

Optimal Structure,
Market Dynamism, and
the Strategy of Simple
Rules

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Using computational and mathematical modeling, this study explores the tension between too little and too much structure that is shaped by the core tradeoff between efficiency and flexibility in dynamic environments. Our aim is to develop a more precise theory of the fundamental relationships among structure, performance, and environment. We find that the structure-performance relationship is unexpectedly asymmetric, in that it is better to err on the side of too much structure, and that different environmental dynamism dimensions (i.e., velocity, complexity, ambiguity, and unpredictability) have unique effects on performance. Increasing unpredictability decreases optimal structure and narrows its range from a wide to a narrow set of effective strategies. We also find that a strategy of simple rules, which combines improvisation with low-to-moderately structured rules to execute a variety of opportunities, is viable in many environments but essential in some. This sharpens the boundary condition between the strategic logics of positioning and opportunity. And juxtaposing the structural challenges of adaptation for entrepreneurial vs. established organizations, we find that entrepreneurial organizations should quickly add structure in all environments, while established organizations are better off seeking predictable environments unless they can devote sufficient attention to managing a dissipative equilibrium of structure (i.e., edge of chaos) in unpredictable environments. ●

A longstanding question in strategy and organization theory is how the amount of organizational structure shapes performance in dynamic environments. Given its fundamental importance, this question has been explored in a variety of research traditions, ranging from organizational studies (Burns and Stalker, 1961; Hargadon and Sutton, 1997) and competitive strategy (Rindova and Kotha, 2001; Rothaermel, Hitt, and Jobe, 2006) to network sociology (Uzzi, 1997; Owen-Smith and Powell, 2003) and, more broadly, the complexity sciences (Kauffman, 1993; Anderson, 1999). Although highly diverse, these literatures nonetheless highlight two fundamental arguments.

The first argument is that a balance between too much and too little structure is critical to high performance for organizations in dynamic environments. Organizations with too little structure lack enough guidance to generate appropriate behaviors efficiently (Weick, 1993; Okhuysen and Eisenhardt, 2002; Baker and Nelson, 2005), while organizations with too much structure are too constrained and lack flexibility (Miller and Friesen, 1980; Siggelkow, 2001; Martin and Eisenhardt, 2010). This tension produces a dilemma for organizations, as high performance in dynamic environments demands both efficiency and flexibility. Research shows that high-performing organizations resolve this tension using a moderate amount of structure to generate a variety of high-performing solutions (Brown and Eisenhardt, 1997, 1998). Overall, this suggests an inverted U-shaped relationship between the amount of structure and performance, a relationship often observed when tensions are at work.

The second argument is that achieving high performance with moderate structure is influenced by the changing nature of

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environmental opportunities (Adler, Goldoftas, and Levine, 1999; Rindova and Kotha, 2001). Highly dynamic environments require flexibility to cope with a flow of opportunities that typically is faster, more complex, more ambiguous, and less predictable than in less dynamic environments. Research shows that high-performing organizations cope with dynamic environments with less structure (Eisenhardt and Martin, 2000; Rowley, Behrens, and Krackhardt, 2000). Conversely, less dynamic environments favor efficiency, and so high-performing organizations have more structure in these environments (Pisano, 1994; Rivkin and Siggelkow, 2003). Overall, this suggests that the optimal amount of structure decreases with increasing environmental dynamism, a consistent finding within multiple literatures.

Yet although these arguments are widely understood in general, unresolved issues remain. First, the empirical evidence that supports an inverted-U shaped relationship is modest. It primarily consists of qualitative case comparisons (Mintzberg and McHugh, 1985; Brown and Eisenhardt, 1997) and quantitative confirmations such as statistical tests of quadratic relationships and interaction effects that are not sufficiently precise to identify a specific functional form (Bradach, 1997; Gibson and Birkinshaw, 2004; Rothaermel, Hitt, and Jobe, 2006), such as an inverted-U. Rather, the evidence simply points to a unimodal shape for the relationship between structure and performance that increases on one side and decreases on the other. So the evidence does not rule out other shapes (e.g., broad plateau or inverted-V) and related functional forms. The shape of the structure-performance relationship has consequential theoretical and managerial implications. For instance, if the relationship is a broad plateau with a wide range of optimal structures, then balancing between too much and too little structure is easy and unimportant. In contrast, if the shape is an inverted-V, in which the optimal structure is a narrow peak, sometimes called an "edge of chaos," then balancing between too much and too little structure is challenging and crucial.

Second, the theory that underlies the relationship between the amount of structure and performance is incomplete. As sketched above, the basic theoretical argument is that organizations with too much structure are too inflexible, while organizations with too little structure are too inefficient. Although appealing, this argument neglects key factors such as limited attention, time delays, and the fleeting and varied nature of opportunities that might influence this tradeoff. So, for example, the theory does not consider that, although less structure enables flexible improvisation, improvisation is an attention-consuming and mistake-prone process (Hatch, 1998; Weick, 1998). As a result, the theory fails to clarify precisely how structure influences efficiency and flexibility, and thus the exact nature of the efficiency-flexibility tradeoff, including whether it is advantageous to err toward too much or too little structure.

Third, the theory that underlies the argument that environmental dynamism influences the optimal structure is imprecise. In particular, environmental dynamism is a multidimensional construct (Dess and Beard, 1984), and yet the theory does

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not unpack how the dimensions of dynamism operate. The empirical literature also reflects this imprecision, as studies often mingle dimensions such as complexity, velocity, unpredictability, and ambiguity (Eisenhardt, 1989; Pisano, 1994) that may have distinct effects. Understanding the influence of different dimensions is important because they may have unexpected implications for theory and practice. For example, it may be that only one or two dimensions shift optimal structure or that the structure-performance relationship has distinct shapes in specific environments, such as highly ambiguous nascent markets and high-velocity “bubble” markets.

Overall, these unresolved issues suggest a lack of specific understanding in diverse literatures of the fundamental relationships among structure, performance, and environment. This is the gap that we address by exploring the relationship between structure and performance, the underlying tradeoff between efficiency and flexibility, and the influence of environmental dynamism. There are many definitions of structure, with varied attributes such as formalization (e.g., rules, routines), centralization (e.g., hierarchy, use of authority, verticality), control systems (e.g., span of control), coupling and structural embeddedness (e.g., tie strength, tie density), and specialization (e.g., role clarity) (Weber, 1946; e.g., Burns and Stalker, 1961; Pugh et al., 1963; Galbraith, 1973; Mintzberg, 1979; Granovetter, 1985; Scott, 2003). But although the definitions include varied attributes, they all share an emphasis on shaping the actions of organizational members. Entities are more structured when they shape more activities of their constituent elements and thus constrain more action. Conversely, entities are less structured when their constituent elements have more flexibility in their behavior. Thus we define structure broadly as constraint on action.

