Why does successful imitation fail?

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Abstract

In the strategy literature, discussions of imitation have predominantly focused on how successful firms deter imitation - rather than the drivers of positive or negative outcomes for imitating firms. This focus reflects an implicit assumption that imitating the practices, methods, and technologies of successful firms makes economic sense. More recent research has directed attention to the process of imitating. We extend this line of research in an attempt to enrich our understanding of the mechanisms underlying the wide heterogeneity in performance outcomes from imitation. Our central claim is that the efficacy of imitation is a function of, not one, but two related learning processes. Foremost in the literature is the intuitively appealing claim that performance outcomes from imitation are a function of the efficacy of the process by which a target's knowledge is acquired. We argue that this view overlooks a second process that occurs because imitation seeds subsequent efforts at internal knowledge generation, particularly via experiential learning. Thus, poor imitation outcomes may result from an ineffective imitation process as the prior literature suggests, or from successful imitation that negatively affects the efficacy of post-imitation experiential learning.

1. Introduction

Imitation is among the most common firm activities (Levitt 1966). Yet, in the strategy literature, discussions of imitation have predominantly focused on how successful firms deter imitation (e.g., Rivkin 2001, Lippman and Rumelt 1982) — rather than the drivers of positive or negative outcomes for imitating firms. This focus reflects an implicit assumption that imitating the practices, methods, and technologies of successful firms makes economic sense (e.g., Winter 1982, Klepper 2002). The current resurgence of interest in imitation in the strategy literature (e.g., Csaszar and Siggelkow 2010, Ethiraj and Zhu 2008, Lieberman and Asaba 2006, Posen, Lee, and Yi 2013, Rivkin 2000, 2001) has directed attention to the process of imitating, often through the lens of organization theory (e.g., Baum and Ingram 1998, Greve 2009, 2011, Terlaak and Gong 2008). We extend this line of research in an attempt to enrich our understanding of the mechanisms underlying the wide heterogeneity in performance outcomes from imitation (Ethiraj and Zhu 2008, Lieberman and Asaba 2006). Our central claim is that the efficacy of imitation is a function of, not one, but two related learning processes. Foremost in the literature is the intuitively appealing claim that performance outcomes from imitation are a function of the efficacy of the process by which a target's knowledge is acquired (e.g., Winter 1987). We argue that this view overlooks a second process that occurs because imitation seeds subsequent efforts at internal knowledge generation, particularly via experiential learning (Argote 1999, Levinthal and March 1981, March and Olsen 1975). Thus, poor imitation outcomes may result from an ineffective imitation process as the prior literature suggests, or from successful imitation that negatively affects the efficacy of post-imitation experiential learning.

The dominant logic used in explaining imitation outcomes focuses on what we term the endowment effect of imitation — the extent to which the imitated practices solve the firm's current technical, economic, or managerial problems (Winter 1995). According to this logic, poor performance outcomes from imitation result primarily from imitation mistakes that reduce the accuracy of the replica — incomplete imitation that overlooks key practices (Csaszar and Siggelkow

2010), inaccurate imitation that misunderstands practices (Winter and Szulanski 2001), or imitation of an inappropriate target (Denrell 2003, Greve 2011, Posen, Lee, Yi 2013, Williams 2007, Ghosh et al 2013). Consider two examples of Southwest Airline imitators: Song (a division of Delta) and Ryanair. Song failed, with the outcome often attributed to the fact that they overlooked a subset of practices that were key drivers of Southwest's high performance. Ryanair has been very successful, and according to Southwest founder Herb Kelleher, Ryanair succeeded because it produced the "best imitation of Southwest Airlines."

In contrast to the endowment effect, we point to what we term the generative effect of imitation. Post-imitation knowledge generation occurs when knowledge acquired via imitation seeds a firm's subsequent effort at knowledge generation via experiential learning. The generative effect of knowledge (Ahuja, Lampert, and Novelli 2013, Arrow 1962) acquired via imitation has largely been overlooked in discussions of imitation in the literature. As we will argue, the generative effect is interesting because it interacts with the endowment effect in non-obvious ways. It is tempting to believe that a more effective imitation process that "gets imitation right" — engendering a greater endowment effect — will positively influence the efficacy of post-imitation experiential learning. While this may indeed be the case under some conditions, it need not be unambiguously so. Effort to build upon imitated knowledge may lead to outcomes that are inferior to those that would be achieved in the absence of imitation, even when the imitated practices reflect elements of the very best solution. For example, while Samsung successfully imitated Apple, HTC appears to have failed. Our theory implies that these divergent outcomes need not arise simply because Samsung was more effective than HTC at copying features of the iPhone (endowment effect of imitation), but rather, because Samsung was more successful in using the imitated knowledge to seed subsequent knowledge generation (generative effect of imitation).

To examine the generative effect of imitation, we focus on imitative entry. We have in mind a decidedly simple but common situation — a new firm seeks to enter a market by imitating a successful imitatee (target of imitation). The entrant identifies and analyzes the current market leaders' practices, observing and imitating a subset of practices (Rivkin 2000, 2001), then engages in experiential learning to bridge the gap between its knowledge acquired via imitation and the knowledge necessary to compete effectively (Posen and Chen 2013, Winter 1995).

To illustrate, consider the case of Canadian retailer Dollar Giant. The founder observed the emergence and diffusion of the “dollar store” retail format in the US during the early 1990s. He identified a leading firm's marketing strategy, pricing policy, location strategy, and merchandising practices through in-depth store visits and employee poaching. He then enters the Canadian market in 1994, adopting these imitated practices, although many of the US market leader's practices remain somewhat non-observable, including procurement, inventory management, and staffing practices. The entrepreneur enters the industry in Canada, and in short order realizes the benefits from the knowledge endowment acquired via imitation. The entrepreneur then holds the imitated practices fixed, because they are known to be successful, engaging in trial and error search to discover solutions to the non-observable practices. At Dollar Giant, the entrepreneur finds that the imitated practices guided his search for solutions to the remaining practices — e.g., his effort to identify suitable inventory management practices was constrained by earlier imitated choices on store design. In this case, the generative value of imitation was positive — experiential learning built upon the imitated practices quickly leading to a highly effective operation, and ultimately a national retail chain of over 100 locations. Yet this entrepreneur recognized in his other ventures, distinctly poor imitative outcomes not because his copies were poor, but because it seemed to lead post-imitation learning in a particularly unfruitful direction.

To study how the outcome of imitation depends of the dual processes of imitation underlying endowment and generative effects, we construct a formal computational model of learning under complexity (e.g., Csaszar and Siggelkow 2010, Ethiraj and Levinthal 2004, Lenox 2006, Rockart, Lewin 2007, Levinthal 1997, Rivkin 2000, 2001). Our model embodies two important assumptions.

First, to isolate the generative from endowment effect of imitation, we assume that entrants are rather effective at imitation — selecting the best target and accurately imitating a subset of its practices. We assume that the only challenge of imitation is non-observability of some practices (Rivkin 2001, Winter 1987, Winter and Szulanski 2001). Second, we assume that the imitator engages in trial-and-error search using standard search heuristics (Simon 1957, Nelson and Winter 1982) to build upon the imitated practices. In particular, the entrant searches locally for better solutions (Levinthal 1997) while focusing its search efforts on the non-imitated practices (Cyert and March 1963, Greve 2008, Baumann and Siggelkow 2013, Ocasio 1997).

We find that poor performance outcomes from imitation may well result from an imitation process that engenders a poor replica of the target's practices, thereby limiting the endowment effect of imitation as the prior literature suggests. However, we find that poor performance outcomes may also result from difficulties that arise in the generative process of post imitation experiential learning. In our model, the generative effect of imitation produces a bimodal performance distribution that suggests while some firms achieve significant benefits from imitation, many other firms find themselves significantly worse-off than they would have been in the absence of imitation. We then examine the underlying driver of this outcome distribution, and identify mechanisms by which a firm can shift the likelihood of bad versus good outcomes from imitation.

We proceed as follows. In the next section, we provide background on the drivers of the efficacy of imitation. Section 3 introduces our computational model based on the NK landscape. In Section 4, we analyze the conditions under which imitation has positive and negative performance implications. Finally, in Section 5 we conclude by discussing the implications of our results for theory and practice.

2. Theoretical Background

At the core of our theory on the mechanisms underlying the outcome of imitation is the claim that the dual processes of organizational learning (Posen and Chen 2013) — learning from own experience (Argote 1999, Lieberman 1984, March and Olsen 1975) and learning from others' experience (Levitt and March 1988, Miner and Haunschild 1995, Posen, Lee, and Yi 2013) — are fundamentally interrelated. In the discussion below, we unpack the way in which the extant literature has examined the relationship between learning from others and own experience.

