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How can imitation increase inter-firm heterogeneity

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Abstract
Imitation is thought to lead to a decrease in inter-firm heterogeneity. This outcome rests on the assumption that imitation engenders only one type of implication for the imitating firm: an endowment of knowledge (technologies, product designs, strategies, etc.) about successful practices that makes the imitator more similar to its target. Yet research in the Carnegie tradition points to a second mechanism ? imitation moderates a firm's post-imitation adaptation, which we term the generative effect of imitation. In this paper, we use a computational model to examine the implications of this dual role of imitation for inter-firm heterogeneity. As intuition suggests, we find the endowment effect of imitation reduces inter-firm heterogeneity. However the generative effect of imitation is double-edged: it tends to make firms more similar in practices but more different in performance. Our results suggest that the generative effect of imitation produces a bimodal performance distribution; some firms achieve significant benefits from imitation, while many others find themselves significantly worse-off than they would have been had they foregone imitation. Because of its generative effect, imitation can lead to an increase in performance heterogeneity.

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Abstract

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1. Introduction

Imitation of successful firms is often thought to lead to performance gains by the imitator (e.g., Rivkin 2000, Ethiraj and Zhu 2008) but also to decreases in inter-firm heterogeneity (e.g., Abrahamson and Rosenkopf 1993, Haunschild and Miner 1997, March 2010). This conclusion rests on the assumption that imitation engenders only one type of implication for the imitating firm: an endowment of knowledge. Yet, as we will discuss, research in the Carnegie tradition (Cyert and March 1963) suggests that imitation engenders not only a direct knowledge endowment effect, but also a moderating effect on a firm's post-imitation adaptation. We term this second effect the "generative effect" of imitation. In this paper, we consider the implications of this dual role of imitation for inter-firm heterogeneity. We identify industry characteristics under which the generative effect leads to an increase in performance heterogeneity, even though firms become more similar in their practices. For example, we show that the characteristics of knowledge in an industry, such as the observability of the target's practices (Winter 1987), may give rise to circumstances in which imitation leads to an increase in inter-firm heterogeneity.

The dominant logic used to explain the implications of imitation focuses on what we term the "endowment effect" of imitation. The endowment effect reflects the standard observation that, by imitating a superior firm, the imitator is endowed with knowledge in the form of successful practices (technologies, product designs, strategies, etc.) that makes it more similar to the target. Accordingly, inter-firm heterogeneity in practices and performance diminish as a consequence of imitation. This homogenizing influence of imitation is limited primarily by imitation mistakes (Alchian 1950) that arise from incomplete imitation that overlooks key practices (Csaszar and Siggelkow 2010, Szulanski 2003), inaccurate imitation that misunderstands practices (Winter and Szulanski 2001), or inappropriate imitation of poor quality targets (Denrell 2003, Denrell and Liu 2012, Greve 2011) or those in different environments (Csaszar and Siggelkow 2010, Winter, Szulanski, Ringov, and Jensen 2012, Williams 2007). Additionally, imitation may act as a mechanism of recombination (Schumpeter

1934) that engenders heterogeneity when firms mix and match the practices of many targets (Posen, Lee, and Yi 2013, Miner, Haunschild, and Schwab 2003).

In contrast to the endowment effect, we point to the generative effect of imitation. The generative effect of imitation results from the way imitation moderates a firm's post-imitation adaptation process. We are not the first to consider the implications of the generative effect of knowledge (regardless of its source, imitation or otherwise). Indeed, related claims are made in research on absorptive capacity (Cohen and Levinthal 1990, Zahra and George 2002, Posen and Chen 2013), entrepreneurs' pre-entry knowledge (Gruber, MacMillan, and Thompson 2008, Dencker, Gruber, Shah 2009), and imitative learning (Rivkin 2001, Lenox, Rockart, and Lewin 2006, 2007, Csaszar and Siggelkow 2010, Posen, Martignoni, and Levinthal 2013). While this research points to the implications for the efficacy of adaptation, and others point to appropriability (Ahuja, Lampert, and Novelli 2013), we differ because we consider the implications of the generative effect of knowledge, in particular, knowledge acquired via imitation, for inter-firm heterogeneity.

To examine the generative effect of imitation, we focus our discussion on imitative entry. We have in mind a simple but common situation — new firms entering a market by imitating the market leader. The entrants identify and analyze the market leader's observable practices, and imitate them (Rivkin 2000, 2001). They then engage in adaptation to bridge the gap between this knowledge acquired via imitation and the knowledge necessary to compete effectively (Winter 1995, Posen and Chen 2013, Rockart and Dutt 2013).

To illustrate, consider Canadian retailer Dollar Giant.[1] The founder observed the emergence and diffusion of the "dollar store" retail format in the US during the early 1990s. He identifies a leading firm's marketing strategy, pricing policy, location strategy, and merchandising practices through in-

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[1] This illustration is based on an actual startup in which one of the authors of this paper was a co-founder. Details have been modified to protect the identity of the firms involved and more clearly convey the theoretical mechanisms.

depth store visits. He enters the Canadian market in 1994, imitating these observed practices. Yet, many other practices of the US market leader remain somewhat non-observable, including procurement, inventory management, and staffing practices. In short order, the entrepreneur realizes the benefits from the knowledge endowment acquired via imitation. He then engages in a trial and error search process to discover solutions to the non-observable practices. The founder of Dollar Giant was not the only entrepreneur in Canada to imitate the same practices, of the same market leader, with similar accuracy. Yet among those imitators, there was substantial long-run heterogeneity in performance. While this heterogeneity may be attributed to the capabilities of the entrepreneurs or even luck, we suggest that the generative process of imitation inherently produces variation in performance — indeed, more variation than is produced by *de novo* entry.

We construct a formal computational model of learning and adaptation under complexity (e.g., Csaszar and Siggelkow 2010, Ethiraj and Levinthal 2004, Lenox, Rockart, and Lewin 2006, 2007, Levinthal 1997, Rivkin 2000, 2001) to study how the outcome of imitative entry depends on the endowment and generative effects. To rule out alternative sources of variation, we assume entrants are effective at imitation — all firms target the same market leader and accurately imitate the same subset of its observable practices. We focus on one of the primary challenges to imitation: limited observability of the target's practices (Winter 1987, Rivkin 2001, Winter and Szulanski 2001).[2] Post imitation, 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). Thus, by construction, we rule out heterogeneity introduced through mistakes in imitating observable practices and recombination so that we may focus on the implications of the generative effect of imitation for inter-firm heterogeneity.

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[2] We follow Rivkin (2000, 2001) and Lenox, Rockart, and Lewin, (2006, 2007) in assuming that the imitator seeks to copy the full set of the target's practices, but is limited in its ability to do so by the characteristics of the task environment (observability, complexity, tacitness, etc.). In recent work, Csaszar and Siggelkow (2010) extend this prior literature by assuming that the breadth of imitation is itself a strategic choice and as such, the imitator may copy only a subset of the potentially imitable practices that are observable.

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We find that, as intuition suggests, the endowment effect of imitation reduces inter-firm heterogeneity. However the generative effect of imitation is double-edged: It tends to make firms more similar in practices but more different in performance. In particular, when the practices of the target firm are moderately observable, 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 by entering the industry and engaging in adaptation without any imitation. As a consequence, rather than a decrease, we observe an increase in performance heterogeneity from imitation; indeed, we observe more heterogeneity than if entrants do not imitate.

In the remainder of the paper, we proceed as follows. In the next section, we provide background on the relationship between imitation and adaptation. Section 3 introduces our computational model based on the NK landscape. In Section 4, we analyze the effect of imitation on inter-firm heterogeneity, and then examine industry factors that may alter the extent to which imitation engenders heterogeneity. Finally, we conclude by discussing the implications of our results for theory and practice.

2. Theoretical Background

To understand the implications of imitation for inter-firm heterogeneity, our theoretical starting point is the recognition that imitation has both an endowment effect and a generative effect. This mirrors the two main forms of organizational learning (March 2010): learning from own experience (e.g., Argote 1999, Lieberman 1984, March and Olsen 1975) and learning from others' experience (e.g., Levitt and March 1988, Miner and Haunschild 1995, Posen, Lee, and Yi 2013). March (2010) observes that these two forms of learning are fundamentally interrelated. Below, we decompose the extant literature based on the features of the interaction between learning from own and others' experience.

