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DYNAMIC ADAPTIVE STRATEGY-MAKING PROCESSES FOR ENHANCED STRATEGIC RESPONSIVENESS

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INTRODUCTION

The frequent reporting of major corporate incidents and restructuring efforts combined with the sobering impacts of financial crisis over the past decade has focused our attention on the importance of strategic responsiveness in turbulent business environments. The global business environment is exposed to potentially extreme economic events (e.g., Taleb, 2007), technological shifts (e.g., Bettis and Hitt, 1995), and natural phenomena (e.g., Meyer and Kunreuther, 2017) that create disruptive strategic discontinuities. Organizations are facing complex dynamic business contexts where risk events often are difficult to predict and therefore hard to manage and respond to. Various studies suggest that large companies have a 10 percent chance of losing more than 25 percent of their market value (in a single month) due to dropping demand, flawed products, or competitor moves without being able to recover the loss (e.g., Andersen and Schrøder, 2010). Hence, the life expectancy of established Fortune 500 firms is waning with only a fifty-sixty percent chance to survive in their current forms over the next decade (e.g., Goodburn, 2015). That is, the ability to make proper adaptive decisions and engage in effective responsive actions seems as important as ever in a risk landscape characterized by high uncertainty and a potential for extreme events. This has relevance for public policy-makers and corporate decision-makers alike as the ability to respond to the changing conditions affect corporate performance and thereby the wealth creating business activities that support society.

To assess the implications of adaptive decision-making and responsive strategies, we develop a simple model of firms with heterogeneous response capabilities as they experience ongoing environmental changes and adjust business activities to achieve a better fit with the evolving context. As a common approach in social science studies, we introduce a (simple) generic computational model to gain deeper insights into internal organizational processes that are hard to study empirically (e.g., Levinthal and March, 1981; March, 1988; Levinthal, 1997). We first establish the basic strategic responsiveness model and extend it subsequently to investigate the effects of more fine-grained strategy-making processes.

Computational analyses have demonstrated how strategic responsiveness is associated with the favorable performance and risk outcomes consistently observed in empirical data of corporate performance collated across different industry contexts. This preliminary result can be derived as the consequence of a generic model that captures the adverse (penalty) effects of a poor strategic fit, or environmental mismatch, caused by failed adaptation linked to various irrational decision behaviors. The generic model is extended by introducing a more refined strategy-making process that incorporates decentralized experiential insights as the source of ongoing updates to the strategic projections made in the central planning process. The analyses show how this dynamic adaptive strategy-making approach is associated with enhanced performance outcomes and lower performance variance.

The following frames the study in the extant management literature before the rationale of the generic strategic responsiveness model, and the logic of interactive strategy-making, are developed and explained in more detail. We then present the effects of the generic strategic responsiveness model where results are validated empirically by industry data before the model is extended to consider the favorable effects of interactive strategy-making. Finally, we use the analytical results to consider adaptive strategies discussing the implications for effective strategy-making processes.

BACKGROUND

In empirical studies it is consistently observed how some (a few) firms outperform their peers in the industry within given time-periods and display inverse risk-return relationships (e.g., Andersen, Denrell and Bettis, 2007) while the majority of firms are contained in an extreme left-skewed tail of poor performers (e.g., Alfarano *et al*., 2012; Bloom and Reenen, 2007; Williams *et al*., 2016). This display of extreme negative performance outcomes across industries is a highly systematic phenomenon that typically is overlooked in mainstream management research and therefore remains underexplored and unexplained (e.g., Boisot and McKelvey, 2011).

The observed phenomenon of some firms outperforming in given time-periods with favorable risk-return effects is a regular empirical artifact with particular significance in turbulent environments (Bromiley, 1991a, b; Henkel, 2009). This reflects the so-called 'Bowman paradox' where high average performance is associated with low variance in performance outcomes over given periods typically measured as five-year intervals in empirical studies. The phenomenon can be derived as the effect of heterogeneous organizational adaptation processes where firms within the same industry display differences in their ability to respond to major environmental changes. Andersen *et al*. (2007) use empirics, simulations and mathematical derivations to demonstrate that heterogeneous strategic response capabilities among firms will lead to the inverse risk-return relationships. Hence, for a given technological state of the economy a few firms with optimal adaptive capabilities will show favorable returns whereas a great many of the firms realize (extreme) adverse outcomes in a negative tail. This set of conditions is imperative for the inverse risk-return relationships that are closely associated with the negatively skewed performance outcomes (Andersen and Bettis, 2014; Henkel, 2009). All the while, there is little evidence that effective strategic adaptation of outperforming firms can persist over multiple, or extended time-periods, which highlights the challenge of effective strategic adaptation. It is difficult to achieve and hard to retain. Accordingly, the results of computational model simulations, validated further by empirical data, find that longitudinal risk-return relationships are significantly lower in absolute size compared to the cross-sectional risk-return outcomes (Andersen and Bettis, 2015).