Much early progress in understanding organizational learning was facilitated by the assumption that learning from one's own and others' experience are theoretically additive (e.g., Argote et al. 1990, Herriott et al. 1985). As a consequence, research has often attended to the endowment effect of imitation in isolation of processes of experiential learning that constitute the generative effect of imitation. In particular, research has examined two dimensions of the endowment effect, highlighting the potential contribution of imitated knowledge, and the extent to which that potential is realized (Zahra and George 2002). The potential of imitation reflects the ability to acquire and assimilate imitated knowledge, which drives the quality of the replica achieved via imitation. This may be circumscribed by limited absorptive capacity (Cohen and Levinthal 1990), and characteristics of the task environment including knowledge tacitness (Argote and Ingram 2000, Winter 1995, Zander and Kogut 1995), non-observability (Rivkin 2001, Winter 1987, Szulanski and Winter 2001), uncertainty (Greve 2009, Lieberman and Asaba 2006), and causal ambiguity (Lippman and Rumelt, 1982; Ryall, 2009). Together, these factors engender imitation mistakes, which reduce the accuracy of the replica, in the sense that firms: (i) omit important practices from imitation, (ii) imitate incorrectly because they misunderstand practices (Winter and Szulanski 2001), and (iii) imitate inappropriate (poor) targets (Denrell 2003, Greve 2011) or those in different environments (Winter, Szulanski, Ringov, and Jensen 2012, Williams 2007). Relatedly, the extent to which the potential of imitated knowledge is realized stems from the firm's ability to transform and utilize the acquired knowledge to solve its current technical, economic, or managerial problems (Winter 1995). This in turn depends on the extent to which the imitated knowledge requires complementary knowledge, and thus is sensitive to the extent of interdependence (Levinthal 1997).

A related but small body of research focuses on imitation as separable from post-imitation experiential learning at the population level of analysis (rather than the firm level). The key idea is that the endowment effect of imitation may be reduced if high quality targets are unavailable. Building on March (1991), this research observes that effective imitation depends on the existence of firm heterogeneity in the population, such that other firms have knowledge worth imitating — but imitation also reduces heterogeneity in the population. This research examines performance implications of network structural impediments to knowledge flows (Fang, Lee, and Schilling 2010), and the inability to identify a good imitation target (Posen, Lee, and Yi 2013). The key result is that imitation that is less effective in an endowment sense (less accurate replica of the target's practices) may be more effective at the population level. Less effective imitation increases population heterogeneity as well as the quality of potential imitation targets.

More recently, research on organizational learning has begun to examine the interrelationship between learning from own and others' experience. Within this research, three strands are most closely related to our work. First, in work on organizational learning, research has sought to examine how experiential and vicarious learning interact (Baum and Dahlin 2007, Schwab 2007, Simon and Lieberman 2010, Williams 2007). For instance, research examines the temporal sequencing of experiential and vicarious learning (Bingham and Davis 2012), and conditions under which they act as substitutes or complements (Baum and Dahlin 2007, Posen and Chen 2013, Schwab 2007, Simon and Lieberman 2010). This research tends to point to the benefits of engaging in both experiential and vicarious learning, without strongly attending to the possibility that there may be conditions under which using them jointly may be detrimental to performance.

Second, the strategy and entrepreneurship literature includes a range of studies that assume, implicitly or explicitly, that an initial knowledge endowment would affect a firm's subsequent knowledge generation process (Sydow, Schreyögg, and Koch 2009, Schreyögg and Sydow 2010). In these literatures, the initial knowledge endowment may accrue from acquisitions and alliances (Puranam, Singh, and Zollo 2006, Puranam, Singh, and Chaudhuri 2009), prior efforts at learning or pre-entry knowledge (Agarwal, Franco, Echambadi, and Sarkar 2004, Dencker, Gruber, and Shaw 2009, Ganco and Agarwal 2009, Gruber 2010), or employee mobility (Corredoira and Rosenkopf 2010). For example, Puranam, Singh, and Zollo (2006) examine how an acquiring firm organizes to allow an acquired firm to continue to explore within the confines of the larger acquirer. Likewise, Puranam and Srikanth (2007) examine how the acquirer can build upon the knowledge of the acquired firm, focusing on structural mechanisms that integrate the acquired firm's knowledge. This set of studies, while often highlighting the potential to build upon externally acquired knowledge, tends to focus on mechanisms that enhance the efficacy with which the acquired knowledge is internalized by the knowledge-acquiring firm, rather than the subsequent knowledge generation process itself.

Third, research on organizational learning in the computational tradition of the Carnegie school has examined how imitation and experiential learning interact. Csaszar and Siggelkow (2010) examine the optimal breadth of imitation as a function of differences between the target and source. In their model, firms learn experientially until they achieve a moderately good solution (local peak) and then engage in imitation, before once again engaging in experiential learning. Thus, imitation helps the firm overcome challenges of experiential learning under complexity because it acts as a means of exploration that can dislodge a firm from a local peak/competency trap (Levinthal and March 1993, Levinthal 1997, Siggelkow and Levinthal 2003). In an empirical study of learning by new entrants in commercial banking, Posen and Chen (2013) find a similar result, showing that firms use vicarious learning from rivals as a means of solving problems that arise in the process of experiential learning.

Rivkin (2000, 2001) models a firm that imitates a rival, and then engages in post-imitation experiential learning. He examines how complexity drives the efficacy of learning post imitation, and how preferential access to the target of imitation alters the efficacy of imitation. A key assumption in this work, and that of Csaszar and Siggelkow (2010), is that imitated practices are non-persistent — a firm may imitate a practice in one time period, but discard it in the next period. In contexts where externally acquired knowledge reflects the passive absorption of spillovers, this seems a reasonable assumption. Firms passively absorbing external knowledge may be relatively unaware of its source or quality, and will have invested little effort in its acquisition, and as such, they are willing to rather rapidly abandon the absorbed knowledge.

In contrast to Rivkin (2000, 2001), Ghemawat and Levinthal (2008) study how knowledge endowments affect the performance of experiential learning, across problems that vary in their interaction structures (hierarchy versus centrality). While Ghemawat and Levinthal (2008) are agnostic about the source of knowledge endowments, they assume that the knowledge endowment is held fixed in subsequent learning. If one assumes that knowledge endowments are sourced via imitation, then their work can be read as suggesting that imitated practices are somewhat persistent across time — practices imitated in one period may not be open to reexamination in the next period. For example, a firm that imitates the design of a retail store, or the rectangular architecture of a smartphone, tends to hold these features fixed, engaging in trial-and-error learning only on the non-imitated practices. This assumption would reflect contexts where externally acquired knowledge demands costly effort — a firm must choose to imitate, evaluate potential targets of imitation, invest in the absorptive capacity to understand the target's practices, allocate effort to learning about specific target practices, and implement the imitated practices.

To the extent that imitated practices are persistent, as we assume, then post-imitation experiential learning is focused on the non-imitated (non-observed) practices. Focus is a common theme in research in the Carnegie tradition (Simon 1957, March and Simon 1958, Cyert and March 1963).

Focus economizes on search effort, allowing more exhaustive search in the domain of the remaining sub-problems. Focus is also consistent with theoretical arguments for sequential attention to problems (Cyert and March 1963, Greve 2008, Baumann and Siggelkow 2013) and organizational structure and process as a means to direct attention (Ocasio 1997, Rivkin and Siggelkow 2003). Recent empirical work finds support for the idea that prior knowledge engenders focus. In a study of technology entrepreneurs, Gruber, MacMillan, and Thompson (2012 p.16) argue that pre-entry knowledge focuses firms subsequent search behavior in the sense that "the visible area of the landscape is a more, or less, constrained subset of the total landscape." Many other studies examine the performance implications of persistent practices. Knott (2001) studies quick-printing franchises and finds those few firms that abandon key practices that are known to be good, in order to engage in local experiential learning, have inferior performance. In a case study of internal replication at Mail Boxes Etc, Szulanski and Jensen (2006) find that focusing, adhering closely to the original practices, led to much faster growth.

This distinction between persistent and non-persistent practices is important. If imitated practices are persistent, then the endowment and generative effects of imitation interact. We expect the main component of the endowment effect to be an increasing function of the observability of the imitated practices. To the extent the imitated practices accurately reflect good solutions, imitation endows the entrant with a better starting position from which to engage in experiential learning and enhances the efficacy of new knowledge accumulation (Dierickx and Cool 1989). That is, imitation positions the entrant in a good location on the fitness landscape — more proximate to good solutions.