The traditional view on the mechanisms by which imitation may engender inter-firm heterogeneity focuses on the endowment effect of imitation alone, in isolation of processes of own adaptation. This research identifies a broad range of factors that limit the extent imitation engenders an endowment of knowledge, focusing on the characteristics of knowledge and the task environment: knowledge tacitness (Argote and Ingram 2000, Winter 1995, Zander and Kogut 1995), complexity (Rivkin 2000, 2001, Ethiraj, Levinthal, and Roy 2008), uncertainty (Greve 2009, Lieberman and Asaba 2006), and causal ambiguity (Lippman and Rumelt 1982, Reed and DeFillippi 1990, Ryall, 2009). Together, these factors may lead to imitation mistakes that: (a) reduce the accuracy of the replica, and (b) sometimes turn out to be useful or valuable (Alchian 1950, Posen, Lee, and Yi 2013).

While strategy scholars have pointed to many of the mechanisms above, scholars in the evolutionary tradition embed firms in a population of imitators (e.g., March 1991, Miner and Raghavan 1999). This stream of research observes that effective imitation depends on the existence of inter-firm heterogeneity in the population (Campbell 1965, Fang, Lee, and Schilling 2010, Posen, Lee, and Yi 2013). If the target of imitation varies across imitators, due to structures that prevent common focus on a single target (Fang, Lee, and Schilling 2010) and errors in identifying the best target of imitation (Posen, Lee, and Yi 2013), or if imitators' mix and match the practices of multiple targets, then imitation may generate recombinations (Schumpeter 1934) that increase inter-firm heterogeneity. Nonetheless, in a population of imitators, inter-firm heterogeneity is diminished over time as variation is removed by subsequent imitation (March 1991).

While we are not the first to suggest that imitation may increase inter-firm heterogeneity (e.g., Scott 1991, Powell 1991, Lomi and Larsen 1999, Miner and Raghavan 1999, Rao and Singh 1999, Miner, Haunschild, and Schwab 2003), we focus on a very different mechanism. In particular, we do not focus on the role of errors in acquiring an endowment of knowledge from rivals via imitation, or on the population level implications of recombination and diffusion. Our study is also not on the generation of variation through imitation from several sources. Indeed, we purposely construct our

model to rule out these factors. We focus on how imitation that engenders an endowment of knowledge for an imitating firm alters the outcome of subsequent own adaptation — and thus, inter-firm heterogeneity.

Starting with Cohen and Levinthal's (1989, 1990) articulation of absorptive capacity, research has begun to examine the inter-relationship between learning from own and learning from others' experience. They theorize a directional relationship between own experience and the efficacy of subsequent efforts at imitation. In particular, prior knowledge, acquired via prior experience, is an important driver of a firm's ability to absorb external knowledge. For example, Cassiman and Veugelers (2006) study Belgian manufacturing firms and find evidence of a complementarity between a firm's own R&D and the returns to external knowledge acquisition. Lenox and King (2004) study information and communications technology manufacturers and find that prior knowledge, along with specific organizational practices, enables firms to absorb and adopt pollution prevention practices.

Building on these foundations, research on organizational learning and adaptation theorizes an interaction between own and others' experience (Baum and Dahlin 2007, Schwab 2007, Simon and Lieberman 2010, Williams 2007), without making assumptions about the directionality of this interaction (own adaptation on subsequent imitation versus imitation on subsequent own adaptation). This literature 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). The main idea is that a performance enhancing interaction exists between learning from own and others' experience, although there are few articulated implications for inter-firm heterogeneity.

Zahra and George (2002) extend absorptive capacity by theorizing that firms must possess processes that enable them to "realize" the potential of external knowledge. A firm must be able to transform and exploit imitated knowledge to leverage it, which reflects a post-imitation process of

own organizational adaptation and an interaction between learning from own and others' experience. This interaction is evident in research on organizational learning and adaptation in the computational tradition of the Carnegie school that examines two distinct aspects of the interaction: content and process, which we discuss below.

Rivkin (2000, 2001) models a firm that imitates a rival, and then engages in post-imitation adaptation. He examines how complexity drives the efficacy of own post imitation adaptation, and how preferential access to the target of imitation alters the efficacy of imitation. The interaction between learning from own and others' experience occurs primarily because of the *content* of imitated practices. The set of imitated practices seeds a firm's subsequent adaptation efforts by positioning the firm closer to a good set of practices on the performance landscape. The extent of learning from own experience is thus a function of imitated knowledge.

Relatedly, Csaszar and Siggelkow (2010) assume content-based interdependence (Rivkin 2000, 2001) and examine the optimal breadth of imitation. In addition, they assume that the *processes* of own learning and imitation are interdependent. In their model, firms engage in adaptation, and imitate when the returns to adaptation are exhausted. Imitation helps firms overcome challenges of adaptation 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). Thus, *process*-based interdependence in Csaszar and Siggelkow (2010) is driven by a mechanism that determines when imitation and adaptation trigger each other.

Ghemawat and Levinthal (2008) study how knowledge endowments affect the performance of subsequent adaptation across problems that vary in their interaction structures. While they are agnostic about the source of knowledge endowments, their model functionally assumes the process of imitation employed in Rivkin (2001). In particular, Ghemawat and Levinthal (2008) assume content interdependence takes the form of the set of imitated practices that seeds subsequent adaptation

(Rivkin 2000, 2001). Further, they assume that the processes of adaptation and imitation are interdependent because imitating practices acts to focus subsequent adaptation on the non-imitated practices, an idea consistent with behavioral theory of the firm's understanding of the implications of attention (Cyert and March 1963, Greve 2008, Baumann and Siggelkow 2013, Ocasio 1997). Relatedly, Gavetti and Levinthal (2000) examine how knowledge endowments (acquired by analogical reasoning) affect subsequent adaptation by constraining search to particular areas of the performance landscape. In a study of technology entrepreneurs, Gruber et al. (2012, p.16) observe this type of process interdependence, noting that prior knowledge focuses a firm's subsequent search behavior so that "the visible area of the landscape is a more, or less, constrained subset of the total landscape." 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 primarily on the non-imitated practices.

We build on this prior literature that posits imitation may affect subsequent adaptation via both content- and process-based mechanisms. Although this research has begun to explore the performance implications of imitation for subsequent adaptation, the implications of imitation for inter-firm heterogeneity have been largely unexplored. That is, how does imitation affect the extent post-imitation adaptation engenders more or less inter-firm heterogeneity?

3. Model

To examine the effect of imitation on inter-firm heterogeneity, we use a standard NK model (e.g., Kauffman 1993, Levinthal 1997, Rivkin 2001, Ethiraj and Levinthal 2004, Siggelkow and Rivkin 2005, Levinthal and Posen 2007, Knudsen and Levinthal 2007, Csaszar and Siggelkow 2010, Billinger, Stieglitz and Schumacher 2013). It has three basic features: (1) a complex performance landscape; (2) firms that are represented by positions on the performance landscape; and (3) a search strategy that guides the search process firms use to learn and improve their positions on the

performance landscape. Following Rivkin (2000, 2001), we assume that the entrants' initial sets of practices, their locations on the performance landscape, are a function of both the market leader's set of practices which the entrants seek 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 $\boldsymbol{a}$ as representing an entrant's configuration of practices (policy choices).

The interdependence among 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 $\Pi(\boldsymbol{a}) = \frac{1}{N}\sum_{i=1}^{N} c_i(\boldsymbol{a})$. 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 global minimum equals 0 and the global maximum equals 1. The "local peaks" on the performance landscape represent positions for which an entrant cannot improve its performance through 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

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later analysis, we identify other positions on the landscape that are neither global nor local peaks. We will refer to such solutions as "poor solutions."

3.2 The Effect of Imitation on the Content and Process of Entrants' Search

We treat the observability of the market leader's practices as exogenous (Winter 1987, Szulanski and Winter 2001). In our model, $E>1$ entrants seek to imitate the market leader's practices as closely as possible but inherent characteristics of the practices (e.g. tacitness), as well as strategic effort by the market leader, may not make all practices of the market leader observable to the imitator. Further, we assume that the entrants imitate the leader's observable practices accurately.