Strategic adaptation can essentially be conceived as an ability to gain updated information about changes in the business environment and engage in responsive actions across the organization, so the firm moves towards a better fit with the prevailing environmental conditions. A featured literature also refers to this phenomenon as dynamic capabilities described as sequential processes of environmental sensing, opportunity seizing, and reconfiguring of organizational activities to respond better to the changing environment (e.g., Teece, Pisano and Shuen, 1997; Teece, 2007). However, strategic decision-making processes rarely circumscribe to the idealized prescriptive conditions due to a variety of imperfections like lack of information, uncertainty, time pressure, and cognitive limitations that force decision-makers to act under bounded rationality. Nonetheless, some organizations are markedly better at adapting to the changing conditions than others and are more likely to create value from the ability to create a better strategic fit with the business environment. Such a strategic responsiveness model with heterogeneous response capabilities among firms is associated with favorable risk-return outcomes (Andersen *et al*., 2007). Their study analyzes the cross-sectional risk-return effects across firms operating in similar industry contexts but it does not consider the extent to which particular strategy-making processes may be associated with differentiated effects on performance outcomes. We attempt to address this shortcoming in the subsequent sections presenting such extensions to the proposed model and assessing the implications for effective strategic adaptation.

The basic perspective or argument is that strategy conduct relates to managerial decision-making where good strategic decisions are associated with better outcomes and thus significantly higher and more stable performance outcomes. This view is expressed in a simple strategic responsiveness model reflecting enacted strategic decisions, or responses, to adapt the firm strategy where the effective responses lead to favorable performance and risk outcomes. This assumes more or less effective strategic planning decisions, e.g., captured by a major organizational move per period. However, the model is subsequently extended to consider a more nuanced interactive strategy-making process combining a central planning approach with decentralized emergent initiatives in response to changes in the local task environments. The dispersed, and more frequent local responses, generate faster experiential insights that can update the strategic plans and restructure the organizational activities accordingly on an ongoing basis. We analyze the (expected) effects on the basic model from faster updating of the planned projections compared to the generic responsiveness model.

The generic model is expressed as a performance function reflecting the firms' ability to respond to the business environment displaying heterogeneous response capabilities across peers in the industry as they respond to assumed changes in the context. Based on strategic fit theory, we model performance as (partially) determined by the fit between the firm's actual, or realized, (strategic) position and the true (market) conditions at given points in time (e.g., Fiegenbaum, Hart and Schendel, 1996). Hence, a firm achieves high performance outcomes when the strategy and organization structures are internally consistent and aligned with conditions in the prevailing conditions in the environment (e.g., Pennings, 1987; Siggelkow, 2001). This reasoning is consistent with a resource-based economic logic, which argues that superior performance outcomes arise from the best applications of unique firm resources (Barney, 1986; Winter, 1995; Barney, 2002).

MODEL DEVELOPMENT

In a dynamic complex environment where the context is constantly changing, the ability to maintain a good strategic fit over time requires an ability to sense ongoing market changes and orchestrate responses that continue to bring the firm towards a better fit with the market conditions (Barney, 1986, 2002; Fiegenbaum *et al*., 1996). Organizations that can perceive the ongoing market changes and more accurately assess the efficacy of proposed resource combinations in responsive propositions are more profitable because they acquire the resources at lower costs than competitors in the industry (Barney, 1986). The strategic responsiveness, and dynamic capabilities, concepts depict such an organizational ability to identify available resources and activate them in effective responses to the changing market conditions (e.g., Andersen *et al*., 2007; Teece *et al*., 1997; Teece, 2007).

Hence, the profitability of competing firms within a given industry context depends on their relative ability to sense ongoing market changes and devise effective responses to the changing environmental conditions. This simple profit dynamic can be expressed in a formal model where a given resource endowment accessible to a firm will enable it to generate an optimal level of performance, K, using state-of-the-art management technologies. Hence, if a firm can respond perfectly to the environmental conditions in the market at a given point in time by matching current requirements for, e.g., customer demand, technology applications and management processes, it will generate the optimal performance outcome. The optimal performance level, K, can differ among firms in the industry as business prospects and resource access are different and may vary stochastically over time due to environmental uncertainty and unexpected developments. To the extent a single firm cannot sense the ongoing market changes accurately, it will not be able to match the changing conditions and gain strategic fit with the new requirements through effective responses, so performance will drop below the optimal level, K. This relationship is expressed in the following performance function for a given firm in period t:

$$R_t = K - b|c_t - d_t|^a - C_t \qquad (1)$$

R_t = performance, or return, for a firm in period "t"

c_t = the market conditions that prevail at time "t"

d_t = actual position realized by the firm at time "t"