Yet given persistent imitated practices, we expect the generative effects of imitation to be a double-edged sword. On one hand, when imitated practices are persistent, they tend to point the firm's trial-and-error effort in a more promising direction, and stop the firm from pursuing overtly bad lines of trial-and-error inquiry. This increases the likelihood of finding a very good solution. On the other hand, given interdependence between practices, imitation presents potential roadblocks to subsequent experiential learning (Siggelkow and Levinthal 2005) - a condition that we term a "behavioral impasse." Thus, we expect a bimodal performance distribution — a few firms benefit from imitation and many firms suffer, not because they made imitation mistakes, but rather, because imitation alters the efficacy of post-imitation knowledge generation. Yet there is no reason to believe that all firms suffer equally. Just as the Samsung versus HTC example suggests, two firms imitating the same Apple practices may have very different outcomes from subsequent generative effort.

In the next section we briefly lay out the details of our computational model. We then proceed to decompose imitation into is endowment effects in terms of the immediate value of the imitated practices, and the generative effect of imitation that seeds subsequent effort at knowledge generation via experiential learning.

3. Model

To examine how the performance outcome of imitation depends of both the endowment and generative effects, we use a standard NK model (e.g., Kauffman 1993, Levinthal 1997, Rivkin 2001, Ethiraj and Levinthal 2004a, Siggelkow and Rivkin 2005, Levinthal and Posen 2007, Knudsen and Levinthal 2007, Ganco and Hoetker 2009, Csaszar and Siggelkow 2010). It has three basic features: (1) a complex performance landscape, (2) a firm that is represented by a position on this performance landscape, and (3) a search strategy that guides the search process firms use to learn and improve its position on the performance landscape. Our model of imitative entry differs from prior NK models in how we define the entrant's initial location on the landscape — which is a function of both the market leader's set of practices, which the entrant seeks to imitate, and the degree of observability of those practices. In the following subsections, we provide detailed descriptions of our model.

3.1 Complex Performance Landscapes

The starting point of our model is an N-dimensional vector $\boldsymbol{a}=(a_1, a_2,.., a_N)$ of binary practices $a_i \in \{0,1\}$ with $i \in I=\{1,..,N\}$, yielding a total of 2^N possible combinations of choices. We interpret the vector a as representing an entrant's configuration of practices (policy choices).

The degree of interdependence among an entrant's practices is determined by the parameter $K \in \{0,..,N-1\}$, which describes the number of practices a_j that (co-)determine the performance effect of practice a_i. This effect is characterized by the contribution function $c_i = c_i\ (a_i,\ a_{i1},\ a_{i2},..,a_{iK})$ where $i_1, i_2 ..., i_K$ are K distinct practices other than i. The realizations of the contribution function are drawn from a uniform distribution over the unit interval, i.e., $c_i \sim U[0;1]$. The performance of a given vector of practices $\boldsymbol{a}$ is calculated as the arithmetic mean of the N contributions c_i according to the performance function $\phi(a) = \frac{1}{N}\sum_{i=1}^{N} c_i(a)$. The parameter K is interpreted as a measure of complexity. The lowest value, K=0, implies the practices do not depend on each other, yielding a smooth performance landscape with a single (global) peak; the highest value K=N-1 implies that each practice depends on all other practices, yielding a rugged landscape.

A "landscape" represents a mapping from all 2^N possible outcomes of the vector of practices onto performance values. We normalize each landscape to the unit interval such that the mean value of the normalized landscape equals 0.5 and the global maximum equals 1.0. The "local peaks" on the performance landscape represent vectors of practices for which an entrant cannot improve its performance through a given type of local search (Levinthal 1997). The "global peak" is the highest peak in the landscape. For ease of exposition, we describe the global peak on the landscape as the "best solution" and an average local peak as an "average solution." In later analysis, we identify other sticking points on the landscape that are neither global nor local peaks (Rivkin and Siggelkow 2003). We will refer to such solutions as "poor solutions."

3.2 The Effect of Imitation on a Firm's Starting Position

A standard assumption in models of search and learning in the NK tradition is that firms start their search process from a random position on the landscape (Levinthal 1997). In our model of imitative entry, we assume that entrants imitate the market leader (residing at the global peak) and thus are endowed with a subset of the its practices (Rivkin 2000, 2001, Ghemawat and Levinthal 2008). In particular, we model an entrant's initial position as a vector of practices $(x_1^*, \ldots, x_\gamma^*, x_{\gamma+1}, \ldots, x_N)$, where γ reflects the degree of observability on the range [0, N]. We assume that the observability of the market leader's practices is exogenous to the model, they may result from inherent features of the practices, or strategic effort on the part of the market leader. If $\gamma>0$, the entrant can observe some of the market leader's practices. We assume that it imitates them accurately when entering the market, in doing so we hope to better isolate the generative from endowment effect of imitation. In other words, γ of the entrant's practices are correct in that they correspond to the setting of the market leader (global peak), and N-γ practices are incorrect (we label these as x_i^* and x_j respectively).[1] Thus, if there is perfect observability ($\gamma=N$), the entrant starts its search process at the global peak. In contrast, if there is perfect non-observability ($\gamma=0$), the entrant starts its search process from a position that is furthest away from the global peak.[2]

In sum, given a particular degree of observability of the market leaders practices, the entrant may enter the market by imitating the market leader' ("imitation") or enter the market without imitation ("no imitation"), which we refer to as an *ex novo* entrant.[3] The *ex novo* entrant then forms the baseline against which we compare the imitative entrant.

3.3 The Effect of Imitation on a Firm's Search Process

Following entry into a new market, the entrant engages in a process of local search to further improve its performance (Levinthal 1997). Following standard procedure, local search involves randomly selecting a single practice and inverting its value. If the modified vector of practices yields higher performance, it is adopted and the search continues from this new vector in period t+1.

[1] The assumption that an entrant imitates the market leader (global peak) is for analytical convenience alone. In later analysis, we examine entrants that do not imitate the market leader but rather an average incumbent represented by a local peak. We find that the qualitative pattern of results is unchanged.

[2] The results are robust to alternative assumptions about the non-observable practices, e.g., N-γ non-imitated practices are set randomly.

[3] *Ex novo*, from Latin, is something that has been built from scratch.

Otherwise, this modification is discarded and the next search step starts from the unchanged vector defined in period t. This process may be interpreted as off-line search for better positions on a high-dimensional performance landscape ("hill climbing"). Pursuing local search, the entrant will eventually converge to a vector of practices from which performance cannot be improved by changing one of the N practices. When this occurs, the entrant is at either an average solution (local peak), the best solution (global peak) or what we term a "behavioral impasse" (poor solution, on which we provide more detail in the analysis below).

We assume that imitated practices are persistent because both acquiring accurate knowledge about the market leader's practices and switching to new practices are costly. The imitated practices are persistent in the sense that subsequent local search is focused on the practices that were non-observable and thus non-imitable. We then compare the results that derive from the persistence assumption (Ghemawat and Levinthal 2008) with those that derive from an assumption that imitated practices are non-persistent/transient (Csaszar and Siggelkow 2010, Rivkin 2000, 2001).

4. Analysis

We use the NK model described above as an analytical tool to study the efficacy of imitative entry. We initialize the model by setting $N=15$ and $K=7$, which reflects an intermediate level of complexity, and examine the full range of observability of practices, γ, [0, 15]. We report results of experiments that each involve 10,000 entrant replications, and we observe entrants for 200 periods, which is sufficient to ensure that the model reaches steady state. We engage in three sets of analyses. First, we unpack the long-run performance implications of imitative entry as a function of the degree of observability. Second, we examine mechanisms through which entrants are able to overcome the problems associated with imitation. Finally, we examine the sensitivity of our results to alternative model specifications.

4.1 Experiment 1: The Effect of Imitation on Performance

Understanding the performance implications of imitative entry

In the first experiment, we seek to understand the baseline properties of the model. We examine average long-run performance (200 periods post entry) across contexts that differ in the observability of practices in Figure 1. These results reflect the joint outcome of the endowment and generative effects of imitation. Subsequently, we decompose these two effects to gain a deeper understanding of the implications of imitative entry.

The dotted line in Figure 1a reflects the performance achieved by an *ex novo* entrant (i.e., enter without imitating), for whom the extent of observability does not matter. The solid line reflects the performance achieved by an imitative entrant. If none of the market leaders practices can be observed, the imitation strategy generates performance equal to an *ex novo* entrant. At the other extreme, if observability is very high, the imitative entrant can imitate all of the market leaders practices, which produces performance equal to the imitated market leader.

< Insert Figure 1 about here >

The key result in this figure is that, at low to moderate observability, imitative entry may be inferior to *ex novo* entry in terms of long-run performance. We observe a U-shaped relationship between the level of observability of the market leader's practices and long-run performance, with a minimum observed in the case of moderate observability (γ=7). Positive effects of imitative entry materialize only if the level of observability is relatively high (i.e., γ>9). Thus, this experiment suggest that if the entrant cannot substantially imitate the market leader's practices, it may be better off not imitating at all. That is, attempts to learn, starting with relatively incomplete imitated practices may lead to outcomes inferior to entry without imitation.

