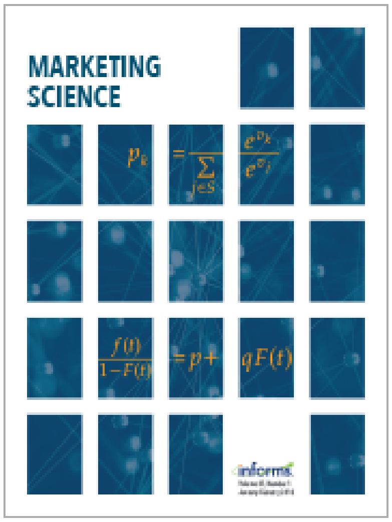

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What Are We Really Good At? Product Strategy with Uncertain Capabilities

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Abstract. Firms often learn about their own capabilities through their products' successes and failures. This paper explores the interaction between learning about capabilities and product strategy in a formal model. We consider a firm that can launch a sequence of products, where each product's success probability depends on the fit between the firm's capabilities and the product. A successful new product always causes the firm to become more optimistic about the capability most relevant for that product; however, it can also cause the firm to become less optimistic about some of its other capabilities, including capabilities the new product does not use. The firm's optimal forward-looking product strategy accounts for short-run expected profits as well as for the information value of learning for future decisions. We find that a product sharing few or even no capabilities with potential future products can have a greater information value than a product that shares more capabilities with future products and that learning about capabilities can affect the optimal sequence of product launch decisions.

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1. Introduction

It is widely accepted that a firm's product strategy should exploit its existing capabilities and help to build new ones (Wernerfelt 1984, Teece et al. 1997, Dutta et al. 1999, Slotegraaf et al. 2003). Implementing this advice can be challenging, however, because capabilities are deeply embedded in a firm's people, processes, and culture (Day 1994, Grewal and Slotegraaf 2007), making them difficult or impossible to observe directly. For example, a recent field study finds that managers have difficulty "abstracting away from products to the technological competence that is embedded in the products," leading the author to conclude that "technological competence is thus not obvious; it is hard to identify" (Danneels 2002, p. 1109). In other words, knowing a firm's successful (and failed) product launches provides managers with only imprecise information about their firm's underlying capabilities.[1]

For managers who do not fully know their firms' capabilities, many strategic decisions involve a trade-off between maximizing current profits and obtaining information that will improve future decision making. Consider a product launch decision. A firm can *exploit* its knowledge to date and launch the product with the highest expected direct profit. A firm can also *explore* its capabilities further, for example, by launching a product that generates a low expected profit, but whose success or failure will be of great help in assessing the firm's capabilities and thus future product opportunities. Active learning about capabilities is costly in this case because it requires knowingly sacrificing short-term profits for the sake of improving future product launch decisions. Our paper explores the implications for optimal product strategy of this trade-off between exploiting and exploring capabilities.

Product failures can be valuable in our model because, like product successes, they enable learning about capabilities. For instance, a product failure may allow a firm to infer which of its capabilities drove a past success in a related product category. It follows that launching a product with a high failure probability can sometimes be optimal. This recommendation is consistent with advice to practitioners that managers should follow "Strategies for Learning from Failure" (Edmondson 2011) or embrace "Failing by Design" (McGrath 2011). Our results on the informational value of failure are also consistent with statements by successful executives emphasizing their willingness to invest in products with a high risk of failure. For example, Amazon CEO Jeff Bezos said in a recent interview, "I've made billions of dollars of failures at

Amazon.com . . . . None of those things are fun. But they also don't matter . . . . What really matters is, companies that don't continue to experiment, companies that don't embrace failure, they eventually get in a desperate position where the only thing they can do is a Hail Mary bet at the very end of their corporate existence" (Kim 2015). Similarly, the founders of Google wrote in a letter to shareholders before their initial public offering, "Do not be surprised if we place smaller bets in areas that seem very speculative or even strange when compared to our current businesses . . . . Most risky projects fizzle, often teaching us something" (Brin and Page 2004).[2]

As an illustration of how a firm, over time, can learn about its various capabilities from its products' successes *and* failures and adapt its product strategy in response, consider Eastman Kodak. The company's long-time dominance of the camera-film business arguably rested on some combination of expertise in two main areas, i.e., imaging and chemical engineering. In the early 1980s, when Kodak's management foresaw the eventual decline of film and began to look for new opportunities, the prevailing view was that Kodak was primarily a chemicals company, which prompted several costly investments to diversify into pharmaceuticals (Feder 1988). A failure to develop any profitable new drugs, however, caused a shift in the leadership's beliefs about the company's strengths (along with turnover of the leadership itself), and by the early 1990s, the company's leadership "decided that its expertise lay not in chemicals but in imaging" (*The Economist* 2012). This change in beliefs led to a major shift in the strategic focus toward digital photography (Gavetti et al. 2005), which, however, was ultimately ill-fated because of competition from low-cost electronics companies.[3]

Another example involves the website eHarmony, which matches men and women interested in long-term relationships based on their responses to a detailed questionnaire. Its success arguably resulted from a combination of (i) expertise in romantic relationships, and (ii) the capability to use data analytics to create matches. In an attempt to leverage its expertise in romantic relationships, in 2010 the company introduced Jazzed.com, a dating website for people interested in short-term relationships. (For short-term relationships, high levels of compatibility are less important than physical attraction; Harwell 2015, so the company's complex matching expertise was less relevant in this new market.) The Jazzed.com website failed to attract many customers and was closed down two years after its launch. In a remarkable shift in strategy, the company recently launched a new website, Elevated Careers, that matches potential employees with jobs (O'Brien 2016), and is contemplating other matching services in the future, such as helping people find friends or financial advisors (Jacobs 2014). It appears that the company has concluded that its core competence is matching, not romantic relationships, and has adjusted its strategy accordingly.[4]

In our formal model, as in the examples above, there is a two-way link between a firm's product strategy and the firm's beliefs about its own capabilities (or "skills"). Naturally, the firm would like to introduce new products that rely on skills the firm believes it has, based on its past product experiences. Each new product introduction, in turn, causes the firm to update its beliefs about its skills, which affects the expected profitability of future product introductions.

We assume the firm is "born" with prior beliefs about its set of skills and updates its beliefs upon launching new products and observing their success or failure. The likelihood of success in any market depends on how well the firm's skills match the skills that are relevant for that market.[5] Skills can differ in importance across and within markets. For skills never used before, we can think of the firm as already possessing a latent skill, or equivalently, as *acquiring* the skill when it enters a market that uses that skill. The firm's learning process is imperfect because success or failure in any market depends on multiple skills, and on luck.

We show that success in a market always leads to an upward revision of beliefs about the skill most relevant for that market. At the same time, however, a success may lead to a *downward* revision of beliefs about some of the firm's other skills. Importantly, the multidimensional nature of skills implies that a (successful or failed) product introduction can generate information about skills that the product itself does *not* use. This occurs, for example, if the success or failure of the current product helps the firm determine which skill is likely to have caused the success of a previously launched product. Interpreting Kodak's story in the context of our model, the failure of the company's pharmaceutical products cast doubt on its general chemical expertise, which, given its earlier success in the camera film business, reinforced management's belief that the company had strong imaging skills. Hence, failure in one market (pharmaceuticals) led to an upward revision of beliefs about a skill (imaging) not used in that market.

An intuitive implication of this learning process is that if a company repeatedly launches successful products that are similar in one respect but differ in others, the firm (and outsiders) will come to view the capability supporting the intersection of those products as a core capability (or "core competence," Prahalad and Hamel 1990). For instance, a company like Honda that successfully launches motorcycles, then cars, and eventually a broad line of products including garden power tools and outboard motors and most recently small jets (Ostrower 2015) would be inferred to possess a core competence in engine design, even without detailed direct knowledge of organizational processes.

Building on Wernerfelt's (1984, p. 179) argument that new products may be "stepping stones" for future products, we analyze the *information value* of a new product for potential future product launch decisions. As one would expect, a product has a positive information value for a future product if the two products are related. Less obviously, a product also has a positive information value if it is unrelated to the future product, as long as it is related to a past product and the past product is related to the future product. For instance, Kodak's negative experience with pharmaceuticals led management to believe that the company had strong imaging skills, which would be useful information for a potential future product unrelated to pharmaceuticals but relying on the imaging skill.

Not only is the information value of an indirectly related product positive, we also show that it may exceed the information value of a directly related product. More generally, we show that the information value of suitably comparable products for the same future product is not necessarily increasing in the products relatedness with the new product. A product that fully overlaps with the future product in terms of the required skills can have a lower information value than a product that has only partial (or no) direct overlap with the future product, and a product with partial overlap may have a lower information value than a product without any direct overlap.