$|c_t - d_t|$ = mismatch between market conditions and firm position at time "t"

K = maximum possible performance, or return in the industry

a, b = coefficients that penalize the performance of a mismatch

C_t = the costs of sensing and engaging in adaptive responses at time "t"

t = a time-period, e.g., depicting years or quarters [t = 1 , 2 , 3 … T]

In the outlined model, c_t can be interpreted as an important market factor at time t, such as, total demand, customer need, technology choice, and the like, where d_t reflects the firm's position on that factor at time t after sensing and responding to observed market changes during t-1. Managers (and employees) in the firm observe ongoing market changes from period to period and generate adaptive responses to gain a better fit with the environment in the coming period. They identify responsive actions and try to deploy resources in responses that can give the firm a better match between its actual position and prevailing market conditions at any point in time. It follows intuitively that a firm with a better ability to match the market conditions consistently over time will score higher returns and with less variation in those outcomes from period-to-period, i.e., higher performance corresponds to a lower level of performance risk. In a portfolio of firms with heterogeneous response capabilities competing in the same industry, this effect will be expressed as an inverse risk-return relationship, i.e., the correlation between average return and the standard deviation in return across firms over a given time-period will be negative.

The coefficients b and a in the model are assumed to be positive, so any deviation from a perfect fit between actual position and market conditions ($d_t \neq c_t$) will incur a mismatch penalty that results in suboptimal performance outcomes where b expresses a linear effect and a an exponential effect on performance. The larger the values of b and a, the higher the mismatch penalty with a, the exponential coefficient, exerting a more pronounced influence than b, the linear coefficient. The higher the coefficients of b and a, the more hostile the competitive environment with more adverse effects on performance in case of a mismatch, or poor strategic fit, with the environment. This means that the inverse risk-return phenomenon will be stronger in hostile, or highly competitive industries, observed as significantly higher negative correlations between average return and the variance in return.

The simple one-factor model can in principle be extended to consider multiple (M) (strategic) market factors, e.g., $d_{1,t}$, $d_{2,t}$, $d_{3,t}$, … $d_{m,t}$, … $d_{\mathrm{M,T}}$, and the performance function is then extended accordingly:

$$R_t = K - \sum b|c_{m,t} - d_{m,t}|^a \ ; t = 1 , 2 , 3 \ldots \mathrm{T}; m = 1, 2 ,3 \ldots \mathrm{M}$$

This arguably makes the analysis more realistic and complete, but it also makes things somewhat more complicated as we are attempting to develop a general logic with basic arguments and (relatively) simple reasoning. Since the implications derived from the simple model with only one market factor are similar to those derived from a more complex model, we base the ensuing analysis on the simple generic version of the model.

Hence, the argument is that the larger the discrepancies between the actual positions of the firm and the prevailing market conditions, the more firm performance will be reduced from the optimal possible level with a given resource endowment. And, if the firm cannot match the market factors (c_m's), then performance will suffer in proportion to the size of the mismatch dependent on the competitive nature of the industry. The more competitive and hostile the market environment, the higher the penalties imposed on the mismatched positions. The optimal performance outcomes are achieved if the firm is able to perfectly match the actual positions, d_t (or d_m's) with market conditions c_t (or d_m's) at all points in time.

However, organizations are rarely able to match the market conditions completely, due to imperfect information, uncertainty, organizational inertia, judgmental errors, time pressure, etc. Reflecting these more realistic conditions, we can assume that d_t and c_t develop stochastically following a normal distribution with variance σ^2 in each period t (Andersen *et al*., 2007). As a consequence, most organizations are imprecise in their ability to sense environmental changes and agglomerate resources into effective strategic responses. This is obviously a very basic depiction of the uncertainties associated with strategic adaptation. Since we are facing evolving business contexts formed by human interactions, in contrast to (more) regular relationships observed in natural science, we are probably dealing with environments characterized as path-dependent random walks. For the same reason, we probably ought to describe the firm responses as adaptive learning processes driven by intelligent beings operating under bounded rationality, which after all is more in line with general management thinking where outcomes derive from conscious managerial decisions.

Hence, the market context the firms are operating in can be extended from a simple stationary stochastic process to a more realistic path-dependent random walk.