We conducted this research using simulation methods, which are effective for research such as ours in which the basic outline of the theory is understood, but its underlying theoretical logic is limited (Davis, Eisenhardt, and Bingham, 2007). In this situation, there is enough theory to develop a simulation model, yet the theory is also sufficiently incomplete that it warrants examination of its internal validity (i.e., the correctness of its theoretical logic) and elaboration of its propositions through experimentation, which are both strengths of simulation (Sastry, 1997; Zott, 2003). Simulation is also a particularly useful method for research such as ours when the focal phenomenon is nonlinear (Carroll and Burton, 2000; Rudolph and Repenning, 2002; Lenox, Rockart, and Lewin, 2006). Though statistical and inductive methods may indicate the presence of nonlinearities, they offer less precise identification, particularly of complex ones such as tipping points and skews. Simulation is also a particularly useful method when empirical data are challenging to obtain (Davis, Eisenhardt, and Bingham, 2007). For example, simulation enables us to study mistakes that informants might be reluctant to reveal (Carroll and Burton, 2000; Finkelstein, 2003) and to unpack environmental dimensions that may be difficult to disentangle in actual environments (Dess and Beard, 1984). Finally, simulation is especially effective for research such as ours

that involves longitudinal and process phenomena because such phenomena can be studied over extended time periods that would be difficult to observe with empirical data (March, 1991; Zott, 2003). Using these methods, we seek to understand the effects of varying amounts of structure on performance in different environments.

ORGANIZATIONAL STRUCTURE AND ENVIRONMENTAL DYNAMISM

Several research streams focus on the fundamental relationships among structure, performance, and environment. One general argument is that organizations with too little structure are too confused and lack efficiency, while organizations with too much structure are too constrained and lack flexibility. By contrast, moderate structure balances between these two states and so is likely to be high performing (Weick, 1976; Brown and Eisenhardt, 1997). Support for this general argument emerges in several literatures. Studies in network sociology point to the “paradox of embeddedness” wherein moderately connected actors outperform those who are either less or more connected (Uzzi, 1997; Baum, Calabrese, and Silverman, 2000; Owen-Smith and Powell, 2003). Uzzi (1997) found that firms in the garment industry that combined more and less structured partnerships were more effective than those firms that used only one type. Similarly, studies of partially connected technology standards (Garud and Jain, 1996) and “leaky” networks in the Boston-area biotechnology field (Owen-Smith and Powell, 2003) suggest that balancing too much and too little structure improves industry-level performance.

The argument for structural balance is also supported in areas of organizational studies in which loose coupling, ambidexterity, and improvisation are key, including creativity (Amabile, 1996), innovation (Davis, 2009), group problem solving (Bigley and Roberts, 2001; Okhuysen and Eisenhardt, 2002), organizational change (Tushman and O’Reilly, 1996; Gilbert, 2005), and organizational learning (Tripsas, 1997; Hansen, 1999). For example, Brown and Eisenhardt (1997) found that high-tech firms with a moderate number of simple rules (i.e., semi-structure) are more flexible and efficient—quickly creating high-quality, innovative products while responding to market shifts—than firms with more or fewer rules.

In the strategy literature, there is also support for this argument in studies of vertical integration (Schilling and Steensma, 2001; Rothaermel, Hitt, and Jobe, 2006), loose internal coupling (Galunic and Eisenhardt, 2001; Williams and Mitchell, 2004; Martin and Eisenhardt, 2010), innovation (Katila and Ahuja, 2002; Fleming, Sorenson, and Rivkin, 2006), and moderately structured capabilities with simple rules (Burgelman, 1996; Bingham, Eisenhardt, and Furr, 2007). Rindova and Kotha (2001) found that Yahoo’s initially high performance in a dynamic environment was partially due to its simple-rules structure for the critical process capabilities of acquisitions and alliances.

More broadly, research in the complexity sciences also examines the tension between too much and too little structure. A repeated finding is that moderately structured

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computational systems evolve more effectively than systems with too little or too much structure (Kauffman, 1989; Langton, 1992; Gell-Mann, 1994). A related finding is that systems tend to fall away from the optimal “edge-of-chaos” amount of structure into catastrophes without constant intervention (Anderson, 1999; Eisenhardt and Bhatia, 2001). In the language of nonlinear dynamics (Strogatz, 2001), the optimal structure is often an unstable or dissipative critical point that is difficult to maintain. Overall, these literatures suggest the following well-known proposition:

Proposition (P1): Performance has an inverted-U shaped relationship with the amount of structure.

Several streams of research also focus on how environmental dynamism influences the relationship between the amount of structure and performance. The general argument is that as the environment becomes more dynamic, it becomes advantageous for the organization to be more flexible and so less structured. Conversely, as the environment becomes less dynamic, greater efficiency and so more structure are preferred. This general argument finds extensive support in a number of literatures. Contingency theory (Lawrence and Lorsch, 1967; Thompson, 1967; Galbraith, 1973) is particularly prominent. In an early study, Burns and Stalker (1961) found that a more structured mechanistic organization (e.g., role specialization, centralization, and formalization) is high performing in stable environments because it is highly efficient in these routine situations. In contrast, a less structured organic organization (e.g., decentralized decision making, broader and more fluid roles, wider span of control) is high performing in dynamic markets because it enables flexible action. Similarly, Eisenhardt and Tabrizi (1995) found that more structure (e.g., planning, numerous and well-defined process steps, specialization) is faster and more effective for innovation processes in the stable mainframe computing industry, whereas less structure and more improvised action (e.g., prototyping) is better in the dynamic personal computing industry. Pisano (1994) found a similar contrast for new process development in the dynamic biotech industry vs. the stable chemical industry.

The argument is supported by strategy research that has found less structured emergent strategies to be higher performing in dynamic environments, whereas more structured deliberate strategies work better in stable ones (Mintzberg and McHugh, 1985). Similarly, network studies have shown that loosely coupled networks are more effective in highly dynamic industries (Tushman and Katz, 1980; Uzzi, 1997; Ozcan and Eisenhardt, 2008). Rowley, Behrens, and Krackhardt (2000) observed that the high-performing firms in the dynamic semiconductor industry have loosely coupled alliance networks, whereas high-performing firms in the stable steel industry have more structured dense networks. Overall, these literatures suggest the following well-known proposition:

Proposition 2 (P2): As environmental dynamism increases, the optimal amount of structure decreases.

Central to the underlying theory of these two propositions is the insight that the amount of structure influences both

efficiency and flexibility, but in opposite directions (Gibson and Birkinshaw, 2004). By efficiency, we mean the rapid, less costly, mistake-free execution of opportunities like new products, new market entry, or new acquisitions (Miller and Friesen, 1980; Adler, Goldoftas, and Levine, 1999). Structure creates the framework that enables reliable, rapid, smooth execution in well-grooved routines that is efficient. In contrast, flexibility refers to open, fluid execution of these opportunities (Weick, 1993; Sine, Mitsuhashi, and Kirsch, 2006). Removing structure creates latitude for improvisation that is flexible. In dynamic environments, high performance depends on balancing the tradeoff between flexibility and efficiency.

