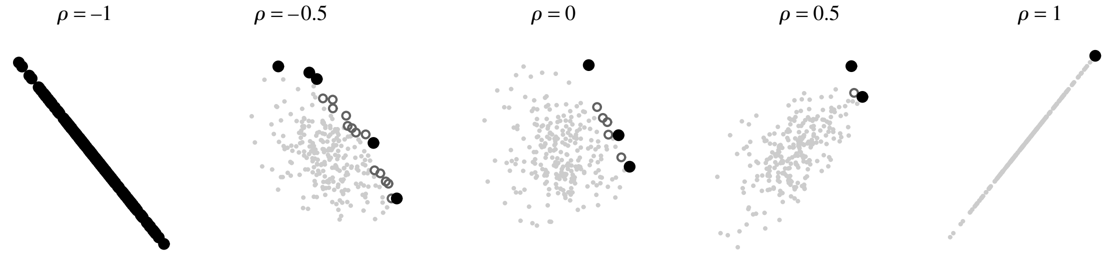


Figure 5 also shows that the number of efficient positions is actually *decreasing* in K, which implies that the potential for industry heterogeneity is decreasing with interdependencies.[7] This result seems to contradict the result in the NK literature that industry heterogeneity is positively associated with increases in K because of an increasing number of local peaks (Levinthal 1997).

To resolve this contradiction, it is important to note that there is not a one-to-one mapping between concepts in the single-attribute NK model and the multiattribute landscape. In traditional (unidimensional) NK models, industry heterogeneity is a function of the number of local peaks in a landscape; and local peaks increase with K (as K controls how non-linear the relationship between policies and fitness is; Levinthal 1997). In contrast, in a multidimensional landscape, industry heterogeneity depends on a different concept:

[7] A careful examination of Figure 5 reveals that, at $\rho = 0.75$ and $\rho = 0.875$, the ordering of the three lines is slightly altered (i.e., the $K = 1$ line appears just below the other two lines). This nonmonotonicity with respect to the effect of K is the result of a geometrical property that only arises in high ρ settings. To illustrate this phenomenon, imagine a cloud with $\rho = 1$ and $K = 0$ (i.e., a perfectly straight and upward-sloping collection of points, as for every $\mathbf{s}$, $a_1(\mathbf{s}) = a_2(\mathbf{s})$). If ρ is decreased to 0.875 (i.e., so that the two fitness functions differ by a single contribution function), then (i) the entire set of possible positions is distributed along two parallel lines (because, by Equation (1), $a_2(\mathbf{s})$ must now be equal to either $a_1(\mathbf{s}) - c_1^j(0) + c_2^j(0)$ or $a_1(\mathbf{s}) - c_1^j(1) + c_2^j(1)$, where $c_i^j(\cdot)$ is the one contribution function that differs between $a_1(\mathbf{s})$ and $a_2(\mathbf{s})$); and (ii) it can be shown that, when $K = 0$, there is a 50% probability that the two parallel lines will lead to just one efficient position. With higher values of K, the distribution of the set of possible positions looks less and less like a pair of parallel lines and more and more like a cloud. However, the less-well-ordered distribution leads to a greater chance of producing more than one efficient position. This K-driven effect is evident only at extremely high values of ρ, since lower ρ values lead to a cloudlike distribution for all values of K.

Figure 6 Graphical Intuition of the Effect of Attribute Correlation ρ on the Number of Viable (•), Efficient But Not Viable (∘), and Dominated (•) Positions

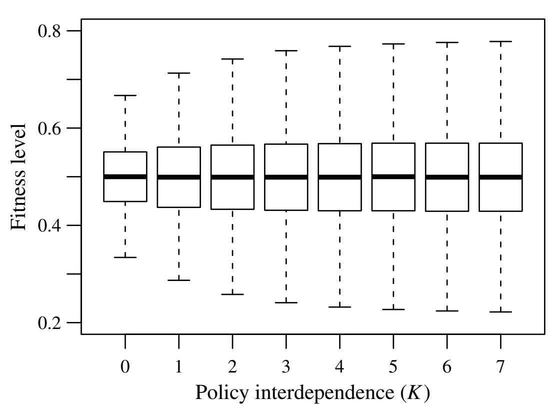


Note. Each panel plots a single simulation, and its x and y axes are, respectively, a_1 and a_2; in all panels, $N = 8$, $K = 3$, and ρ varies from -1 to 1.

the number of viable positions in this landscape. One can understand why the number of viable positions decreases with K by taking a closer look at how each attribute depends on K. As K increases, each of the contribution functions that make an attribute can take an exponentially larger number of values (recall from Equation (1) that each attribute is defined in terms of N contribution functions and that each contribution function depends on the configuration of 2^{K+1} policies). For instance, if $K = 0$, each contribution function can take two values, whereas if $K = 3$, each contribution function can take 16 $(= 2^{3+1})$ values. This implies that as K increases, each attribute depends on more sources of variability and, consequently, has more chances of achieving an extreme value.

Figure 7 numerically illustrates this phenomenon: as K increases, the range of the landscape (i.e., the spread between the minimum and maximum) increases. But note that the bulk of the landscape (i.e., the spread between the upper and lower quartiles) does not change much as a function of K. In other words, as K increases, the "tails" of the landscape become longer and thinner, which means that there are fewer outliers. In a multidimensional landscape, this sparsity of outliers gets translated as fewer efficient (and thus viable) positions.

Figure 7 Distribution of Fitness Levels as a Function of K



Notes. Averaged statistics computed from 50,000 simulations per level of K and with $N = 8$. The levels in each bar (from top to bottom) correspond to maximum, upper quartile, median, lower quartile, and minimum.

4.2. Viable Positions

The viability of a position is determined by its ability to attract customer demand even if the other efficient positions are occupied by rivals. The number of viable positions is of interest because it captures an important aspect of industry heterogeneity; namely, the number of different strategies that can coexist in the market.

Figure 8 plots the number of viable positions as a function of attribute correlation (ρ) for different levels of policy interdependence (K). As was the case with efficient positions, the likelihood of a position becoming an outlier and "standing out from the cloud" is decreasing in both ρ and K.

At either $\rho = 1$ or $\rho = -1$, the number of viable positions is equal to the number of efficient positions. As in the results for number of efficient positions, if $\rho = 1$, then there is only one efficient (and thus viable) position. If $\rho = -1$, then all positions are efficient and lie along a perfectly straight, downward-sloping line and—because the log utility function is convex (which assures that all the positions along this downward-sloping straight frontier will maximize the utility of at least one customer)—all these positions, too, are viable.

For intermediate values of ρ, the qualitative trends regarding ρ and K are the same as for the case of efficient positions, but the number of viable positions is substantially lower. This result is expected because the conditions for being viable are more stringent than those for being efficient. In particular, a position that is not close enough to the upper right edge of the cloud will not be able to capture customers, who will be better served by other, better-located rivals, as illustrated in Figure 6.

By characterizing the nature of viable positions, we follow Porter (1996) in showing that there are important positioning choices that must be made by firms even after they have reached the efficiency frontier. An overarching regularity is that the extent of trade-offs increases the number of positions that can be supported in the landscape (i.e., the more negative is ρ, the more viable positions there are). In practical terms this suggests that, when trade-offs are high, choosing a

Figure 8 Number of Viable Positions as a Function of Attribute Correlation ρ and Policy Interdependence K

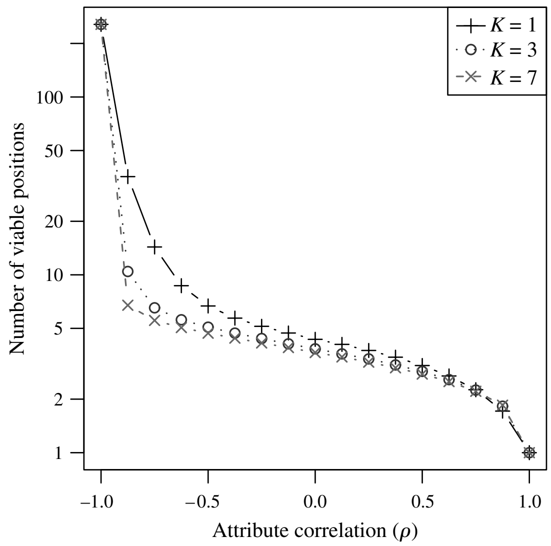
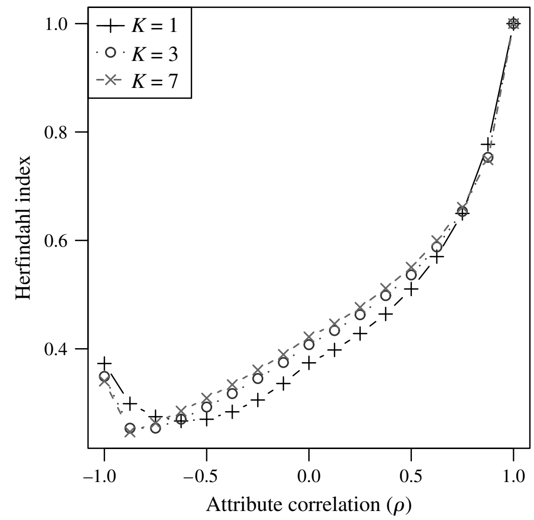


Figure 9 Herfindahl Index as a Function of Attribute Correlation ρ and Policy Interdependence K



position becomes a more elaborate decision because there are more viable positions from which to choose.