It is important to note that this result — the negative impact of imitation on entry outcomes — occurs even though we have ruled out, by model construction, many of the standard reasons why imitation may lead to poor outcomes. In particular, entrants imitate the very best possible firm (one at the global peak) and do so without error. In addition, we abstract from contextual differences, i.e., the entrant and the imitated firm operate on the same landscape. The only obstacle to imitation is that of limited observability of the imitated firm's practices.

Before we proceed to decompose the endowment and generative effects of imitation, we examine the distribution of performance outcomes. While our results suggest that - on average - imitation may not be a good strategy when observability is low to moderate, it does not imply that no firms benefit from imitation at entry.

In Figure 1b, we examine the performance distribution for an imitative entrant in a context of moderate observability (solid line, γ=9) and an *ex novo* entrant (dotted line). The resulting distributions are quite different. The *ex novo* entrant exhibits a performance distribution that is relatively normal in shape, centered at 0.82. Moreover, none of the *ex novo* entrants are able to match the target of imitation by reaching the global peak. In contrast, imitative entrants (solid line) exhibit a bimodal distribution. A small percentage of entrants do very well, some even reaching the global peak. However, the remaining entrants appear to reside in a normally distributed distribution with mean of 0.72. This basic pattern of results holds across a broad range of observability, γ, with the share of entrants in the right (minor) mode growing as observability increases. Yes, across a broad range of observability, the left mode remains the major mode.

In sum, Figure 1 suggests that under low to moderate observability, imitation at entry tends to be performance reducing (relative to *ex novo* entry) for a vast majority of entrants, with only a small minority obtaining stark performance gains. Even when the average performance of imitative entry turns positive (γ=10), a large fraction of firms are likely to be worse off than if they had not imitated. In the remainder of this section, we examine the mechanisms underlying this result.

We decompose the long-run performance implications of imitative entry observed in Figure 1 into two components: (1) an endowment effect driven by the immediate contribution of practices derived from imitation, and (2) a generative effect driven by the subsequent effort to build upon this imitated practices. The results of this decomposition are shown in Figure 2.

< Insert Figure 2 about here >

The endowment effect, represented by the dotted line in Figure 2, reports performance in t=1 and reflects the extent to which the imitated practices solve the firm's technical, economic, or managerial problems (Winter 1995). The generative effect, represented by the dashed line, is the change in performance post imitation due to the fact that imitation seeds a firm's subsequent (post-imitation) effort at knowledge generation via experiential learning. The net of the endowment and generative effects of imitation is plotted as the solid line, which fully reconstructs the main performance result in Figure 1a.

The endowment effect is negligible in magnitude at levels of observability up to (and somewhat above) the level of complexity, above which point the endowment effect becomes quite large. When observability is low relative to complexity, the endowment effect is limited because the rewards to implementing one practice acquired via imitation depend on possessing the correct attributes of other practices (that may not be imitated given limited observability). As observability grows large ($\gamma >> K$), entrants are likely to imitate entire sets of practices that are jointly valuable, and thus the endowment effect grows rapidly at higher levels of observability (Rivkin 2000, 2001, Ghemawat and Levinthal 2008).

The generative effect of imitation — the implications of imitation that seeds post-imitation experiential learning — is more interesting and less straightforward. At low levels of observability, a marginal increase in observability reduces the magnitude of the generative effect of imitation. Given the current parameterization, this effect turns positive at γ=8, above which a marginal increase in observability turns the performance contribution of the generative effect positive. At the highest levels of observability, when the entrant can observe and imitate all practices from the market leader at the global peak, the generative effect converges to zero because the entrant has nothing to learn post imitation.[4]

In the following analysis, we seek to uncover the mechanisms underlying the generative effect of imitation, and its relationship to observability of the target's practices. To answer this question, recall that we assume that, because imitation is costly in the context of entry, imitated practices are persistent. This assumption is consistent with work Ghemawat and Levinthal (2008) and suggest a Carnegie school notion of attention to current problems (observable practices are "solved" via imitation, so non-observable practices remain as problems).[5] We find that imitation, when it is persistent, drives the types of steady state solutions discovered by an imitative entrant.

Imitation seeds the entrant's effort at post-imitation experiential learning. The imitated practices form the starting point for subsequent search. An entrant must converge to one of three kinds of solutions: an average solution (local peak, dashed line), the best solution (global peak, dotted line), or what we term a "behavioral impasse" (solid line), i.e. a solution that is neither a local nor a global peak.

< Insert Figure 3 about here >

First, imitation ensures that the entrant is not led astray from its starting-point — it stays within the region of the best solution. This enhances the likelihood that the entrant discovers the global peak

[4] In the sensitivity analysis we demonstrate that the basic pattern of results are insensitive to K, as long as K>0.

[5] In contrasts, Rivkin (2000, 2001) assumes that imitated practices are transient — practices imitated in one period may be abandoned in the next — an assumption that suggests that imitation is relatively low cost. We return to this in distinction in the next sub section of the paper.

(dotted line, Figure 3a). The magnitude of this effect is increasing in observability. Second, imitation decreases the likelihood that the entrant converges to a local peak (dashed line). Third, imitation leads to an inverse u-shaped relationship between observability and a "behavioral impasse" (solid line).

When imitated practices are persistent, post-imitation search effort on the non-imitated practices excludes certain practice configurations in one period, and by implication, other practice configurations are necessarily inaccessible in future periods.[6] As a consequence, an entrant at a behavioral impasse tends to find a solution that is inferior to the local (global) peak associated with its current basin of attraction.[7] An entrant at a behavioral impasse finds a "poor solution," with performance approximately 11 percent lower than that of a firm with an "average solution" (local peak). The emergence of behavioral impasses in our model is consistent with empirical research that shows entrepreneurs' pre-entry knowledge focuses their subsequent search behavior in the sense that "the visible area of the landscape is a more, or less, constrained subset of the total landscape" (Gruber, MacMillan, and Thompson 2012 p.16).

As an example of a behavioral impasse, consider Microsoft and Dell's failed efforts to imitate Apple's successful iPod/iTunes business model. One interpretation of why Microsoft and Dell failed is that they did not fully imitate Apple's complete set of practices (Porter 1996). Given interdependence, incomplete imitation may result in dramatically lower performance. Our model suggests an alternative explanation because we assume that the initial imitation attempt is not the final solution employed by the imitator. Rather, Microsoft and Dell's partial knowledge obtained via imitation is the starting point for their subsequent effort at search and learning by which they attempt to reconstruct the remainder of Apple's practices.

[6] Technically, persistent imitation implies search on a constrained landscape consisting of only the set of the non-imitated practices. A behavioral impasse is a local peak on this constrained landscape. An impasse occurs because a peak on the constrained landscape may not be a peak on the unconstrained landscape; these constrained landscape peaks are then behavioral impasses that foreclose future advancement along a particular search path.

[7] The basin of attraction of local peak is the set of locations on the landscape for which local search leads to this local peak (Kauffman 1993).

It is commonly understood that Apple's close integration of hardware (iPod) and software (iTunes) was one of the key elements of their success. Microsoft and Dell engaged in search, but were reluctant to abandon this integrated business model, even temporarily (e.g., Dell's Digital Jukebox and Microsoft's Zune). Both Microsoft and Dell get stuck at behavioral impasses, unable to replicate the remainder of Apple's practices via local search. Moreover, because of their focus response to partial knowledge, Microsoft and Dell failed to identify other practice configurations, such as Spotify's software-based product, which may have provided a better solution to the one they identified.

Thus, our model suggests that Microsoft and Dell did not fail in digital music because they persisted with outdated or incorrect knowledge, or imperfectly imitated a successful template. Rather, our model suggests that the opposite may be true – Microsoft and Dell performed poorly in digital music because the persistent practices they imitated from Apple made subsequent experiential learning subject to a high likelihood of ending up at a behavioral impasse.

We compute the performance implications associated with each of the three types steady-state solutions. For example, to identify the performance contribution of an increased probability of finding the best solution (dotted line), we multiply the performance improvement of moving from the average peak in the absence of imitation to the global peak with the probability of converging to the global peak. Similarly, we compute the performance contribution associated with the decreased probability of converging to a local peak (dashed line) and behavioral impasse (solid line).

The solid line in Figure 3b indicates that the performance implications of a behavioral impasse are always negative. In addition, the dashed line shows that the performance implications of entrants that converge to a local peak are also negative. The dotted line indicates that the performance implications of ensuring that the entrant stays within the basin of attraction of the global peak are always positive. When observability of practices is relatively low, the negative effects of an impasse (and local peak) dominate. When observability is more complete, the positive effects of getting pulled to the global peak dominate.[8] The generative effect (dotted-dashed line) is the net result of these opposing mechanisms.