But though these general theoretical arguments are widely understood, unresolved issues remain. First, the empirical evidence for an inverted-U shaped relationship is modest, consisting of qualitative case comparisons (Brown and Eisenhardt, 1997; Gilbert, 2005), and quantitative statistical tests of quadratic functions or interactions between efficiency and flexibility that are not precise enough to determine that the relationship is, in fact, an inverted-U (Hansen, 1999; Gibson and Birkinshaw, 2004; Rothaermel, Hitt, and Jobe, 2006). The evidence does not rule out other shapes and functional forms that may have critical theoretical and practical consequences. For example, if the shape is a broad plateau, such that there are a variety of high-performing structures, then it is easy and unimportant to find the optimal structure. Conversely, if the shape is an inverted-V, such that there are only a few high-performing structures, then the optimal structure is challenging to find and crucial to maintain. An inverted-U relationship also requires very specific functional forms, the simplest being that structure has linear relationships (and opposite slopes) with efficiency and flexibility. But there is no clear theory for why these relationships would be, for example, linear.

A second unresolved issue is that the theory underlying the relationship between structure and performance is incomplete, particularly the theoretical logics tying structure with efficiency and flexibility.¹ Neglected considerations such as attention limits, mistakes, and the fleeting, varied nature of opportunities suggest that these relationships are more complex than extant theory indicates. For example, structure improves efficiency by constraining the behaviors of organizational members within well-established guidelines determined by rules, roles, reporting relationships, and other forms of structure (Feldman and Pentland, 2003; Rivkin and Siggelkow, 2003). Siggelkow's (2001) study of Liz Claiborne provides an illustration. Here, executives created organizational structures (e.g., hierarchies, rules, roles) to address a series of product opportunities in the apparel industry. Rules were a particularly key form of structure that guided basic decisions. For example, rules about apparel design stipulated that each season's clothing line comprise four to seven concept groups, sizes should be the same across styles, and colors should not change across years. Together, these and other structures constrained organizational actions and enabled Liz Claiborne to be highly efficient. Moreover, because Liz Claiborne

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We appreciate the suggestion of an anonymous reviewer to focus on the relationships of structure with efficiency and flexibility.

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executives fit these structures to match specific environmental opportunities focused on a growing number of professional women, the firm was able to execute a series of lucrative and very related opportunities consistently, quickly, cheaply, and with few mistakes (Siggelkow, 2001).

Although greater structure improves efficiency, the rate of improvement often declines, and the range of opportunities that can be captured narrows as well. So organizations may be able to execute specific opportunities efficiently but not diverse or higher-payoff ones. Brown and Eisenhardt (1997) described a highly structured product development process that could rapidly and flawlessly capture similar product opportunities but could not flexibly adjust to capture highly profitable, new product opportunities. Similarly, Gilbert (2005) described how highly structured, traditional newspaper firms were too rigid to execute new Internet opportunities, whereas more loosely coupled ones were more successful. The key point is that increasing structure can trap organizations in a few or low-payoff opportunities with a declining rate of efficiency improvements. Organizational action becomes frozen, approaching a non-adaptive state that complexity theorists call a "complexity catastrophe" (Kauffman, 1993; Anderson, 1999).

Similarly, the relationship between structure and flexibility is likely to be more complicated than extant theory suggests. Decreasing structure increases flexibility because it gives executives more degrees of freedom to operate (Weick, 1998; Gilbert, 2005). There is greater latitude of action and thus a wider range of possible opportunities that can be addressed as managers combine some structured actions and some actions improvised in real-time (Miner, Bassoff, and Moorman, 2001; Davis, 2008). But in reality, improvised actions consume more attention than rule-following actions because they require managers to figure out what actions to take (Hatch, 1998; Miner, Bassoff, and Moorman, 2001). Likely mistakes pose further demands on attention. Because attention is constrained (March and Simon, 1958; Ocasio, 1997), it limits the number of possible actions in a given time period. In other words, the benefits of flexibility depend on having enough attention to figure out what to do (Weick, 1998; Okhuysen and Eisenhardt, 2002). As an example, Brown and Eisenhardt (1997: 15) described a high-tech firm with few rules, priorities, and formal roles that "revels in the excitement of panicked product development" but engendered "enormous time wasting" and many mistakes. Though some participants enjoyed the "Silicon Valley organic management," this firm ultimately generated too many ineffective products that were behind schedule. Thus limits of attention complicate the structure-flexibility relationship.

Similarly, the fleeting nature of opportunities complicates the structure-flexibility relationship. Although organizations could take enough time to engage in extensive trial-and-error actions to capture any opportunity, opportunities actually have limited time windows in which they are viable (D'Aveni, 1994). Moreover, mistakes during improvisation introduce time delays that are particularly damaging because opportunities are fleeting (Tyre and Orlikowski, 1994; Perlow, Okhuysen,

and Repenning, 2002). Figuring out successful improvised actions becomes especially difficult with low structure because so much is changing that it is hard to get everything right at once (Moorman and Miner, 1998; Bingham, Eisenhardt, and Davis, 2009). As structure decreases, action becomes increasingly chaotic, approaching a non-adaptive state that complexity theorists call an "error catastrophe," in which organizations make too few correct actions to succeed (Reynolds, 1987; Kauffman, 1993).

A third unresolved issue is that the theory underlying the argument that more environmental dynamism lowers the optimal structure is imprecise. Specifically, environmental dynamism is a multidimensional construct. For example, environmental dynamism includes velocity—the speed or rate at which new opportunities emerge (Eisenhardt, 1989). The Internet bubble is a good example of a high-velocity environment (Goldfarb, Kirsch, and Miller, 2007). But dynamism also includes ambiguity—lack of clarity, such that it is difficult to interpret or distinguish opportunities (March and Olsen, 1976). Nascent markets like nanotechnology are examples of environments with high ambiguity (Santos and Eisenhardt, 2009). It also refers to unpredictability—disorder or turbulence, such that there is no consistent pattern of opportunities. Growth markets such as Web 2.0 and wireless services often have unpredictable opportunities. Environmental dynamism can also include complexity—the number of opportunity contingencies that must be addressed successfully. Opportunities within "green" power, for example, involve many scientific, regulatory, safety, and commercial aspects and so are highly complex (Sine, Haveman, and Tolbert, 2005).