4.3. Market Shares

We have shown that not all positions are efficient and that not all efficient positions are viable. We now consider the market shares of the viable positions.

We start by characterizing market concentration via a Herfindahl index across positions. Figure 9 shows the relationship between market concentration as a function of attribute trade-offs and policy interdependence. The figure indicates that concentration generally increases with ρ. This is consistent with the decrease in viable positions observed with increasing ρ, as shown in Figure 8: fewer viable positions lead to greater market shares. Similarly, we find that concentration increases with K, which is consistent with the reduction in viable positions that was found to accompany an increase in policy interdependence (shown in Figure 8).[8] Only at the extremely low levels of $\rho \leq -0.75$ does concentration increase slightly. This is because when ρ is strongly negative, the numerous viable positions in between the extremes of the cloud are almost perfect substitutes for its neighbors, pushing the market share of these points close to zero, in effect leaving the bulk of the market to be supplied by either of the two extreme positions.

To better gauge heterogeneity in demand across positions, Figure 10 explores what we call the "market shares at the extremes"—that is, the sum of the market shares of the first viable position at the upper left of the efficient frontier and the last viable position at the lower right of the efficient frontier. Interestingly, we find significant heterogeneity across positions. Whereas the Herfindahl index in Figure 9 mostly increases with attribute correlation ρ, Figure 10 shows a richer relationship: the positions that lie at the extremes of the frontier capture a disproportionate share of sales throughout the range, which results in a U-shaped profile. At $\rho = 1$, there is only one viable position, so it holds the entire market. At $\rho = -1$, all 256 positions are viable, but the two positions at the extreme ends of the frontier capture well over half the market.

The logic driving this large market share of the extremes is that such positions have no competitors on one side (i.e., the upper left extreme has no competitors to the left and vice versa for the lower right position). In our model consumers are evenly distributed in the 0–1 range (from $\alpha_1 = 0$ to $\alpha_M = 1$), but positions in the NK landscape arise from a stochastic process that leads to a nonuniform distribution that is unlikely to cover the whole 0–1 range (as seen in Figure 7). Thus, in any given simulation there is likely to be a segment of customers who are better served by positions at the extremes of the frontier. In other words, the extreme positions are the best possible choice for customers with a high WTP for one of the two attributes. A real-world example is the highest quality producer of high-fidelity equipment being preferred by audiophiles, who seek even better sound than what is available.

Note, however, that this result is sensitive to the distribution of customers. For instance, if the bulk of consumers were to be located in the middle of the market (and so can be characterized by, e.g., a low-dispersion Normal distribution centered around $\alpha = 0.5$), then the extreme positions would be less attractive; the converse would be true if the bulk of customers had extreme preferences.

[8] The slight alteration in the line ordering at $\rho = 0.875$ is explained by the arguments presented in Footnote 7.

Figure 10 Fraction of Market Share Served by the Two Viable Positions at the Extremes of the Frontier, as a Function of Attribute Correlation ρ and Policy Interdependence K

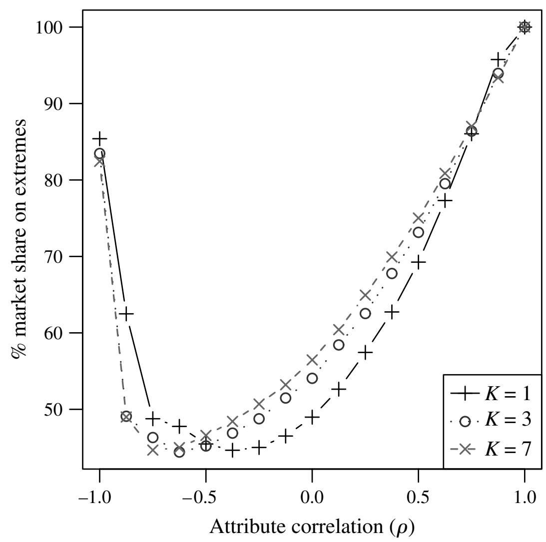
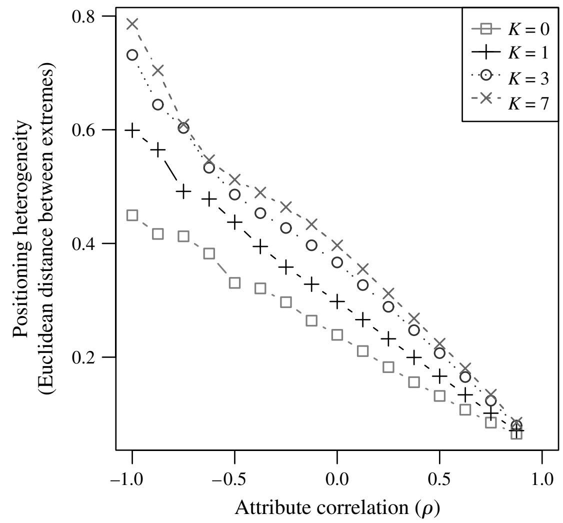


Figure 11 Positioning Heterogeneity as a Function of Attribute Correlation ρ and Policy Interdependence K



4.4. Strategy Heterogeneity and Positioning Heterogeneity

So far, we have analyzed heterogeneity based on a count of distinct viable positions and market share across these positions. We now go deeper and look at the extent to which the viable positions are actually different from each other in terms of their product attributes and their underlying business policies.

Formally we define two critical dimensions of heterogeneity: *positioning heterogeneity*, which we measure in terms of differences in attribute levels (i.e., differences between (a_1, a_2) pairs); and *strategy heterogeneity*, which we measure in terms of differences in policy choices (i.e., differences between $\mathbf{s}$'s). To gauge both types of heterogeneity, we create measures of the distance between the two positions at the extremes and consider how changes in ρ and K affect these distances.[9] With our measure, greater distance reflects greater heterogeneity among the positions or strategies being compared.

Figure 11 plots positioning heterogeneity measured as the Euclidean distance in attribute space between the extremes. In the context of Figure 4(a), this equates to the length of a straight line connecting positions A and C. Increases in ρ result in a reduction in the Euclidean distance between the extremes.[10] This corresponds with the effect of ρ illustrated in Figure 6: the viable frontier, and the distance between viable positions, shrinks as ρ approaches unity. In contrast, increases in K increase the Euclidean distance between the extremes. This is because, as documented in the context of Figure 7, increasing K leads to fewer and more distant viable positions.

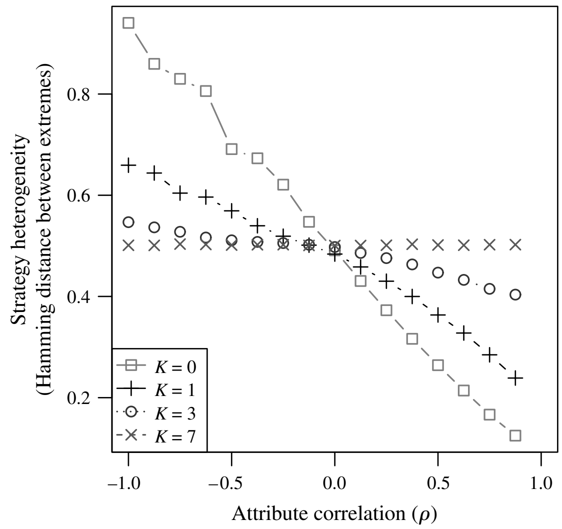
To measure strategy heterogeneity we use the Hamming distance between the policy choices of the positions at the extremes of the frontier. The Hamming distance is the number of bits that differ between two sets of policy choices. For example, the Hamming distance between 11000011 and 11000000 is 2, and the Hamming distance between 11111111 and 00000000 is 8. For presentation clarity, in our figures we show normalized Hamming distances (i.e., we divide the Hamming distance by 8). Whereas distance in attribute space can be thought of as reflecting differences in the physical manifestations of products, distance in policy space is analogous to differences in the underlying organizational structure, strategy, and routines that give rise to the product itself.