These findings have implications for a firm's optimal forward-looking product strategy. When the firm faces a choice between launching different products, its optimal decision can be to launch a product with a low, or even negative, expected direct profit but a high information value. Moreover, active learning about skills through product successes and failures can also impact the optimal sequence in which products should be explored.

In summary, the key features of our model are that the firm learns about its capabilities from observed product outcomes, that capabilities are multidimensional, and that a firm's various capabilities differ in their relevance and importance across markets. These features imply that an outcome in one market can affect the firms' beliefs about its success probability in other markets. These cross-market learning effects, in turn, have implications for a firm's optimal forward-looking product strategy.

Our paper proposes a new perspective on firm learning. The firm learns about its own capabilities, rather than about buyer preferences or other market variables, which we assume to be known. This new perspective explains why success or failure in one market can affect the firm's beliefs about its success probability in other markets, even if the markets are unrelated in terms of preferences and competitive interactions. For instance, in the Kodak example, although camera film and pharmaceuticals are unrelated markets on the demand side (and did not share any competitors), internal learning about capabilities on the firm side implies a link between the two markets. By contrast, no such link would exist if learning pertained to characteristics of individual markets rather than the firm's capabilities. The insight that learning about capabilities creates links between different markets in turn implies that the optimal product strategy is dynamic and forward-looking.

In practice, both types of learning, i.e., learning about markets and learning about capabilities, are important. Learning about markets helps identify opportunities for new product launches, while capabilities are crucial to successfully exploit any such opportunities. The firm's beliefs about its capabilities should therefore guide its investments into market research that evaluates the potential of individual markets. At the same time, the degree of uncertainty about the market itself affects the extent to which a success or failure enables the firm to learn more about its capabilities, thus creating a complementarity between the two types of learning, which could be explored in future research.

2. Related Literature

A sizeable literature in marketing uses game-theoretic models to study optimal product line strategy (e.g., Desai 2001, Kuksov and Villas-Boas 2010, Guo and Zhang 2012, Thomadsen 2012, Amaldoss and Shin 2015), analyzing how a firm's strategic interactions with competitors and consumers affect the number as well as (horizontal and vertical) positioning of a firm's products. This literature, however, largely ignores the role played by a firm's capabilities in shaping its optimal product line decisions. Our work, by contrast, does not explicitly model consumer choice or competition; in our model, these factors are implicitly reflected in the profits that arise from a product's success or failure. Abstracting away from strategic interactions with consumers and competitors, we focus instead on how the company's capabilities drive its product line decisions.

In the strategy field, a large literature has studied how a firm's resources, competencies, and capabilities determine which products it should launch (e.g., Wernerfelt 1984, Barney 1991, Teece et al. 1997). Our paper differs from this literature in two main respects. First, the majority of this literature assumes that firms are fully aware of their existing capabilities.[6] By contrast, we explore the implications for product strategy when a firm cannot directly observe its capabilities but learns about them based on its products' successes and failures. Second, few existing papers have used a formal modeling approach to study capabilities.[7] By developing a formal model of how capabilities drive market outcomes and of the associated learning about capabilities, we can derive explicit conditions for each of our results to hold, thus providing boundary conditions for the key insights of our paper.

Our work also relates to the literature on optimal experimentation, which has analyzed the trade-off between exploitation and exploration in a variety of settings. In that literature, however, the agent typically learns about a one-dimensional parameter (Easley and Kiefer 1988, Aghion et al. 1991), or, in multi-armed bandit problems, about alternatives that are statistically independent (Gittins 1979; Bergemann and Valimaki 1996, 2006; Lin et al. 2015). By contrast, in our model, each experiment (product launch) reveals information about multiple skills; moreover, because products can overlap in their skill requirements, an experiment may lead to learning about a skill that has no direct impact on the outcome of that experiment.[8] This richness in learning patterns allows us to address new questions. While much of the existing literature analyzes the limit properties of beliefs and actions, we investigate how the skill usage of different products affects learning and the information value of new products.

Recent work by Dzyabura (2014) considers a consumer who learns about her own multidimensional preferences as she searches products sequentially. Dzyabura (2014) models preference discovery as "surprise," however, so the consumer does not account for future learning about her preferences when deciding which product to evaluate. By contrast, our approach involves active learning through experimentation.

Our work also differs from models of strategic experimentation with multiple agents (Bolton and Harris 1999, Keller et al. 2005). That literature considers learning through experimentation as part of the market equilibrium. The information obtained from experiments is a public good, which leads to information and learning externalities between agents. By contrast, we consider a single-agent decision problem in which the information obtained from experimentation is private and investigate the value of acquiring such information for the firm's own future decision making, absent any strategic interaction among agents.

The result that a success can result in positive belief updating about one skill and, at the same time, negative belief updating about another skill is reminiscent of a key insight from comparative cheap talk models. As shown by Chakraborty and Harbaugh (2010, 2014), unsubstantiated claims about a seller's strengths can be credible in settings with multidimensional private information, but such claims come at an implicit cost: Advertising that raises buyers' updated estimate of one product attribute, for example, lowers the updated estimate of another product attribute. While this research addresses seller communication strategies and buyer beliefs, we analyze a decision-theoretic model of single-agent learning.

Finally, although our paper is not concerned with consumer beliefs or brands, there are noteworthy parallels between a firm's learning about its skills in our model and consumer evaluations of brand extensions. In particular, lab experiments and survey data have shown that customers evaluate brand extensions more favorably if the new product is a good fit with the firm's previous products (Aaker and Keller 1990, Broniarczyk and Alba 1994), and that new product success or failure can have feedback effects on how customers evaluate brands (Luo et al. 2010). More strikingly, similar to the intuitive and counterintuitive belief updating in our model, lab experiments have shown that a successful brand extension can strengthen some associations with a brand while weakening other associations (Dacin and Smith 1994). These parallels with our results suggest that consumer evaluations of brand extensions resemble multidimensional learning about what attributes a brand stands for.

3. Model

There are N skills, indexed by $n = 1, 2, \ldots, N$. We focus on the decisions of a single firm whose skill set is represented by the vector θ, with each element $\theta_n \in \{0, 1\}$ indicating whether the firm has skill n. The firm does not know which skills it has, but it can draw inferences about its skills based on the performances (success or failure) of the products it launches. Before any product introductions, the firm's beliefs about its skills are independently distributed with probabilities $P(\theta_n = 1) = \alpha_n \in (0, 1)$ for all n.

There are many ways to model the firm's opportunities to launch products over time. The simplest setting rich enough to convey our results is a three-period model where in each period, the firm can launch, or not launch, an exogenously available product.[9] With a slight abuse of notation, we use $t \in \{1, 2, 3\}$ to denote both time period t and the product that becomes available in period t.

For each product t, exactly two skills (out of N) are relevant, and we denote by $I(t)$ the set of those skills (that is, their skill indices). The two skills in $I(t)$ can differ in their importance for product t, and we use $H(t) \in I(t)$ and $L(t) \in I(t)$ to denote the indices of the high- and low-importance skill. In case of equal importance, $H(t)$ is taken to be the skill with the lower index.[10] For example, if skills 1 and 2 are both relevant for product 1, but skill 1 matters more for product 1's performance than skill 2, then $I(1) = \{1, 2\}$, $H(1) = 1$, $L(1) = 2$. Similarly, if skills 1 and 3 are both relevant for product 2's performance, with skill 3 mattering more for this product, then $I(2) = \{1, 3\}$, $H(2) = 3$, and $L(2) = 1$.

The function $R_t(\theta_{H(t)}, \theta_{L(t)}) \in [0, 1)$ specifies the probability that product t succeeds ($q_t = S$) given the firm's skills.[11] With the complementary probability, $1 - R_t(\theta_{H(t)}, \theta_{L(t)})$, product t fails ($q_t = F$). The following assumption on this function ensures that each of the skills in $I(t)$ increases product t's success probability, and that skill $H(t)$ matters (weakly) more than $L(t)$ for product t.

Assumption 1. *For each* t, $0 \le R_t(0,0) < R_t(0,1) \le R_t(1,0) < R_t(1,1) < 1$.

This assumption is flexible enough to allow skills to have equal or unequal importance. Assumption 1 also allows for complementarity or substitutability between the skills used by product t in the sense that having one of the skills may increase or decrease the return to having the other skill. Formally, complementarity and substitutability can be defined as follows (see also Vives 1999, p. 24):

Definition 1. The skills used by product t are *complementary* for product t if the function $R_t(\cdot, \cdot)$ exhibits strictly increasing differences, i.e., if

$$R_t(1,1) - R_t(0,1) > R_t(1,0) - R_t(0,0),$$

and *substitutable* for product t if the function $R_t(\cdot, \cdot)$ exhibits strictly decreasing differences, i.e., if $R_t(1,1) - R_t(0,1) < R_t(1,0) - R_t(0,0)$.