To represent imitative entry, we follow prior modeling efforts and assume that entrants imitate the practices of a target that is at the global peak, i.e., the market leader (Rivkin 2001, Ghemawat and Levinthal 2008).[3] As such, we model the entrants' initial positions (in $t=1$) as a vector of practices $(x_1^*,..., x_\omega^*, x_{\omega+1},.., x_N)$, where ω reflects the degree of observability on the range $[0, N]$. This engenders context-based interdependence between imitation and post-imitation adaptation. To rule out heterogeneity in practices and performance across the entrants at the time of entry, we assume that the $N-\omega$ non-imitated practices are incorrect. In other words, ω of the entrants' practices are correct in that they correspond to the setting of the market leader (global peak), and $N-\omega$ practices are incorrect in $t=1$ (we label these as x_i^* and x_j respectively). As a consequence, all E entrants are endowed with the same set of practices in $t=1$. This approach allows us to focus exclusively on the implications of the generative effect of imitation for inter-firm heterogeneity. Note that our results are robust to alternative assumptions, e.g., the $N-\omega$ non-imitated practices are set randomly (see sensitivity analysis).

Given a particular degree of observability of the market leaders practices, the entrants may enter the market by imitating the market leader (imitation) or enter the market without imitation (no

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[3] The assumption that an entrant imitates the market leader (global peak) is solely for analytical convenience. In the sensitivity 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.

imitation), which we refer to as *de novo* entrants. The *de novo* entrants form the baseline against which we compare the imitative entrants.

After entering into a new market, both imitative and *de novo* entrants engage in adaptation to further improve their performance (Levinthal 1997). We follow Ghemawat and Levinthal's (2008) implementation of process-based interaction between imitation and post-imitation adaptation by assuming imitative entrants concentrate subsequent adaptation on the N-ω non-imitated practices.[4] Following standard procedure, adaptation takes the form of local search in which an entrant randomly selects a single practice and inverts 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. 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).

4. Analysis

We use the NK model described above as an analytical tool to study the implications of imitative entry for inter-firm heterogeneity and entrant performance. We examine how the characteristics of knowledge in an industry, in particular, the observability of the target's practices (Winter 1987), may give rise to circumstances in which imitation leads to an increase in inter-firm heterogeneity.

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, $\omega \in [0, 15]$. We report results of experiments that involve 10,000 industry (landscape) replications, each with *E=25* entrants and a single target firm at the global peak. We observe each industry for 200 periods, which is sufficient to ensure that the model reaches steady state. We engage in two primary sets of analyses. First, we

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[4] We adopt this assumption (Ghemawat and Levinthal 2008) of process-based interdependence to remove a further source of potential heterogeneity. Our results are qualitatively robust to relaxing this assumption.

explore the effect of imitation on inter-firm heterogeneity both in the types of practices they employ and their performance as a function of the degree of observability of practices. Second, we examine how different industry and firm characteristics moderate the effect of imitation on inter-firm heterogeneity. Finally, we analyze the sensitivity of our results to alternative model specifications.

4.1 Experiment 1: Understanding the Implications of Imitative Entry

The Effect of Imitative Entry on Inter-firm Heterogeneity

In the first experiment, we seek to understand how imitation may affect inter-firm heterogeneity in practices and performance. In Figure 1, we report inter-firm heterogeneity (y-axis) in terms of practices (dashed line) and performance (solid line) in steady state (200 periods post imitation) across contexts that differ in the observability of practices (x-axis). We measure the heterogeneity in practices as the mean variance in the binary practices among the 25 entrants seeking to imitate the same target. Similarly, we measure the heterogeneity in performance as the mean variance in performance among the 25 entrants. Both measures of heterogeneity are normalized by the level of heterogeneity resulting from 25 *de novo* entrants entering the industry without any imitation: a value of one (dotted line) indicates that the level of heterogeneity resulting from entry without imitation (*de novo* entry) is identical to that of entry with imitation. A value higher than one indicates that inter-firm heterogeneity is higher for imitative entry than for *de novo* entry; a value lower than one indicates that inter-firm heterogeneity is lower for imitative entry.

< Insert Figure 1 about here >

The key result in Figure 1 is that while imitation makes entrants more similar in practices, as the prior literature and intuition would suggest, it leads to higher variance in performance (compared to *de novo* entrants). We find that performance heterogeneity peaks at a moderate degree of observability, where the variance of imitative entrants is more than double that of *de novo* entrants. In other words, intuition about the implications of imitation for inter-firm heterogeneity holds at high levels of

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observability of practices. Then, imitation indeed decreases heterogeneity in both practices and performance. However, at moderate levels of observability, imitation may make entrants more similar in practices, but also may engender differences in their performance.

Before proceeding, it is important to reiterate that we ruled out imitation mistakes as a driver of inter-firm heterogeneity, because all entrants are in the same industry, facing the same task environment. Further, we assume that entrants are effective at imitation: they all select the same market leader as their target and accurately imitate the observable subset of its practices, ruling out repeated recombinative processes. As a consequence, all firms garner the same knowledge endowment from imitation, and immediately post imitation they exhibit exactly the same set of practices (and, by implication, exhibit no heterogeneity in practices and performance). Thus, inter-firm heterogeneity in our model must arise from the process of post-imitation adaptation.

To understand why we observe an increase in performance heterogeneity, in Figure 2 we compare the performance distributions of *de novo* entrants (dotted line) and imitative entrants (solid line) in contexts of low observability (ω=6, Panel a), moderate observability (ω=9, Panel b), and high observability (ω=12, Panel c).

< Insert Figure 2 about here >

For *de novo* entry, the distribution of performance follows a normal distribution like pattern with a mean around 0.82. For imitative entrants, in contrast, the distribution is bimodal. For all three levels of observability, we observe two more or less strong modes for imitative entry. While a small percentage of imitative entrants do very well, some even reaching the global peak, the remaining entrants appear to reside in a symmetric distribution with a mean of 0.75, a value below that for *de novo* entrants. As observability increases, the right mode (i.e., those entrants that catch up with the target of imitation, reaching the global peak) becomes more and more pronounced. Yet across a broad range of observability, a majority of entrants remain in the left mode.

The distributional properties of imitative entry suggest that imitation may lead to performance outcomes that are worse or better than those that can be achieved by *de novo* entry, even when the observability of the market leader's practices is relatively high. Moreover, two entrants, identical in terms of non-imitated practices, and perfectly imitating the same set of observable practices of the market leader, will be more similar in practices than they would have been had they refrained from imitation; however, they may end with substantially different long-run performance outcomes.

These results seem to reflect an empirical phenomenon. Consider the large set of Apple iPhone imitators. Samsung has been the most successful imitator, while HTC, Nokia, and LG have achieved far inferior results. Our theory implies that these divergent outcomes need not arise because Samsung simply was more effective than other imitators at copying features of the iPhone (endowment effect of imitation), or Samsung possessed complementary assets that the others did not possess, whether technologies or managerial expertise. Rather, our model suggests that imitation, when it seeds subsequent efforts at post-imitation adaptation, inherently leads to heterogeneity in performance outcomes.

Given that all entrants observe and accurately imitate the same set of successful practices, why do we observe an increase in inter-firm performance heterogeneity in which some entrants perform substantially worse and others perform substantially better? In the remainder of this subsection, we seek to uncover the mechanisms that generate this performance bifurcation.

Why Imitative Entry Can Lead to Inter-firm Heterogeneity

Imitated practices form the starting point for subsequent search and, thus, influence the quality of the solution identified post imitation. Recall that in each simulation run, all 25 entrants are endowed with knowledge about the same set of successful practices from the market leader (endowment effect). In other words, at the time of entry, we assume there is no heterogeneity in practices and performance across the entrants, and thus, the endowment effect of imitation cannot explain the emergence of inter-

firm heterogeneity. Instead, we point to the generative effect of imitation, which results from the way imitation may moderate a firm's post-imitation adaptation process.

In Figure 3, we examine the long-run implications of post-imitation adaptation. Given local search in the $N\text{-}\omega$ non-imitated practices (Ghemawat and Levinthal 2008), the entrants converge to one of three kinds of solutions: an average solution (local peak, dashed line), the best solution (global peak, dotted line), or an impasse at a solution that is neither a local nor a global peak (poor solution, solid line). We report the probabilities (y-axis) that entrants converge to any of these three solutions across contexts that differ in the observability of practices (x-axis).