Figure 12 plots the normalized Hamming distance between the strategies of the two viable positions located at the opposite extremes of the frontier as a function of ρ and K. We find that policy interdependence K is a critical moderator of the relationship between strategy heterogeneity and ρ, affecting both the absolute level (intercept) as well as the intensity (slope) of the relationship. Specifically, when policy interdependence is low, greater trade-offs lead to lower

[9] There are several possible ways of measuring heterogeneity (see, e.g., Page 2011, Chap. 2). In this paper we use the direct measure of the distance between the extremes for several reasons: (i) this measure is not a function of the number of firms in the frontier, and hence it does not confound strategy and positioning heterogeneity with number of viable firms; (ii) the firms in the extremes get a disproportionate number of the customers, hence it is natural to consider them as particularly relevant to determine heterogeneity; and (iii) unlike more abstract measures, distance between extremes has a clear intuition. Many common measures of heterogeneity, such as entropy, fail in most of these criteria.

[10] We do not plot values at $\rho = 1$, since in that case there is only one viable position and thus no distance between extremes.

Figure 12 Strategy Heterogeneity as a Function of Attribute Correlation ρ and Policy Interdependence K



strategy heterogeneity; when policy interdependence is high, this relationship weakens such that strategy heterogeneity is entirely unresponsive to attribute correlation when $K = 0$.

To understand these relationships, it is helpful to recall that our model maps strategies to attributes and attributes to consumer valuations. In shorthand notation, we say that the model goes from **s**-space into a-space into v-space. Consider how distances are transformed when moving from one space to another: in a-space (e.g., Figures 4(a) and 6) the distance between points indicates the extent of similarity between products (i.e., as points get closer together, the products get more alike); and the relative position of points indicates their relative value (i.e., points to the northeast are more valuable than points to the southwest). Hence, there is a direct relationship between a-space and v-space.

In contrast, the relationship between **s**-space and a-space (and therefore between **s**-space and v-space) is not direct; rather, it depends on the value of K. When $K = 0$, flipping a single bit of the strategy **s** from 1 to 0 affects the contribution of just that one bit: a small (one-bit) change results in a small change in attribute performance. In a low-K environment there is usually a direct (positive) relationship between the number of bits that are switched and the magnitude of the change in performance. Therefore, when K is low, Hamming distance in policy space behaves similarly to Euclidean distance in attribute space (i.e., the lines for $K = \{0, 1, 3\}$ in Figure 12 are all downward sloping, just as in Figure 11).

But when K is high (e.g., $K = 7$), flipping a bit from 1 to 0 affects not only the contribution of that one bit (either up or down) but also the contribution of K other bits (either up or down). This means that a small change in **s** can result in either a large or a small change in performance. In a high-K environment, there is a high level of variation in the effect of changing one policy on performance; in other words, the relationship becomes increasingly random as K increases. Thus, when $K = 7$, changing one bit (which changes the contribution of all the bits) is equivalent to changing all eight bits. In Figure 12 this is reflected in the horizontal line for $K = 7$.

Distinguishing between strategy and positioning as two distinct aspects of industry heterogeneity raises some interesting, and potentially testable, implications. First, policy interdependence K plays a much more important role in driving qualitative differences in strategy heterogeneity than in positioning heterogeneity (i.e., shifts in K have a much more pronounced impact on the slopes in Figure 12 than in Figure 11). Second, whereas positioning heterogeneity always increases with K (see Figure 11), strategy heterogeneity only increases with K when attribute correlation is positive, but decreases with K when attribute correlation is negative (see Figure 12).

A direct implication of this analysis is that policy interdependence (K) plays an important role in determining the equifinality of different strategies. For example, if policy interdependence is low (e.g., $K = 0$) and there are strong trade-offs between the attributes (e.g., $\rho = -1$), then firms in the extremes of the efficient frontier will probably use quite different strategies (e.g., 00001111 versus 11110000) and will offer products that are perceived to be quite different (e.g., $(0.1, 0.9)$ and $(0.9, 0.1)$; perhaps this is the case of McDonald's versus Starbucks in the restaurant industry). But if policy interdependence is high (e.g., $K = 7$) and there are synergies between the attributes (e.g., $\rho = 0.75$), then different strategies could lead to similar products (e.g., Toyota's and Ford's approaches to delivering a hybrid vehicle may be quite different in policy space but can still result in cars that look quite similar in attribute space).

5. Discussion

There is a long tradition of studying the drivers of firm heterogeneity in both the IO and NK literatures. Our model, however, offers a fundamentally different perspective on the question than its predecessors. In this section we show how our integrated approach adds value over "pure" IO and NK approaches. We do so in two ways: (i) we qualitatively relate our results to results in the received IO and NK literatures; and (ii) we build two additional models (a pure IO and a pure NK model), which allow us to disentangle the drivers of the results in the integrated model vis-à-vis pure approaches.

To create a pure IO model, we replace the NK part of the main model by traditional IO assumptions. To create a pure NK model, we remove the IO elements in the main model and focus only on a traditional NK analysis of fitness levels.

5.1. Contrast and Contribution to Traditional IO Results

5.1.1. Comparison with IO Results. A central concern of this paper has been to understand the effect of multiple product attributes on industry heterogeneity. In our model, with $\rho = 1$ (attribute levels are perfectly correlated, such that there is a single dimension of differentiation) we find that there is a single viable position and hence no industry heterogeneity. Decreasing ρ in our model serves to introduce an increasingly distinct second dimension along which firms can differentiate.

In our model, as described in §4.4, we find that as this second dimension is introduced (i.e., as ρ decreases) our measure of positioning heterogeneity increases. In contrast, pure IO models of vertical and horizontal differentiation that introduce a second dimension of differentiation commonly find that heterogeneity decreases. Under vertical differentiation with one dimension, Shaked and Sutton (1982) find that two firms will choose *different* levels of quality, whereas Rhee (1996) shows that adding a second random dimension leads firms to choose *identical* quality levels, resulting in minimal differentiation. In a similar fashion, under horizontal differentiation with one dimension, d'Aspremont et al. (1979) show that in a linear city model with quadratic transportation costs, firms choose *maximal differentiation*,[11] whereas de Palma et al. (1987) and Ben-Akiva et al. (1989) show that adding a second dimension can produce *minimal differentiation*.

Our model incorporates both a unique set of economic assumptions as well as a novel NK technology. To isolate the impact of these two elements, we now formally analyze a pure IO version of the model and contrast the results with those of our main model. We find that the marked contrast between our results and the received IO literature is *not* rooted in the NK elements of our model. Rather, our model captures different economic drivers of heterogeneity than the traditional IO models. The main source of heterogeneity in game theoretic IO models is the incentive of firms to soften price competition. For instance, the random second attribute in papers such as that by de Palma et al. (1987) serves as an alternate source of differentiation, which reduces rivalry and hence the incentives to further soften competition by differentiating on the first attribute. In contrast, we consider a form of perfect competition in which softening price competition is not a factor. Rather, it is value creation considerations that drive competitive outcomes, and it is the multiattribute landscape that allows for a multiplicity of viable positions.

5.1.2. Contrast with a Pure IO Model. To construct a pure IO model we replace the NK landscape with a smooth technology frontier. Specifically, we replace Equation (1) with a straight line segment in attribute space. The orientation of this line determines the trade-offs firms face when they choose positions. For instance, under a 135° frontier (i.e.,), there is a perfect trade-off between the attributes; under a 45° frontier (i.e.,), there is a perfect positive association between the attributes. The angle of the line is then analogous to the role played by parameter ρ in our base model. As with typical IO models, firms can now directly choose which position to occupy from a continuous set. Other model elements are as before. Here we report on the main qualitative results of the pure IO model. Additional details of the pure IO model, along with quantitative results, are contained in Appendix B.

The pure IO model confirms that trade-offs continue to be a key driver of behavior. Moreover, important comparative statics carry over to the pure IO model. As in the main model, the number of viable positions and positioning heterogeneity increase with trade-offs. The mechanism is similar to the one in the main model: when there are high trade-offs (e.g., the angle of the line segment is greater than 90°), different positions along the frontier serve different customers.

As in the main model, we find that not all efficient positions are viable.[12] However, the mechanism generating this result differs between the models. The pure IO model (and IO in general) assumes a continuous, convex frontier. Some positions in such a frontier are efficient but not viable, because there is a finite number of customers. In contrast, in the main model the number of customers is larger than the number of positions. What drives the difference between viability and efficiency in the main model is that a given position may be efficient, but if its neighbors on the frontier produce more value, they will leave this position "sandwiched," without customers (as illustrated by position B in Figure 4). This discrete, nonconvex frontier is caused by how our model maps policies onto attributes (i.e., Equation (1)). The difference between efficient and viable positions does not go away as the number of discrete positions becomes large (e.g., as the number of policy choices, N, increases). A demonstration of this point is available in Appendix D.