For each $t \in \{1, 2, 3\}$, product t's success results in a gross profit of π_t, while failure results in a gross profit of zero. The profits π_t as well as the skill requirements and technologies $R_t(\cdot, \cdot)$ of all three products are assumed to be known to the firm. The assumption that the firm knows with certainty what products will be available for launch in future periods is made to simplify the exposition of our analysis. The key insights of our analysis would remain unchanged even if the firm faced uncertainty over which potential products will be available in the future.

The within-period timing in each period $t \in \{1, 2, 3\}$ is as follows. At the beginning of time period t, the firm observes the cost c_t of launching product t, which is drawn from a uniform distribution with support $[0, \pi_t]$.[12] Having observed the random launch cost c_t, the firm then decides whether to launch product t. If the firm launches product t, its performance is realized and the firm earns $\pi_t - c_t$ if $q_t = S$ and $-c_t$ if $q_t = F$.[13] Finally, if product t was launched, the firm updates its beliefs about its skills based on q_t using Bayes' rule.

The information set at the beginning of period t is denoted by Ω_t. At time $t = 1$, it is empty: $\Omega_1 = \varnothing$. At time $t = 2$, $\Omega_2 = \{q_1\}$ if the firm chose to launch product 1 in period 1, and $\Omega_2 = \varnothing$ otherwise. At time $t = 3$,

Table 1. Overview of Notation

N	Number of possible skills (indexed by n)
$\theta_n \in \{0, 1\}$	Firm's true skill level for skill n (not observed by the firm)
$\alpha_n \in (0, 1)$	Prior probability the firm has skill n
$t \in \{1, 2, 3\}$	Index of time periods *and* products
$I(t)$	Set of skills used for product t
$H(t)$	Index of the skill with *higher* importance for product t
$L(t)$	Index of the skill with *lower* importance for product t
$R_t(\theta_{H(t)}, \theta_{L(t)})$	Function that maps firm's skills into success probability for product t
$q_t \in \{S, F\}$	Product t's performance (success or failure) if it is launched
$c_t \in [0, \pi_t]$	Cost of launching product t
π_t	Gross profit from *successful* launch of product t
δ	Firm's discount factor
Ω_t	Information set at the beginning of period t

$\Omega_3 = \{q_1, q_2\}$ if the firm chose to launch products 1 and 2, $\Omega_3 = \{q_1\}$ if the firm chose to launch product 1 but not product 2, $\Omega_3 = \{q_2\}$ if the firm chose to launch product 2 but not product 1, and $\Omega_3 = \varnothing$ otherwise.

The firm has a discount factor $\delta \in (0, 1]$ and maximizes expected discounted profits. Note this is a finite-period dynamic programming problem. See Table 1 for a summary of notation.

In reality, in addition to uncertainty over skills, firms face uncertainty about product success outcomes for other reasons as well. One could interpret our model as reflecting these other factors in two ways. First, profits π_t could be considered *expected* gross profits given a successfully executed launch, accounting for uncertainty over factors such as customer preferences and competitive offerings. Second, our model allows for uncertainty over the product t outcome through the success function R_t. An increase in other sources of uncertainty (such as errors in product execution that even a skilled firm could make) would add noise to this function, thereby reducing the amount of information the firm learns about its skills from observed outcomes. Nonetheless, product successes and failures provide some information about a firm's skills as long as these skills have a strictly positive effect on the success probability of a product (i.e., as long as Assumption 1 holds).

4. Learning About Skills

Our analysis proceeds in two steps. In this section, we analyze how the firm learns about its skills from the observed performances of introduced products. In Section 5, we use these findings to explore the firm's optimal forward-looking product-introduction decisions.

In learning models with a *single* skill dimension, a standard finding is that product success provides favorable news, that is, it leads to positive belief updating about the firm's skill level. Conversely, product failure provides unfavorable news and leads to negative belief updating. In what follows, we refer to such a pattern as "intuitive belief-updating."

When each product uses *multiple* skills, on the other hand, then, as we show, belief updating about some skills can be "counterintuitive." In that case, a success provides *unfavorable* news about a particular skill, while a failure provides favorable news. The main goal of this section is to provide conditions under which belief updating about a particular skill is "intuitive" or "counterintuitive" in our framework.

Formally, we define the following terms:

Definition 2 (Intuitive vs. Counterintuitive Belief-Updating). "Intuitive belief-updating" occurs at time t for skill n if

$$E[\theta_n \mid q_t = S, \Omega_t] > E[\theta_n \mid \Omega_t] > E[\theta_n \mid q_t = F, \Omega_t]. \quad (1)$$

"Counterintuitive belief-updating" occurs at time t for skill n if conditions (1) are reversed.[14]

The simplest case to analyze is where the current product uses only skills that have not been used by any previously launched product. Because the beliefs about such skills are independently distributed at the beginning of the current period, and each of the skills increases the current product's success probability, success is favorable news about both of them. The following lemma summarizes the implications for belief updating in periods 1 and 2. (Learning in the third and last period is neglected throughout because it has no impact on future product introduction decisions in our simple three-period model.) Formal proofs of all results are provided in the online appendix.

Lemma 1. *In period $t = 1$, intuitive belief-updating occurs for any skill that is used by product 1 (and no belief updating occurs for all other skills). In period $t = 2$, if there is no skill overlap between products 1 and 2 or product 1 was not launched, then intuitive belief-updating occurs for any skill that is used by product 2 (and no belief-updating occurs for all other skills).*

The remainder of this section will focus on learning in the second period, where Lemma 1 leaves open the possibility of counterintuitive belief-updating in case of skill overlap between products 1 and 2.

4.1. Belief-Updating with *Partial* Skill Overlap

Suppose that products 1 and 2 have exactly one skill in common ("partial skill overlap"). Let n denote the skill used only by product 1, n' denote the skill used by both products, and n'' denote the skill used only by product 2. That is, $I(1) = \{n, n'\}$ and $I(2) = \{n', n''\}$. The following lemma states that intuitive belief-updating must occur in period 2 for both skills that product 2 uses.

Lemma 2. *If there is partial skill overlap between products 1 and 2, then in period $t = 2$, intuitive belief-updating occurs for the skill that is used by both products (skill n') and for the skill that is used only by product 2 (skill n'').*

By contrast, the performance of product 2 can lead to counterintuitive belief-updating for the skill used only by product 1 (skill n). The general condition for this to happen, given the previously realized q_1, can be written as follows:

Condition 1. The likelihood ratio

$$l(q_1 \mid \theta_{n'}) \equiv \frac{\Pr(q_1 \mid \theta_n = 0, \theta_{n'})}{\Pr(q_1 \mid \theta_n = 1, \theta_{n'})}$$

is strictly increasing in $\theta_{n'}$.

Condition 1 is a statement about the relative likelihoods by which different skill profiles generate the observed product outcome in the first period (q_1). The condition implies that having skill n' increases the likelihood of q_1 if the firm does *not* have skill n relative to the likelihood of q_1 if the firm *does* have skill n. When this condition holds, after observing q_1 in the first period, any good news about skill n' obtained in the next period is bad news about skill n.

To gain further insight into Condition 1, consider cases in which $q_1 = S$ and n is the high-importance skill of product 1. Condition 1 then becomes

$$\frac{R_1(0,0)}{R_1(1,0)} < \frac{R_1(0,1)}{R_1(1,1)},$$

which is equivalent to

$$\frac{R_1(1,0) - R_1(0,0)}{R_1(1,0)} > \frac{R_1(1,1) - R_1(0,1)}{R_1(1,1)}. \quad (2)$$

Condition (2) compares the marginal effect of having skill n on the success probability of product 1 with and without having skill n'. If the marginal effect of skill n is lower when the firm has skill n' than when it does not have skill n', then, given product 1's success, favorable news about skill n' leads to negative belief updating about skill n; conversely, unfavorable news about skill n' leads to positive belief updating about skill n.

Note that (2) is a weaker condition than skill substitutability for product 1. Since $R_1(1,0) < R_1(1,1)$, skill substitutability, as captured by decreasing differences in product 1's technology (see Definition 1), is a sufficient but *not* a necessary condition for (2). Even if the two skills are complementary for product 1's success, favorable news about skill n' after the first period may lead to negative belief updating about skill n.

Note also that (2) always holds if $R_1(0,0) = 0$, that is, if product 1 cannot succeed unless the firm has at least one of the relevant skills. In this case, the firm knows that if it does *not* have skill n' (the skill shared by products 1 and 2), this means that it *must* have skill n (the skill used only by product 1). Therefore, any unfavorable news about skill n', e.g., due to a failure of product 2, leads to positive belief updating about skill n.