Static stochastic process: $c_t = c_0 + \sum_{p=1}^{t} c_p$; where $c_p = N(c_0, \sigma)$ (1)

Path-dependent random walk: $c_t = c_0 + \sum_{p=1}^{t} c_p$; where $c_p = N(c_{p-1}, \sigma)$ (2)

Similarly, the firm responses can de depicted as a simple stationary stochastic process, or a more realistic organizational learning process where the firm is sensing to gain insights about ongoing market changes.

Static stochastic process: $d_t = d_0 + \sum_{p=1}^{p} d_p$; where $d_p = N(d_0, \sigma)$ (3)

Adaptive learning process: $d_t = (l)c_{t-1} + (1 - l)d_{t-1}$; l = learning rate, $0<l<1$ (4)

Depicting the organizational responses as an adaptive learning process responding to a path-dependent random walk is a much more precise and realistic specification of the generic strategic responsiveness model with some interesting implications. The initial responsiveness model (Andersen *et al*., 2007) analyzed the effects of adaptation to the environment described by two stationary stochastic processes. The updated model version leads to performance outcomes that are more compatible with the empirically observed (cross-sectional and longitudinal) risk-return relationships.

Successful strategic adaptation, or adaptive learning, requires an ability to create a good *fit* between the actual position and the prevailing market conditions at any given point in time by engaging in effective firm responses over time. As market conditions change following new trends and influences from emerging events, the firm must sense these changes and devise adaptive responses that can moderate the firm's business activities, so they provide a good strategic fit. This corresponds to the idea behind the dynamic capabilities concept as constituting an organizational ability to orchestrate effective responses to the changing market conditions (e.g., Helfat *et al*., 2007; Teece, 2007).

The generic strategic responsiveness model describes such a dynamic adaptation process where the firm is sensing the ongoing changes and try to engage in responsive actions to form a better match with the prevailing market conditions period-by-period (Figure 1). The firms operate under similar market conditions (within a given industry context), but display heterogeneous response capabilities, e.g., they engage in more or less effective learning processes. Due to the penalty associated with (the size of) the mismatch between the actual positions and market conditions period-by-period, the firms will realize vastly different performance outcomes over time as a function of the competitive intensity among peers even though they operate in the same market context.

Insert Figure 1 about here

The formalized model can be used as a computational platform to generate simulated performance outcomes among firms in a (fictive) industry providing periodic profit outcomes (t = 1, 2, 3, … T) that can be interpreted as annual returns. The performance data generated from the model simulations allow us to examine average returns and standard deviation in returns within given time-periods to determine cross-sectional and longitudinal risk-return relationships across firms and outlining the resulting performance distribution.

The average return and standard deviation in returns are determined for each firm for the chosen time-period, for our purposes set at, e.g., 25 consecutive periods. The cross-sectional risk-return relationship is then calculated as the correlation coefficients between the average returns and the standard deviation in returns based on a sample of 5,000 firms in the industry. The longitudinal risk-return relations are determined from the average return and standard deviation in return over 5-period intervals calculating the correlations between average 5-year returns and the standard deviation in returns in subsequent 5-year periods (e.g., Fiegenbaum and Thomas, 1986, 1988). The adoption of 5-period sequences to measure average return and variation in returns corresponds to the approach taken in earlier empirical studies (e.g., Miller and Bromiley, 1990).

The model simulations produce risk-return outcomes that are quite comparable to those observed in analysis of empirical performance data and consistent with variations in the risk-return relationships observed across different industry contexts. Hence, Andersen and Bettis (2014) use simulations to find a cross-sectional risk-return relationship of -0.89 and a longitudinal risk-return relationship of -0,36 in the updated generic model. This compares favorably to empirically observed correlation coefficients ranging between -0.94 – -0.47 (cross-sectional) and between -0.85 – -0.14 (longitudinal). A quick examination of the computational findings suggests that the updated version of the generic strategic responsiveness model with a relatively low learning rate (l = 0.1) generates outcomes that are quite plausible compared to the observed empirical data on firm performance. Hence, a stochastic path-dependent market environment where firms display modest ongoing learning produces risk-return characteristics similar to those observed empirically. The simulated performance outcomes further show that the responsiveness model with low adaptive learning generates left-skewed return outcomes with performance truncated at the upper level (Figure 2). These outcomes are consistent with the observations derived in previous empirical studies of accounting performance (e.g., Bowman, 1980, 1982; Henkel, 2000, 2009).