Although environmental dynamism is multidimensional, existing theory does not unpack how different dimensions operate. Empirical research reflects this imprecision. Some research focuses on specific environmental features such as unpredictability (Lawrence and Lorsch, 1967) and ambiguity (March and Olsen, 1976). Other research mixes several dimensions together, such as ambiguity and complexity, to describe environmental dynamism in an industry (Pisano, 1994). Still other research uses a single term such as velocity but then actually combines multiple dimensions such as unpredictability, ambiguity, and velocity (Eisenhardt, 1989). Adding to the imprecision, these dimensions are often correlated in many actual environments. For example, high-velocity environments can be unpredictable (Eisenhardt, 1989), and complex environments can involve multiple ambiguities (Gavetti, Levinthal, and Rivkin, 2005). Unpacking the dimensions of environments, as we do in our simulation study, will provide a better understanding of optimal structure in different environments.

METHODS

We used stochastic process modeling to study the structure-performance relationship in distinct environments. This approach enables a custom design of the simulation because it is not constrained by an explicit problem structure (e.g., cellular automata) (Davis, Eisenhardt, and Bingham, 2007).

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Rather, it allows the researcher to piece together processes that closely mirror the focal theoretical logic, bring in multiple sources of stochasticity (e.g., arrival rates of opportunities), and characterize them with a variety of stochastic distributions (e.g., Poisson, Gamma) (Law and Kelton, 1991).

Stochastic modeling is an effective choice for our research because the problem structure does not fit well with any structured approach. This enables more accurate representation of our phenomena rather than force-fitting them into an ill-suited structured approach.² Further, because our baseline theory is well established in the empirical literature, we enhance the likelihood of realism by building a model from the ground up (Burton and Obel, 1995) and thus mitigate a key criticism of simulation. This approach also enabled us to include several sources of stochasticity that are theoretically important (e.g., improvisational action, opportunity flow) and to experiment flexibly with theoretically relevant environmental dimensions (e.g., velocity, ambiguity). Stochastic process modeling also has an influential tradition in our focal literatures, such as the garbage can model (Cohen, March, and Olsen, 1972), dynamics of culture (Carroll and Harrison, 1998), and exploration versus exploitation (March, 1991).³

Modeling Organization Structure and Environment

Our simulation model includes two primary components: organization structure and environment. We modeled *organization structure* as rules. Though we could have used other types of structure (e.g., roles, networks) or other aspects of structure (e.g., centralization, verticality), we chose rules in order to create a parsimonious model that captures the fundamental features of structure. As Burton and Obel (1995) explained, effective simulation reveals the minimal elements of the problem at hand and so uses the least complex conceptualization that still captures the essence of the phenomenon. That is, the model's purpose is to represent the core features of the phenomenon (e.g., organization structure), not be a literal replication of the phenomenon (Lave and March, 1975; Rivkin and Siggelkow, 2003). As described earlier, rules are a particularly important type of structure in dynamic environments (Burgelman, 1994; Brown and Eisenhardt, 1997; Rindova and Kotha, 2001; Zott, 2003). They also fit especially well with our research because rules directly relate to how structure generates actions to execute (or fail to execute) environmental opportunities (Bingham, Eisenhardt, and Furr, 2007; Bingham, Eisenhardt, and Davis, 2009). Rules are also very commonly used to represent structure in simulations (e.g., Baligh, 2006) because of their direct link to action (March, Schultz, and Zhou, 2000; Eisenhardt and Sull, 2001). Thus our study follows a long, influential tradition of simple yet powerful computational models that rely on rules to represent structure (Nelson and Winter, 1982; March, 1991; Rivkin, 2000).

We modeled the *environment* as a flow of heterogeneous opportunities, consistent with our earlier discussion that organizational structure constrains action in the capture and execution of varying environmental opportunities (Burgelman, 1996; Eisenhardt and Martin, 2000; Miner, Bassoff, and

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We develop a matching model whose fundamental feature is to allow for varying degrees of match between opportunities and rules, something that is not present in other, more constrained modeling approaches. We appreciate the comments of an anonymous reviewer in suggesting that we make this point in explaining our use of stochastic process modeling.

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Stochastic process modeling is more fully described in references such as Burton and Obel (1995) and Davis, Eisenhardt, and Bingham (2007). Interested readers can also refer to the exemplars cited in the text, such as March (1991) and Carroll and Harrison (1998). We appreciate the comments of an anonymous reviewer that we provide more information about this modeling approach.

Moorman, 2001). Our focus on heterogeneous opportunities is also consistent with the Austrian economics (Hayek, 1945; Kirzner, 1997) and entrepreneurship (Shane, 2000; Schoonhoven and Romanelli, 2001) literatures in which environmental dynamism is also a core interest. Conceptualizing the environment as a flow of heterogeneous opportunities also permits a rich modeling of environmental dimensions. It enables us to unpack and explore environmental dynamism more fully, a key theoretical aim of our research.

To capture heterogeneity, we modeled each opportunity as having 10 features that can be either 1 or 0 (e.g., 0101101101) and included four environmental dynamism dimensions, described below. In contrast, many simulation models assume a fixed environment, a single environmental jolt, or a single environmental dimension and so preclude the kind of rich exploration of environmental dynamism that we seek. Although a parsimonious simulation is important (Burton and Obel, 1995), the richness of the simulation should focus on the part of the model in which the primary exploration will occur (Burton and Obel, 1995; Davis, Eisenhardt, and Bingham, 2007).

As in all research, we made several assumptions, some fundamental to our modeling. For instance, we assumed that organizations take actions to capture opportunities, actions require attention, and attention is limited (Ocasio, 1997). We also assumed that organizations use a combination of rule-based and improvised actions and that improvised actions require more attention than rule-based ones because they involve real-time sensemaking (Weick, 1993). These assumptions are well grounded in field studies of improvisation (Brown and Eisenhardt, 1997; Miner, Bassoff, and Moorman, 2001; Baker and Nelson, 2005).

Other assumptions that are less essential to the theory simplify the model. For example, to focus on the effects of structure on performance, not learning, we assumed that the rules have already been learned and that adaptation to new opportunities occurs through improvised actions in real time. This is consistent with empirical research showing that heuristics are learned quickly and stabilize rapidly (Bingham, Eisenhardt, and Davis, 2009) and that real-time, improvisational learning is often not retained in new heuristics (Weick, 1996; Moorman and Miner, 1998). Similarly, to focus on effects of structure, we assumed that all rules are appropriate for at least some opportunities. We also assumed that the effects of competitors are realized through the flow of opportunities, an assumption that mirrors the Austrian economics argument that market dynamism is endogeneously created through competitive interaction and technological innovation (Kirzner, 1997).

In our model, the organization has a set of rules to capture opportunities in its environment. In each time step, the organization takes a combination of rule-based and improvised actions to attempt to execute a given opportunity. When enough of these actions match the opportunity, the opportunity is captured, and firm performance increases by the value

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of the opportunity. Because attention is limited and actions (rule-based and improvised) consume attention, however, the organization can take only a limited number of actions in each time step.