Now consider cases in which the first-period product has failed ($q_1 = F$). Condition 1 then becomes

$$\frac{1 - R_1(0,0)}{1 - R_1(1,0)} < \frac{1 - R_1(0,1)}{1 - R_1(1,1)},$$

which is equivalent to

$$\frac{R_1(1,0) - R_1(0,0)}{1 - R_1(1,0)} < \frac{R_1(1,1) - R_1(0,1)}{1 - R_1(1,1)}. \tag{3}$$

Because $1 - R_1(1,0) > 1 - R_1(1,1)$, skill complementarity (i.e., R_1 exhibiting increasing differences) is a sufficient, but not a necessary, condition for inequality (3) to hold. Thus, if skills are complements for product 1, once product 1 has failed, favorable news about skill n' always leads to negative belief updating about skill n.

The following lemma states our formal result (see the online appendix for the proof):

Lemma 3. *Suppose there is partial skill overlap between products* 1 *and* 2. *Then for the skill that is used only by product* 1 (*skill* n), *counterintuitive belief-updating occurs in period* $t = 2$ *if and only if Condition* 1 *holds; if Condition* 1 *is reversed, i.e., if the likelihood ratio* $l(q_1 \mid \theta_{n'})$ *is strictly decreasing in* $\theta_{n'}$, *then intuitive belief-updating occurs.*

For illustration, consider the following example:[15] $\alpha_1 = \alpha_2 = \alpha_3 = 0.5$, and

$$I(1) = \{1,2\} \quad \text{and}$$
$$(R_1(0,0), R_1(0,1), R_1(1,0), R_1(1,1)) = (0.1, x, x, 0.9),$$
$$I(2) = \{2,3\} \quad \text{and}$$
$$(R_2(0,0), R_2(0,1), R_2(1,0), R_2(1,1)) = (0.1, 0.5, 0.5, 0.9).$$

The parameter $x \in [0.1, 0.9]$ describes a family of production technologies for product 1 that are symmetric in the use of skills 1 and 2 but differ in how complementary or substitutable the skills are, with $x = 0.5$ representing the borderline between substitutes and complements in the sense of Definition 1. If product 1 succeeded, then using (2), Condition 1 holds if and only if $x > 0.3$; that is, as long as product 1's skills are substitutes or weak enough complements. By contrast, if 1 failed, then using (3), Condition 1 holds if and only if $x < 0.7$; that is, as long as product 1's skills are complements or weak enough substitutes. Thus, for $x \in (0.3, 0.7)$, belief updating about skill 1 in the second period is counterintuitive after either outcome in the first period. For example, for $x = 0.5$, a launch of product 2 leads to the following belief updating relative to conditional expectations based on the outcome of product 1:

Product outcomes	$E(\theta_1)$	$E(\theta_2)$	$E(\theta_3)$
$q_1 = S$	0.7	0.7	0.5
$q_1 = S, q_2 = S$	0.67	0.84	0.67
$q_1 = S, q_2 = F$	0.74	0.5	0.26
$q_1 = F$	0.3	0.3	0.5
$q_1 = F, q_2 = S$	0.26	0.5	0.74
$q_1 = F, q_2 = F$	0.33	0.16	0.33

Hence, for either outcome of product 1, belief updating is intuitive for skills 2 and 3, but counterintuitive for skill 1. By contrast, if product 1 succeeded and its skills were highly complementary, success (for example) of product 2 would be good news not only about skill 2 but, via the complementarity for product 1, about skill 1 as well. Similarly, if product 1's skills were strong substitutes and product 1 failed, success of product 2 would be good news about the unused skill 1: In effect, "blame" for the failure of product 1 would be shifted retroactively to bad luck rather than a lack of skills 1 and 2.

4.2. Belief-Updating with *Full* Skill Overlap

Finally, consider cases in which products 1 and 2 use the same skills ("full skill overlap"); i.e., $I(1) = I(2) = \{n', n''\}$. Suppose without loss of generality that n' is the more important skill for product 2: $H(2) = n'$ and $L(2) = n''$.

Lemma 4. *Suppose there is full skill overlap between products* 1 *and* 2. *Then in* $t = 2$, *the firm updates its beliefs as follows*:

(a) *For product* 2*'s high importance skill* (*skill* n'), *intuitive belief-updating occurs.*

(b) *For product* 2*'s low importance skill* (*skill* n''), *intuitive belief-updating occurs unless* (i) *Condition* 1 *holds and* (ii) *skill* n'' *is sufficiently unimportant for the performance of product* 2, *i.e.,* $R_2(0,1) - R_2(0,0)$ *and* $R_2(1,1) - R_2(1,0)$ *are sufficiently small relative to* $R_2(1,1) - R_2(0,1)$.

Lemma 4 implies that if products 1 and 2 fully overlap and both skills are equally important for the success of product 2, then the belief updating about both skills is intuitive. If skills differ in their importance for product 2, belief updating about the more important skill continues to be intuitive. Updating about the less important skill n'' may be counterintuitive, however, if Condition 1 holds: As skill n'' becomes less important to product 2's success, the full-overlap case resembles the partial-overlap case. In the limit, if products 1 and 2 only overlap on a single skill that has a significant impact on the success probability of both products (skill n'), then counterintuitive belief-updating can occur for the skill that has a significant impact on product 1 but not on product 2 (skill n'').[16]

To illustrate these results, consider the following example:[17] $\alpha_1 = \alpha_2 = 0.5$, $x \in (0, 0.5)$, and

$$I(1) = \{1,2\} \quad \text{and}$$
$$(R_1(0,0), R_1(0,1), R_1(1,0), R_1(1,1)) = (0, 0.4, 0.4, 0.8),$$
$$I(2) = \{1,2\} \quad \text{with } H(2) = 2, \quad \text{and}$$
$$(R_2(0,0), R_2(0,1), R_2(1,0), R_2(1,1)) = (0, x, 0.5, 0.5 + x).$$

Here, the parameter $x \in (0, 0.5)$ describes a family of production technologies for product 2 that differ in the importance of the less important skill 2. It is easy to check that Condition 1 holds for $q_1 = S$ and $q_1 = F$ in this case. Now consider updated beliefs. At the end of the first period, assuming that product 1 was successfully introduced, we have $E[\theta_1 \mid q_1 = S] = E[\theta_2 \mid q_1 = S] = 0.75$. If product 2 is launched and succeeds, then $E[\theta_2 \mid q_1 = q_2 = S] = (3+4x)/(3+6x) > 0.75$ for any $x \in (0, 0.5)$, which implies that intuitive updating occurs for the more important skill 2. By contrast, the belief about the less important skill becomes $E[\theta_1 \mid q_1 = q_2 = S] = (2+6x)/(3+6x)$, which exceeds $E[\theta_1 \mid q_1 = S] = 0.75$ if and only if $x > 1/6 \approx 0.17$. That is, if skill 1 is relatively unimportant for the success of product 2 (low x), the success of product 2 makes it more likely that the firm attributes the success of product 1 to having skill 2 than skill 1.

5. Product Strategy

We now examine the interaction between the firm's product introduction decisions and learning about its own capabilities. The results and examples in this section illustrate two key points of our paper. First, when a firm is uncertain about its skills, new products can generate valuable information about the firm's likelihood of having various skills, which helps the firm make better product launch decisions in the future. Second, information value can arise through direct skill overlap with a potential future product, or through skill overlap with a past product which, in turn, has skill overlap with a potential future product. The firm should consider both possible channels of learning when it assesses the total information value that a new product will generate.

5.1. Myopic vs. Forward-Looking Product Strategy

We define a *myopic* product strategy as the strategy of introducing in each period the product that maximizes the firm's expected profit *in that period*. In our simplified setting with only one product available per period, a myopic firm introduces the available product if and only if its expected profit is positive. Our main concern will be to determine when and why the firm's optimal strategy will be *forward-looking* instead of myopic. A forward-looking product strategy takes into account how learning about one's skills from the success or failure of the next product will affect optimal product launches in the future.

We solve for the optimal product launch decision rules backwards. Consider the product launch decision in the final period. Given the observed cost c_3 and past product performances, as summarized in the information set Ω_3, launching product 3 is optimal if and only if

$$\Pr(q_3 = S \mid \Omega_3)\pi_3 \geq c_3.$$

Using this decision rule, the firm's expected profit in period 3 given the history of past products Ω_3, but before learning the entry cost c_3, is

$$\begin{aligned} V_3(\Omega_3) = {} & \Pr\big(c_3 \leq \Pr(q_3 = S \mid \Omega_3)\pi_3\big) \\ & \cdot \big(\Pr(q_3 = S \mid \Omega_3)\pi_3 \\ & \quad - E[c_3 \mid c_3 \leq \Pr(q_3 = S \mid \Omega_3)\pi_3]\big). \end{aligned} \tag{4}$$

Now consider the firm's decision in period 2, after the realization of c_2. If the firm launches product 2, its expected discounted profit over periods 2 and 3, given Ω_2, is

$$\begin{aligned} & \Pr(q_2 = S \mid \Omega_2)\pi_2 - c_2 + \delta\big[\Pr(q_2 = S \mid \Omega_2)V_3(\Omega_2, S) \\ & \qquad + (1 - \Pr(q_2 = S \mid \Omega_2))V_3(\Omega_2, F)\big], \end{aligned}$$

where $\delta > 0$ is the discount factor. If the firm does not launch product 2, it earns no profit and receives no additional information about its skills in period 2. In this case, the firm's total expected discounted profit from period 2 onwards is simply $\delta V_3(\Omega_2)$.