In sum, in this experiment, which we conduct at moderate levels of complexity, we find that imitative entry outperforms *ex novo* entry only if most of the market leader's practices can be observed and imitated. If observability is low, entrants are better-off refraining from imitating the market leader. While imitation has both an endowment and generative effect, the latter is the primary driver of these results.

Persistent versus non-persistent imitation

In the previous analysis, we assumed that imitation is persistent, i.e. imitators do not discard practices they have acquired through imitation as they engage in the process of post-imitation learning (Ghemawat and Levinthal 2008). While this assumption is consistent with costly imitation, in other situations, imitation may be less costly, and firms may be willing to relatively quickly abandon imitated practices (Rivkin 2000, 2001). In Figure 4, we compare the long-run performance effect of persistent and non-persistent imitation across contexts that differ in the observability of practices. The dotted line reflects the long-run performance implications of non-persistent imitation, while the dashed line reflects the long-run performance implications of persistent imitation. The difference between these types of imitation is the performance effect of persistence (solid line). For analytical reasons, we normalize all performance effects by an *ex novo* entrant. Note that for both types of imitation, the endowment effects are identical; thus, any performance difference is due to differences in the generative effect.

< Insert Figure 4 about here >

[8] Clearly, in the extreme case of full imitation the generative converges to zero.

We find that persistence has a negative performance implication when observability is low and a positive implication when observability is high. This effect acts via the generative effect because when imitated practices are non-persistent, entrants avoid coming to a behavioral impasse. While this latter mechanism dominates at low to moderate observability, at higher levels of observability, when imitation is non-persistent, imitators have a lower likelihood of converging to the global peak. Yet persistence engenders a trade-off. For example, at γ=9, the probability of finding the global peak is 25% given persistence, and zero in the absence of persistence — even though non-persistent imitation engenders better performance on average.

Imitation and complexity

In the experiment above, we examine the performance implications of imitation in task environments with moderate complexity (K=7). As demonstrated in prior modeling efforts (Rivkin 2000, 2001), the degree of complexity is an important moderator of the efficacy of imitation — from an endowment perspective. In Figure 5, we examine the performance implications of imitation for different levels of complexity: low complexity K=3 (solid line), moderate complexity K=7 (dotted line) and high complexity K=12 (dashed line). In addition, we display the performance distributions for imitative entry at moderate observability γ=9 (solid line) and *ex novo* entry (dashed line) in low complexity environments (Figure 5b) and high complexity environments (Figure 5c).

< Insert Figure 5 about here >

The key result in Figure 5a is that under low observability the negative consequences of imitation are increasing in the level of complexity. As complexity increases, the malign performance effects of imitation are more pronounced and materialize for even higher degrees of observability. Obviously, in the absence of complexity (K=0), there are no long-run performance differences between imitative entry and *ex novo* entry (we do not graph this case). Imitation has an endowment effect proportional to the number of imitated practices, and the generative effect of post-imitation experiential learning leads all entrants to converge to the global peak (even *ex novo* entrants, although they converge more slowly). As complexity increases, the negative implications of imitative entry grow more pronounced. This is driven by the fact that an increase in complexity decreases the performance outcomes from the endowment effect. At the same time, it increases the likelihood that the generative effect will lead the entrant to a behavioral impasse rather than the global peak, which can be seen in the diminished right-side mass as we proceed from Figure 5b and 5c. Nonetheless, the qualitative pattern of results does not change markedly.

Imitating an average target

In the analysis above, we focused on entrants that imitated targets that were at the global peak (Rivkin 2000, 2001, Ghemawat and Levinthal 2008). In doing so, we abstracted from the challenges of identifying a good target of imitation. In Figure 6, we relax the assumption that the entrant imitates the market leader (global peak). Instead, it imitates only an average target (local peak). Technically, we assume that the entrant imitates a target that is at a local peak of rank 30, which corresponds to a performance of 0.88.[9]

< Insert Figure 6 about here >

In Figure 6a, we again decompose the performance implications of imitating this average target (solid line) into the endowment effect (dotted line) and the generative effect (dashed line) across contexts that differ in the observability of practices. Figure 6b displays the probability that the entrant catches up with the target (solid line), overtakes the target (dotted line), and remains below the target (dashed line) in terms of performance as a function of observability. The results in Figure 6a suggest that the positive performance outcome of the endowment effect is somewhat diminished, and the negative implications of the generative effect are somewhat strengthened. Nonetheless, the qualitative

[9] Note that on a landscape with N=15 and K=7, there are on average 370 local peaks and a firm that starts from a random position obtains a long-run performance of 0.83.

pattern of results remains unchanged. Figure 6b indicates that the entrant can outperform the target. This probability (dotted line) is a decreasing function of the level of observability. In contrast, the probability the entrants catch up with the target (solid line) increases in the level of observability. At moderate levels of observability, the probability of remaining below the target (dashed line) is maximized — and this inverted u-shaped relationship between observability and probability of remaining below the target coincides with the probability of a behavioral impasse, which peaks at 60% for moderate observability $\gamma=8$.

4.2. Experiment 2: Mitigating the Problems of Non-Observability

In Experiment 1, we found that imitative entry is not always superior to ex novo entry — even when the target of imitation is at the global peak. Indeed, imitative entry may lead to a bifurcation of performance outcomes where some entrants achieve significant benefits from imitation, while other entrants find themselves significantly worse-off than they would have been without imitating the market leader. In Experiment 2, we are interested in mechanisms through which an entrant may overcome the malign effects of imitation and instead, only harvest the benign effects. First, we analyze entrants that are able to search more broadly or more deeply for a given unit of search effort (Katila and Ahuja 2002, Eggers 2012). Second, we examine entrants have some knowledge of the interaction structure between practices and can actively reorganize the problem into a more modular structure (Baldwin and Clark 2000, Brusoni and Prencipe 2006, Ethiraj and Levinthal 2004). Finally, we study entrants possess pre-entry knowledge on the non-imitated practices (Agarwal, Franco, Echambadi, and Sarkar 2004, Dencker, Gruber, and Shaw 2009, Ganco and Agarwal 2009, Gruber 2010).

Extended Search Breadth and Depth

In Experiment 1, entrants employed standard local search (e.g., Levinthal 1997). Standard local search has a radius of one; in each period, the entrant considers a randomly chosen alternative that differs from its current practice configuration by only a single practice. We examine the implications of imitative entry in which entrants search with extended search breadth or search depth. The results are presented in Figure 7a, where the solid line represents the baseline performance from Experiment 1 and the dotted/dashed lines report the implications of extended search breadth. Figure 5b reports the implications of increased search depth, to which we return later.

< Insert Figure 7 about here >

Entrants may have the ability to efficiently search a broader breadth of alternatives (March 1991, Katila and Ahuja 2002, Eggers 2012) than the single alternative per period assumed in purely local search. To model broader search, we extend the search radius from one to three or five. In each period, an entrant can identify and evaluate an alternative that simultaneously differs in up to three/five practices from its current practice configuration (Rivkin and Siggelkow 2007). We find that increasing search breadth has a strong positive effect on performance. Indeed, when breadth is sufficiently large (at least 5), imitation is unambiguously performance enhancing — regardless of the level of observability. At low to moderate levels of observability of practices, increased search breadth interacts with observability — and the benefits of increased search breadth that would be achieved by an *ex novo* entrant are magnified under imitative entry.

Increasing search breadth has no implications for the endowment effect of imitation, thus it must alter performance outcomes only through the generative effect of imitation. To identify the mechanism underlying this result, recall from Experiment 1 that the positive effect of imitation is driven by the enhanced probability that an entrant reaches the best solution (global peak), while the negative effect is driven by an increased probability of a behavioral impasse. The balance between these two mechanisms determines the magnitude of the generative effect of imitation. With broader search, we find that the probability of an impasse decreases substantially. At the same time, increasing breadth strongly increases the probability that the entrant finds the best solution.

Next, we consider increased search depth, which we model as follows. We allow entrants to pursue the steepest gradient by exhaustively examining all fifteen local alternatives in each period, selecting the best (Rivkin 2001, Rivkin and Siggelkow 2003, Csaszar and Siggelkow 2010). This accelerates local search (Ganco and Hoetker 2009). The dotted line in Figure 7b represent deeper search and the solid line is the baseline from Experiment 1 with standard local search. In contrast to extended search breadth, we find that deeper search does not reduce the negative implications of imitation. We observe an increase in the probability of ending up in a behavioral impasse for low observability. The deleterious effects stem from the fact that with deep search, an entrant follows the steepest gradient to the local peak (average solution). This, in turn, implies there is only one acceptable pathway to the peak. Any obstacle (local peak on the constrained landscape) that blocks this path will trap an entrant at a non-local peak location. Because imitating the market leader generates such obstacles, deep search compounds the negative implications of imitation for moderate observability.

In sum, sufficiently capable entrants that are able to search more broadly, but not those that can search more deeply, can overcome the barriers erected by behavioral impasses, and imitation may unambiguously enhance the efficacy of subsequent experiential learning for these entrants.