[11] Recall that Hotelling's (1929) original claim of minimal differentiation when firms compete in a linear city was not robust to formal game theoretic modeling; as d'Aspremont et al. (1979) show, Nash equilibria need not exist in Hotelling's original model.

[12] The fact that not all efficient positions are viable is particularly relevant, as a common result in prior IO models is that in the absence of sunk or fixed costs all positions are viable. Our model highlights that this prediction of a full offering need not be the case. We thank an anonymous reviewer for highlighting this point.

A difference with the main model is that concentration (measured both in terms of the Herfindahl index and the market shares at the extremes) follows an inverted U shape in the main model, whereas it is monotonically increasing in the pure IO model. This happens because under high trade-offs the intermediate positions in the main model's cloudlike frontier (which is curved outward) are more appealing than intermediate positions in the IO model's (flat) linear frontier. Thus, in the main model concentration is minimal at an intermediate level of trade-offs (i.e., around $\rho = -0.5$ in Figures 9 and 10), whereas in the pure IO model, concentration is minimal when trade-offs are maximal (i.e., angle of the line segment equals 135°).

There are both similarities and differences in the results, but perhaps the most important impact of moving to a pure IO model is a loss of richness in the phenomena the model can address. In the pure IO model firms choose positions directly rather than having positions arise from the choice of business policies. Hence the pure IO model is silent on important strategy considerations that we address in the main model. First, there is no analogue to the parameter K for the interdependence of business policies. This is relevant, as important streams of research in organizational economics (e.g., Milgrom and Roberts 1995), organization theory (e.g., Simon 1962), and strategy (e.g., Levinthal 1997) argue that such interdependence is a fundamental characteristic of firms. Second, the pure IO model cannot speak about strategy heterogeneity (i.e., there is no analogue to Figure 12), a key concern in the strategy literature (see, e.g., Nelson 1991).

5.2. Contrast and Contribution to Traditional NK Results

5.2.1. Comparison with NK Results. Our model has three main differences with respect to extant models in the NK literature in strategy. A first difference is that our model supports heterogeneity in the absence of myopia. In the received NK literature, increasing K increases landscape ruggedness, which in turn leads to greater heterogeneity, which is customarily measured as the number of surviving organizational forms in steady state or equilibrium (see, e.g., Levinthal 1997). Central in this literature has been the assumption of search by myopic firms—the ruggedness of the landscape affects heterogeneity "as long as the organization's vision is such that it can not scan the entire landscape" (Levinthal 1997, pp. 940–941). In other words, myopia is a key assumption in models that use a single dimensional landscape, as otherwise all firms would locate on the global peak.

In contrast, we show that introducing even just one additional attribute opens up a multiplicity of viable positions in the market, and that this heterogeneity does not depend on myopic firms. A casual analysis might have supposed that shifting from one attribute to two would allow the number of viable positions to double from one to two, but we show that, depending on the extent of attribute correlation (ρ), the number of viable positions can increase dramatically.

A second difference relates to the direction of the relationship between policy interdependence (K) and industry heterogeneity. In the received NK literature, the number of different forms in equilibrium *increases* with K (because myopic searchers are more likely to get stuck in more rugged landscapes). In contrast, in our model the number of different form in equilibrium (i.e., the viable positions) *decreases* with K. The mechanism underlying this result was explained in the context of Figure 7.[13]

A third difference with respect to NK models is that our model considers both consumer heterogeneity and product market competition. This allows us to be explicit about how a rival's position in one part of the market affects outcomes in other parts. This addresses the call of Baumann and Siggelkow (2011) for analyzing how competition affects the landscape that firms must navigate.

5.2.2. Contrast with a Pure NK Model. To isolate the impact of the IO elements in driving these differences, we now analyze a pure NK version of the model and contrast the results with those of our main model. Although the pure IO model retains several important elements of our main model, we find that the analysis and behavior of a pure NK model is radically different.

We retain the NK elements from the main model (as defined in §2.2): each strategy $\mathbf{s}$ maps into two attributes $a_1(\mathbf{s})$ and $a_2(\mathbf{s})$ that exhibit policy interdependence K and attribute correlation ρ. Because the IO elements of the main model are removed, the new model does not explicitly capture customers and competition (i.e., as defined in §2.3). Instead, the new model follows the NK modeling tradition and defines a "fitness" function, which describes how good or bad each strategy is. This fitness function is assumed to capture all elements that determine the performance of a product. The fitness function in the new model is $f(\mathbf{s}) = wa_1(\mathbf{s}) + (1-w)a_2(\mathbf{s})$, where $w \in [0, 1]$ determines the relative weight of each attribute on fitness. Details of the pure NK model along with formal results are contained in Appendix C.

[13] Interestingly, the only other work that has combined NK and IO approaches—i.e., Lenox et al. 2006, 2007—coincides with our unusual result on the effect of K. Although their model is different from ours (i.e., they rely on Cournot competition and myopic firms on a single-attribute landscape), the fact that we coincide on finding that increasing K decreases competition suggests that this result may be robust to a wider range of competitive models. We thank an anonymous reviewer for this insight.

Without customers and competition, many of the key concepts we study are no longer well defined. In particular, without consumers one cannot compute market shares and thus cannot define viability. One can consider the efficiency of positions, but with the unidimensional fitness function there will be typically only a single efficient position.

The main takeaway from having tried to compare our main model to a pure NK model is to realize that both models speak about essentially different phenomena. Because "pure" NK models do not have consumers and because they use a unidimensional measure of performance (i.e., fitness), none of the analyses we provide for the main model are appropriate—specifically, the results regarding market shares (i.e., Figures 9 and 10) rely on the model having customers, and all the other results in §4 rely on the model having two dimensions of performance. Essentially, NK models describe a production function. Because pure NK models lack market outcomes, the strategy literature has generally used the NK model to understand nonmarket aspects of organizations, such as modularity, search, and organizational heterogeneity. It is the addition of IO considerations (such as a demand function and a description of competitive interactions) to the NK characterization of a production function that allows us to enrich our understanding of positioning.

6. Conclusion

This paper presents a parsimonious theory of positioning that considers both the interdependence of business policies, as articulated in the NK modeling literature, and an explicit treatment of competition and demand, as developed in the IO literature. We examine how these factors interact in the context of a market in which consumers assess value creation along multiple attribute dimensions.

Our contribution to the positioning literature is rooted in two departures from the extant approaches. First, we depart from the assumption, implicit in IO models, that firms can directly choose what position to occupy in attribute space. This matters because it is policies, not positions, that are the levers that managers set directly. Second, we depart from the assumption of NK models that fitness landscapes have just one dimension of performance. This matters because, as we have argued, multiattribute landscapes are more representative of the environments of interest to strategy than the single-attribute representation that has dominated the NK literature. In particular, our setup allows distinguishing between strategies (in **s**-space) and positions (in *a*-space) and to begin to uncover the mechanisms by which decisions in one space affect the other. By combining elements of NK and IO models into one, we leverage the strengths of each approach.

Although each of these departures is straightforward, together they give rise to a landscape whose topography is significantly different from that characterized by traditional approaches. Using this structure, we can formally address a number of important strategy questions, including "What drives the number of viable positions in an industry?" and "How does the viability of a position differ from its efficiency?" By decoupling business policies from product attributes, our novel use of a multidimensional NK structure allows us also to ask a rich set of questions regarding industry heterogeneity—for example, "What is the extent of heterogeneity among firms in an industry in terms of positions, business policies, and market shares?" We show that answers to such questions depend nontrivially on the joint impact of trade-offs between the product attributes (ρ) and the interdependence among business policy choices (K).

We identify four unexpected results. First, not all positions on the efficient frontier are viable. Second, we qualify the strategy literature on NK models, by showing that results derived in a single-attribute setting do not necessarily generalize beyond that setting. Specifically, we find that, in the a multiattribute setting, increases in business policy interdependence (i.e., increases in K) can decrease the number of viable positions. Third, heterogeneity can be characterized in terms of either strategies or positions, and the relationship between these two facets of heterogeneity is moderated by the extent of business policy interdependence. Finally, we find that in a multiattribute setting, the effect of attribute trade-offs on competitive outcomes (e.g., market share and industry concentration) is larger than the effect of policy interdependence.

An interesting area of application of our model is the research on business models and competitive advantage (e.g., Casadesus-Masanell and Ricart 2010, Zott and Amit 2008). By positing a clear set of mechanisms and deriving various relationships—among (for example) strategy heterogeneity, the extent of attribute trade-offs, and the extent of policy interdependence—our model presents testable hypotheses regarding the range of business model heterogeneity in the face of competition in a market.