It follows that launching product 2 is optimal for the firm if and only if

$$\begin{aligned} & \Pr(q_2 = S \mid \Omega_2)\pi_2 \\ & \quad - c_2 + \delta\big[\Pr(q_2 = S \mid \Omega_2)V_3(\Omega_2, S) \\ & \qquad + (1 - \Pr(q_2 = S \mid \Omega_2))V_3(\Omega_2, F) - V_3(\Omega_2)\big] \geq 0. \end{aligned} \tag{5}$$

A firm that follows a myopic product strategy launches product 2 if and only if the expected profit from that product alone, in the first two terms of (5), is positive. A forward-looking firm, however, should also take into account the difference in expected third-period profits represented by the terms inside brackets in condition (5), which captures the *information value* of launching product 2. Intuitively, beyond its direct profitability, launching product 2 can be valuable for the firm because the resulting learning about its capabilities can lead to better product introduction decisions in the future.

Formally, we denote this information value of launching product 2, given Ω_2, by

$$\begin{aligned} \Delta_2(\Omega_2) = {} & \Pr(q_2 = S \mid \Omega_2)V_3(\Omega_2, S) \\ & + (1 - \Pr(q_2 = S \mid \Omega_2))V_3(\Omega_2, F) - V_3(\Omega_2). \end{aligned}$$

By revealed preference, Δ_2 is nonnegative: The optimal product launch choices based on information sets $\{\Omega_2, q_2 = S\}$ and $\{\Omega_2, q_2 = F\}$, respectively, are weakly better than the optimal choice based on Ω_2 only (a formal statement appears in the proof of Proposition 1).

To understand when and to what extent the optimal strategy can deviate from the myopic strategy in the second period, we need to study how product and firm characteristics affect Δ_2. Our first result follows from our earlier findings on belief updating:

Proposition 1. *Generically,*[18] *launching product* 2 *has a positive information value* ($\Delta_2(\Omega_2) > 0$) *if and only if at least one of the following two conditions holds*:

(i) *Product* 2 *has* (*partial or full*) *skill overlap with product* 3.

(ii) *Product* 1 *was launched in period* $t = 1$, *and product* 1 *has skill overlap with products* 2 *and* 3.

Proposition 1 provides necessary and sufficient conditions for product 2's information value to be positive.[19] Importantly, product 2's performance can yield useful information about the success probability of product 3 even in the absence of any skill overlap between products 2 and 3 (see condition (ii) in Proposition 1). In our three-period setting, this happens if product 1 was launched, products 1 and 2 have partial skill overlap, and products 1 and 3 overlap in the skill used by product 1 but not product 2. Table 2 illustrates such a pattern of skill overlaps in a "resource-product matrix" (Wernerfelt 1984, p. 176), where an × indicates that a product uses a given skill. By Lemma 3, because of its partial skill overlap with product 1, product 2's performance is informative about both of product 1's skills. This in turn implies that product 2's performance leads to learning about one of the skills that product 3 uses (skill 1 in Table 2), even if there is no skill overlap between products 2 and 3.

Now consider the first period of the game. Given the realized first-period cost c_1, launching 1 is optimal if and only if

$$\begin{aligned}\Pr(q_1 = S)\pi_1 \\ - c_1 + \delta\big[\Pr(q_1 = S)V_2(S) + (1 - \Pr(q_1 = S))V_2(F)\big] \\ \geq \delta V_2(\varnothing),\end{aligned} \tag{6}$$

where $V_2(\Omega_2)$ denotes the firm's expected profit over periods 2 and 3 given the history Ω_2 generated in period 1. Using the optimal second-period decision rule from (5), we obtain that

$$\begin{aligned}V_2(\Omega_2) = \delta E[V_3 \mid \Omega_2] + \Pr(c_2 \leq \bar{c}_2(\Omega_2)) \\ \cdot \big(\Pr(q_2 = S \mid \Omega_2)\pi_2 - E[c_2 \mid c_2 \leq \bar{c}_2(\Omega_2)] + \delta\Delta_2(\Omega_2)\big),\end{aligned} \tag{7}$$

where[20]

$$\bar{c}_2(\Omega_2) = \min\{\Pr(q_2 = S \mid \Omega_2)\pi_2 + \delta\Delta_2(\Omega_2), \pi_2\}. \tag{8}$$

The first term in (7) represents the expected profit over the last two periods that the firm can obtain without launching product 2. The second term represents the *additional* payoff that the firm generates by launching product 2 whenever doing so is optimal, which is the case for $c_2 \leq \bar{c}_2(\Omega_2)$; this additional payoff includes the expected direct second-period payoff and the information value from launching product 2.

As in the second period, the optimal first-period decision takes the profit in the current period into account in the first line of (6), as well as the information value of launching product 1, which we denote by

$$\Delta_1 = \Pr(q_1 = S)V_2(S) + (1 - \Pr(q_1 = S))V_2(F) - V_2(\varnothing).$$

The next proposition establishes necessary and sufficient conditions for $\Delta_1 > 0$:

Proposition 2. *Generically, launching product* 1 *has a positive information value* ($\Delta_1 > 0$) *if and only if at least one of the following two conditions holds*:

(i) *Product* 1 *has* (*partial or full*) *skill overlap with product* 2.

(ii) *Product* 1 *has* (*partial or full*) *skill overlap with product* 3.

The "only if" part of Proposition 2 is straightforward: Product 1 cannot have a positive information value if it does not overlap with either of the other products. The "if" part is straightforward for product 3, but not for product 2. If 1 overlaps with 2 but not with 3, it is possible that 2's information value is so large that 2 is launched for *all* realizations of c_2, regardless of product 1's outcome, which would suggest that 1 has no information value. This reasoning turns out to be incomplete. If 1 and 2 have skill overlap and 2 has positive information value for 3, then $\Pr(q_3 = S \mid q_1, q_2) \neq \Pr(q_3 = S \mid q_2)$ even in the absence of any direct skill overlap between 1 and 3. Learning in the second period is affected by the outcome of period 1 because of the skill overlap between 1 and 2; this is relevant for product 3 because 2 has positive information value.

Table 2. Product 2 Has a Positive Information Value in the Absence of Any Skill Overlap with Product 3

	Product 1	Product 2	Product 3
Skill 1	×		×
Skill 2	×	×	
Skill 3		×	
Skill 4			×

5.2. Information Value and Product Characteristics

In this section, we discuss how the characteristics of products 2 and 3 affect the size of the information value Δ_2. Our first result states that the information value of product 2 increases with the scale of product 3, provided that it is positive.

Proposition 3. *If* $\Delta_2 > 0$, *then the information value* Δ_2 *of product* 2 *is strictly increasing in* π_3.

This finding is intuitive. When the information gained from launching product 2 permits the firm to make a better decision in period 3, then the value of this information is increasing in the importance of the period 3 decision, as captured by π_3.[21]

The next lemma will prove useful for examining how the degree of skill overlap between products 2 and 3 affects the size of product 2's information value.

Lemma 5. *Keeping* $\Pr(q_2 = S \mid q_1)$ *and* $\Pr(q_3 = S \mid q_1)$ *constant, the information value* Δ_2 *of product* 2 *is strictly increasing in* $|\Pr(q_3 = S \mid q_1, q_2 = S) - \Pr(q_3 = S \mid q_1)|$.

Lemma 5 states that the information value of product 2 is greater when its performance leads the firm to more strongly revise its belief about the success probability of product 3.[22] It is the *absolute* value of this impact that matters: If the success of product 2 means bad news for 3 (or conversely failure of 2 means good news for 3), it is just as informative for the decision whether to launch product 3 as when success of 2 means good news for 3.

Lemma 5 helps us compare the information value of potential period 2 products. For example, suppose product 1 has no skill overlap with products 2 and 3 (so the second and third periods can effectively be treated as a two-period version of our model). Suppose further that potential second period products 2 and 2′ have the same success function R and have the same high importance skill n''. However, product 2 has low importance skill n, whereas product 2′ has low importance skill n', and the prior probability of having these two skills is equal, $\alpha_n = \alpha_{n'}$. Given this set-up, products 2 and 2′ have the same success probability. If product 3 uses skills n' and n'', then the success of product 2 or 2′ provides the same amount of favorable information about skill n'' used by product 3, but the success of product 2′ also provides favorable information about the other skill n' used by product 3. Therefore, the second period product 2′ that fully overlaps with product 3 provides more information about the period three success probability than the second period product 2 that only partially overlaps with product 3. Lemma 5 implies that product 2′ has greater information value than product 2.