Prior Knowledge

A key challenge to the generative effect of learning post-imitation is that of complexity. Indeed, as is typically the assumption, firms know little of the underlying interaction structure. We now examine entrants that have been endowed with some knowledge of the interaction structure, and can actively reorganize the problem into a more modular structure (Baldwin and Clark 2000, Brusoni and Prencipe 2006, Ethiraj and Levinthal 2004). In particular, we assume that entrants can selectively imitate practices that are tightly interdependent. Thus, if they imitate practice 1, they will know that it depends on practices two and three. This is equivalent to entrants modularizing the problem. In particular, we assume that entrants can divide the problem space that consists of 15 practices into 3 modules, and imitate practices within a module preferentially. Figure 8a displays average long-run performance. For baseline comparison, we include the performance of entrants that are not able to reorganize the problem (solid line).[10] We normalize all performance effects by an *ex novo* entrant. Results suggest that a partial understanding of the interaction structure enhances the performance outcomes of imitative entry. It does so through the endowment effect — by increasing the magnitude of the endowment effect, the negative generative effects at low to moderate levels of observability are offset.

< Insert Figure 8 about here >

Finally, we study entrants that possess pre-entry knowledge on the non-imitated practices in the sense that their non-imitated practices are more correct vis-à-vis the best solution (global peak). The knowledge on the non-imitated practices is consistent with a notion of absorptive capacity — as Cohen and Levinthal (1990 p.128) argue: "the ability to evaluate and utilize outside knowledge is largely a function of the level of prior related knowledge." That is, knowledge on the non-imitated practices can be considered prior (pre imitation) related knowledge. The dotted (dashed) line in Figure 8b displays average long-run performance over the full range of observed practices in the case that 50% (80%) of the N-γ non-imitated practices are correct and thus correspond to the global peak. The solid line is the baseline from Experiment 1. As the extent of correct non-imitated practices increases, the negative implications of imitation diminish. Yet even if 80% of the non-imitated practices are correct, imitative entry still has negative consequences relative to *ex novo* entry. In additional analysis, we find that prior knowledge tends to positively influence the endowment effect (thus the general upward shift in the curve in Figure 8b), but the generative effect is still negative over the region of moderate observability. These results indicate that even very capable entrants, those with significant

[10] Note that for the baseline we chose K=4 to make it comparable to the modularized setting.

knowledge independent of imitation, may not be able to completely overcome the challenges of imitative entry that arise via the generative effect of imitation.

4.3 Sensitivity Analysis

In this section, we examine the sensitivity of our results to alternative model initializations and specifications.

First, we examine the sensitivity of our key findings with respect to initial firm performance. We examine the performance of entrants in t=1 that have observed the same number of practices from the market leader, but have heterogeneous initial performance. Results indicate that entrants with low initial performance suffer slightly less and benefit slightly more from imitation, but the qualitative results are robust.

Second, we consider the possibility that the short run results are different from the long-run results (used in the main experiments). We find that the qualitative pattern of results is consistent between the short and long runs. We do observe that in the short run (first five periods), the benign effects of imitation tend to be magnified, while the malign effects are diminished. Thus, one might conclude that in contexts where there is very early intermediate selection (Posen and Levinthal 2007), imitation is more beneficial.

Third, we consider the situation in which the imitated practices are less correct vis-à-vis the market leader. This may reflect imitated practices that have degraded due to environmental turbulence, or have degraded because they represent practices across industries or geographies. In both situations, we observe magnified negative effects of imitation and diminished positive effects. If the imitated practices have become random with respect to the world (perhaps because of an extreme turbulence event), we observe an unambiguously negative effect of imitation — with the negative effect increasing with the observability of the market leader's practices.

Fourth, we examine a task environment that consists of more (and fewer) practices. In particular, we varied the parameter N and analyzed $N=\{8,10,12,20\}$. The observed pattern of results is qualitatively the same across the number of practices.

Finally, we analyze how imitation affects the speed of convergence to steady state. As expected, a higher level of observability of the market leader's practices increases the speed of learning. However, differences in the speed of learning are significant only when the task environment is low complex (low K) or the observability of practices is relatively high.

5. Conclusions and Discussion

Although imitation is among the most common firm activities (Levitt 1966, Lieberman and Asaba 2006), it can generate large positive or negative outcomes for individual firms (Lieberman and Asaba 2006). This variation in outcomes has directed attention to the process of imitation (e.g., Winter 1987). Accordingly, positive outcomes are often attributed to the imitators' ability to correctly imitate the practices, methods, and technologies of successful firms (e.g., Winter 1982, Klepper 2002). Negative outcomes, in contrast, result from mistakes in imitation process - incomplete imitation that overlooks key practices (Csaszar and Siggelkow 2010), inaccurate imitation that misunderstands practices (Winter and Szulanski 2001), or imitation of an inappropriate target (Denrell 2003, Greve 2011, Posen, Lee, Yi 2013, Williams 2007, Ghosh et al 2013). Put differently, the (performance) outcome of imitation processes is understood as primarily a function of quality of the process by which an appropriate target is identified and its knowledge is acquired (e.g., Winter 1987). We argue that this view overlooks a second process that occurs because imitation seeds subsequent efforts at internal knowledge generation, particularly via experiential learning (Argote 1999, Levinthal and March 1981, March and Olsen 1975). Thus, negative imitation outcomes may result from an ineffective imitation process as the prior literature suggests (endowment effect), or from successful imitation that negatively affects the efficacy of post-imitation experiential learning (generative effect).

To examine the implications of the endowment and generative effect of imitation, we focus on imitative entry. When entering a new market, the entrant can chose between imitating or not-imitation (ex novo) a successful imitatee. When seeking to imitate a successful firm, however, not all of the targets practice might be observable to the imitator (Rivkin 2001, Winter 1987, Winter and Szulanski 2001), because, for example, successful firms may seek to deter imitation (e.g., Rivkin 2001, Lippman and Rumelt 1982) or the tacit nature of the practices to be imitated (Argote and Ingram 2000, Winter 1995, Zander and Kogut 1995). We assume that entrant engages in experiential learning to bridge the gap between its knowledge acquired via imitation and the knowledge necessary to compete effectively (Posen and Chen 2013, Winter 1995).

We find that negative outcomes from imitation may well result from an imitation process that engenders a poor copy of the target's practices, thereby limiting the endowment effect of imitation as the prior literature suggests. However, we find that negative performance outcomes may also result from difficulties that arise in the generative process of post imitation experiential learning. In our model, the generative effect of imitation produces a bimodal performance distribution that suggests while some firms achieve significant benefits from imitation, many other firms find themselves significantly worse-off than they would have been through an ex-novo entry.

Our study contributes to the strategy literature in several other ways: First, while we focus our discussions around the imitators choice whether or not to imitate when entering a new market, our study also contributes to our understanding of the imitatee's strategic choice to deter imitation (e.g., Rivkin 2001, Lippman and Rumelt 1982). With few notable exceptions (Polidoro and Toh 2011, Almeida and Zemsky 2012), both the innovation and strategy literature suggests that imitatee's should seek "to keep the knowledge underlying an innovation secret or to protect it by patents (or other means)” (Harhoff, Henkel, and von Hippel, 2003: 1754) because these “spillovers (...) should represent a loss that innovators would seek to avoid." (ibid, 1974). In our study, the extent to which spill-overs occur is reflected in the extent to which the imitator can observe its’ targets practices. Consistent with Almeida and Zemsky (2012), we find that the imitatee can benefit from revealing some information to the imitator. Revealing some information may delay the diffusion of an innovation to imitators (Almeida and Zemseky 2012). Our study complements this line of inquiry by identifying a differential effect of disclosure on imitators - some firms may indeed achieve significant benefits from imitation, many other firms find themselves significantly worse-off than they would have been through an ex-novo entry.

Second, imitation is often thought to result in homogeneity across firms, both in the types of practices firms employ (Meyer and Rowan 1977, DiMaggio and Powell 1983, Miner and Raghavan 1999) and their performance (Kogut and Zander 1995). Our study only finds partial support for these claims. Imitation increases the probability that a firm adopts the market leaders practices and achieves its performance. Imitation indeed drives out diversity, in particular if is persistent. Yet, at the same time, persistence in imitation may also generate particularly poor outcomes for some firms. These firms exhibit not only poor, below-average performance but also adopt practices that are substantially different from those of the market leader. The net effect of these two opposing forces may even lead to an increase in diversity. It is important to note that this effect is driven entirely by the generative effect of imitation. From an endowment perspective, imitation always increases the homogeneity across firms.