< Insert Figure 3 about here >

For *de novo* entrants, the dominant outcome from local search is a convergence to local peaks (Levinthal 1997), with a very low probability of finding the global peak, except at the lowest levels of complexity. Yet, entrants imitating the market leader, located at the global peak, have different outcome distributions from post-imitation adaptation. When more practices of the market leader are observable (and thus imitable), imitators are placed closer to the market leader in the performance landscape. As a result, the probability that imitators will converge to the market leader's position (dotted line), the global peak, increases. This enhanced probability of converging to the global peak is one source of performance heterogeneity.

In more abstract terms, the increased probability of converging to the global peak is also consistent with the notion that prior knowledge (acquired via imitation) may enable subsequent adaptation (Cohen and Levinthal 1990). At the same time, prior knowledge may also constrain subsequent adaptation efforts (e.g., Ghemawat and Levinthal 2000). For example, Henderson and Clark (1990), argue that knowledge acquired in the past may "blind" firms in their adaptation process. A reliance on such knowledge "is not only not useful but may actually handicap the firm" (p.13). Prior knowledge affects subsequent adaptation efforts in the sense that "the visible area of the landscape is a

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more, or less, constrained subset of the total landscape" (Gruber, MacMillan, and Thompson 2012, p.16).

We also observe a constraining effect of prior knowledge acquired via imitation in our analysis. Some entrants may end up in what we call "impasses" (solid line). Post-imitation adaptation is constrained to non-imitated practices, which excludes certain practice configurations in one period. By implication, other practice configurations are inaccessible in future periods (process-based interaction between imitation and post-imitation adaptation).[5]

These impasses are a second source of heterogeneity. They are solutions that are inferior to local (or global) peaks. Entrants at an impasse tend to converge to a solution that is inferior to the local (global) peak associated with its current basin of attraction.[6] An entrant at an impasse finds a poor solution, with performance approximately 11 percent lower than that of entrants with an average solution (local peak) and approximately 25 percent lower than that of entrants with the best solution (global peak). These impasses inflate the left tail of the performance distribution and, as a result, performance heterogeneity increases.

In Figure 4, we compute the contributions of each of the three types of steady-state solutions to the overall performance heterogeneity across the 25 imitative entrants. For example, we calculate the variance contribution associated with an increased probability of finding the best solution (dotted line) by identifying entrants that ultimately find the global peak and calculating the variance in their performance. Similarly, we compute the variance contribution associated with the decreased probability of converging to a local peak (dashed line), and the variance contribution associated with

[5] An impasse in our model is related to, but different from a sticking point in Rivkin and Siggelkow (2002). In hierarchical organizations, Rivkin and Siggelkow (2002) show that coordination problems in the adaptation process may lead firms to get stuck at a location that is neither a local nor a global peak. In contrast, an impasse results from local search on the constrained landscape consisting of only the set of the non-imitated practices. 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 impasses that foreclose future advancement along a particular search path.

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

an impasse (solid line). Adding up the different variance contributions fully reconstructs the overall performance variance across the 25 imitative entrants (dotted-dashed line).

< Insert Figure 4 about here >

The dashed line in Figure 4 indicates that the contribution to overall variance of entrants that converge to a local peak monotonically decreases with observability. Recall that imitation decreases the likelihood of entrants converging to a local peak, and consequently, the contribution of this outcome to overall variance diminishes. The dotted line indicates that the variance contribution of entrants that ultimately find the global peak follows an inverted u-shaped curve in observability. The same is true for the variance contribution of entrants that end up in an impasse (solid line).

When observability of practices is relatively low, the impasse outcome already contributes to overall variance (the solid line is above zero), while the global peak outcome does not yet contribute to it (the dotted line is zero).[7] In this range of observability, the increasing contribution of the impasse outcome balances out the decreasing contribution of entrants that converge to the local peak. As a result, overall variance remains flat when observability is relatively low. When observability is moderate, the contributions to overall performance of both outcomes – impasse and global peak – dominate. Recall that the probability of an impasse attains its maximum at moderate observability, In addition, at this level of observability, 20 percent of entrants find the global peak. Due to the large performance difference between global peak and impasse, overall variance in performance is highest at moderate observability. When observability is relatively high, most entrants catch up with the target by finding the global peak, and thus, overall variance in performance decreases and, in the extreme, converges to zero.

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[7] Recall from Figure 3 that when observability is low, most entrants end up at an impasse, while very few entrants find the global peak.

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In sum, we find imitative entry reduces heterogeneity across firms in the types of practices they employ, but it can lead to increased performance heterogeneity. In our model, the generative effect of imitation leads to a bifurcation of performance outcomes. Some entrants achieve significant benefits from imitation, while other entrants find themselves significantly worse-off than they would have been by engaging in adaptation without any imitation. As a consequence, we find that imitation may engender more, not less, inter-firm performance heterogeneity.

4.2. Experiment 2: Firm and Industry Characteristics and their Effect on Inter-Firm Heterogeneity

In Experiment 1, we examine how the observability of practices alters the extent imitative entry gives rise to inter-firm heterogeneity. When observability of practices is relatively high, imitation decreases performance heterogeneity, but it increases heterogeneity when observability is moderate. In Experiment 2, we are interested in how other industry characteristics (complexity and modularity) and firm characteristics (search breadth and prior knowledge) moderate the relationship between observability and performance heterogeneity.

Moderating Effect of Industry Characteristics: Complexity and Problem Modularity

Prior modeling efforts (Rivkin 2000, 2001) demonstrate that the level of complexity of the task environment is an important moderator of imitation outcomes. In our first experiment, we examine how imitation affects inter-firm heterogeneity in task environments with moderate complexity (K=7). Now, we examine the implications of imitation on heterogeneity in industries characterized by different levels of complexity. Figure 5a displays the mean variance in performance (200 periods post imitation) among the 25 entrants for task environments with low complexity K=1 (solid line), moderate complexity K=3 (dotted line), and high complexity K=12 (dashed line). Again, we normalize the variance in performance by dividing it by the corresponding variance of *de novo* entrants. Figure 5b examines a modularized setting to which we return below.

< Insert Figure 5 about here >

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The main result in Figure 5a is that inter-firm performance heterogeneity is increasing in the level of complexity. Indeed, with low complexity (K=1), performance heterogeneity behaves as intuition suggests – it decreases in observability and it is always lower for imitative entrants than for *de novo* entrants. Yet, as complexity increases, inter-firm performance heterogeneity becomes more pronounced. Recall from Experiment 1 that we observed a bifurcation in outcomes for imitative entry; some entrants catch up with the market leader while others end up in particular unattractive positions (impasses). The balance between these two mechanisms determines the inter-firm performance heterogeneity across entrants. Obviously, in the absence of complexity (K=0), there is no performance heterogeneity among the entrants (we do not graph this case); sooner or later, all entrants will converge to the global peak, regardless of how well they can observe the market leader. As complexity increases, the likelihood that the generative effect will lead the entrants to an impasse rather than the global peak increases as well. In an additional analysis (not reported here), we find when K=3, the probability that an entrant comes to an impasse attains its maximum, 43 percent, at low observability (ω=5), while for K=12, this probability attains its maximum, 60 percent, at ω=10. The shape of the impasse probabilities for different levels of complexity qualitatively matches the shape of the variance in performance, and thus, can explain why inter-firm performance heterogeneity increases in complexity.

Next, we compare industries that differ in the extent to which the problem is modularized (Baldwin and Clark 2000, Brusoni and Prencipe 2006, Ethiraj and Levinthal 2004). Industries may vary in the extent problems can be modularized. In our analysis below, we hold the number of interactions (reflected in the parameter K) constant. The problem space consists of three modules with strong intra-module interactions but no inter-module interactions. Figure 5b reports the heterogeneity in performance (200 periods post imitation) among the 25 entrants in the modularized setting (dotted line). For baseline comparison, we include the mean variance in performance among entrants that are

not able to reorganize the problem (solid line).[8] Again, we normalize the variance in performance by dividing it with the corresponding variance of *de novo* entrants. Our results suggest that in industries where the search problem is quite modular, imitation is less likely to lead to inter-firm heterogeneity.

Moderating Effect of Firm Characteristics: Search Breadth and Prior Knowledge

In Experiment 1, entrants employ 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 by only a single practice from its current practice configuration. Now, we examine entrants that 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 among the N-ω non-imitated practices, we extend the search radius from one to five practices. That is, in each period, an entrant can identify and evaluate an alternative that simultaneously differs in one to up to five practices from its current practice configuration (Rivkin and Siggelkow 2007).