Next, we examine more generally how the degree of skill overlap between products 2 and 3 affects the information value of product 2 in our three-period model. Intuitively, one might expect that (as in the example above), all else being equal, product 2's information value is greater the more product 2 overlaps with product 3 in the skills used; more overlap would seem to lead to more learning about the skills that are relevant in period 3. However, this intuition is not complete. Because product 1's outcome can generate a correlation in beliefs about skills (so that, in period $t = 2$, good news about one skill could imply good or bad news about another), product 2's success or failure can indirectly affect skill beliefs in such a way that more overlap with product 3 does not always imply greater information value.

To investigate conditions in which greater overlap implies a higher information value, we vary one of the skills that product 2 uses while holding the characteristics of products 1 and 3 constant. Comparing two different period 2 products is generally challenging because the products can differ not only in the skills they use but also in their success probabilities. To make comparisons meaningful, we therefore rely on the following definitions:

Definition 3 (Weak and Strong Comparability). Consider a product t' that uses skills n and n' and a product t'' that uses skills n and $n'' \neq n'$. We will say that products t' and t'' are "weakly *comparable*" (*given* Ω_t) if

(i) the shared skill n is the high-importance skill for both or the low-importance skill for both ($H(t') = H(t'') = n$, or $L(t') = L(t'') = n$),

(ii) $R_{t'}(\cdot,\cdot) = R_{t''}(\cdot,\cdot)$, and

(iii) $\Pr(q_{t'} = S \mid \Omega_t) = \Pr(q_{t''} = S \mid \Omega_t)$.

The products t' and t'' are "strongly *comparable*" *if instead of* (iii), *the following condition holds* (*which implies* (iii)):

(iii′) $\Pr[\theta_n = x, \theta_{n'} = y \mid \Omega_t] = \Pr[\theta_n = x, \theta_{n''} = y \mid \Omega_t]$ for all $\{x, y\} \in \{0,1\} \times \{0,1\}$.

Both weak and strong comparability require that products t' and t'' have their high importance skill or their low importance skill in common, have the same success function R, and have the same success probability. Strong comparability, however, requires not only equal overall success probabilities of t' and t'' but also identical marginal distributions over the respective skills used by each product, conditional on information Ω_t (requirement (iii′)). Note that requirements (iii) and (iii′) imply that comparable products have the same success probability given all information available at the start of period t. In particular, the success probability in period t depends on the prior distribution of skills and on the outcomes of products launched before period t.

These definitions allow us to explore how the information value of product 2 depends on its degree of skill overlap with product 3, holding constant product 2's success probability and other characteristics of product 2. We show that, even under these restrictive conditions on the comparability of period 2 products, it is not always true that more skill overlap with product 3 implies more information value.

Proposition 4. *Let* n *and* n' *denote the skills used by product* 3. *Consider a product* 2″ *that uses skills* n *and* $n'' \neq n'$

(partial skill overlap with product 3) and a product 2′ that uses skills n and n′ (full skill overlap with product 3).

(a) *If products 2′ and 2″ are strongly comparable, then* $\Delta_{2'} > \Delta_{2''}$*; that is, the product that has full skill overlap with product 3 has a greater information value than the product with only partial skill overlap.*

(b) *If products 2′ and 2″ are weakly but not strongly comparable, then the product that has full skill overlap with product 3 can have a smaller or greater information value than the product with only partial skill overlap.*

Recall the intuition that product 2 has a higher information value the more its skills overlap with those of product 3. Proposition 3 shows that the conditions for this to be true are quite restrictive. The relation is unambiguous only if 2′ and 2″ are strongly comparable (Proposition 3(a)). Even with weak comparability, which is still a strong requirement, the product with *less* overlap may have a *greater* information value. The following example provides an illustration.

Example A. To see how a less-overlapping product can have a higher information value, suppose that product 1 was successfully introduced ($q_1 = S$). The products have the following skill requirements, where × marks skills of symmetric importance, while H and L denote high- and low-importance skills:

	Product 1	Product 2′	Product 2″	Product 3
Skill 1			×	
Skill 2	×	×	×	L
Skill 3	×	×		H

Production technologies are as follows:

• For product 1, skills 2 and 3 are substitutes: $R_1(1,1) = 0.8, R_1(1,0) = R_1(0,1) = 0.7$, and $R_1(0,0) = 0$. Note that this implies that Condition 1 holds after $q_1 = S$, which, in turn, implies that 2″'s performance leads to counterintuitive belief-updating about skill 3 (see Lemma 3).

• For $i \in \{2',2''\}$, skills are complements: $R_i(1,1) = 0.8$, $R_i(1,0) = R_i(0,1) = 0.1$, $R_i(0,0) = 0$;

• For product 3, skill 3 is much more important than skill 2: $R_3(1,1) = 0.9$, $R_3(1,0) = 0.8$, $R_3(0,1) = 0.1$, $R_3(0,0) = 0$.

The prior beliefs about skills 2 and 3 are $\alpha_2 = \alpha_3 = 0.2$. Under these assumptions, $\Pr(q_{2'} = S \mid q_1) = \Pr(q_{2''} = S \mid q_1)$, as required by weak comparability, if $\alpha_1 = 0.3$. Intuitively, since products 1 and 2′ use the same skills, success of product 1 is relatively good news for product 2′. For 2″ to have the same probability of success, conditional on q_1, the prior probability of skill 1 must be larger than those of skills 2 and 3.[23]

The probabilities of success of product 3, conditional on different histories, become

History Ω	$\Pr(q_3 = S \mid \Omega)$
$q_1 = S$	0.506
$q_1 = S,\ q_{2'} = S$	0.690
$q_1 = S,\ q_{2'} = F$	0.464
$q_1 = S,\ q_{2''} = S$	0.314
$q_1 = S,\ q_{2''} = F$	0.551

The success of 2′ reveals good news about product 3, and failure bad news, whereas for product 2″ it is the other way around. However, the performance of product 2″ has a larger *absolute* impact than that of 2′ on 3's success probability. By Lemma 5, the information value of 2″ therefore exceeds that of 2′. In this example, therefore, the second-period product that has less overlap with product 3 has a greater information value.

Intuitively, the success of product 1 implies favorable beliefs about skills 2 and 3. The success of product 2′, which uses the same skills, provides some additional information pointing in the same direction. It increases $\Pr(q_3 = S \mid \Omega)$. By contrast, success of 2″ is very bad news for product 3. Because skills 1 and 2 are strongly complementary for product 2″, the firm is likely to have both skills if 2″ succeeds. Yet because skills 2 and 3 were substitutes for product 1, success of 2″ leads to a strong *downward* revision of the belief about skill 3. That, in turn, is bad news about product 3, whose success probability depends strongly on having skill 3. Conversely, failure of product 2″ leads to a strong upward revision of the belief about skill 3.

We now turn to cases in which one of the second-period products overlaps partially with product 3, while the other does not overlap with 3.

Proposition 5. *Let n and n′ denote the skills used by product 3. Consider a product 2″ that uses skills n and n″ ≠ n′ (partial skill overlap with product 3), and a product* $\hat{2}$ *that uses neither skill n nor skill n′ (no skill overlap with product 3).*

(a) *If product 1 overlaps neither with product* $\hat{2}$ *nor with product 3, then the product that has partial skill overlap with product 3 has greater information value than product that has no skill overlap with product 3:* $\Delta_{2''} > \Delta_{\hat{2}} = 0$.

(b) *If product 1 overlaps with product* $\hat{2}$ *and product 3, then the product that has partial skill overlap with product 3 (product 2″) can have smaller or greater information value than the product that has no skill overlap with product 3 (product* $\hat{2}$*). This is true even if 2″ and* $\hat{2}$ *are strongly comparable.*

Proposition 5(a) follows from Proposition 1. If the product that is available in the second period has no overlap with product 3 and does not affect the beliefs about the skills indirectly used by product 3 (through overlap with product 1), then its information value is zero. The information value of a product that has partial overlap with product 3 is positive, on the other hand (see Proposition 1).

Proposition 5(b) extends the result from Proposition 1 that, even in the absence of any direct overlap with product 3, product 2 has a positive information value if it overlaps with 1, and 1 overlaps with 3, because 2's performance then leads the firm to update its beliefs about one of the skills used by product 3. In this case, we obtain a striking result. Even if the two second-period products under consideration are *strongly* comparable, the product that has zero skill overlap with product 3 can have a higher information value than the product that has partial skill overlap.