Environmental Dynamism

We modeled four environmental dynamism dimensions based on our review of the structure-environment research in the organizational and strategy literatures: velocity, complexity, ambiguity, and unpredictability (Burns and Stalker, 1961; Lawrence and Lorsch, 1967; March and Olsen, 1976; D'Aveni, 1994; Eisenhardt and Tabrizi, 1995). These four dimensions are important, frequently used, and distinct from each other, though some research uses alternative terms for them. This is particularly true of unpredictability. For example, instead of unpredictability, terms like uncertainty, turbulence, and volatility are also used to capture the same notion of disorder or dissimilarity in the environment. Terms like turbulence and volatility focus particularly on disorder, while terms like unpredictability and uncertainty focus more on the lack of pattern that disorder implies. Finally, though there may be other dimensions of environmental dynamism, these four are among the most important. A strength of our model is its rich representation of the environment.

Velocity is the speed or rate at which new opportunities emerge. The Internet bubble is an example of an environment with a high velocity of opportunities. We operationalized velocity as the rate that new opportunities flow into the environment (Eisenhardt, 1989; Eisenhardt and Tabrizi, 1995). We used a Poisson distribution to model the stochastic arrival time of opportunities into the environment where velocity is λ . A Poisson distribution, $p(k)$, describes the probability of k opportunities arriving in t time steps and is determined by the single rate parameter λ :

$$p(k) = (\lambda t)^k e^{-\lambda t} / k! \quad (1)$$

Poisson is a well-known probability distribution used to model arrival flow (Cinlar, 1975; Glynn and Whitt, 1992). It is attractive here and in many simulations because it makes few assumptions about the timing of opportunities (Law and Kelton, 1991). Although λ can range from 0 to infinity, we fixed an upper bound on the rate of execution because bounded rationality and limited attention constrain the number of opportunities that can be addressed (March and Simon, 1958; Shane, 2000).

Complexity was operationalized as the number of features of an opportunity that must be correctly executed to capture that opportunity. Complexity increases the difficulty of capturing opportunities because organizations have less latitude for errors when there are numerous, relevant contingencies (Gavetti, Levinthal, and Rivkin, 2005). Like computational complexity, complexity can be conceptualized as the minimum number of correct steps that are needed to execute a plan (Simon, 1962; Sipser, 1997). Biotechnology is an example of a high-complexity environment because many features of the opportunity must be correct to achieve success (Hill and

Rothaermel, 2003). Complexity is an integer indicating the number of actions that must be correct in order to execute an opportunity successfully. Because each opportunity has 10 features, complexity ranges from 0 to 10.

Ambiguity was defined as lack of clarity such that it is difficult to interpret or distinguish opportunities. Because ambiguity makes the misperception of opportunities more likely (March and Olsen, 1976), we operationalized environmental ambiguity as the proportion of perceived opportunity features that differ from actual ones. Nascent markets like nanotechnology are typically highly ambiguous (Santos and Eisenhardt, 2009). The *actual features* of an opportunity are represented by a 10-element bit string (i.e., vector) of 1s and 0s—e.g., 0100100110. The *misperceived features* of the same opportunity are also a 10-element bit string of 1s and 0s but differ from the actual features by those features for which perception does not match reality—e.g., 0110100110. Ambiguity was operationalized as the proportion of misperceived opportunity features. For example, the actual and perceived features of the two bit strings above differ by one element of 10, so the ambiguity = .1. This is an especially useful way to model ambiguity because it allows us to capture the difficulty of interpretation that leads to misperception of opportunities. Ambiguity ranges from 0 to 1.

Unpredictability was defined as the amount of disorder or turbulence in the flow of opportunities such that there is less consistent similarity or pattern. An implication of increasing unpredictability is that managers are less able to adjust or “tune” their structures to the environment because there is less pattern to match (Galbraith, 1973).⁴ We manipulated unpredictability by changing the probability that any opportunity feature will be a 1 or a 0—i.e., $p(1)$ and $p(0)$. Opportunities with features that have a higher probability of 1 or 0 are less unpredictable than opportunities with features having an equal probability of 1 or 0. This approach has the advantage of stochastically generating similar opportunities without the researcher’s bias as to what those patterns should be.

To have a monotonically increasing measure of unpredictability, we converted these probabilities using a well-known disorder computation from mathematical information theory (Cover and Thomas, 1991). Unpredictability, U , of a flow of opportunities depends on the probability, p , of a feature being either a 1 or a 0 and is given by:

$$U = - \sum p * \log_2(p) \quad (2)$$

To illustrate, when $p(1) = .7$ and $p(0) = .3$, then unpredictability is relatively low. There is a 70/30 split of 1s and 0s in the features vector of each opportunity (making 1s more likely than 0s) such that $U = -.7 * \log_2(.7) + .3 * \log_2(.3) = .88$. By contrast, when unpredictability is high [$p(1) = p(0) = .5$ and $U = 1$], the distribution of 1s and 0s in the opportunity features is random. Both opportunities and rules have a 50/50 split of 1s and 0s (making 1s and 0s equally likely), and there is no consistent similarity or pattern in the flow of opportunities. Unpredictability ranges from 0 to 1.

⁴ We appreciate the insightful recommendation of an anonymous reviewer that we clarify the meaning of unpredictability and its implications for whether there are patterns in the environment that managers can use to adjust or “tune” their organizational structures to better match the environment.

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Organizational Structure as Rules

We modeled structure as a set of rules for capturing opportunities, with each rule specifying particular actions for executing opportunities. Rules as structure are common in our focal literatures. For example, Galunic and Eisenhardt (2001) described rules for carrying out “patching” opportunities in a high-performing, multi-business corporation, including that new product-market charters should always be assigned to business units that (1) have relevant product-market experience and (2) are currently assigned charters with shrinking markets or fading profit margins. Similarly, Rindova and Kotha (2001) described rules for executing alliance opportunities at Yahoo!, such as (1) making the basic service free and (2) having no exclusive deals. Overall, rules specify actions for addressing opportunities and are central to organizational processes and capabilities such as interfirm collaboration, product development, and country entry (Burgelman, 1996; Eisenhardt and Sull, 2001; Rindova and Kotha, 2001; Bingham, Eisenhardt, and Furr, 2007; Davis, 2008).

Rules were operationalized with a 10-element vector of 1s, 0s, and ?s (e.g., 0?1?10???0). When an organization attempts to execute an opportunity with a rule, it generates 10 specific actions. That is, each 1 or 0 generates a rule-based action in that position. The proportion of 1s and 0s in a rule was set equal to the probability of 1s and 0s in the flow of opportunities. This captures the insight noted earlier that organizations can adjust their structures to approximately match patterns in the flow of opportunities if they exist (March and Simon, 1958). Additionally, for each “?” the organization improvises either a 1 or 0 “improvised action” with a 50/50 likelihood. For example, a combination of rule-based and improvised (underlined) actions using the rule above could produce the vector 0111100110. The computer program then compares this set of 10 actions to the opportunity’s 10 features. If the number of actions (both rule-based and improvised) that match the actual features of the opportunity equals or exceeds the value of the environmental *complexity* parameter, then the opportunity is executed and the firm gains the payoff value of that opportunity. For example, if *complexity* = 6 and the actions above—0111100110—are compared to the opportunity 0110101010, then the opportunity is successfully executed because 7 of the actions were correct. This operationalization captures the idea that structure constrains some actions, while others are left open to improvisation (Brown and Eisenhardt, 1997; Miner, Bassoff, and Moorman, 2001).