In Figure 6a, we show the implications of imitative entry on inter-firm performance heterogeneity for entrants who search with extended search breadth among the non-imitated practices. The solid line in Figure 6a represents the baseline variance in performance from Experiment 1 and the dotted line reports the implications of extended search breadth. In Figure 6b, we examine prior knowledge, which we will address below.

< Insert Figure 6 about here >

Figure 6a shows that in industries where firms can search with larger breadth, inter-firm performance heterogeneity from imitation is diminished. With broader search, the probability that an entrant ends up in an impasse decreases substantially. At the same time, increasing breadth strongly

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[8] For the baseline we chose $K=4$ to make it comparable to the modularized setting.

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increases the probability that entrants find the best solution. As a result, the bifurcation in outcomes diminishes, leading to a decrease in performance heterogeneity.

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. That is, knowledge on the non-imitated practices can be considered prior (pre-imitation) related knowledge. The dotted line in Figure 6b displays the normalized variance in performance (200 periods post imitation) when 80 percent of the N-ω non-imitated practices are correct, and thus, correspond to the global peak. The solid line is the baseline from Experiment 1.

Results indicate that even if 80 percent of the non-imitated practices are also correct, imitative entry generates more inter-firm performance heterogeneity than *de novo* entry. However, while the magnitude of inter-firm performance heterogeneity is largely unaffected, the threshold of observability for which imitative entry generates more heterogeneity than *de novo* entry changes: In the baseline result, imitative entry generates performance heterogeneity unless observability is relatively high ($\omega=12$). If 80 percent of the non-imitated practices are correct, this threshold decreases to $\omega=8$. Again, this pattern can be explained by the change in the probability of entrants coming to an impasse.

In sum, our model suggests that in industries characterized by high complexity or in which modularization is difficult, and industries in which firms are unable to search more broadly or do not possess significant pre-entry knowledge, imitative entry may generate strong inter-firm performance heterogeneity among entrants.

4.3 Sensitivity Analysis

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

First, 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. Even if we adopt a time horizon that is extremely short (five periods), the qualitative pattern of inter-firm performance heterogeneity is unchanged.

Second, we examine the sensitivity of our key findings with respect to the quality of the imitated target. In the analysis above, we focus on entrants that imitate the practices of the market leader, i.e. the firm in 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. When entrants can only imitate an average target (e.g., a local peak of rank 5), rather than the market leader (global peak), inter-firm performance heterogeneity decreases slightly, but the qualitative pattern of results remains unchanged.[9]

Third, we consider the situation in which the N-ω non-imitated practices are set randomly in t=1 so that there is heterogeneity among the entrants at the time of entry. In contrast, in Experiment 1 we assumed that the N-ω non-imitated practices are incorrect so that there is no heterogeneity at the time of entry. Randomly setting the non-imitated practices slightly increases inter-firm performance heterogeneity (compared to the situation in which the non-imitated practices are incorrect) but the qualitative results are robust.

Fourth, we examine a task environment that consists of more (and fewer) practices. In particular, we vary the parameter N and analyze 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, higher observability of the market leader's practices increases the speed of convergence. However,

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[9] On a landscape with N=15 and K=7, there are on average 370 local peaks; a firm that starts from a random position obtains a long-run performance of 0.83. A local peak of rank 5 corresponds to a performance of 0.94, while the global peak (rank 1) has a performance of 1.

differences in the speed of convergence are significant only when the task environment is low complexity (low K) or the observability of practices is relatively high.

5. Conclusions and Discussion

Imitation is often thought to result in homogeneity across firms, both in the types of practices they employ (Meyer and Rowan 1977, DiMaggio and Powell 1983, Miner and Raghavan 1999) and in their performance (Kogut and Zander 1995). Building on the Carnegie tradition's focus on learning (Simon 1947, March and Simon 1958, Cyert and March 1963), research has begun to examine the process of imitation. Increases in inter-firm heterogeneity are typically attributed to: (1) mistakes that arise from incomplete imitation that overlook or misunderstand key practices (Alchian 1950), and (2) recombinations that arise because firms imitate a variety of different targets (e.g., Miner and Raghavan 1999).

This line of reasoning rests on the assumption that imitation engenders only one type of implication for the imitating firm: an endowment of knowledge in the form of successful practices (technologies, product designs, strategies, etc.) that makes the imitator more similar to the target. Research in the Carnegie tradition also points to a second mechanism. Imitation moderates a firm's post-imitation adaptation, which we term the generative effect of imitation. We examine the implications of the generative effect of imitation for inter-firm heterogeneity, across industry contexts that differ in, for example, the observability of the target's practices.

In contrast to the endowment effect of imitation, which decreases inter-firm heterogeneity as observability of the target firm's practices increases, the implications of the generative effect of imitation are less straightforward. Imitation directs a firm's post-imitation search effort in a more promising direction and restrains the firm from pursuing overtly inferior search directions. As a result, many firms may match, or come close to matching, the target's performance. However, many other firms will have particularly poor outcomes from the process of post-imitation adaptation. While the

observed practices of the target firm are imitated, the generative effect may lead many imitators to very different, and potentially very poor outcomes on the unobserved/unimitated practices. Under some conditions, this bifurcation may translate into an increase, rather than a decrease, in inter-firm performance heterogeneity. We observe increased performance heterogeneity through imitative entry despite the fact that we constructed our model to rule out heterogeneity that arises through imitation mistakes or recombination.

Our model also generates testable hypotheses about industry and firm characteristics that should alter the extent to which imitative entry engenders an increase in performance heterogeneity. In particular, our theory suggests that the heterogeneity inducing properties of imitative entry will be most pronounced at moderate levels of observability. In industries where target's practices are easily observable, imitation tends to reduce inter-firm performance heterogeneity. Our model also suggests that in industries with higher complexity, the heterogeneity inducing implications of imitative entry are greater, but occur at increasingly high levels of observability. In contrast, in industries where interdependent practices are grouped into modules, imitative entry may introduce much less performance heterogeneity. Finally, in industries where entrants can search more broadly, or where entrants have more prior knowledge (on the non-observed practices), our model would predict that imitative entry induces less inter-firm heterogeneity. We leave it to subsequent research to test these hypotheses.

Our study contributes to the literature in several other ways. First, while we focus our discussions around the imitator's choice of whether to imitate when entering a new market, our study also contributes to the understanding of the implications of a target's efforts to deter imitation (e.g., Rivkin 2001, Lippman and Rumelt 1982). The innovation and strategy literatures suggest that targets should seek "to keep the knowledge underlying an innovation secret or to protect it by patents (or other means)" (Harhoff et al. 2003, p. 1754) because these "spillovers (...) should represent a loss that innovators would seek to avoid." (p. 1974). Recent contributions have begun to question this

assumption, focusing on an incentive-based argument. In particular, they examine how purposeful knowledge revelation may alter the incentive of rivals to imitate (Pacheco-de-Almeida and Zemsky 2012) or invest in finding substitutes (Polidoro and Toh 2011). Complementing this interesting line of research, we focus on how revelation (purposefully increasing observability) alters the ability of imitators to reliably generate knowledge via post imitation adaptation.

Second, our study builds upon a body of research that points to the importance of knowledge generation. Nickerson and Zenger (2004) argue that the "key knowledge-based question the manager faces is not how to organize to exploit already developed knowledge or capability, but rather how to organize to efficiently *generate knowledge*" (p. 617, italics added). There is significant interest in how knowledge and capabilities are built in the literatures on both the knowledge-based view (e.g., Grant 1996) and the resource based view (e.g., Ethiraj et al. 2005). Work on absorptive capacity (Cohen and Levinthal 1989, 1990) points to a positive interaction between own experience and the efficacy of imitation. Our analysis of how imitation may alter subsequent processes of internal adaptation points us to an interaction in the opposite direction — imitation may moderate the process of post-imitation adaptation.

