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Performance Implications of Replicating Practices Inaccurately

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Abstract

Replicating a successful ?template? or best practice in a number of different economic settings is an important strategy for growth and performance improvement. In this paper, we use an NK landscape model to analyze how organizations may innovate and adapt to their environment through ?imperfect replication?. We identify conditions under which imperfect replication might be result in better performance than complete and accurate replication. We also uncover the specific mechanisms through replication errors may affect organizational performance. In that, our study also contributes to our understanding of how the existence of templates may affect replication processes.

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Abstract

Replicating a successful "template" or best practice in a number of different economic settings is an important strategy for growth and performance improvement. In this paper, we use an NK landscape model to analyze how organizations may innovate and adapt to their environment through "imperfect replication". We identify conditions under which imperfect replication might be result in better performance than complete and accurate replication. We also uncover the specific mechanisms through replication errors may affect organizational performance. In that, our study also contributes to our understanding of how the existence of templates may affect replication processes.

(Key Words: Replication, Errors, NK Simulation Model)

1. Introduction

Replicating organizational routines, business models, and best practices are important means of both organizational growth and performance improvement (Nelson and Winter 1982, Teece et al. 1997, Argote and Ingram 2000, Rivkin 2000, Winter and Szulanski 2001, Winter et al. 2011).[5] For example, organizations such as McDonald's, Blockbuster, Starbucks, or Walmart grow primarily through replicating a template of how to operate their business in large number of similar outlets. Similarly, non-retail firms seek to enhance their performance by replicating successful practices within the firm.

Yet, replicating a practice in every detail is not trivial. Perfect replication is often not only very costly (Mansfield et al. 1981) but also – due to causal ambiguity what constitutes the elements of success (Lippman and Rumelt 1982) – almost impossible. Indeed, as observed by Nelson and Winter (1982), "perfect replication is not more of an ultimate objective than perfect control" (p. 121). If incomplete and inaccurate replication is the rule rather than the exception, this raises two broad questions. First, what are the performance implications of incomplete replications? Second, when are these performance implications particularly pronounced? While scholars have long noted that errors or noise in replication and imitation can introduce variety in the population (e.g., Holland 1975, Aldrich 1979, Winter 2005), in our study, we are interested in the effect on the firm level rather than population level. This an important difference because while errors or mutations may have a favorable effect for the population of firms but an adverse effect on the firm that suffers from these errors (March 1991).

In seeking to answer these questions, we consider organizations as complex adaptive systems that have to match the complexity of their environment. Particularly, we are using the standard NK landscape simulation model with local search (Levinthal 1997, Winter et al. 2007).[6] Implicit in this choice is also the assumption that we adopt a dynamic perspective of

[5] On a very general level, replication can be understood as the attempt to reproduce at multiple internal sites the outcome of an existing activity (Nelson and Winter 1982). Imitation, by contrast, denotes the process of replication at external sites by, for example, competitors (Teece et al. 1997).

[6] Levinthal (1997) was the first to apply the NK model to the field of organization science by showing that the existence of interdependencies among firm choices can explain persistent organizational heterogeneity. Since then, research that utilizes

organizational search and adaptation in which, however, adaptive processes lead to improvements over time but also often fail to achieve global maxima on a complex[7] performance landscape (Nelson and Winter 1982, Becker, Knudsen, and March 2006). While our study focuses on the effects of replication errors on the search and adaptation processes, other perspective like institutional theory (DiMaggio and Powell 1983, Meyer and Rowan 1977) would highlight the (negative) effects of incorrect replication on the acquisition of acceptance and legitimacy. These effects, however, are beyond the scope of our study.

Recent empirical research suggests that replication errors are dysfunctional (Winter et al. 2011). Other studies are more optimistic. For example, Becker et al. (2006) portray replication errors as source of novelty and variation. Similarly, Winter (2005) argues that perfect replication impedes any adaptation and improvement and thus might come at a cost if adaptation to the local context is required (Teece 1997, Winter et al. 2007) and the current practice is suboptimal.

The purpose of our study is twofold. First, we will seek to identify conditions under which replication errors may prove functional and dysfunctional. Second, we will try to uncover the specific mechanisms through which replication errors may affect organizational performance.