There are numerous avenues for extending our model and analysis. Our focus has been on the extent and nature of heterogeneity, yet other important links between competitive positioning and firm performance in a multiattribute setting remain to be explored. For instance, further work could relax some of our assumptions and study settings with fewer entrants or higher entry costs. On the demand side, future work could relax the assumption of a uniform distribution of consumers and examine the role of consumer heterogeneity on positioning choices (e.g., Adner and Zemsky 2005, 2006). Finally, in terms of methods, subsequent work could move toward the game-theoretic IO literature or toward the boundedly rational search of traditional evolutionary NK models.

Given that positioning is such a central concern for the strategy field, we believe that furthering our understanding of its determinants and implications is worthwhile. Our paper advances this agenda by developing a formal theory of positioning that brings together the notions of trade-offs, interdependencies, heterogeneous consumer demand, multiple attributes, and competitive interactions in a single model. An important byproduct of taking a formal approach to positioning is that we are able to provide unambiguous definitions of important constructs such as efficiency, trade-offs, viability, and even positioning itself. Furthermore, we are able to ground key notions that have become part of the strategy lexicon (e.g., the "shape" of the technology frontier) by deriving them from first principles, and we use these to posit clear mechanisms (i.e., "how" explanations) connecting the inputs and outputs of the process of positioning. We hope that this approach can serve as a platform for future investigations of key questions in competitive strategy.

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Appendix A. Equivalency of the Model with Bertrand and Biform Variations
In this appendix we show that the set of viable strategies is equivalent to the set of equilibrium strategies of two fully rational models of competition: (i) a biform game (Brandenburger and Stuart 2007) that uses coalitional games to model competition (MacDonald and Ryall 2004); and (ii) a two-stage, noncooperative game that is common in the IO literature with an assumption of price discrimination. The equivalencies we show are consistent with the finding in Stuart (2004) of the general efficiency of spatial games under biform competition and the finding in Lederer and Hurter (1986) on the efficiency of noncooperative spatial games with price discrimination, so that positioning is driven by value creation, as generally occurs under perfect competition without externalities.

A.1. Model Variations
The biform and two-stage variations share a number of features. First, in both there are a large number (at least 2^N) of profit-maximizing potential entrants. Second, both variations have a two-stage structure. In the first stage, the potential entrants decide whether to enter and, if they do so, they choose a strategy. As in the base model, an entrant's strategy is an element of $\mathcal{S} = \{0, 1\}^N$. We denote the number of firms that actually enter in stage I by m and their strategy choices by $\mathcal{E} = \{\mathbf{s}_1, \ldots, \mathbf{s}_m\}$. Third, value creation is exactly as in the base model. That is, an entrant's strategy determines the attribute levels of the firm's product according to the functions $a_1(\mathbf{s})$ and $a_2(\mathbf{s})$. We assume that these attribute functions are common knowledge. There is a constant marginal cost of production given by c, and firms compete for a set of customers $\mathcal{A} \subset [0, 1]$ whose WTP is given by $v(a_1, a_2; \alpha)$.

The two model variations differ in how competition takes place in stage II. In the classic two-stage approach, we assume that there is Bertrand competition with price discrimination. That is, each firm simultaneously names a price for each customer; the price of firm i for customer α is denoted by $p_{i\alpha}$. Customers buy one unit of the product that gives them the most surplus. As is typical under Bertrand competition, if customers are indifferent between two or more products, they are assumed to buy the one that generates the most profit for the selling firm. The profit of firm i in the two-stage game is then given by

$$\Pi_i^{\mathrm{TS}} = \sum_{\alpha \in \mathcal{A}} (p_{ia} - c) I_{i\alpha},$$

where $I_{i\alpha}$ indicates whether firm i sells to customer α.

In the biform game, we solve for the core of the coalitional game involving the m entrants and the customers in $\mathcal{A}$. Denote by $[\underline{x}_i, \bar{x}_i]$ the range of payoffs to firm i in the core. Then the profit of firm i in the biform game is given by $\Pi_i^{\mathrm{B}} = \gamma \underline{x}_i + (1-\gamma)\bar{x}_i$, where γ is a parameter reflecting the confidence of firms in their ability to negotiate with customers within the constraints provided by the core (Brandenburger and Stuart 2007).

We solve the two-stage game for a pure strategy subgame perfect equilibrium. That is, we first solve for the Nash equilibrium of the Bertrand pricing game in stage II for any set of entrants. We then require that entry decisions in stage I form a Nash equilibrium with profit functions given by ${\Pi_i}^{TS}$ from equilibrium play in stage II. Similarly, for the biform game, we solve for Nash equilibrium entry strategies in the first stage, where payoffs are now given by Π_i^{B}. As is common with entry models, we restrict our attention to equilibria in which all entrants have strictly positive profits in equilibrium, for both variations.

A.2. Characterization of Stage II Payoffs
As is standard, we work backward and begin by characterizing the stage II payoffs for both variations. We start with the biform game by defining value creation and added value in our setting. Let the function $V(\mathcal{E}, \mathcal{A})$ be the total value creation (equivalently, economic surplus) for any set of entrants $\mathcal{E}$ and any set of customers $\mathcal{A}$. Given constant marginal costs that are the same for all firms, total value creation is maximized when each customer buys the product

for which she has the highest WTP. Hence, we can decompose total value creation as follows:

$$V(\mathscr{E}, \mathscr{A}) = \sum_{a\in\mathscr{A}} \max_{\mathbf{s}\in\mathscr{E}} v(a_1(\mathbf{s}), a_2(\mathbf{s}); \alpha) - c.$$

The added value of entrant i for any set of entrants $\mathscr{E}$ is defined as the increase in value creation that results from including i in the game:

$$AV_i(\mathscr{E}) = V(\mathscr{E}, \mathscr{A}) - V(\mathscr{E}\backslash \mathbf{s}_i, \mathscr{A}).$$

We know from Brandenburger and Stuart (2007) that added value places an upper bound on the payoff of a player in a coalitional game. Furthermore, Chatain and Zemsky (2007) identify a class of models with buyers and suppliers and constant marginal costs of production, in which the core always exists and payoffs are proportional to added value. It is straightforward to verify that our biform game satisfies the conditions in Chatain and Zemsky (2007; specifically Assumptions A1 and A2 required for their Proposition 1). Hence we have the following result.

Lemma A.1. *In the biform model, the profits of each entrant are proportional to its added value:*

$$\Pi_i^{\mathrm{B}}(\mathscr{E}) = \gamma AV_i(\mathscr{E}).$$

We turn now to the classic two-stage variation. Given the assumptions of price discrimination and constant marginal costs, the second stage of this model can be decomposed into independent Bertrand price games, where entrants compete in prices for each customer in $\mathscr{A}$. Each customer is then served by the entrant with the greatest value creation for that customer, and the firm's profit is the increase in value creation over the next highest value creation. This is precisely the added value for that customer. Summing over all customers now yields the following result.

Lemma A.2. *In the two-stage variation, the profits of each entrant are given by its added value:*

$$\Pi_i^{\mathrm{TS}}(\mathscr{E}) = AV_i(\mathscr{E}).$$

Proof. Consider the equilibrium prices for a given customer $\alpha \in \mathscr{A}$. In a standard Bertrand price game, firms sell a homogeneous product but vary in their marginal costs. In equilibrium, the lowest cost firm sells with a margin equal to its cost advantage, and the firm with the next lowest cost prices at its marginal cost. Firms in our model have the same marginal costs but vary in the WTP of customers, but this has little substantive impact on the equilibrium analysis (Vives 1999, Chap. 5). The firm with the second highest WTP prices at marginal cost and the firm with the highest WTP is then able to charge a margin exactly equal to its advantage in WTP. Letting $v_{i\alpha} = v(a_1(\mathbf{s}_i), a_2(\mathbf{s}_i); \alpha)$, an equilibrium price vector is given by[14]

$$p_{i\alpha} = \begin{cases} c & \text{if } \max_{j\in\{1,\ldots,m\}\backslash i} v_{j\alpha} \geq v_{i\alpha}, \\ c + v_{i\alpha} - \max_{j\in\{1,\ldots,m\}\backslash i} v_{j\alpha} & \text{otherwise.} \end{cases}$$

Thus, an entrant's profit is

$$\begin{aligned} \Pi_i^{\mathrm{TS}}(\mathscr{E}) &= \sum_{\alpha\in\mathscr{A}} (p_{i\alpha} - c) \\ &= \sum_{\alpha\in\mathscr{A}} \max\left\{0, v_{i\alpha} - \max_{j\in\{1,\ldots m\}\backslash i} v_{j\alpha}\right\} \\ &= V(\mathscr{E}, \mathscr{A}) - V(\mathscr{E}\backslash \mathbf{s}_i, \mathscr{A}) \\ &= AV_i(\mathscr{E}). \quad \square \end{aligned}$$

Comparing these two lemmas reveals that the stage II profit function of the classic two-stage game is a special case of the profit function in the biform game with $\gamma = 1$.