Third, our study also sheds new light on the role of knowledge endowments in explaining performance differences among firms. The resource-based view (Rumelt 1984, Barney, 1991, Peteraf 1993) proposes inter-firm performance heterogeneity arises because firms differ in their resource endowments (i.e., assets, capabilities, organizationally embedded practices, knowledge etc.) that allow them to improve their efficiency and effectiveness (Daft 1983). By implication, we would expect declines in inter-firm performance heterogeneity if differences in knowledge endowments decrease (Barney 1991). Our study only finds partial support for this conjecture. In our model, all firms in the industry are endowed with identical knowledge, yet it does not necessarily result in a decrease of inter-firm performance heterogeneity. Indeed, it may increase performance heterogeneity. This increase is driven by the post-imitation (or post-resource-acquisition) adaptation process through which firms

seek to build upon their (knowledge) endowments. In this post-imitation adaptation process, firms search and learn about the optimal use of their endowments. Given that firms are boundedly rational, there is no guarantee that they all identify the optimal way to use their initial knowledge endowment — some may find very poor uses. In other words, performance differences may arise.

Finally, while access to successful practices is one motivation for imitation, another motivation is risk reduction (Lieberman and Asaba 2006, Ordanini, Rubera, and DeFillippi 2008). By imitating successful firms, imitators economize on cost and reduce risks from own-experimentation (Dutton and Freedman 1985, Ordanini et al 2008). While imitation may not carry the potential upside of *de novo* entry (or innovation), some research suggests that imitation avoids the risk of generating particularly poor outcomes (Ordanini et al. 2008). Our findings indicate that these claims only hold if observability is rather high. With low to moderate observability, in contrast, imitation has a higher probability to generate particularly poor outcomes than *de novo* entry. Outcomes are less certain because imitation engenders both a bifurcation in performance (into two distinct performance groupings), and also a much higher variance. Thus, there are conditions under which imitation can be a more risky strategy than *de novo* entry.

In sum, imitation is a common mechanism of organizational adaptation and plays a central role in the strategy literature. We seek to understand how imitation may affect inter-firm heterogeneity. If we consider only the endowment effect of imitation, the answer is straightforward: imitation decreases inter-firm heterogeneity. By recognizing that imitation may also alter post-imitation adaptation, we argue that imitation may, in certain circumstances, increase rather than decrease inter-firm performance heterogeneity.

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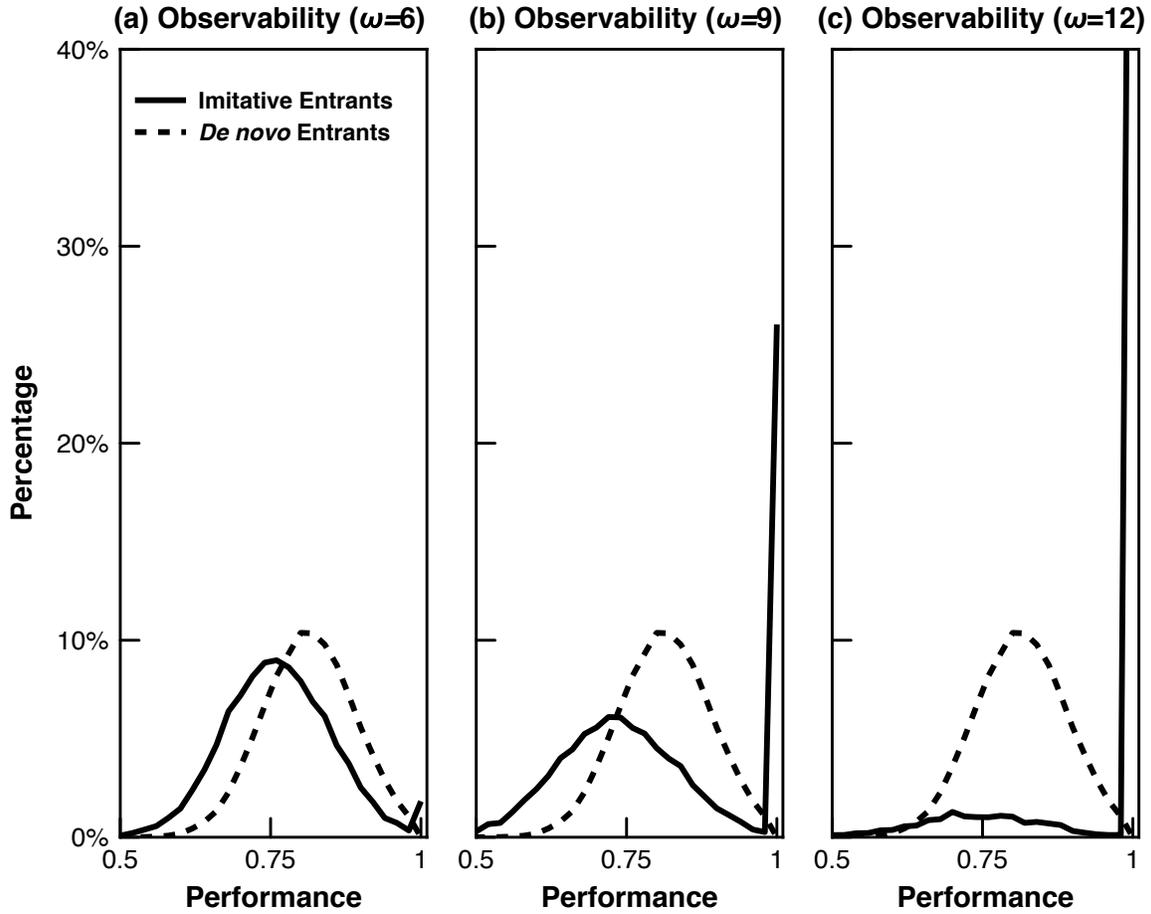
Figures

**Figure 1. The Implications of Imitative Entry for Heterogeneity**
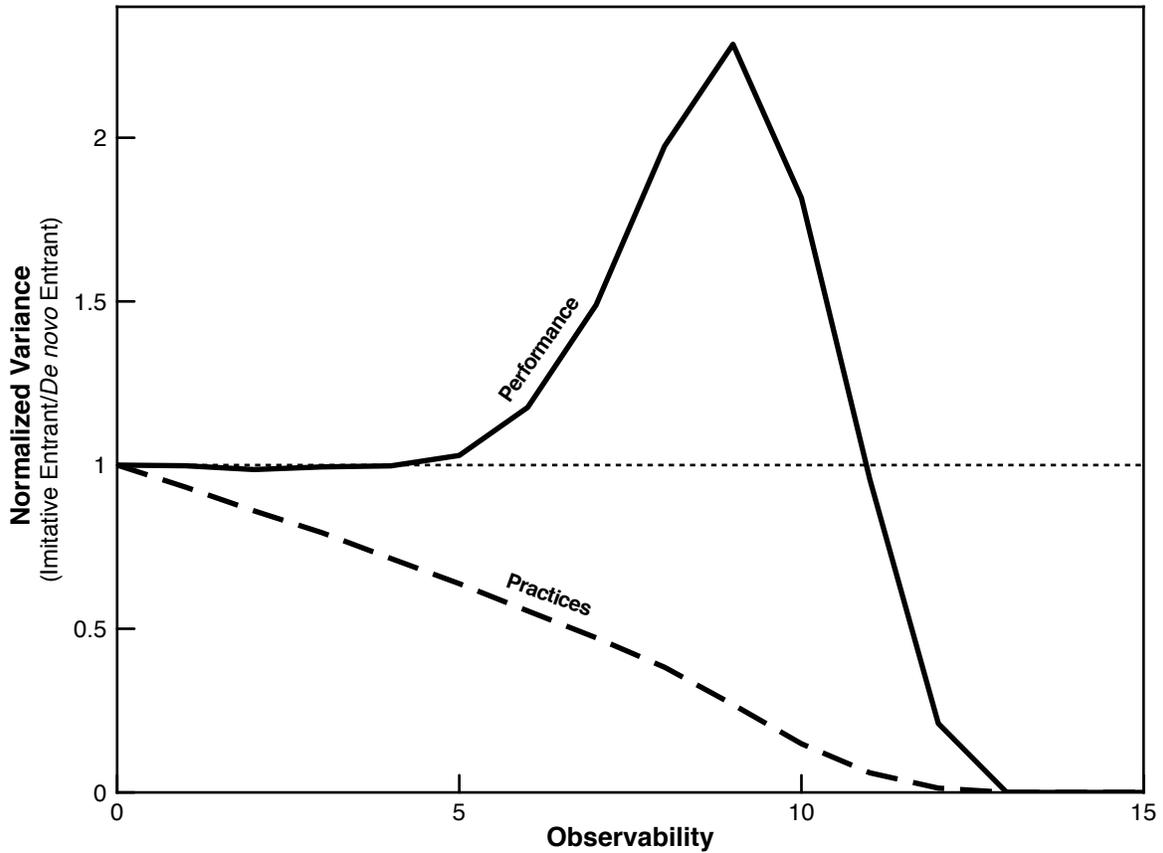
Notes: Figure 1 reports the variance in entrants' performances and practices (y-axis) across contexts that differ in the observability of practices (x-axis). In particular, we display the variance in performance (solid line) and practices (dashed line) of entrants that imitate the same target (global peak). We report normalized variances, i.e., the variance of imitative entrants divided by the variance of *de novo* entrants. The results reflect long-run outcomes (t=200) and are based on 10,000 landscapes (with N=15 and K=7).