The central argument of our study is that all replication errors have negative short run performance consequences but in the long run, small replication errors can indeed improve organizational performance (while large replication errors are still dysfunctional). This is consistent with Winter's (2005) speculation that it is the *size of replication errors* that determines the performance implication of incorrect replication. Interestingly, we also find that only replication errors that affect interdependent (or core) elements of the replication template can improve long-run performance. If independent (or peripheral) elements are replicated incorrectly, long-run performance is not affected.

the NK framework is flourishing and has been conducted on a broad range of topics such as organizational development and change (Ruef 1997), innovation (Frenken 2000, Fleming and Sorenson 2001, Almirall and Casadesus-Masanell 2010), organizational design (Gavetti 2005, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003) and strategy (Siggelkow and Rivkin 2005, Csaszar and Siggelkow 2010, Levinthal and Posen 2007). Porter and Siggelkow (2008) provide a comprehensive overview on NK models in the context of organizational search.

[7] Simon (1962) defines complexity as having two aspects: An item is complex if it consists of many elements and those elements interact richly.

In sum, our analyses suggest that the long-run performance implications of replication errors depend on the size of the replication error and on which elements of the template are replicated incorrectly. All replication errors have the potential to dislodge the organization from its current position on the performance landscape. With small errors, however, the probability to get dislodged from a low local optimum is much higher than for a high local optimum or the global optimum. In more abstract terms, the probability of getting dislodged from the current position is an increasing function of the quality of the current position. For large replication errors, this probability is independent of the quality of the current position. Replication errors that only affect independent elements of the template are self-correcting and never dislodge an organization from its current position.

The remainder of the paper is structured as follows. First, we briefly review the existing literature and describe our contribution. Second, we introduce our extensions of the standard NK landscape model (Levinthal 1997). We then examine the performance consequences of replication errors and identify conditions under which these consequences are particularly pronounced. In the final section, we discuss the results of our analyses.

2. Literature Review

There is little doubt that perfect replication is hard if not impossible to achieve (Nelson and Winter 1982, Szulanski 2003). It is hard to achieve because knowledge embedded in the template is often tacit and cannot be easily transferred (Nelson and Winter 1982, Kogut and Zander 1992, Szulanski 2003). To make things even worse, often it is not even clear what constitutes the elements of success of a template ("causal ambiguity", see Lippman and Rumelt 1982).

Yet, there is much less consensus on performance implications of replication errors. On the one hand, Rivkin's (2000, 2001) work is often interpreted as suggesting that replication errors always have a negative performance impact. However, it is important to note that in Rivkin's studies, the template is always the global peak. If the template is a global peak, by definition, replication errors cannot improve performance; there is no way to become better than the global peak. For local peaks, however, small errors can help organizations to become dislodged from their local peak and discover the global peak. As noted by Rivkin (2000), the probability that the global peak is discovered from a random starting position through local search can be very low, in particular in complex environments. For example, for N=24 and *K=11*, this probability is below *1%*. This, then, of course suggests that templates are more often than not local rather than global peaks. Another interpretation of existing studies on replication errors is that with increasing complexity, replication errors become particularly costly.

On the other hand, other studies suggest that errors or deviations from the original template might have some positive performance implications. For example, by deviating from the original template (i.e., replicating it incorrectly), organizations may achieve local adaptation (Csaszar and Siggelkow 2010, Winter et al. 2010). Different contexts may have different optimal solutions and, by implication, using the solution that is optimal in one context doesn't guarantee high performance in another context in particular if the contexts are quite different (Kaufmann and Eroglu 1999). Sticking to closely to a template inhibits local adaptation (Bartlett and Ghoshal 1989). While certainly true, this is not the focus of your study. In our study, we assume that there are no contextual differences.

Beyond allowing for local adaptation, deviations from the template may also be a source of innovation (or "adaptation" in the sense of search). Inaccuracies in replication can be thought of as "mutations" (Nelson and Winter 1982), providing the necessary variation to stimulate adaptation processes. In our model, we assume that the template to be replicated is always a local or global peak on the performance landscape.[8] In other word, search and adaptation has come to an end; performance is not improving any more. If the template is the landscape's global peak, perfect replication is particularly desirable. If the template is a local peak on the landscape, perfect replication still guarantees above average performance. From a static perspective, any deviation from the template is associated with an immediate performance decrease. From a dynamic perspective, this decrease in performance might only be temporarily if errors can be corrected subsequently, i.e. if the organization converges back to the peak associated with the template. Some deviations, however, dislodge an organization permanently from its current local peak and lead to the discovery of a new peak. Only if this happens, performance can improve beyond the template's performance. This of course raises the question why and when do organizations discover a better practice than its original template?

[8] Technically, we implemented this by (1) putting a firm on random position on the landscape in t=0 and (2) let it search locally for 200 periods. By period=200, a firm has always found either a local or global peak. In other prior modeling efforts such as Rivkin (2000, 2001), the global peak is always the template to be (incorrectly) replicated.