Insert Figure 2 about here

MODEL EXTENSION

It is suggested that timely adaptive responses associated with dispersed decision authority in a formal organization structure is associated with stronger resilience to the effects from environmental changes (Van der Vegt *et al*., 2015). That is, effective strategic adaptation seems to thrive on resources devoted to autonomous entrepreneurial initiatives that may (or may not) contravene the rationale of a firm's intended strategy or strategic plan (e.g., Andersen, 2015a; Bower and Gilbert, 2005; Burgelman, 1983, 1996; Pedersen, Ritter and Andersen, 2020). Hence, the combination of (slow) analytics based action plans and (fast) decentralized initiatives can form an effective adaptive dynamic (e.g., Andersen and Hallin, 2016; Burgelman and Grove, 2007) as displayed in an interactive strategy-making approach (e.g., Andersen, 2015b). The strategic planning process is *slow*, because the analytical considerations, deliberations, and discussions constitute an intense and time-consuming sense-making exercise aimed to better understand the surrounding competitive landscape and assess alternative strategic options. The autonomous local initiatives are quick responses to ongoing changes with no need to ask for permission at higher decision nodes thus generating experiential insights from immediate outcomes without bureaucratic delays as a basis for *fast* updated learning.

Humans think in two ways adopting fast and slow systems that are complementary (Kahneman, 2011). The surrounding market conditions are observed in the fast system and the observations are interpreted in the slow system. The human brain seems to operate through complementary fast and slow systems that have been proven through evolution to be very successful in dealing with a changing and at times erratic environment (Kahneman, 2011). The fast system operates with little effort and observes outcomes from various interactions with the surrounding environment. The slow system is an effortful conscious activity that interprets outcomes from interactions with the environment to make sense of the changing context through data driven analytics and facts based reasoning. The interplay between fast observations and slow reasoning can be juxtaposed onto an organization, or a firm, where the central analytical processes try to extrapolate into the future while the decentralized emergent processes respond to and learn from immediate insights from the changing business environment.

The slow planning and control process can form a shared cognitive understanding of the competitive environment engaging people in the exchange and discussion of the experiential insights (e.g., Andrews, 1987; Ansoff, 1988; Hill *et al*., 2000). It can involve decision-makers from different parts of the organization to generate a shared cognition across a broad set of constituents with different sets of expertise and experiences. Hence, central planning can be interpreted as a discourse to reconcile diverse insights and thereby shape a common understanding of potential strategic options to the firm (e.g., Hendry, 2000; Page, 2007) that provide guidance and solutions to on-going developments. The fast local initiatives where empowered managers in different parts of the organization can decide and interact with various stakeholders to try out alternative ways in view of evolving market changes can generate relevant current insights. The autonomous responses allow for local experimentation as a way to uncover opportunities and solutions (Burgelman, 1996; Burgelman and Grove,

2007) that can inform the central planning process. This combination of fast and slow processes can stimulate an underlying *dynamic* that enhances an organizational ability to take actions, interact, and adapt. Hence, a dynamic based on fast and slow processes can create a system that adapts activities in emergent non-linear ways but still in line with a common understanding of the context and guiding principles.

The combination of two strategy-making modes in an organization, a fast emergent approach of decentralized local initiatives, and a slow intended approach with analytically derived projections of adaptive action plans can arguably reproduce the adaptive dynamic of the human brain. We can think of this as the updated 'action plan' generated from an *annual* planning process as the outcome of analytics based reasoning to find the best way to implement adaptive actions across the organization in view of the changing competitive market context. The other strategy-making mode can be described as 'local initiatives' taken by dispersed operational managers in response to observed changes in their local task environments as potential solutions to observed emerging developments (Figure 3).

Insert Figure 3 about here

The strategic planning process is typically conceived as a long-looped learning cycle based on feedback from a strategic control process assessed in periodic diagnostic budget reports. The local initiatives can be taken faster if the local managers have sufficient authority and slack to act locally without going through cumbersome and time consuming approval processes asking for permission at higher levels in the management hierarchy. This can be a source of initiatives for trial-and-error learning with a higher frequency than the annual strategic planning process testing what might work, and what might not work, in the changing market context, say expressed as quarterly action and learning loops. The slower process to generate action plans serves to create a common understanding across all players in the organization with the intent of coordinating various initiatives around a common set of guidelines. The faster process of taking local initiatives serves as a basis to explore for better solutions in the changing market and generate new valuable insights that (ideally) can inform the strategic planning deliberations