**Figure 2. Imitative Entry and Performance Distribution**

Notes: Figure 2 displays the performance distributions for *de novo* entrants (dotted line) and imitative entrants (solid line) in contexts of low observability (ω=6, Panel a), moderate observability (ω=9, Panel b), and high observability (ω=12, Panel c). The results reflect long-run outcomes (*t*=200) and are based on 10,000 landscapes (with *N*=15 and *K*=7).

Figure 3. Imitative Entry and Probability of an Impasse, Local Peak and Global Peak
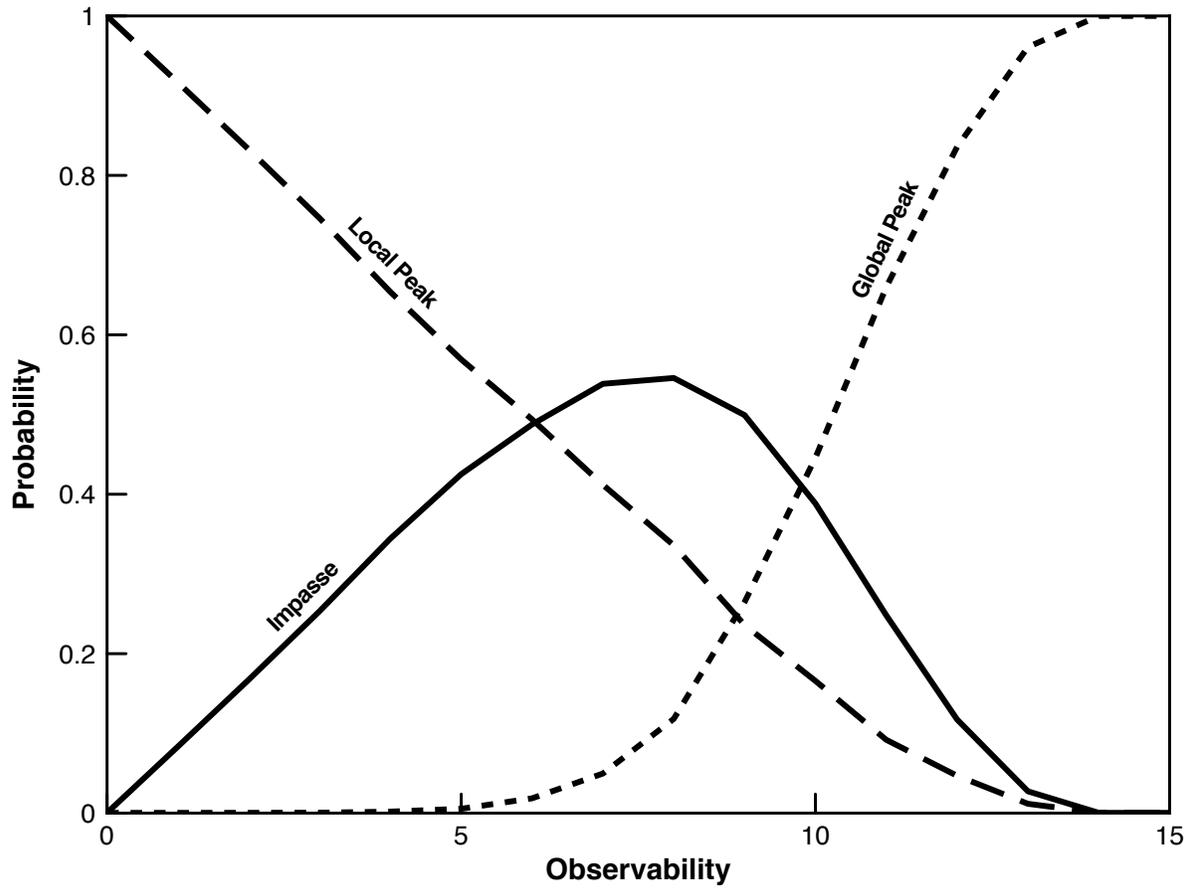

Notes: Figure 3 reports the probability (y-axis) that in *t*=200 an entrant has converged to the global peak (dotted line), a local peak (dashed line), or to an impasse (solid line). We report these probabilities across contexts that differ in the observability of practices (x-axis). The results are based on 10,000 landscapes (with *N*=15 and *K*=7).

Figure 4. Decomposing the Variance Associated with the Generative Effect of Imitation
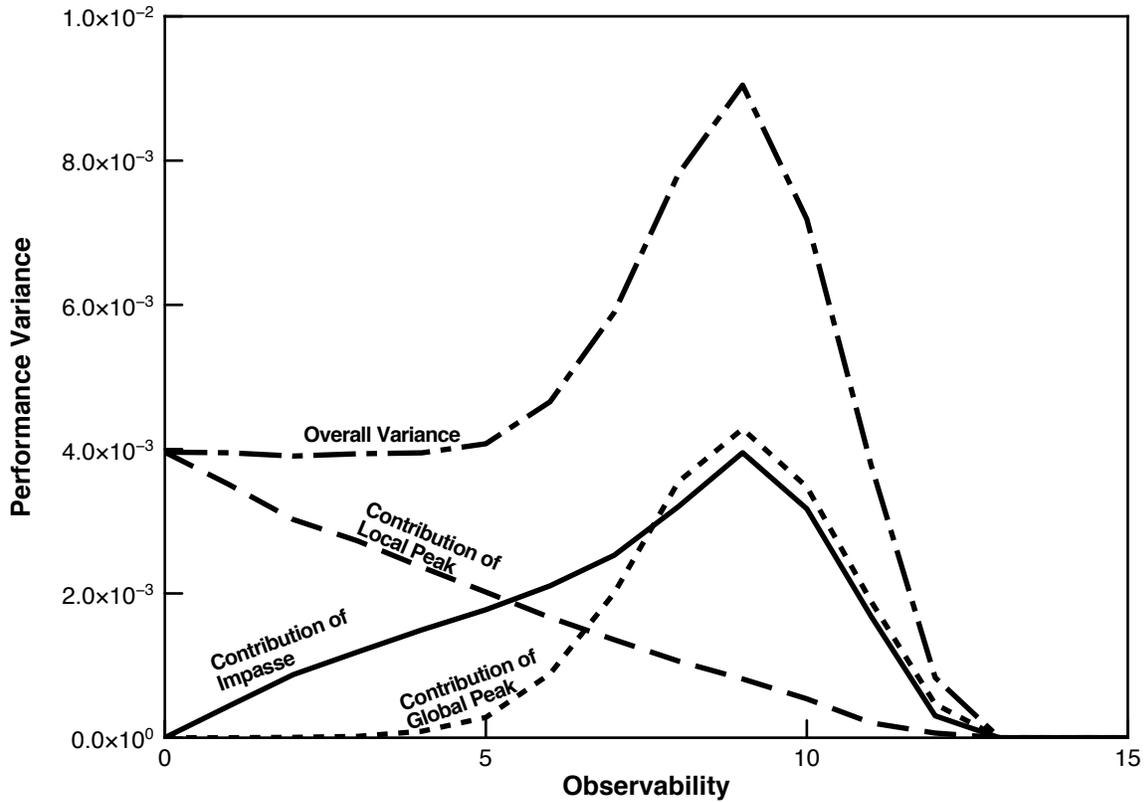

Notes: Figure 5 reports the contributions of each of the three types of steady-state solutions (global peak, local peak, and impasse) to the overall variance in entrants' performances (y-axis) across contexts that differ in the observability of practices (x-axis). We calculate the variance contribution associated with an increased probability of finding the best solution (dotted line) by identifying those entrants that ultimately find the global peak and calculating their variance. Similarly, we compute the variance contribution associated with the decreased probability of converging to a local peak (dashed line), and the variance contribution associated with an impasse (solid line). Adding up the different variance contributions fully reconstructs the overall performance variance across the 25 imitative entrants (dotted-dashed line). The results reflect long-run outcomes (*t*=200) and are based on 10,000 landscapes (with *N*=15 and *K*=7).