Given these inconsistent views on the value and costs of replication errors, more recent research has called for examining the moderating effects of knowledge-related factors on the relationship between replication accuracy and performance (Winter et al. 2011), in particular the template's complexity. Winter (2005) and Winter and Szulanski (2001) cautions against any deviations from a template: any deviation may have unintended consequences and the presence of interaction effects may even amplify these negative consequences. Given that, they recommend keeping "the list (of deviations) as short as possible" (p.248). These unintended consequences seem to be particularly pronounced if the template is very complex or if the replication error affects choices that are highly interdependent.

In our study, we conceive of firms as dynamically searching and learning on a complex performance landscape: the firm is continuously seeking to improve its current practice by modifying one element of its current practice in each period (if this modification decreases performance, the firm returns to the pre-modification template). While one might think of a template as static, even templates in the fast food industry are modified all the time. For example, White Castle, a US hamburger and fast food chain (founded in 1921 and sales in 2011 of $632 million) is currently experimenting with adding wine to its menu. Similar experiments are currently conducted at Starbucks and Burger King (WSJ 2012). There is also some evidence that franchisee often experience considerable autonomy in implementing "their version of the template" (Bartlett and Rangan 1992, Maritan and Rush 2003). McDonald's McCafe concept was created and launched by a franchisee in Australia in 1993. Today, there are more than 1300 McCafe outlets. McDonald's Egg McMuffin was invented by another franchisee in the late 1960s and was introduced nationwide in the US by 1972.

3. Model

In our paper, we consider the standard NK landscape simulation model with local search. The starting point of our model is a N-dimensional vector $\mathbf{a} = (a_1, a_2, ..., a_N)$ of binary decisions $a_i \in \{0,1\}$ with $i \in I = \{1,...,N\}$. This vector represents the set of all relevant decisions made within the "template". Some of these decisions are interdependent and others are not. The results of our analyses are based on random interaction patterns but – given our knowledge about the underlying mechanisms and dynamics - can be generalized to non-random interaction patterns such as the patterns described in Rivkin and Siggelkow (2007). The extent of interdependence is characterized by the parameter $K \in \{0,...,N-1\}$, which describes the number of decisions a_j that together (co-) determine the performance effect of decision a_i. This effect is characterized by the contribution function $C_i = C_i(a_i, a_{i_1}, a_{i_2}, ..., a_{i_K})$ where $i_1, i_2, ..., i_K$ are K distinct decisions other than *i*.[9]

The performance of the firm is calculated as the arithmetic mean of the N contributions C_i according to the performance function $\phi(\mathbf{a})$:

$$\phi(\mathbf{a}) = \frac{1}{N}\sum_{i=1}^{N} C_i(\mathbf{a})$$

Starting from a randomly chosen decision vector $\mathbf{a} = (a_1, a_2, ..., a_N)$ in period $t = 0$, the firm consecutively changes randomly one decision a_i in each period to search for performance improvements ("local search"). If a new decision vector improves performance, it is adopted and the search continues from this new vector in period *t+1*. Otherwise, the next search step starts from the unchanged vector defined in period *t*.

The search process stops after P periods. During the P periods, the firm can get stuck at a decision vector (sticking point) whose performance cannot be improved by changing one of its N decisions.[10] In this case, the firm is either at a local or global maximum. A local maximum can be interpreted as a peak. The global maximum is the highest peak in the landscape.

Like prior modeling efforts, we normalize each performance landscape $(\phi(\mathbf{a}) \rightarrow \tilde{\phi}(\mathbf{a}))$ from the interval $[0;\phi_{\max}]$ to the unit interval such that the mean value $\tilde{\phi}_{\text{mean}}$ on the new scaled landscape is equal to 0.5, i.e.,

$$\tilde{\phi}(\mathbf{a}) = 0.5 \cdot \frac{(\phi(\mathbf{a}) - \phi_{\text{mean}})}{(\phi_{\max} - \phi_{\text{mean}})} + 0.5$$

where $\phi_{\max}$, ϕ_{mean} are respectively the maximum and mean value on the landscape.

[9] The parameter *K* is commonly interpreted as a measure for complexity. The lowest value *K=0* means that the decisions do not depend on each other, while the highest value *K=N-1* characterizes a situation, in which each decision depends on all the others.

[10] In more complex hierarchical organizations, Rivkin (2002) shows that a firm may get stuck at a sticking point that is not a local peak on the fitness landscape of the overall organization. In our model, all sticking points are either local or global peaks.