Amount of structure. We operationalized the *amount of structure* as simply the number of rule-based actions specified by each rule (i.e., number of 1s and 0s). For example, the amount of structure in the rule 01?0??011? is 6. Thus increasing the *amount of structure* for an organization’s set of rules increases their constraint on action. For ease of exposition, we term rules with little to moderate structure (i.e., 3 to 5) simple rules. This operationalization is consistent with theoretical notions of structure such as Simon’s (1962) and Daft’s (1992), in which the amount of structure is associated with the number of components. It is in contrast to some prior research (Rivkin and Siggelkow, 2003) emphasizing the

interactions among structural features and putting less emphasis on the number of structural features. By emphasizing the number of structural features, we focus on the amount of structure in rules. Structure, however, constrains action in both. Thus, for the same research questions, the results should be qualitatively consistent.

Performance. Each opportunity is associated with a randomly determined payoff value. Performance was operationalized as the sum of all payoffs from every opportunity executed, across all time steps. This is particularly appropriate for our research because it is consistent with the empirical studies of dynamic environments indicating that performance is derived from a series of temporary advantages and related payoffs (D'Aveni, 1994; Roberts, 1999; Rindova and Kotha, 2001; Chen et al., 2009).

Simulating the Model

We implemented this model in Matlab software. The computer program flow is outlined below, and the Technical Appendix provides more details. In the beginning, the organization's structure (i.e., its rules) and environment (i.e., flow of heterogeneous opportunities determined by the velocity, complexity, ambiguity, and unpredictability parameters) are randomly initialized using draws from probability distributions (Law and Kelton, 1991). In each time step, opportunities flow into the environment at velocity λ . When the organization tries to capture an opportunity with a rule, the organization generates both rule-based and improvised actions. When the number of these actions that match the opportunity is greater than the environmental complexity, the opportunity is executed and performance increases by the payoff value.

As discussed above, the firm's actions (both rule-based and improvised) require attention, which is limited (Cyert and March, 1963; Ocasio, 1997), so the organization has a limited number of actions that it can take in any time step. When attention runs out, the organization can take no further actions. At the end of $t = 200$ time steps, the simulation run ends and performance is computed. We chose this number of time steps because it is large enough to allow sufficient opportunities to flow into the environment such that any initialization effects on the findings are mitigated (Law and Kelton, 1991), but we also experimented with multiple values for the amount of attention required for improvised action relative to rule-based action, as described further in the Technical Appendix. We found no qualitative differences in the findings and so present the results for this representative value.

Monte Carlo Simulation Experiments

We used Monte Carlo simulation techniques. In the Monte Carlo approach, an experiment is a simulation with fixed parameter settings that is run multiple times (Law and Kelton, 1991). The results are then averaged and confidence intervals calculated (Kalos and Whitlock, 1986). Thus for any given experiment, the result is the mean performance (and confidence interval) over multiple simulation runs, which better reflects the underlying processes under investigation than those produced by a single simulation run.

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Each experiment consists of 30 or 50 simulation runs. We selected $n = 30$ as the number of simulation runs for all experiments, except those on the basic relationship between structure and performance, because exploratory analyses revealed that values of n greater than 30 yielded insignificantly small incremental gains on reliability. We used $n = 50$ for the basic relationship between the amount of structure and performance because the larger range of structure values adds precision to our illustration of this relationship. These results are representative of the findings produced by other construct values during our exploration of the parameter space (see the Technical Appendix for more details).

We ran experiments for a wide range of values for each environmental dimension (e.g., velocity). Given space limitations, we report only relationships using representative low and high values from those experiments. Specifically, we plotted the relationship between the amount of structure and performance for these representative values of the environmental dimensions.⁵ Confidence intervals in the form of error bars (i.e., the square root of the variance over the number of runs) are included to enable more accurate statistical interpretation of the results, as is standard in Monte Carlo experiments (Kalos and Whitlock, 1986).

RESULTS

Amount of Structure and Performance

We begin by examining the two propositions that form the baseline theory. P1 proposed that the amount of structure has an inverted U-shaped relationship with performance. Figure 1 plots the relationship between performance and the amount of structure, with each point representing the average over 50 simulations. The results show that organizations with low or high structure rules perform worse than those with moderate structure (optimal structure at a value of 3). Optimal structure exists, but unexpectedly, the curve is asymmetric. That is, the performance decline from the left endpoint to the optimum is steeper than the performance decline from the right endpoint to the optimum.⁶ Within the bounds of these simulation experiments, too much structure produces a more gradual decline, while too little structure produces a steeper drop in performance for all deviations from the optimum. Thus there is an asymmetric relationship, which suggests a more complicated theoretical logic than a simple tension between too much and too little structure.

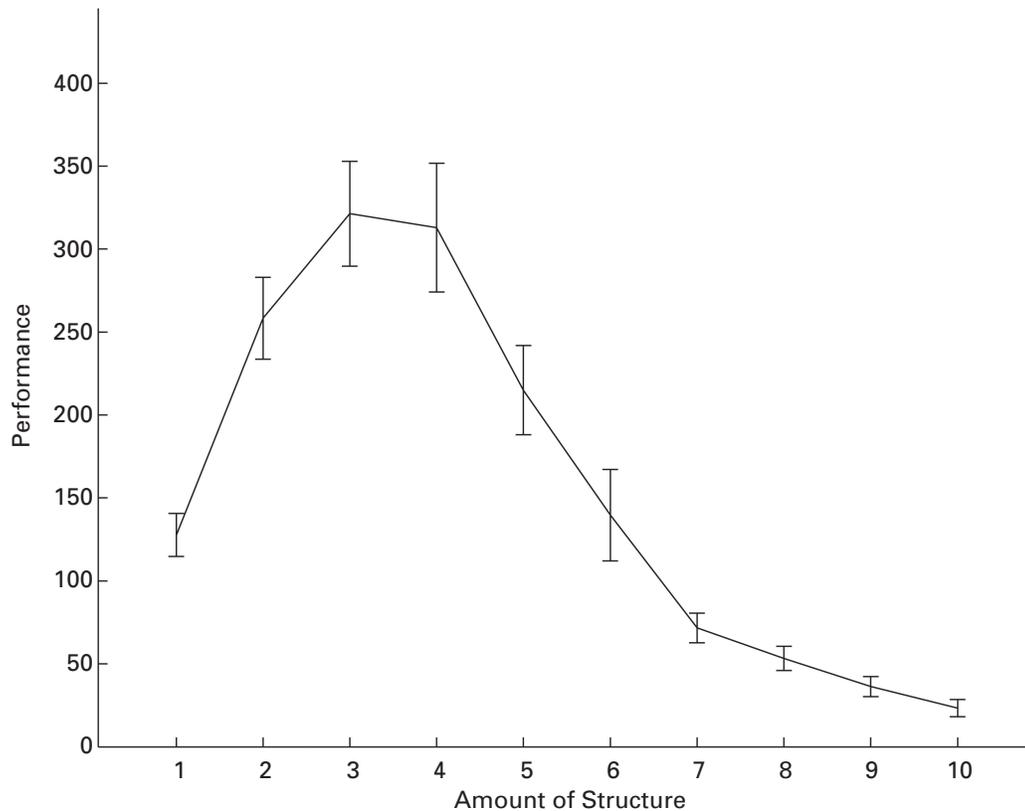
Our model offers some insight into this logic. In particular, rule-based actions are relatively automatic, and so they conserve attention. This enables more actions in a given time frame to capture additional opportunities. So although more structure narrows the range of potential opportunities that can be addressed, there is an “attention advantage” of added structure that partially compensates. This advantage occurs at relatively high values of structure across a broad range of environmental conditions and so favors erring on the side of structure in these environments. This suggests the following modified proposition:

Proposition 1a (P1a): Performance has a unimodal, asymmetric right relationship with the amount of structure.

⁵ Additional results for other values of the environmental dimensions are available from the authors.

⁶ To assess asymmetry, we compared the slope of the line from optimal structure to the endpoint on the left side to the slope of the line from optimal structure to the endpoint on the right side. Median values are used if optimal structure is a range of values. Curves are asymmetric right when the absolute value of the right slope is lower than the left slope.

Figure 1. Relationship between the amount of structure and performance (over 50 runs).



Unpacking the Dimensions of Environmental Dynamism

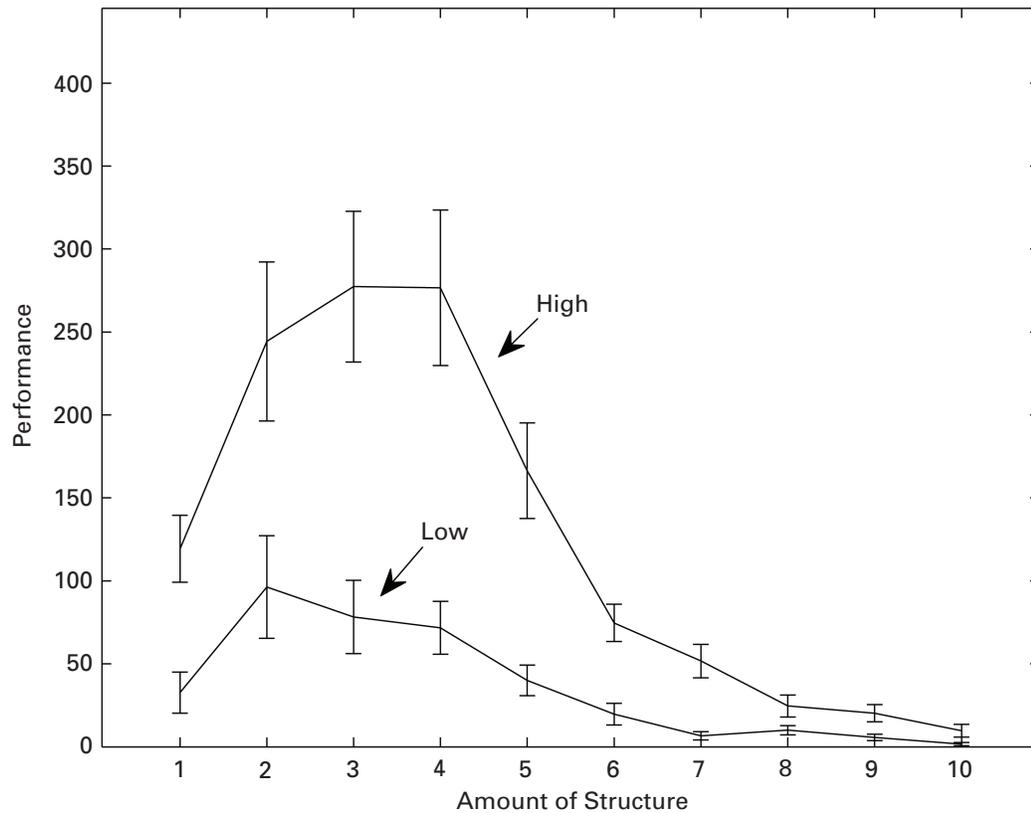
P2 proposed an environmental contingency that the optimal amount of structure decreases with increasing environmental dynamism. We used four experiments to understand which dimensions explain this shifting optimum: we examined P2 by comparing curves with high and low values of each dimension of environmental dynamism (i.e., velocity, complexity, ambiguity, and unpredictability) while holding the other three constant at moderate values.

Environmental velocity. Figure 2 depicts the effect of increasing environmental velocity (i.e., rate of opportunity flow) on performance by superimposing the resulting curves of two representative values. That is, we plotted the results that correspond to low and high values of velocity ($\lambda = .6$ and 1.4) to examine the effects of velocity. P1a is roughly supported in both environments.

In contrast, the results do not support P2. Within the precision of this simulation experiment, the optimal amount of structure—i.e., the amount of structure producing the highest performance—is the same for both high- and low-velocity environments. Further, although the optimal amount of structure is the same in the two velocity conditions, their performance is not. For a given amount of structure, firms in

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Figure 2. Effects of increasing environmental velocity on performance (over 30 runs).