Intuitively, this can happen because the performance of a product with partial skill overlap may cause intuitive belief-updating about one of the skills used by product 3 but counterintuitive belief-updating about its other skill. The two belief updating effects thus partially offset each other, and product 2's performance may have little overall impact on 3's predicted success probability. The performance of the product that has no skill overlap with 3, on the other hand, can cause strong belief updating about one of the skills used by 3 (provided there is a pattern of partial overlaps with product 1). The following example provides an illustration.

Example B: Suppose that product 1 was successfully introduced ($q_1 = S$) and that the products have the following skill requirements:

	Product 1	Product $\hat{2}$	Product 2″	Product 3
Skill 1	×	×	×	
Skill 2	×			×
Skill 3			×	×
Skill 4		×		

Production technologies are as follows:

• For product 1, skills 1 and 2 are substitutes: $R_1(1,1)=0.6, R_1(1,0)=R_1(0,1)=0.5$, and $R_1(0,0)=0$;

• For $i \in \{\hat{2}, 2'', 3\}$, $R_i(1,1) = 0.8; R_i(1,0) = R_i(0,1) = 0.4; R_i(0,0)=0$.

Assume further that $\alpha_1=\alpha_2=\alpha_3=\alpha_4=0.25$. It is then easy to check that products $\hat{2}$ and 2″ are strongly (and weakly) comparable. Moreover, it can be shown that $\Delta_{\hat{2}} - \Delta_{2''} = (69/40{,}000)\pi_3$. The information value of the product that does not overlap with product 3 on any of its skills is thus greater than that of the product that has partial skill overlap with product 3.

Intuitively, because skills 1 and 2 are substitutes for product 1, and neither $\hat{2}$ nor 2″ uses skill 2, success of $\hat{2}$ or 2″ leads to negative belief updating about skill 2. Yet for 2″, success also leads to positive updating about skill 3, counterbalancing the negative effect on skill 2. By contrast, for $\hat{2}$, negative updating about skill 2 is the only learning effect relevant for product 3. As a result, launching product $\hat{2}$ is more informative than launching product 2″.

As we have shown, the information gained from a new product introduction depends on the skill requirements of present, past, and potential future products in complex and sometimes surprising ways. In particular, the amount of information that a new product introduction provides about the success probability of a potential future product can be nonmonotonic in the degree of skill overlap between the products. Perhaps most strikingly, launching a product that has no skill overlap with potential future products can generate useful information, sometimes more so than a product with skill overlap.

Our insights are driven by the multidimensional nature of firm skills. When skills are multidimensional, it makes sense to expect that the firm's beliefs about its different skills are not distributed independently of each other (i.e., that they are correlated). In our model, although prior beliefs are assumed to be independently distributed, beliefs are correlated after the first product introduction because each product relies on a combination of multiple skills. The production functions by which the skills translate into success probabilities shape the joint distribution of beliefs. In other situations, the beliefs about different skills may be correlated simply due to the nature of these skills. For example, it may be reasonable to expect that firms with chemical skills often have strong engineering skills, but may lack design skills.

Once the beliefs about different skills are correlated, be it due to past product performance observations or other reasons, each product's performance can lead to belief updating for a wide range of skills beyond those used by the product itself. It becomes crucial to assess what the firm would learn from the success or failure of a new product about all of its skills, not just those used by the product.

5.3. Choosing Between Products

In our main model, at most one product is available to launch in each period. We now extend our analysis to consider a numerical example in which the firm chooses between multiple products in a given period. In this example, the firm chooses between two potential products in period two, and the outcome of this product launch helps the firm choose between two other possible products in period three. The period two products differ in their myopic profits and their information value. (Online Appendix C provides another numerical example in which the firm decides the *order* in which to launch products.)

Because there is no longer a one-to-one correspondence between periods and products, we label the products with letters, X, Y, etc., and index them by i.

As before, we assume that a product i's launch costs are stochastic and uniformly distributed over $[0, \pi_i]$, and that the firm learns the launch cost (only) when the product becomes available to launch.

Suppose product X succeeded in $t=1$ and that in $t=2$, Y or Y' can be launched, while in $t=3$, Z or Z' can be launched. The products have the following skill requirements, where H and L denote high- and low-importance skills, while $\times$ marks skills of symmetric importance:

	X	Y	Y'	Z	Z'
Skill 1	$\times$	$\times$		H	
Skill 2	$\times$	$\times$	H		H
Skill 3			L		
Skill 4				L	L

Production technologies are all additive, as follows:

- For products X and Y, skills 1 and 2 are symmetric: $R_i(1,1)=0.8, R_i(1,0)=R_i(0,1)=0.4$, and $R_i(0,0)=0$.
- For Y', skill 2 is much more important than skill 3: $R_{Y'}(1,1)=0.8$, $R_{Y'}(1,0)=0.7, R_{Y'}(0,1)=0.1$, $R_{Y'}(0,0)=0$;
- For product Z (Z'), skill 1 (2) is much more important than skill 4: $R_i(1,1)=0.9$, $R_i(1,0)=0.8$, $R_i(0,1)=0.1$, $R_i(0,0)=0$.

All products have the same stake $\pi_i=1$, which means that a product's success probability is also its expected gross profit, not including launch costs. For this example, we assume no discounting, or $\delta=1$.[24] If the prior beliefs about all skills are $\alpha_i=0.2$, then the expected value of the firm's skills after X's success is $E(\theta)=(0.6,0.6,0.2,0.2)$. Given the revised beliefs, the success probabilities of Y or Y' in $t=2$ are 0.48 or 0.44, respectively.

For any launch history, there are now three possible outcomes in $t=3$: If the launch cost c_Z is sufficiently low relative to $c_{Z'}$, the firm launches Z, and vice versa. If both products' launch costs are too high, no product is launched. For Z and Z', we can compute the launch probability and the expected launch cost conditional on launching each product. Finally, we can compute the firm's expected profit for any history leading to $t=3$, taking into account optimal launches of Z or Z'.

By backward induction, we can compute the information values of Y and Y', which are almost zero and 0.055, respectively (the latter figure is 5.5% of the gross profits in case of success).[25] Intuitively, since Y uses the same skills as X, launching Y provides little information that would help the firm choose between Z and Z' in $t=3$. By contrast, launching Y' is very informative regardless of its outcome: Success is very good news about having skill 2, and hence about the success probability of Z'. On the other hand, failure of Y' leads to strong positive (opposite) updating about the unused skill 1 due to product X's use of skills 1 and 2, making the launch of Z much more likely than it would be without prior launch of Y'.

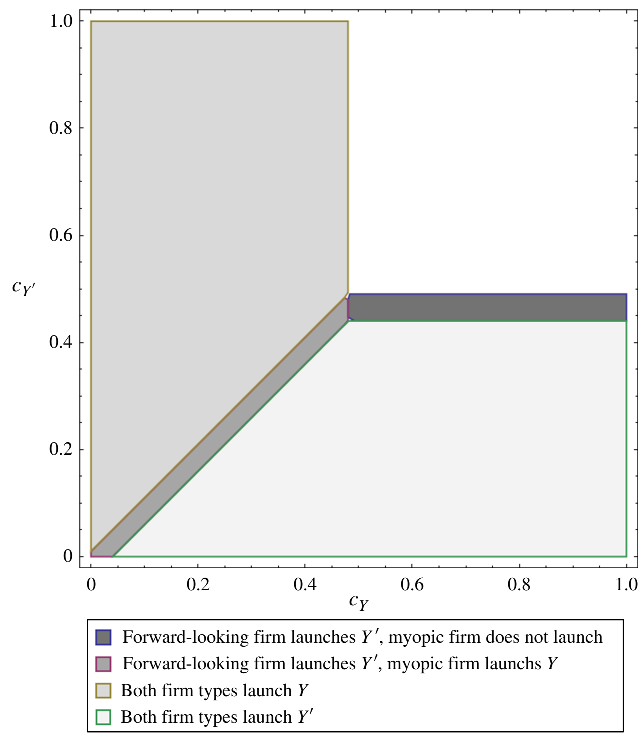

Figure 1. (Color online) Optimal Myopic and Forward-Looking Launch Decisions in Period Two

Figure 1 depicts optimal myopic and forward-looking launch decisions in period two, as a function of the launch costs c_Y and $c_{Y'}$. Because of product Y''s information value, there is a region in which a myopic firm would launch product Y but a forward-looking firm would launch Y', and there is also a region in which a myopic firm would launch no product but a forward-looking firm would launch Y'.

The difference between the impact of myopic and forward-looking behavior on profits can be substantial. For instance, if $c_Y=0.49$ and $c_{Y'}=0.45$, then myopically neither product would be launched, and the (undiscounted) expected profit from launching Z or Z' (with only $q_X=S$ as history) is 0.31. By contrast, a forward-looking firm would launch Y' in $t=2$, resulting in an expected myopic *loss* of -0.01, but an expected profit of 0.35 overall, that is 13% more, thanks to Y''s information value.