In period $t = R$, the firm partly replicates its vector of decisions. This replication process may or may not be perfectly accurate: $\varepsilon \in \{0,...,N\}$ decisions out of N decisions may not be replicated correctly. Technically, a replication error is implemented by a flip from 0 to 1 (or 1 to 0). The ε decisions affected by replication errors are randomly chosen among the whole set of N decisions. In our analyses, the performance in the first 200 periods always reflects the performance of the organizational unit that creates the template or best practice. The following 200 periods reflect the performance of the unit that "receives" the template.[11]

Since any replication error dislodges the firm from its current local or global peak, we let the firm search locally again for another 200 periods. By period 400, the firm is again in either a local or global peak. Figure 1 summarizes the basic aspects of our simulation model.

<Insert figure 1 about here>

In the analysis section, we always report the average results for 50.000 independent replications. This guarantees that the results are not confounded by stochastic effects (of, for example, the (stochastic) local search process, the initial random location on the performance landscape etc.).

3. Analysis

In our first set of experiments, firms are searching in performance landscapes of moderate complexity (N=10, K=4). Figure 1, left panel, reports the (normalized) performance for the first P=400 periods for firms which experience in period in R=200 no replication errors (solid line), small replication errors (errors=2, dashed line), and large replication errors (errors=9, dotted line).

<Insert figure 2 about here>

[11] The "sender's" performance is not affected by the replication error; performance in t=201 to t=400 equals performance in t=200. In our model, we consider the case in which a template is transferred to only one receiving unit. Yet, our results also generalize to multi-unit transfers if we assume that there is no inter-unit learning. It is also important to note that we assume that replication is process that has a distinct start and end, i.e. after period t=201, the receiving unit is only learning through local search (rather than by imitating the "sender").

Both small and large replication errors have a strong immediate negative performance effect in t=R=200 (see Figure 1, right panel, solid line). In the long run, large errors still come at cost: the dotted line in Figure 1, right panel, shows the long-run difference between the performance of firms which suffer from replication errors and firms with no replication errors. Small errors, in contrast, even outperform the benchmark case.

In the following section, we will seek to uncover the mechanisms through which small replication errors can improve average long-run performance and to identify conditions in which the performance effects of replication errors are particularly pronounced. Specifically, why do we observe this inversely U-shaped relationship between size of replication errors and long-run performance? Under which conditions do we observe positive long-run performance effects of replication errors?

Two things are particularly worth noting here. First, replication errors can improve long-run performance only if they lead to the discovery of an alternative practice, an alternative that is better than the current template; if, however, errors can be corrected easily, performance may suffer temporarily but sooner or later the firm converges again to the original template's performance. In other words, replication errors can only have lasting performance impact if they are strong enough to make them hard to correct. Second, in period t=1, all firms start their search process at a randomly chosen location on the performance landscape (with an average performance=0.5).

How can small replication errors improve average long-run performance?

Replication errors change long-run performance only if they trigger exploration, i.e. the firm is permanently dislodged from the local peak it is has achieved by t=R=200. Average long-run performance improves is the peak achieved by period t=400 is higher than peak abandoned in t=R=200. Thus, one potential reason why small replication errors improve long-run performance could be that they lead to the discovery of better peaks in t=400.

In Figure 2, we examine whether replication errors can lead to the discovery of better peaks (i.e. better than the peaks of period t=200). The dashed line shows the performance in t=400 for different levels of replication errors for those firms that had been permanently dislodged from the position that they held in t=200. The solid lines shows the average performance in t=200 (by that time, all firms have converged to either a local or global peak).

<Insert figure 3 about here>

Except for very small replication errors (error size=1), all other errors lead to the discovery of peaks that are below the average local peak in t=100 (for error size=0, firms simply never abandon their t100-position). The larger the error is the smaller is the peak that is discovered by period t=200. In other words, replication errors only lead to a permanent change in performance if they dislodge a firm from its current local peak and let it – sooner or later – converge or discover a different local peak. With the exception of very small replication errors, however, this new local peak is on average always worse than the abandoned local peak. Thus, the performance increase for small replication errors cannot be attributed to the discovery of better practices. If replication errors lead a firm to permanently abandon an established practice, the new practice it will ultimately discover is worse than average practice discovered through random search by period t=100.