A.3. Equilibrium Characterizations

Let $\mathscr{V}^{\mathrm{B}} \subseteq \mathscr{S}$ be the set of strategies used in the equilibrium of the biform game, and let $\mathscr{V}^{\mathrm{TS}} \subseteq \mathscr{S}$ be the set of strategies used in the equilibrium of the two-stage game. Recall that $\mathscr{V}$ is the set of viable strategies as defined in §2.

Entry in stage I depends only on whether or not an entrant expects positive profits in stage II. Given that profits are proportional (by a factor of $\gamma > 0$) in the two variations, it is intuitive that the set of equilibrium strategies will be the same. We also find an equivalence with our base model.

Proposition A.3. *The equilibrium of the biform and the two-stage variations are unique, and the set of equilibrium strategies satisfies* $\mathscr{V}^{\mathrm{B}} = \mathscr{V}^{\mathrm{TS}} = \mathscr{V}$.

Proof. Given the equilibrium definitions, we have that $\mathscr{V}^{\mathrm{TS}}$ satisfies the following two conditions: if $\mathbf{s}_i \in \mathscr{V}^{\mathrm{TS}}$, then $\Pi_i^{\mathrm{TS}}(\mathscr{V}^{\mathrm{TS}}) > 0$; and if $\mathbf{s}_i \notin \mathscr{V}^{\mathrm{TS}}$, then $\Pi_i^{\mathrm{TS}}(\mathscr{V}^{\mathrm{TS}} \cup \mathbf{s}_i) \leq 0$. Similarly, if $\mathscr{V}^{\mathrm{B}}$ satisfies $\mathbf{s}_i \in \mathscr{V}^{\mathrm{B}}$, then $\Pi_i^{\mathrm{B}}(\mathscr{V}^{\mathrm{B}}) > 0$, and if $\mathbf{s}_i \notin \mathscr{V}^{\mathrm{B}}$, then $\Pi_i^{\mathrm{B}}(\mathscr{V}^{\mathrm{B}}) \leq 0$. The proof has three steps.

(i) First, we establish equivalence between the biform and the two-stage variations ($\mathscr{V}^{\mathrm{B}} = \mathscr{V}^{\mathrm{TS}}$). Since $\Pi_i^{\mathrm{B}}(\mathscr{E}) = \gamma \Pi_i^{\mathrm{TS}}(\mathscr{E})$, it follows that $\mathscr{V}^{\mathrm{B}} = \mathscr{V}^{\mathrm{TS}}$. In other words, the two equilibrium strategy sets are equivalent.

(ii) Next, we show that any viable strategy in $\mathscr{V}$ is an equilibrium strategy in the two variations ($\mathscr{V} \subseteq \mathscr{V}^{\mathrm{TS}}$). Suppose that $\mathbf{s}_i \in \mathscr{V}$. Then $AV_i(\mathscr{S}) > 0$ by definition of $\mathscr{V}$. Because $AV_i(\mathscr{E}) \geq AV_i(\mathscr{S})$ for any $\mathscr{E} \subseteq \mathscr{S}$, we have that $AV_i(\mathscr{V}^{\mathrm{TS}} \cup \mathbf{s}_i) > 0$ and hence $\mathbf{s}_i \in \mathscr{V}^{\mathrm{TS}}$.

(iii) Finally, we show that all equilibrium strategies from the variations are viable ($\mathscr{V}^{\mathrm{TS}} \subseteq \mathscr{V}$). The proof is by contradiction. Suppose that $\mathbf{s}_i \in \mathscr{V}^{\mathrm{TS}}$ and $\mathbf{s}_i \notin \mathscr{V}$. Then $AV_i(\mathscr{V}^{\mathrm{TS}}) > 0$ and $AV_i(\mathscr{S}) = 0$. For both conditions to hold simultaneously, there must be at least one strategy in $\mathscr{S} \notin \mathscr{V}^{\mathrm{TS}}$ that keeps $\mathbf{s}_i$ from having added value. Thus, there is a customer α and a strategy $\mathbf{s}_j \notin V^{\mathrm{TS}}$ for which $\mathbf{s}_i$ has the maximum value creation for all $\mathbf{s} \in \mathscr{V}^{\mathrm{TS}}$ but $\mathbf{s}_j$ has greater value creation.[15] But this implies that $AV_j(\mathscr{V}^{\mathrm{TS}} \cup \mathbf{s}_j) > 0$, which contradicts $\mathbf{s}_j \notin \mathscr{V}^{\mathrm{TS}}$.

We conclude that $\mathscr{V}^{\mathrm{TS}} = \mathscr{V}$. $\square$

[14] Although the equilibrium profits are unique, there are multiple possible equilibrium price vectors. As long as the firm with the second highest WTP prices at marginal cost, the other losing firms can price higher.

[15] We do not consider the possibility that they have the same value creation (i.e., $v(\mathbf{s}_j, \alpha) = v(\mathbf{s}_i, \alpha)$) because this happens with probability zero, given that the contribution functions underlying the attribute levels are drawn from continuous distributions.

We have thus demonstrated that the simple model described in the paper's main text—with entry into all positions and market shares determined by value creation for each customer—is equivalent to two rational entry models with low barriers to entry and high levels of rivalry.

Appendix B. Benchmark IO Model

In this appendix we describe and provide a basic set of analyses for the pure IO model discussed in §5.1.2.

B.1. Model's Idea

The demand side and value creation remain as in the main model: there are two attributes a_1 and a_2, heterogeneous consumers value products according to Equation (2), and consumers buy the product that creates the most value for them.

In contrast to the main model, in which firms pick strategies that give rise to positions, in this model firms pick positions directly. The set of possible positions corresponds to the line segment centered at $(0.5, 0.5)$ inscribed in the unit box, as illustrated in Figure B.1. Angle $45 \le \theta \le 135$ characterizes the *technology trade-offs* that determine the set of possible positions. The cases of $\theta = 45$ and $\theta = 135$ correspond, respectively, to the cases of perfectly positive and perfectly negative trade-offs (i.e., they are equivalent to the cases of $\rho = 1$ and $\rho = -1$ in the main model).

B.2. Derivation of Consumer Choice

The technology illustrated in Figure B.1 corresponds to

$$a_2(a_1, \theta) = a_1 \tan\left(\theta \frac{\pi}{180}\right) - \frac{1}{2}\tan\left(\theta \frac{\pi}{180}\right) + \frac{1}{2},$$

and the utility that consumer α gets from buying the product with attribute a_1 under technology θ is

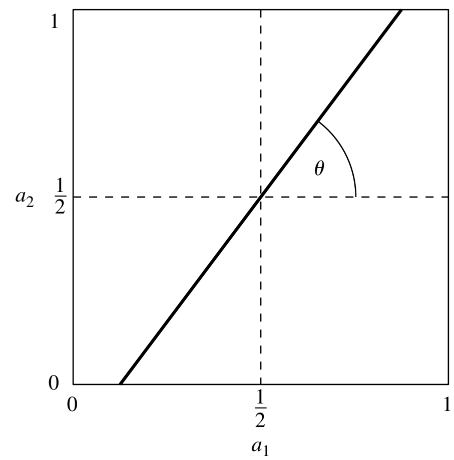
$$u(\alpha, a_1, \theta) = \alpha \log(1 + a_1) + (1 - \alpha)\log(1 + a_2(a_1, \theta)).$$

Given this technology and consumer preferences, we determine what is the product that each consumer would buy. We assume that there are firms at all positions on the frontier and that these firms engage in Bertrand price competition, a form of perfect competition that drives all value creation to consumers.[16] Note that because the technology describes a one-to-one relationship between a_1 and a_2, determining the optimal a_1 unambiguously determines the optimal a_2. Applying first- and second-order conditions implies that consumer α under technology θ would choose the product with attribute 1 equal to

$$a_1^*(\alpha, \theta) = -1 + \frac{3}{2}\alpha - \frac{3}{2}\alpha \cot\left(\theta \frac{\pi}{180}\right).$$

[16] With a discrete number of consumers, there are firms in the immediate neighborhood of any firm that are not serving customers. Thus, competition from these firms without customers drives prices down to marginal cost. As a result, each consumer receives all the value creation and buys from the firm in the position that maximizes value creation for that consumer.