Figure 5. Industry Characteristics and Performance Heterogeneity from Imitative Entry

(a) Complexity

(b) Modularity
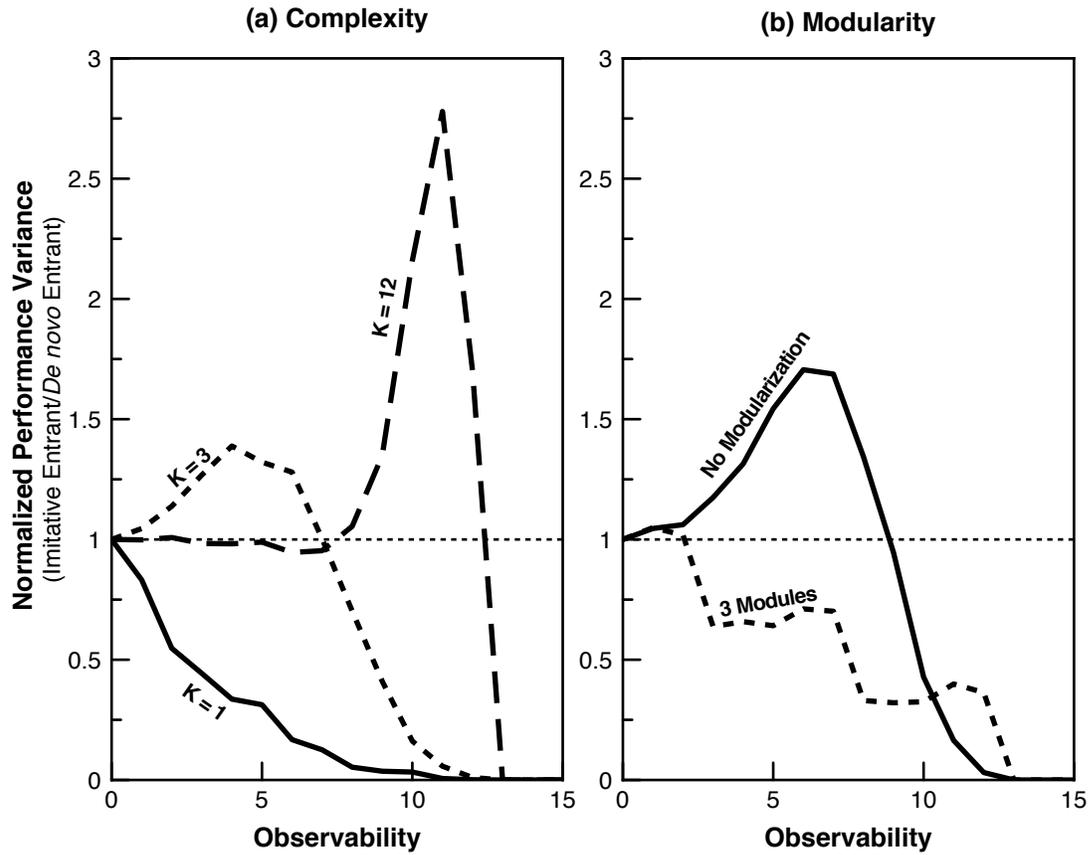
Notes: Figure 5 reports the variance in entrants' performances (y-axis) across contexts that differ in the observability of practices (x-axis). In Figure 5a, we examine the implications for the variance in entrants' performances in industries that differ in their level of complexity: low complexity *K*=1 (solid line), moderate complexity *K*=3 (dotted line) and high complexity *K*=12 (dashed line). In Figure 5b, we examine the implications for the variance in entrants' performances in industries that differ in the extent to which the problem is modularized. The solid line reports the baseline variance from Experiment 1 (problem space cannot be modularized) and the dotted line displays variance for a problem space that consists of three modules with strong intra-module interactions but no inter-module interactions. For the baseline, we chose *K*=4 to make it comparable to the modularized setting. We report normalized variances, i.e., the variance of imitative entrants divided by the variance of *de novo* entrants. The results reflect long-run outcomes (*t*=200) and are based on 10,000 landscapes (with *N*=15).

Figure 6. Firm Characteristics and Performance Heterogeneity from Imitative Entry

(a) Search Breadth

(b) Prior Knowledge
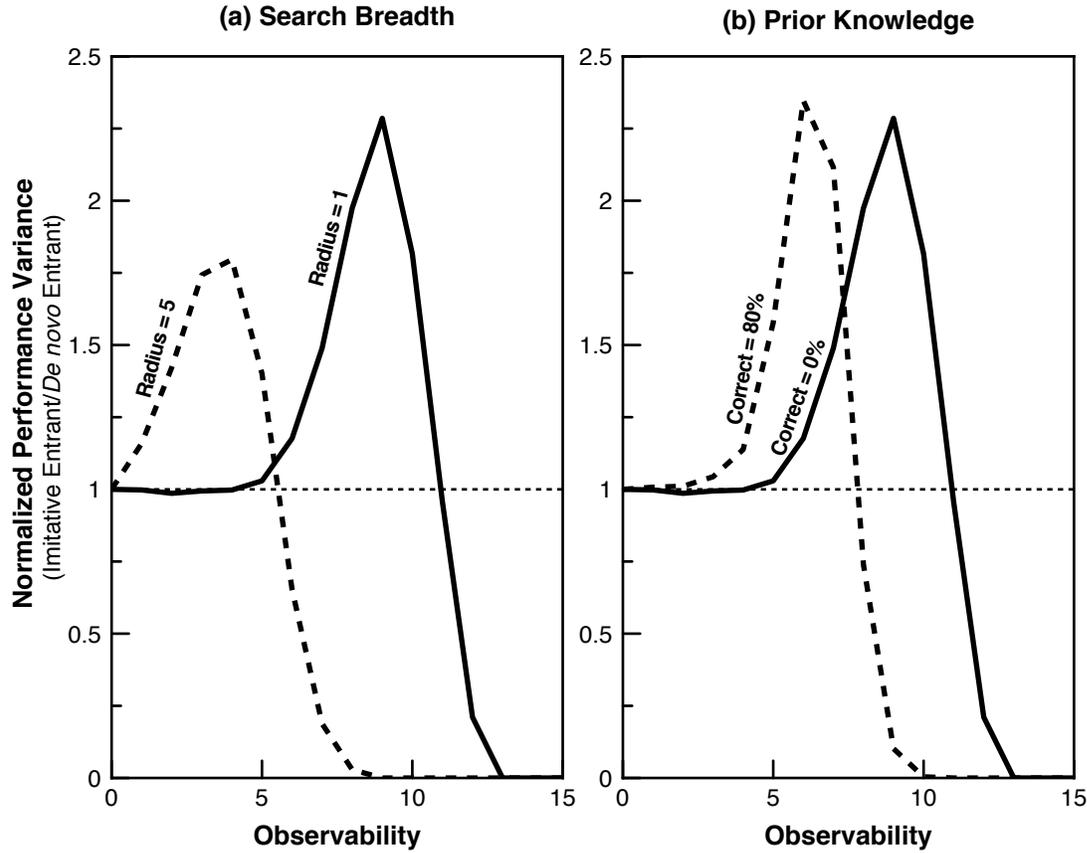
Notes: Figure 6 reports the variance (y-axis) in entrants' performances across contexts that differ in the observability of practices (x-axis). In Figure 6a, we examine the implications for the variance in entrants' performances for firms that search with extended search breadth among the non-imitated practices. Specifically, the solid reports the baseline variance from Experiment 1 (Radius 1) and the dotted line report the implications of extended search breadth (Radius 5). In Figure 6b, entrants 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 solid reports the baseline variance from Experiment 1 (non-imitated practices are incorrect) and the dotted line displays variance in the case that 80 percent of the non-imitated practices are correct and thus correspond to the global peak. We report normalized variances, i.e., the variance of imitative entrants divided by the variance of *de novo* entrants. The results reflect long-run outcomes (t=200) and are based on 10,000 landscapes (with N=15 and K=7).