The size of the replication error may not only affect which peaks are discovered but also which peaks are abandoned. Large replication errors have higher probability to permanently dislodge a firm from its peak than small errors. In Figure 3, the probability that a firm is dislodged from its t100-peak is plotted on the left y-axis (solid line). This probability is an increasing function of the size of the replication error (x-axis). For errors of size=10, it approaches 100%. The dotted line (right y-axis) shows the average performance of the peaks that are abandoned for different levels of replication errors. This is also an increasing function of the size of the replication errors.

<Insert figure 4 about here>

In sum, firms that experience large replication errors are more likely to permanently their current practice than firms with small replication errors. In addition, the practices that they abandon are – on average – better performing than those practices abandoned by firms that experience only small replication errors. In other words, a firm that experiences a small replication error only abandons its current practice if it is a low-performing (below average) practice. Large replication errors, in contrast, let firms abandon almost any practice, regardless of its performance.

The reason is that in the NK model, there is a strong positive correlation between the height of a local peak and the size of its basin of attraction (Kauffmann 1993, Rivkin 2000, Gavetti and Levinthal 2002, Siggelkow and Levinthal 2003). Low local peaks have smaller basins of attractions than high local peaks. As a result, escaping the basin of attraction of a low local peak is easier than that of high local peak.

Consider, for example, a firm which experiences a replication error of size=2 in period t=R=200. If it sits on the global peak, this global peak is associated with a large basin of attraction. Even if the replication error drives the firm several "steps away" from the global peak, it will still find itself in the global peak's basin of attraction. Sooner or later, it will find back to the global peak (through the local search process). Now, let us assume that the firm sits on low local peak in the t=R=200. A low local peak is associated with a smaller basin of attraction. The replication error will drive the firm out of the peak's basin of attraction. Thus, small replication errors lead to the abandonment of below average peaks. Large replication errors, in contrast, do not distinguish properly between low or high peaks – both are abandonment with a probability of almost 100%.

Figure 4, panel A, summarizes our insights on how replication errors affect the quality of the peaks abandoned and discovered. The solid lines shows the average performance in t=200, conditional on that the position was abandoned permanently (this line corresponds to the dashed line in Figure 3). The dashed line shows the average performance in t=400, conditional on that this position was not the firms position in t=100 (this line corresponds to the solid line in Figure 2). The dotted line is simply the difference between these two lines (right y-axis): conditional on that a replication error leads a firm to abandon its period-200-position, what is the net performance effect between the new peak and the abandoned peak?

<Insert figure 5 about here>

This net effect is positive for small replication errors and decreases to negative levels for large replication errors. In Figure 4, panel B, we multiply this net effect between discovery and abandonment ("quantity of exploration") by the probability of exploration ("quality of exploration", compare Figure 3). The resulting line matches the shape of the long-run performance effects of replication errors (in Figure 1, left panel).

In sum, the inversely U-shaped relationship between size of replication errors and long-run performance is the consequence of a monotonic increase in the probability of exploration in error size and a monotonic decrease in the performance gains from each exploration event. In other words, small replication errors have a low probability of triggering an exploration event (i.e. the local peak of t=R=200 is abandoned permanently) but if the firm explores an alternative peak, this new peak will - on average - be better than the abandoned. With large replication errors, in contrast, the probability of abandoning the current practice is very high. Yet, the net effect between the performance of the new peak and the abandoned peak is at best zero if not negative. As a result, firms cannot gain from large replication errors. Both, the abandonment and discovery effect, are driven by the positive relationship between the performance of a local/global peak and the size of its basin of attraction.

When are long-run performance effects most pronounced?

Some of the statistical properties of Kauffmann's NK landscape model are well-known. For example, the positive correlation between the size of the basin of attraction and the performance of a local peak is particularly strong for small K (Kauffman XXXX, p.62). Given that both the abandonment and discovery effect discussed above are driven by this positive correlation, we should expect the positive (negative) long-run performance effects for small (large) errors to vanish with increasing K. Our analysis confirms this intuition: the relative performance effects are strongest for K=2 and K=3. For K=9, there are not positive effects of small errors. Figure 5 reports the average performance for t=1, t=200, t=R=201 (time of replication), and t=400 (long-run performance).

<Insert figure 6 about here>

For K=0, the performance has only a single peak (whose basin of attraction is the entire decision space). Any replication error will only temporarily remove the firm from the global peak. Sooner or later, it will find back its way to the global. Neither small nor large replication errors have any permanent performance effect.