The analytical planning process can generate a deeper understanding about the competitive context and the ongoing market changes, but to be effective, the planning considerations need updated information from the field on a recurring basis to be current. This information is exactly what the autonomous dispersed managers gather in the form of experiential insights derived from local initiatives that respond to observed environmental changes. The important exchange of this information can happen through the implementation of interactive control systems (e.g., Andersen and Torp, 2019). Interactive controls is defined by the involvement of low-level managers and individuals in open discussions with top management in dialogues across hierarchical levels among all organizational members to better understand the market context under conditions of high uncertainty (Simons, 1990, 1991). These interactive discussions can be based on, or supported by, different already existing management reporting systems and do not really require a new set of reports (Simons, 1994). For example, Simons (1995, p. 109) suggests that "annual profit plans or budgets, second year forecasts, and strategic operating and financial plans" can be useful management reports for these open discussions. The interactive discussions of the management reports can "stimulate search and learning, allowing new strategies to emerge as participants throughout the organization respond to perceived opportunities and threats" (Simons, 1995, p. 91). This can update the information available for the strategic planning deliberations with more current and relevant experiential insights as a result of the interactive control intervention. The dialogue across hierarchies also provides top management with opportunities to discuss longer-term strategic objectives for local initiatives taken by autonomous managers. Interactive controls can therefore facilitate valuable two-way communication to collect updated insights from local initiatives and give direction to autonomous dispersed decisions.

DISCUSSION AND CONCLUSION

The generic strategic responsiveness model provides a framework for analyzing the effects of adaptive responses through computational simulations where outcomes can be validated by comparisons to empirically observed performance data. The study provides a more realistic description of strategic responsiveness as an imperfect adaptive learning process responding to an evolving stochastic path-dependent environmental context showing performance outcomes that are (more) compatible with the empirical evidence. The computational approach illustrates the effects on cross-sectional and longitudinal risk-return relationships associated with negatively skewed performance distributions. Yet, it offers no perspective on effects from more nuanced strategy-making processes. Therefore, we introduce an interactive strategy-making model that combines a fast emergent approach with a slow analytical approach thereby reflecting the basic principles of the cognitive dynamic ascribed to the human brain. This extended responsiveness model provides a basis for further analyses of strategic adaptation that can advance our thinking about how to achieve sustainable performance outcomes and enhance organizational longevity.

The expected positive outcomes from open information exchanges facilitated through interactive controls hinge on a number of assumptions, such as, executive receptiveness to experiences and insights from less powerful operational managers and a leadership style that fosters openness within a discursive organizational climate (Figure 3). The ability to generate insights from local initiatives depends on an organization structure with dispersed decision-power and sufficient organizational slack that give local managers leeway to take actions on their own. A proper balance between emergent local initiatives and the generation of central action plans are also influenced by executive characteristics like risk perception and overconfidence. High executive risk propensity and overconfidence will tend to make centrally planned actions dominate as opposed to incorporating insights from dispersed operational managers. These kinds of circumstantial details can be analyzed further in future extended responsiveness models and comprehensive empirical studies.

The ability to incorporate more frequent local learning loops and generate more diverse and specialized knowledge updates from dispersed operational initiatives can have distinct advantages as the ability to adapt organizational activities is accomplished more readily. The learning cycle in a strategic control process based on diagnostic budget reporting by comparison is a relatively slow and long-linked exercise where action plans incorporate projections of environmental data and past performance reports. This means that the (slow) planned adaptive responses have longer time lags than the (fast) emergent responsive initiatives generated in the local operational entities (Figure 4). Hence, the slow adaptive responses are associated with larger mismatches between actual positions and market conditions compared to faster emergent initiatives, which will resulting in lower performance outcomes and more extreme performance variations.

Insert Figure 4 about here

This reflects different information processing features linked to the interactive strategy-making modes that can be expressed in an extended responsiveness model where these outcomes are demonstrated from the computational simulation results. For example, the slow projections can be captured by an ARIMA time-series model with 'optimal' fit as an annual cycle (= four quarters) while the fast updates arise from stochastic assessments of past quarter market conditions. The simulated results can then be validated by comparing the empirical performance data categorized and grouped in accordance with the proposed influencers, e.g., power dispersion, slack, risk propensity and overconfidence. Incorporating different versions of the generic strategic responsiveness model will demonstrate that strategic adaptation with imperfect learning (a low learning rate) in a random path-dependent environment reproduces the cross-sectional and longitudinal risk-return relationships observed in the empirical data across industries. When the models consider adaptation costs, e.g., linked to sensing and adjustment processes, the performance outcomes show better correspondence to the empirical observations. In a turbulent market context with adaptation costs, an updated model with a low learning rate generates the highest performance and the lowest variance. We can also incorporate periodic environmental shocks caused by, e.g., technology shifts, competitive moves, new industry paradigms, etc. This extension can explain observed variations in the empirical risk-return relationships further over sequential time-periods.