Similarly we can compute the information values of Y and Y' following a history of no launch or failure in the first period, and use these to determine the information value of the first-period product X. A myopic firm that only considers current-period expected profits would launch X for $c_X \leq 0.16$. By contrast, the optimal forward-looking strategy is to also launch X for costs between 0.16 and 0.19. The information value of the first-period product is thus 0.03, or 19% of the expected first-period gross profit.

Finally, we compute the total ex ante expected profits for myopic and forward-looking firms, integrating over all possible cost draws in each period, and accounting for the strategy each type of firm follows. The total expected profits for a *myopic* firm are 0.1101, whereas the total expected profits for a *forward-looking* firm are 0.1165, which is a 5.8% improvement. This increase in expected profits reflects the improvement in decision making that results from accounting for each product's information value.

To summarize, in this example, launching a second-period product that only partially overlaps with the successful first-period product helps the firm determine which skill is most likely to have caused the first period product's success. This information is useful for deciding the firm's direction of diversification in period three. Moreover, because of its information value, launching the first-period product can be optimal even in cases where it generates a negative expected profit.

6. Conclusion

Firms often face considerable uncertainty about their resources and capabilities, which makes it difficult to develop a successful product strategy. This paper develops a model of product strategy in which a firm learns about its own capabilities from observed successes and failures in different markets. We show that, due to the multidimensional nature of capabilities, such learning can exhibit complex and sometimes surprising patterns.

The paper has several managerial implications. First, when assessing their firms' capabilities, managers should try to also assess the level of uncertainty about those capabilities. In which skills is the firm particularly confident, for example, because multiple product successes have repeatedly proven that it has these skills? On the other hand, which are the skills that the firm might have, but cannot be sure of, based on current evidence? When deciding whether to launch a new product, managers should then consider the expected direct profit from that product, based on current skill beliefs, and the expected value of the information that the new product will generate about the firm's skills. This information value depends on, among other things, the product's overlap with past and potential future products in terms of skill requirements.

Future research could extend the multi-skill, multi-product model used in this paper to study other interesting phenomena. For example, one could model customer beliefs about the firm's private skill information to study the firm's brand extension decisions (e.g., Wernerfelt 1988, Miklós-Thal 2012, Moorthy 2012). One could also incorporate competition and investment in skill formation into the model (e.g., Fudenberg and Tirole 1984; Ericson and Pakes 1995; Selove 2014a, b). Finally, one could allow certain skills to become more important over time or allow skills to become obsolete, as new technologies arrive and customer preferences change (e.g., Christensen 1997, Chandy and Tellis 1998, Adner and Zemsky 2005).

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Endnotes

[1] For advice on how to conduct a "capabilities audit," see Ulrich and Smallwood (2004).

[2] Note that the firm may not need to conduct a full-scale product launch to acquire useful information. For example, one can interpret product "launch" as a decision to incur the cost of product development and a test market, or of creating a "minimum viable product" (Eisenmann et al. 2013, p. 1), assuming such actions are sufficient to reveal whether the product will succeed, and thus, sufficient to provide the firm with useful information about its capabilities.

[3] In addition to the citations about Kodak listed in the body of the paper, our interpretation of this example is also based on our personal interview with former Kodak executive Larry Matteson.

[4] In the words of founder and CEO Neil Clark Warren, "We have a new approach to what we're trying to do. We want to be a relationship site. We don't want to just match people for marriage, we also want to try to help them find the right job" (Wells 2015).

[5] We are concerned with skills that are fungible rather than specific to particular products. In the words of Teece (1982, p. 45), "…a firm's capability lies upstream from the end products—it lies in a generalizable capability which might well find a variety of final product applications."

[6] Some papers in the strategy literature have argued that a firm might be uncertain about which capabilities caused its past successes (Lippman and Rumelt 1982, Reed and DeFillippi 1990, Barney 1991). Whereas these earlier papers focus on how such "causal ambiguity" might serve as a barrier to resource imitation, we explore how a firm can resolve such ambiguity by launching additional new products.

[7] Matsusaka (2001) develops a formal model in which a firm sequentially searches for a market that is a good fit for its capabilities. A key difference from our paper is that Matsusaka (2001) assumes markets to be independent in terms of organizational fit, whereas in our model the outcome in one market can provide information about the success probability in other markets. Other papers have developed formal models of capabilities that focus on different questions than our paper. For example, Sakhartov and Folta (2014) develop a model in which a high degree of resource relatedness across a firm's products reduces the cost of redeploying resources from one product market to another.

[8] Most of the bandit literature assumes the payoffs to various options are uncorrelated. Recent models that allow for correlated payoffs (e.g., Rusmevichientong and Tsitsiklis 2010) have focused on deriving lower bounds for the performance of various heuristic strategies. Our model is simpler than standard bandit problems in other

respects. In particular, we consider a three-period, rather than infinite horizon, setting, and our baseline model assumes that the firm faces a simple launch versus no-launch decision, rather than a choice between two or more alternatives, in each period.

[9] We will extend the model to allow for choice between multiple products in the same period in Section 5.3 and Online Appendix C.

[10] This assumption has no implications for any of our results.

[11] Ruling out success probabilities of 1 ensures that the firm can never perfectly learn its skills.

[12] A random launch cost, distributed between 0 and π_t, makes the model smooth by ensuring that any new information about a skill that a future product uses is valuable to the firm. The assumption that the probability distribution is uniform is inconsequential and made to simplify the exposition. Allowing π_t to be uncertain in place of (or in addition to) c_t would not affect our qualitative insights.

[13] When a product is launched, it stays on the market for just one time period. This assumption could easily be relaxed. If the profits from a successful product occur over multiple time periods, our assumptions are equivalent to defining π_t as the total discounted profits from a successful product t. The support of the probability distribution for c_t ensures that product launch is always profitable ex post if it succeeds, but unprofitable if it fails.

[14] Note that the law of iterated expectations requires that: $P(q_t = S \mid \Omega_t) \cdot E[\theta_n \mid q_t = S, \Omega_t] + P(q_t = F \mid \Omega_t) E[\theta_n \mid q_t = F, \Omega_t] = E[\theta_n \mid \Omega_t]$. Therefore, for any given skill n, the only possibilities after a new product launch are intuitive updating, counterintuitive updating or no updating. In other words, it is not possible for success and failure to lead to positive updating about a particular skill; and it is also not possible for success and failure to lead to negative updating about a skill.

[15] Details on the numerical computations are available on request.

[16] The precise cutoff needed for counterintuitive updating for the less important skill in period 2 is given in the proof of Lemma 4 in the online appendix; in particular, expression (22) must be less than expression (23) in the online appendix.

[17] Details on the numerical computations are available on request.

[18] Throughout the paper, "generically" means "for almost all parameter values." Defining the Lebesgue measure over the feasible set of parameters, the set of parameters such that $\Delta_2 = 0$ if the conditions in Proposition 1 hold would have a Lebesgue measure of zero.

[19] Our assumption that the cost distribution c_3 has support on $[0, \pi_3]$ guarantees that any additional information about the success probability of product 3 is valuable in expectation. If we assumed instead that product 3's costs were distributed on a narrower range, such as $[c_3^0, \pi_3]$, then product 2 would have positive information value as long as product 2's success or failure outcome affects the firm's period 3 decision for some cost values in this range.

[20] Recall that the distribution of c_2 has upper bound π_2. Hence, defining $\bar{c}_2(\Omega_2)$ as the minimum of $\Pr(q_2 = S \mid \Omega_2)\pi_2 + \delta\Delta_2(\Omega_2)$ and π_2, rather than $\Pr(q_2 = S \mid \Omega_2)\pi_2 + \delta\Delta_2(\Omega_2)$, has no impact on $V_2(\Omega_2)$.

[21] Recall that $c_t \sim U[0, \pi_t]$, so an increase in π_3 implies that the expected value of c_3 also increases.

[22] By the law of iterated expectations, the strength of the belief revision after a success is proportional to the strength of the belief revision after a failure of a product. Therefore, Lemma 5 implies that, all else being equal, the period two product for which *failure* has the greatest absolute impact on period three success probability also has the greatest information value.

[23] Conversely, if product 1 fails, it is bad news for product 2′, and weak comparability holds if $\alpha_1 = 13/135 \approx 0.1$, i.e., a value smaller than the prior. More generally, weak and strong comparability as defined depend not only on the characteristics of the products but also on the information set Ω_2.

[24] If $\delta < 1$, our computed information values would be discounted accordingly, when a forward-looking firm decides its strategy.

[25] As in the previous sections, we define product two's information value as the increase in expected period three profits from launching a given product in period two, relative to the case of launching no product in period two.

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