In our analyses above, errors are random in that the affected dimensions of the choice vector are chosen randomly. For example, an error of size=1 may affect any of N decisions of the choice vector. Yet, for K<N-1, the N different decisions might be quite different in the way they affect value of other decisions (and the way they are affected by other decisions, compare Rivkin and Siggelkow 2007). Thus, we also examined the implications of errors of the same size on choices that are more or less dependent on other choices. Replication errors that affect independent decisions (i.e. decisions that are neither affected by other decisions nor affect other decisions) have no long-run performance effect. Replication errors are self-correcting. For all other kinds of decisions, the general pattern (of positive long-run effects of small errors and negative long-run effects of large errors) persists. Rivkin and Siggelkow (2007) also demonstrate that the same combinations of N and K can generate quite different numbers of local peaks, depending on the type of interaction matrix. Thus, we also explored how the number of local peaks – holding everything else constant – affects our results. Our key results hold for performance landscapes with many local peaks. With just a few local peaks, the probability that the firm converges to the global peak by period R is very high. Obviously, if your practice is already optimal, there is nothing to gain from further search (triggered by incorrect replication); the benefits of small replication errors disappear while the costs of large replication errors remain.

3. Discussion and Conclusion

In our study, we are interested in the performance implications of replication errors. Replicating a successful “template” or best practice in a number of different economic settings is an important strategy for growth and performance improvement (Winter and Szulanski 2001). Using an NK simulation model, we find that replication errors always have negative short-run performance consequences. In the long-run, however, small replication errors can even increase performance: replication errors can help firms to abandon its current practice and discover a better practice. This, of course, raises the question: Why should the new practice be better than the abandoned practice?

In the NK simulation model, some configurations of N and K generate strong positive correlations between the height of local peaks in the performance landscape (associated with different practices) and the size of their basins of attraction. This has two important consequences: replication errors are more likely to dislodge firms from low peaks than for high peaks and, once a firm has abandoned its current position on the performance landscape, it tends to move to relatively high local peaks.

In our study, we disentangle these two effects of abandonment and discovery. Interestingly, we find that firms that can escape their basin of attraction will towards below average peaks. In other words, if the firms were dispersed randomly over the landscape, on average, local search processes would have let them to converge to peaks with a higher performance. Yet, since firms on low performing peaks can escape their basin of attraction, the resulting net effect (of discovered peaks minus abandoned peaks) is positive and, on average, performance is increasing. In simple words, replication errors increase average performance because firms on very low peaks move to bad but better peaks; firms on good peaks, in contrast, stick to their current peak.

Recent empirical research suggests that, in the replication process, deviations from the template may have negative performance implications, both in the short run (Capetta and Szulanski 2005) and long run (Winter et al. 2011). Yet, there is also some evidence that deviations may have some positive performance implications. From an adaptation perspective, these positive effects might occur, for example, if the template is adapted locally, resulting in a better fit to the local host environment (Williams 2007). From a search perspective, deviations from a template might help organizations to dislodge from a suboptimal template. In our study, we adopt the latter perspective and examine the performance implications of errors in the replication process.

While the topic of replication accuracy has been subject to many studies, our study extends prior research in several important ways. First, existing contributions often suggest that organizations should seek to replicate a successful practice as accurate as possible (Winter and Szulanski 2001, Winter et al. 2011). Any deviation from this template is sought to be very costly. This is certainly true if the current template offers no further room for improvement, i.e. it is a global optimum. It is also true that all replication errors generate – often – severe immediate costs. In the long run, however, some replication errors can help organizations to improve their current template. In our study, we identify the type of replication errors that can enhance performance in the long run. We find that small replication errors that only affect 1-2 elements of template can improve long-run performance. Larger errors are associated with high long-run performance decreases. Interestingly, these small errors should affect elements of the template that are not independent. Replication errors in independent elements can be corrected easily – they neither decrease nor decrease long-run performance. Only if errors occur when seeking to replicate dependent elements, the organization might get dislodged from its current template. One might be tempted to conclude that these findings are inconsistent with prior research by Rivkin (2000, 2001) on replication. Yet, in his modeling efforts, the template is always the global peak. In more abstract terms, we extend his analyses by also including the possibility that a template is only a local peak. At first sight, our study also contradicts recent empirical research by Winter et al. (2011). Winter et al. (2011) find that any deviation from template decreases the survival chances of franchise units. Their analysis is based on data of the U.S. units of a single, large, established nonfood franchise chain. Thus, one reason why they do not find any positive implications of small errors could be that in this case, the template is either optimal or close to the optimum. Another reason might be that they focus on survival while we are interested in long-run performance. As described above, all replication errors, regardless of their size, have immediate strong negative performance consequences. Units that deviate from the template may not survive until they can reap the benefits of small deviations.