Figure B.1 Set of Possible Positions in the Benchmark IO Model



Notes. The bold line describes the set of possible positions Angle $45 \le \theta \le 135$ characterizes the trade-offs between attributes a_1 and a_2.

Finally, taking into account the boundary cases[17] leads to the following optimal consumer choice:

$$a_1^{**}(\alpha, \theta) = \begin{cases} \underset{a_1 \in \{a_1^{\mathrm{LB}}(\theta),\, a_1^*(\alpha,\theta),\, a_1^{\mathrm{UB}}(\theta)\}}{\arg\max} u(\alpha, a_1, \theta) & \text{if } a_1^{\mathrm{LB}}(\theta) < a_1^*(\alpha, \theta) < a_1^{\mathrm{UB}}(\theta), \\ \underset{a_1 \in \{a_1^{\mathrm{LB}}(\theta),\, a_1^{\mathrm{UB}}(\theta)\}}{\arg\max} u(\alpha, a_1, \theta) & \text{otherwise.} \end{cases}$$

B.3. Illustrative Results

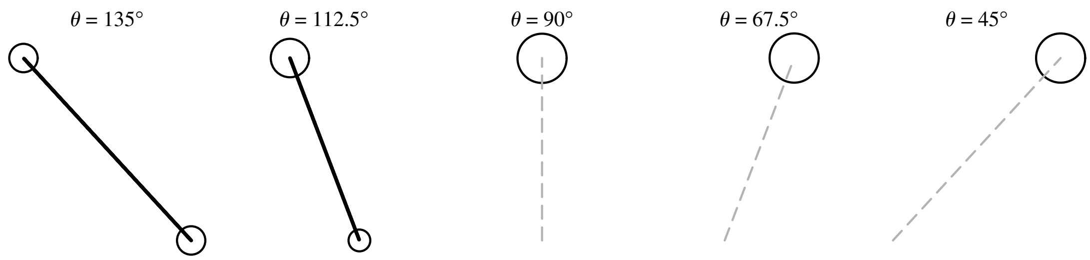
We compare the IO model in this appendix with the model in the main text by looking at figures that are analogous to figures from the main model. As in the main model, the figures assume $M = 1{,}000$ consumers.

Figure B.2 is analogous to Figure 6 in the main text. Because the IO model does not have a stochastic element, the results in Figure B.2 are exact, and not just one possible outcome of the model. To give a sense of the number of products in a given position, the area of each used position in Figure B.2 is made proportional to its market share. For instance, in the $\theta = 135°$ case, each big circle has 333 customers, and the line connecting these big circles is made of 334 small circles (each one corresponding to one customer), adding up to the $M = 1{,}000$ customers. Because in the cases where $\theta \le 90°$ the position at the top right dominates all other positions (and, thus, captures all the customers), a dashed line was added to show where the other possible but unoccupied positions lie.

Panels (a), (b), (c), and (d) in Figure B.3 are analogous to the results in Figures 8, 9, 10, and 11, respectively. Section 5.1.2 discusses the main qualitative differences between these two pairs of results.

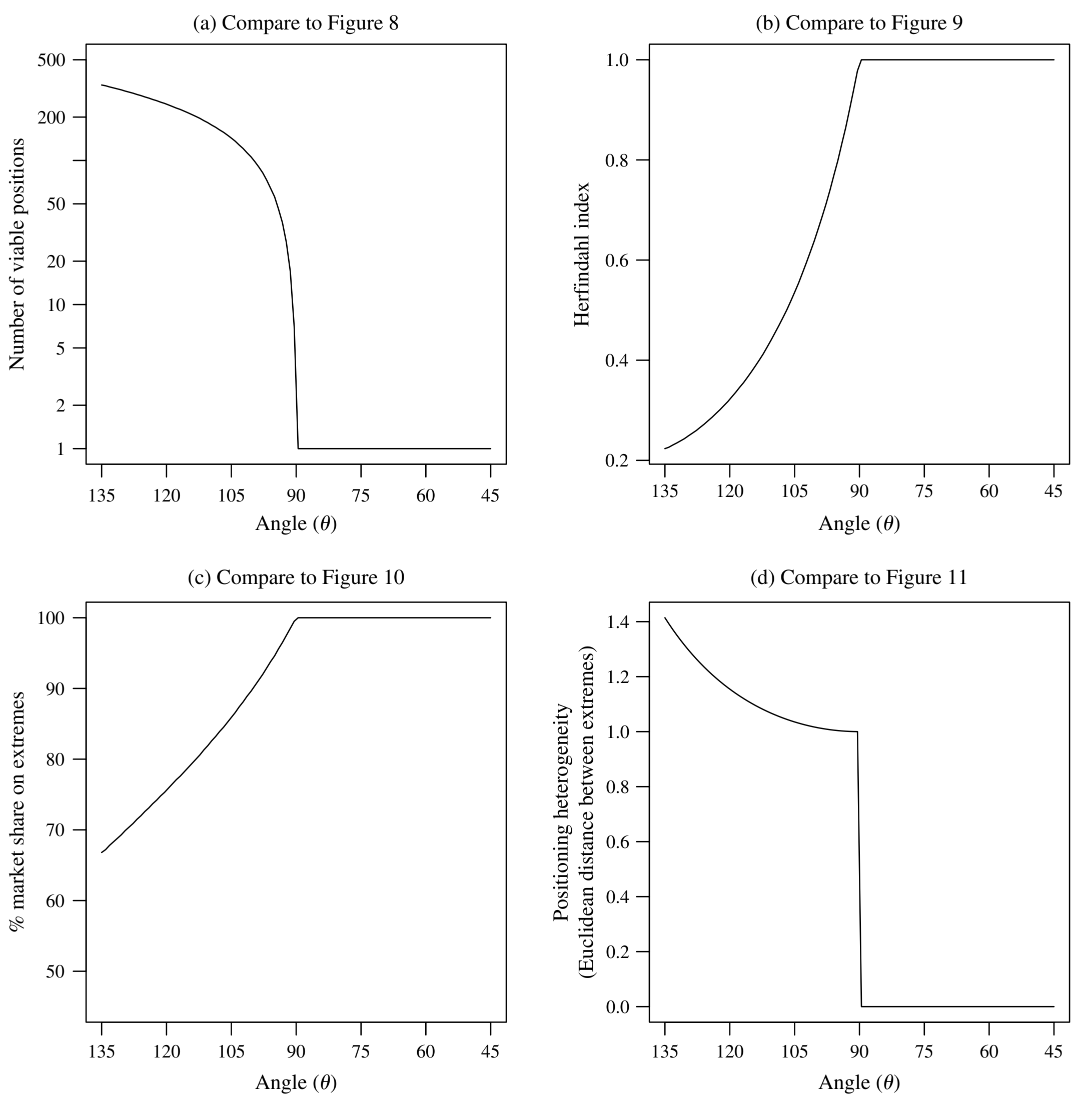
[17] Although a_2 can take any value from 0 to 1, because θ can range from 45 to 135, a_2 can only range between the lower and upper bounds defined by $\frac{1}{2} \pm 1/(2\tan(\theta(\pi/180)))$, which we denote as $a_1^{\mathrm{LB}}(\theta)$ and $a_1^{\mathrm{UB}}(\theta)$, respectively.

Figure B.2 Graphical Intuition of the Effect of Technology Trade-Offs (θ) on the Set of Possible Positions



Note. Compare to Figure 6.

Figure B.3 Main Results from the IO Model



Appendix C. Benchmark NK Model

In this appendix we describe and provide a basic set of analyses for the pure NK model discussed in §5.2.2.