To the extent we face increasingly dynamic and complex environments, we should consider the challenge of responding to irreversible non-linear developments and unpredictable events with abrupt and potentially extreme outcomes. We can think of many exogenous factors that might have such effects on the prevailing market conditions. These events can be modelled as environmental shifts in, say, demand conditions or extraordinary write-downs caused by one-off losses from various natural or manmade disasters. These situations can be modeled in extended simulations where shifts in market demand or dramatic cost increases challenge the adaptive capabilities reflected in increased periodic mismatches between actual position and market conditions thereby causing (somewhat) lower cross-sectional and (particularly) lower longitudinal risk-return relationships.

The analyses consistently demonstrate that the ability to engage strategic response capabilities in ongoing adaptive responses is associated with superior performance (average returns) and lower risk outcomes (standard deviation in returns) particularly in turbulent industry contexts. These findings imply that good (strategic) management conduct where a firm is alert and generates ongoing responses to the changing environment leads to better and more stable performance outcomes. This generally confirms the claims made by strategic responsiveness and dynamic capabilities arguments about the beneficial effects of strategic adaptation to accommodate changing market conditions. In this article, we show how extended strategic responsiveness models can be used as a reliable basis for more detailed studies of effective strategic adaptation combining computational simulations with empirical data analyses. We see much potential in this approach as a fruitful bridge between quantitative analyses and qualitative studies of the empirical evidence.

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Figure 1. The Generic Responsiveness Model of Strategic Adaptation

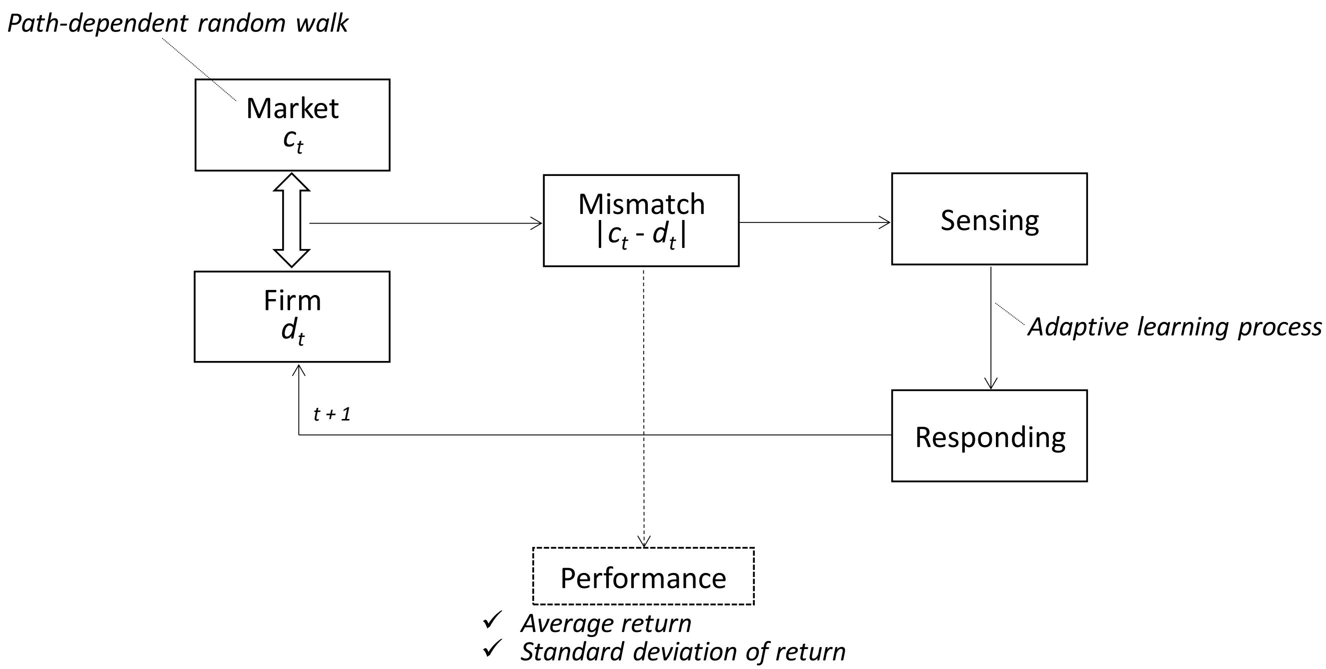
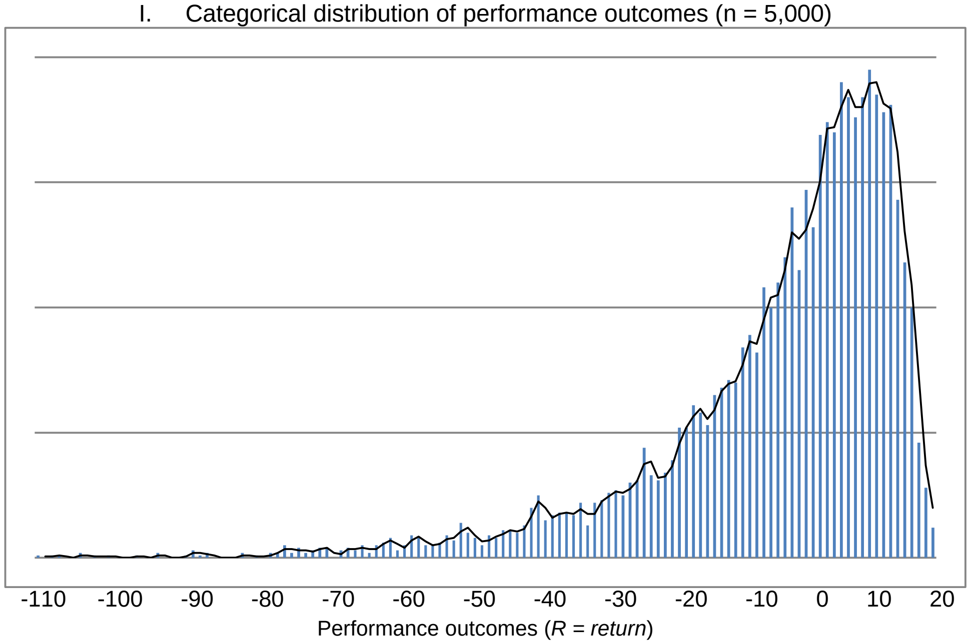