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Figures

Figure 1: Ilustration Simulation Model

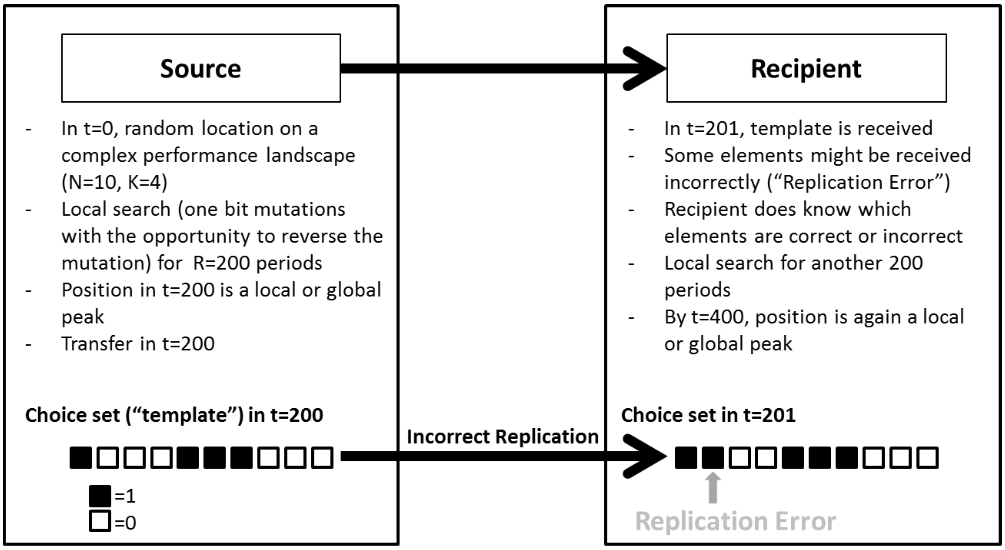

Figure 2: Performance Implications of Replication Errors

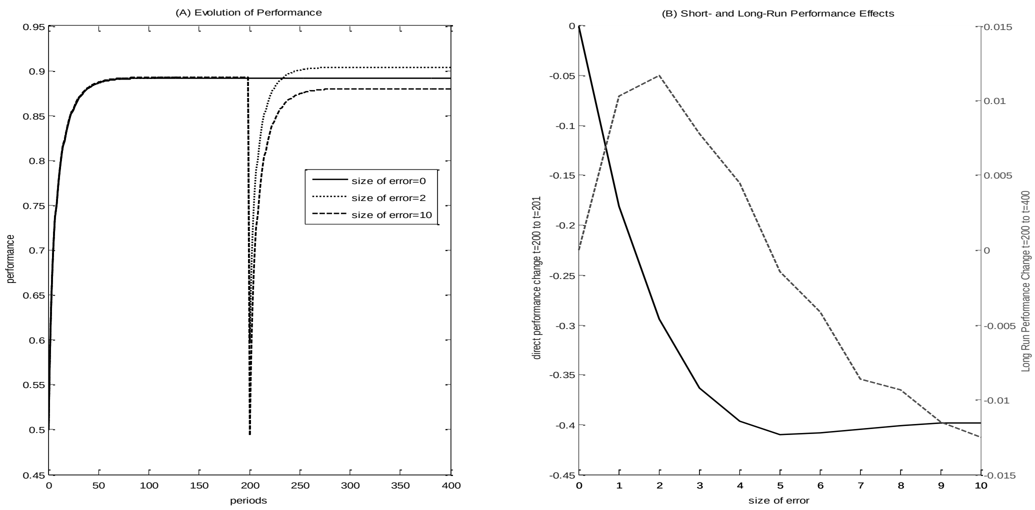

Figure 3: The Performance of “New” Peaks