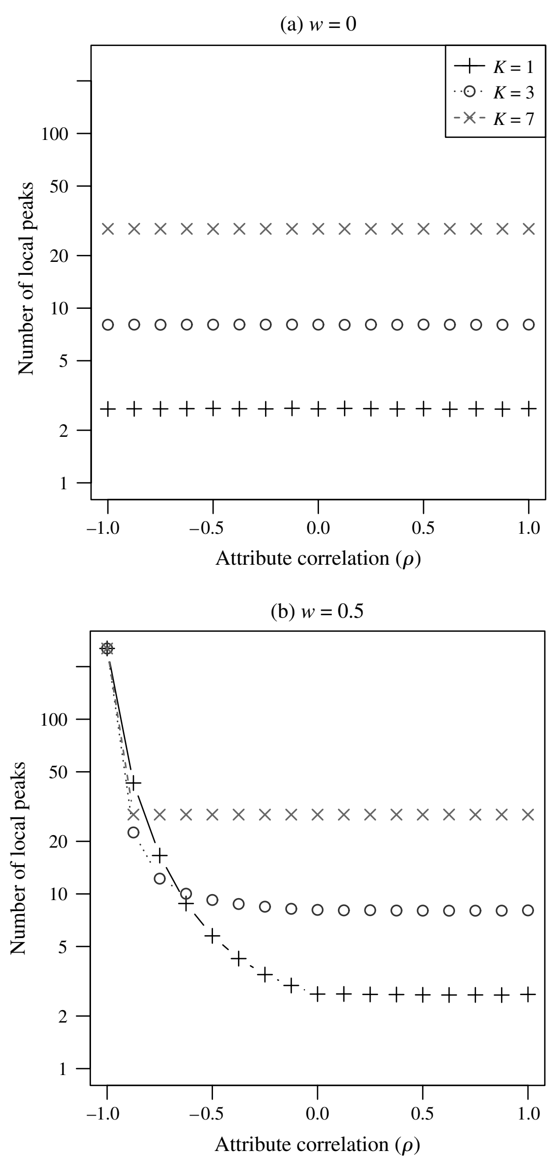
C.1. Model's Idea

The pure NK model keeps the NK elements of the main model (i.e., §2.2) and "turns off" the IO elements of the main model (i.e., §2.3). In the new model, the two attributes (a_1 and a_2) are combined to form a fitness landscape $f(\mathbf{s}) = wa_1(\mathbf{s}) + (1-w)a_2(\mathbf{s})$, where $w \in [0, 1]$ determines the relative weight of each attribute on fitness.

C.2. Illustrative Results

In line with the standard analyses in the NK literature, we study this model by characterizing the number of local peaks in the landscape as a function of the model's parameters (K, ρ, and w). In Figure C.1 we show the number of local peaks in the new landscape f, as a function of policy interdependence (K), attribute correlation (ρ), and attribute weight (w). As

Figure C.1 Results of Naive Multidimensional NK Model



in the main model, the figures assume 256 ($=2^8$) possible products. Panels (a) and (b) in this figure show two extreme levels of w (i.e., only one attribute matters, versus both attributes matter equally). Values of w between these two extremes smoothly transform one panel into the other.

Panel (a) replicates the standard result of the NK literature—that the number of local peaks increases with K. In this panel, attribute correlation ρ does not play any role, as $w=0$ implies that only one attribute landscape matters. Panel (b) shows that the number of local peaks decreases in attribute correlation (ρ). This result can be understood by considering the extreme case of attribute correlation $\rho = -1$. In this case, because the attributes have a perfect negative correlation, attribute 1 fully offsets attribute 2 and thus the overall fitness of the landscape f is constant. That means that each point in the landscape is a peak.[18] As ρ increases from -1, this offsetting effect gradually disappears. In sum, in the new model the number of local peaks increases with K and decreases with ρ and with more unequal landscape weights (i.e., with $|w-0.5|$).

Appendix D. Robustness of the Distinction Between Efficient and Viable Positions

This appendix explores the robustness of the distinction between efficient and viable positions. In particular, we ask what happens to the proportion of viable over efficient positions as the positioning space becomes more densely packed with possible positions. This robustness check is relevant, as the results in the body of the paper assume $N=8$ binary policy choices (which leads to $n=256$ possible positions), but other settings could have more or fewer policy choices or nonbinary policy choices, leading to vastly different numbers of possible positions. In particular, one may wonder what happens if the number of possible positions becomes substantially larger; does the frontier become smooth and convex and all the positions in it viable? The main result of the following analysis is that the distinction between efficient and viable positions is a fundamental one, which does not depend qualitatively on the degree of discreteness of the policy choices.

To formally study the question, we explore what happens to the ratio $r(n) = \#$ of viable points/# of efficient points as a function of the number of points (n) in a cloud of points. To study the effect of n directly, we decoupled the generation of positions from the NK model, and instead generated positions by drawing points from a multivariate normal distribution.[19] Furthermore, to allow us to explore the effect of arbitrarily large values of n, we did not simulate consumers, but instead used the property that under a linear demand function, the viable points correspond to the points in the upper-right convex hull of the cloud of points. Both changes

[18] A strategy $\mathbf{s}$ is at a local peak if $f(\mathbf{s}) \geq f(\mathbf{s}')$ for all $\mathbf{s}'$ such that $\|\mathbf{s}'-\mathbf{s}\|_1 = 1$.

[19] We used a multivariate normal with two dimensions and zero correlation between the dimensions. This distribution is very similar to a $\rho = 0$ multiattribute landscape, as the fitnesses of NK landscapes are roughly normally distributed (Kauffman 1993, p. 53). We also tried multivariate normals with correlated dimensions as well as a multivariate uniform, with the main results in this appendix remaining qualitatively robust.

Figure D.1 Illustration of the Upper-Right Convex Hull

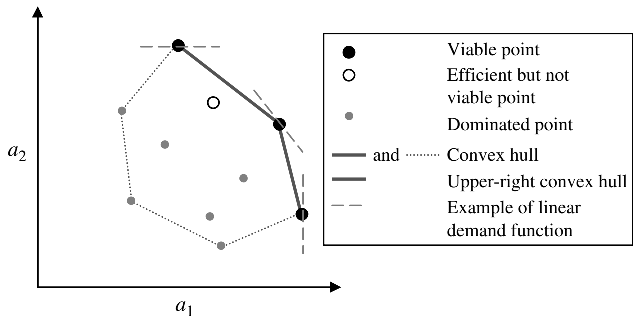


Table D.1 Expected Value of the Viable-to-Efficient Ratio $r(n)$

n: Number of points in the cloud	Expected number of ... Efficient points	Expected number of ... Viable points	$r(n)$: Viable/ efficient points (%)
10	2.93	2.36	80.7
100	5.19	3.22	62.1
1,000	7.49	3.87	51.7
10,000	9.79	4.41	45.1
100,000	12.09	4.89	40.4
1,000,000	14.39	5.31	36.9
10,000,000	16.70	5.70	34.1

to the model (in how the points are generated and how viability is determined) are necessary, as, otherwise, it is computationally unfeasible to use simulation to study large values of n.

Figure D.1, with $n = 10$ positions, illustrates the elements mentioned so far. The hollow point in the previous figure is not viable under linear preferences, as no demand curve would intersect it before intersecting some other point. This is equivalent to saying that this point is not part of the upper-right convex hull. Recall that, intuitively, the convex hull of a set of two-dimensional points is the set of points that would support a tight rubber band around the cloud of points. The upper-right convex hull is simply the subset of the convex hull that lies between the topmost and the rightmost points of it.

Under the previous assumptions, one can use mathematical formulas to compute $r(n)$: computing the expected number of points in the convex hull of a random set of points (i.e., the number of viable points under the aforementioned assumptions) was solved by Efron (1965), and computing the expected number of efficient points in a multivariate distribution is a standard problem in order statistics (David and Nagaraja 2003, §6.8). Table D.1 shows the statistics of interest using this analytic method (the results were also confirmed by using simulation for the values of $n < 10{,}000$).

Two surprising observations emerge from Table D.1: (i) the number of efficient and viable points is very small and increases slowly with n; and (ii) the ratio $r(n)$ does not approach 1 (as one would expect, if the effect of increasing n was to make the frontier smooth and convex), but slowly moves in the other direction. In other words, we found that as the number of points in the cloud increases, the proportion of points that are efficient but not viable also increases. This implies that, no matter how dense is the number of points in the cloud (i.e., due to increasing the number of policy choices or the number of levels per policy choice), the distinction between viable and efficient points still matters (and, in fact, matters more as n increases).

Because the relationship between efficiency and viability—and thus our understanding of positioning—hinges on whether or not the frontier is convex, it is important to have a theory regarding whether or not real-world frontiers are convex. Arguably, the IO literature has assumed convex frontiers for analytical tractability, and not because convexity must be an essential property of positioning.

The following argument suggests that in the real world, nonconvex frontiers should be much more common than convex frontiers. In the real world, the mapping from policies to attributes is likely to have some randomness (e.g., because of causal ambiguity or environmental uncertainty). This randomness makes nonconvexity very likely; to see why, imagine how a set of positions looks when new positions are added to it. If one starts with two positions (e.g.,), there is a 50% chance that if a third position is added, the set of positions will remain convex (i.e., by getting a configuration such as rather than). More generally, for each position that is added, the chance that the set of positions remains convex decreases. Hence, it should be unlikely for a positioning space with more than a handful positions to be convex.

In sum, the analysis in this appendix suggests that in settings in which the set of possible positions are generated by a process that has some degree of randomness (a characteristic of many real-word situations), a convex frontier is most likely to be an exception rather than the rule, as it is improbable that a random distribution of positions will produce a configuration where all efficient positions are also viable.

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