Figure 2. Distribution of Performance Outcomes from Model Simulation

(Adaptive learning against a random walk context)

(σ=2, a=2, b=1, l=0.1)

I. Categorical distribution of performance outcomes (n = 5,000)



Source: Andersen and Bettis (2014)

Figure 3. An Extended Responsiveness Model of Interactive Strategy-Making

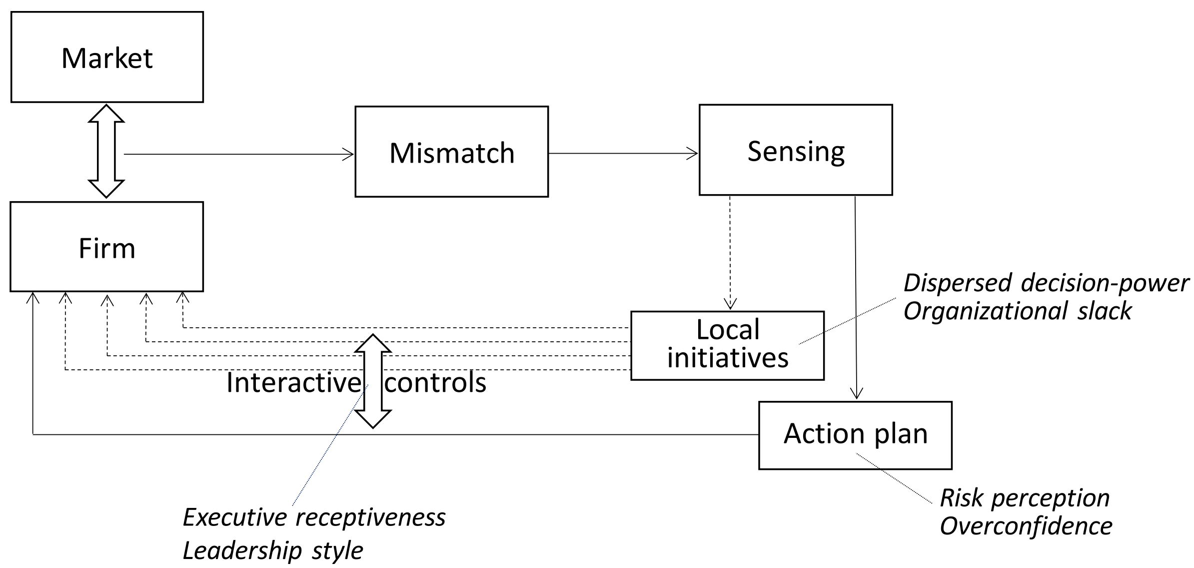


Figure 4. Effects of Fast (*emergent*) versus Slow (*planned*) Adaptation Processes