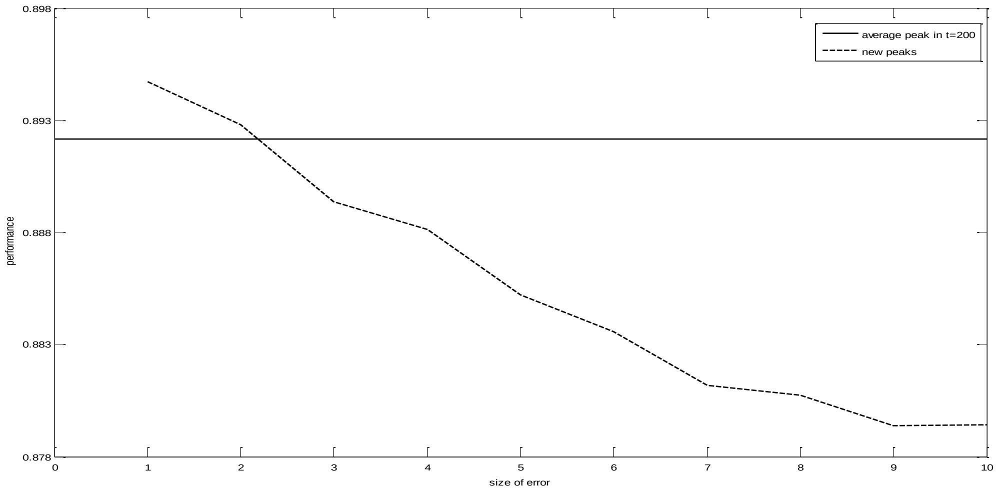

Figure 4: Abandoning Current Peaks

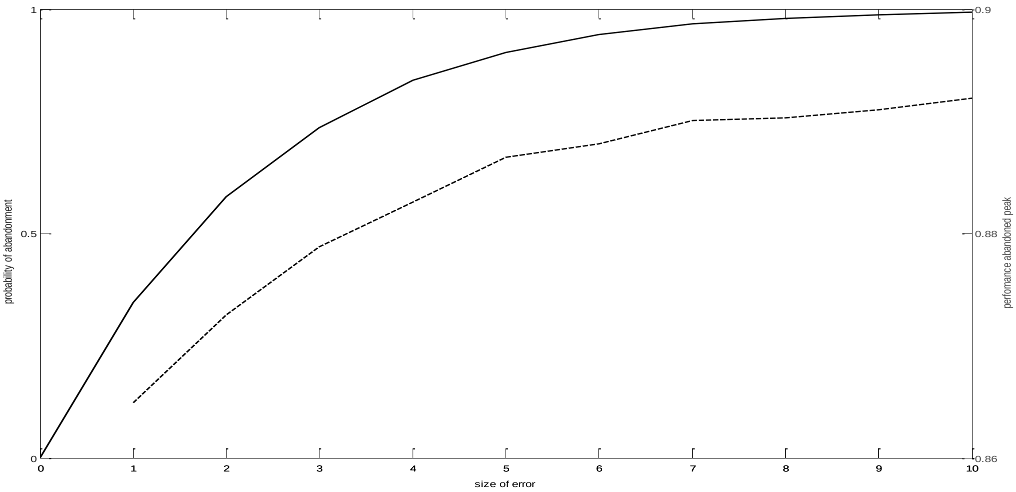

Figure 5: Combined Effects of Discovery and Abandonment

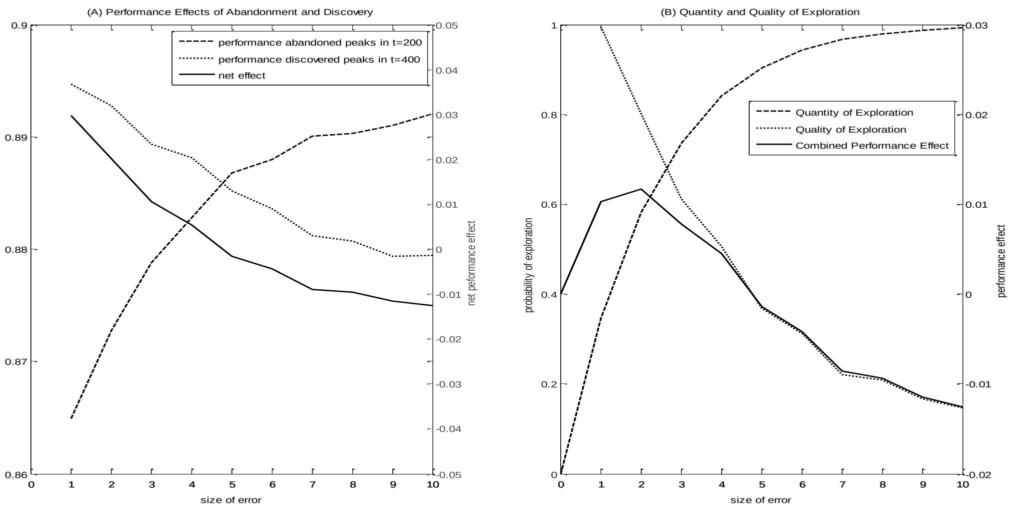

Figure 6: Replication Errors in Complex Landscapes