Third, our study also points to an interesting complementarity between exploitation and exploration. The returns to imitation (=exploitation) are increasing in search breadth (=exploration). These increased returns to imitation, however, only materialize in the post imitation process. This notion of complementarity is related to but distinctively different from the question of balancing exploration and exploitation (March 1991). In our experiments, the target of imitation is always a firm in the global peak. From an endowment perspective, firms should always exploit as much as possible of the imitatee's knowledge. Here, the returns to exploration are at best zero and in the worst-case negative. If firms can exploit through imitating other, successful firms, the balance between exploration and exploitation should always be strongly tilted towards exploitation. Yet, this does not imply that post-imitation, there is no value in exploring. Successful imitators also have to be innovators, i.e. firms that search broadly for better solutions.

In sum, the generative effect of knowledge acquired through imitation has important implications (often more important implications than the endowment effect of imitation) but has been largely overlooked in discussions of imitation in the existing literature. From an endowment perspective, an imitative entry is always superior to an ex novo entry. There are no conditions under which an ex novo entry is a superior entry strategy, even if imitative entrants experience imitation mistakes or imitate the wrong target. Only when we take into account the generative effect of imitation, there are conditions under which ex novo entrants may outperform imitative entrants.

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Figures

Figure 1 Performance of imitative entry

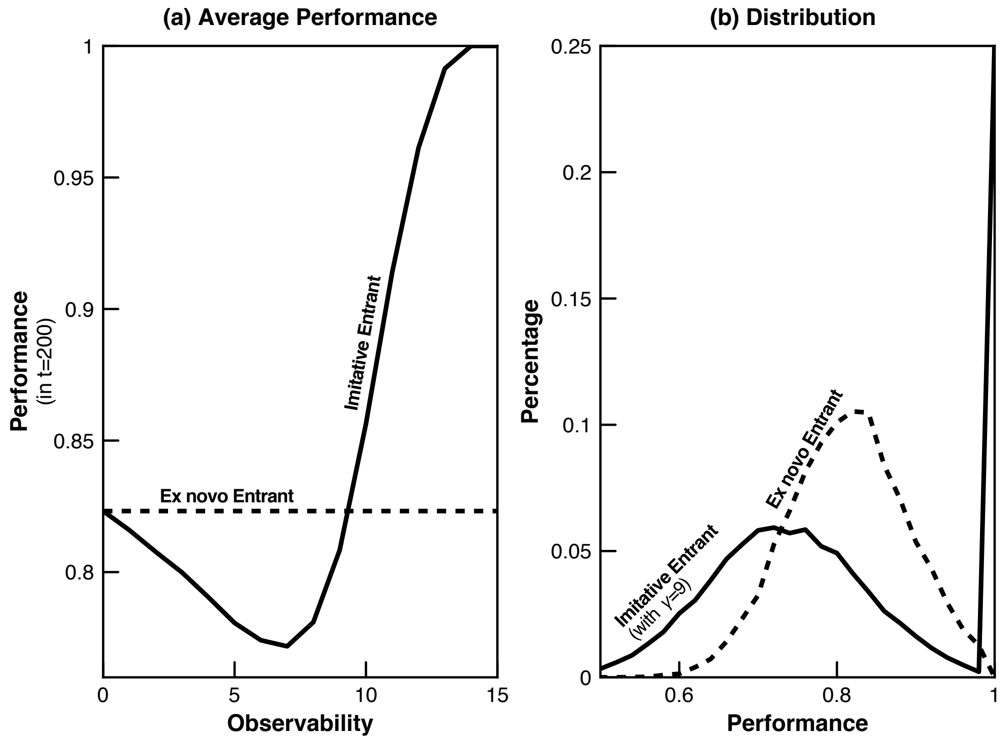

Figure 2 Decomposing the Performance Implications of Imitation

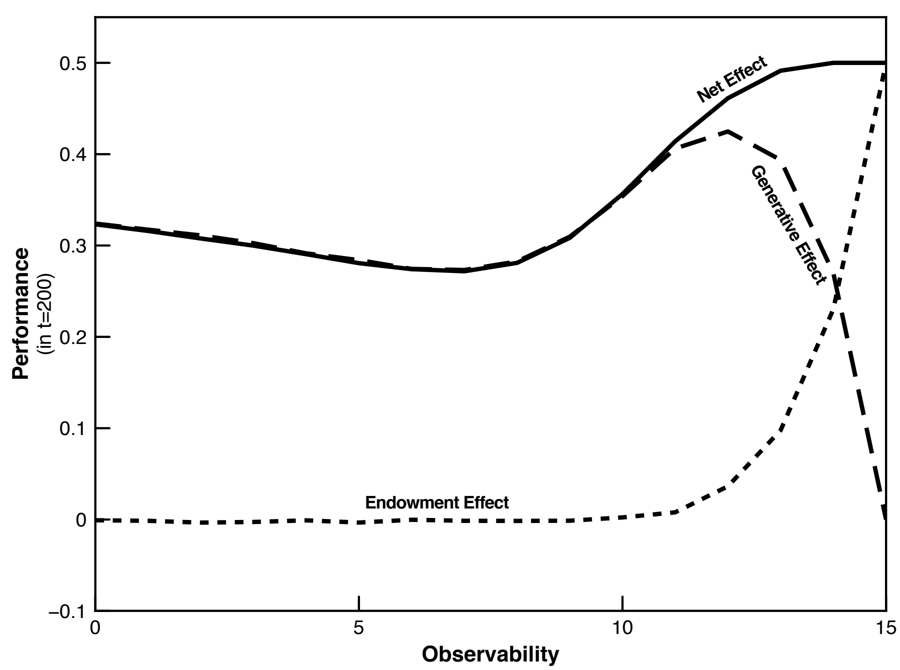

Figure 3 Decomposing the Generative Effect of Imitation

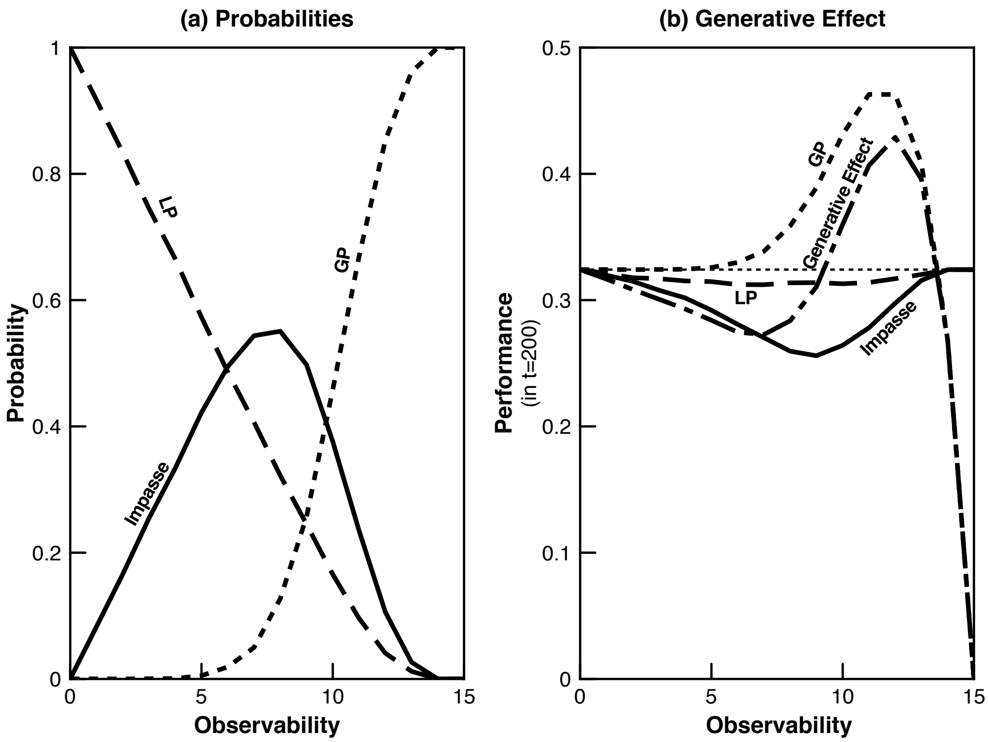

Figure 4 Persistent vs Non- Persistent Imitation

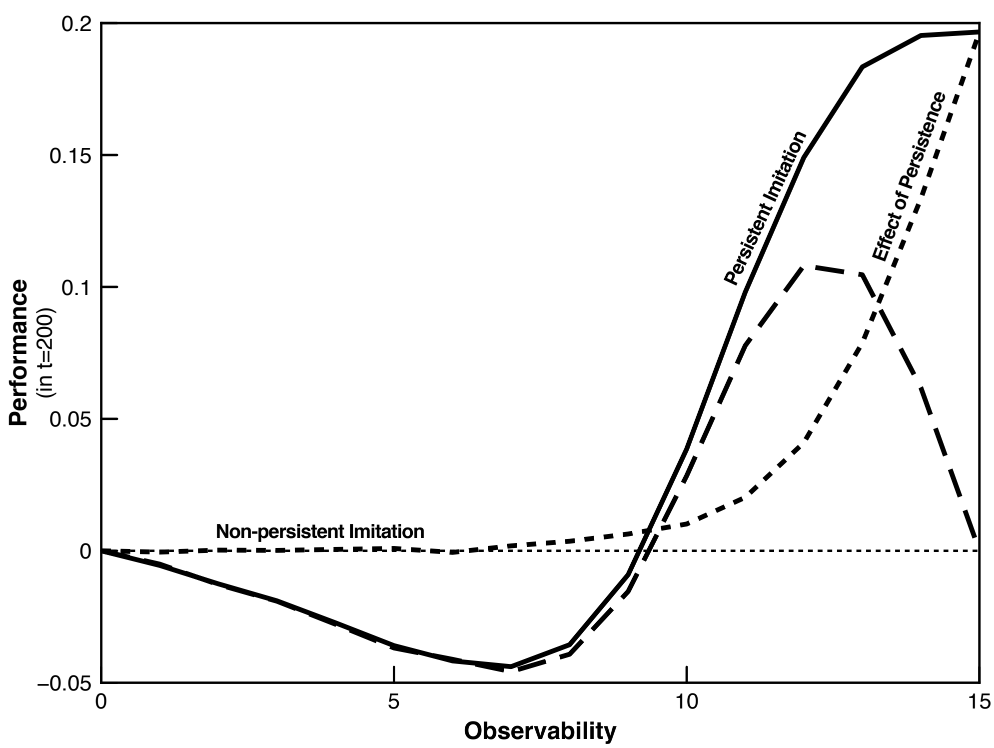

Figure 5 Complexity and Imitative Entry

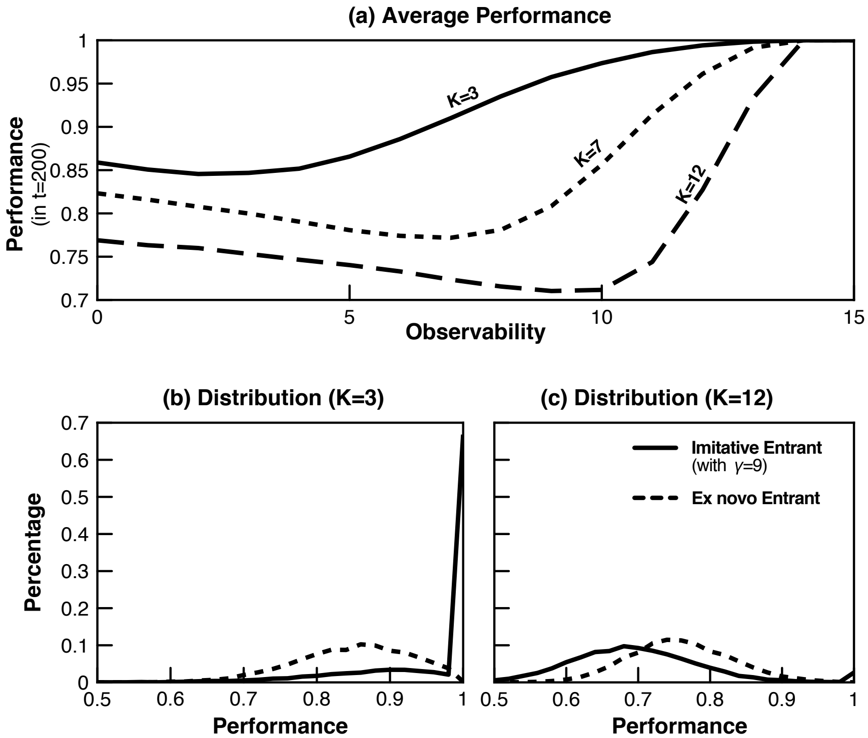

Figure 6 Imitation of an Average Target

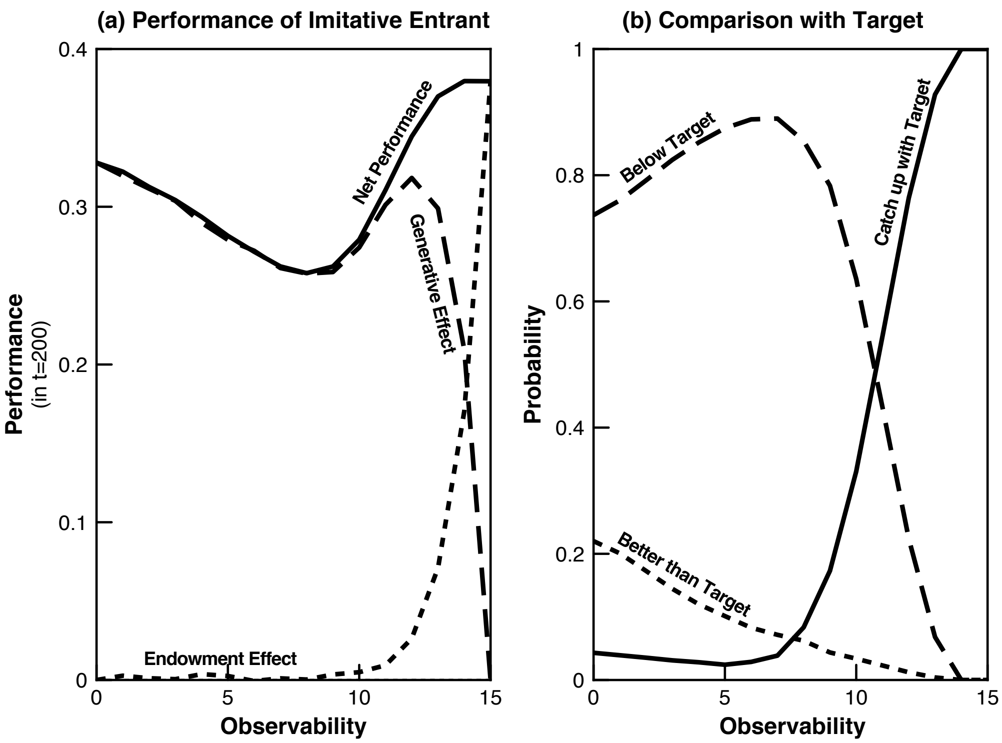

Figure 7 Extended Search Breadth and Deeper Search

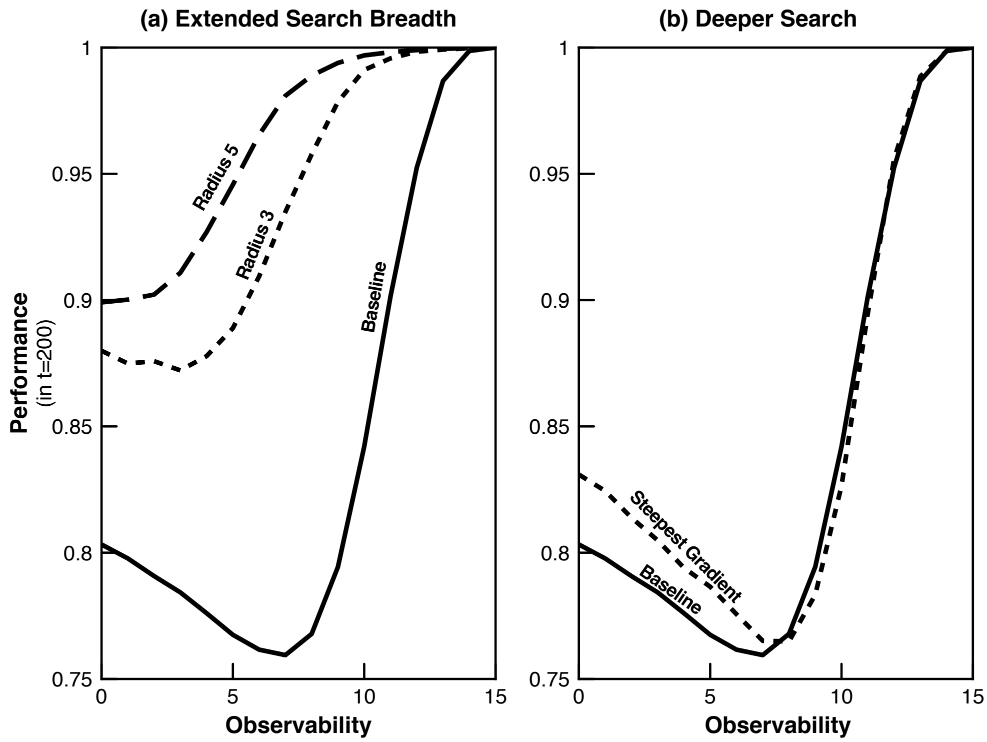

Figure 8 Modularization and Pre-Entry Knowledge