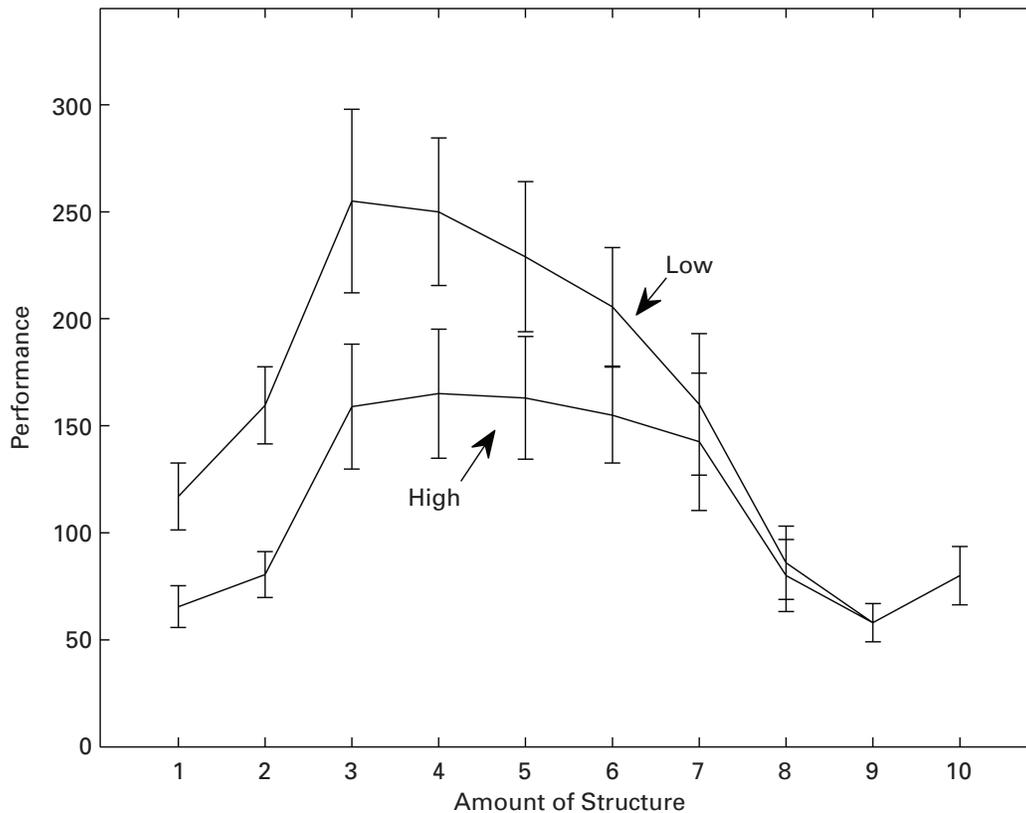


high-velocity environments have higher performance than those in low-velocity ones. In fact, increasing velocity appears to amplify performance and shift the entire curve upward. Overall, this suggests that the large number of opportunities that emerge in high-velocity environments (e.g., Internet bubble, Web 2.0) yields better performance for all levels of structure, other things being equal.

Environmental complexity. Figure 3 depicts the effects of increasing environmental complexity (i.e., the difficulty of capturing opportunities, given numerous relevant contingencies) on performance by superimposing the results of representative low and high values of complexity (4 and 8). P1a is roughly supported in both high- and low-complexity environments by unimodal, asymmetric curves. P2 is again not supported. Within the precision of this simulation experiment, the optimal amount of structure is the same for both high and low environmental complexity. Performance at the optimal structure differs in the two environments, however, with increasing complexity shifting the curve downward. Firms perform worse in high-complexity environments in which opportunities involve many contingencies (e.g., “green” power, biotechnology), in contrast to the velocity findings.

Environmental ambiguity. Figure 4 shows the effect of increasing environmental ambiguity (i.e., lack of clarity of opportunities) on performance by superimposing the results

Figure 3. Effects of increasing environmental complexity on performance (over 30 runs).



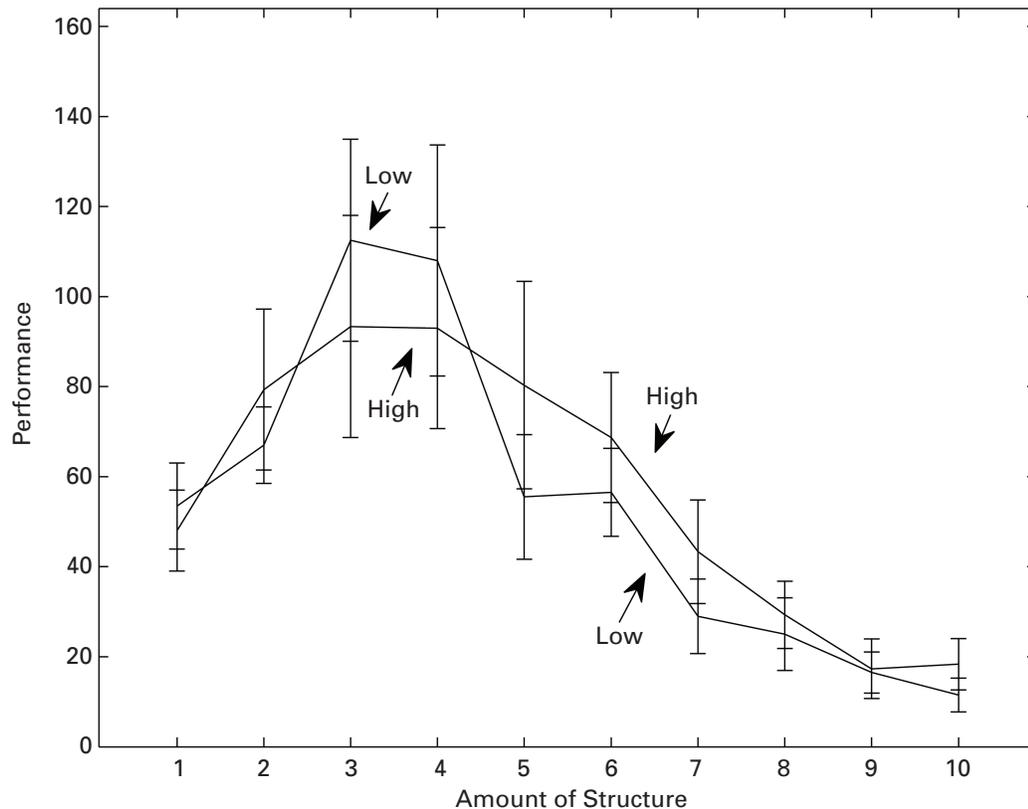
of the two representative cases that correspond to low and high values of ambiguity (0 and 0.2). P1a is again roughly supported in both environments: the curves have unimodal, asymmetric shapes.

P2 is again not supported. The optimal amount of structure is the same in both low- and high-ambiguity environments within the precision of this simulation experiment. Yet both the range of optimal structures and the peak performance at the optimal structure differ in the low- versus the high-ambiguity environments. When ambiguity is low, there is a narrow range of optimal structures and a higher level of peak performance. This suggests an environment in which it is difficult for managers to find and maintain an optimal structure, but they will achieve particularly high performance when they do. To the extent that skilled executives more easily locate and maintain the optimal structure, this is consistent with a skill-dominated environment. In contrast, when ambiguity is high, as in nascent markets, there is a wide range of optimal structures and lower peak performance. This suggests an environment in which it is easy for managers to find and maintain an optimal structure, but they will not achieve particularly high performance. This suggests a chance-dominated environment.

Environmental unpredictability. Figure 5 illustrates the effects of environmental unpredictability (i.e., disorder in the

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Figure 4. Effects of increasing environmental ambiguity on performance (over 30 runs).

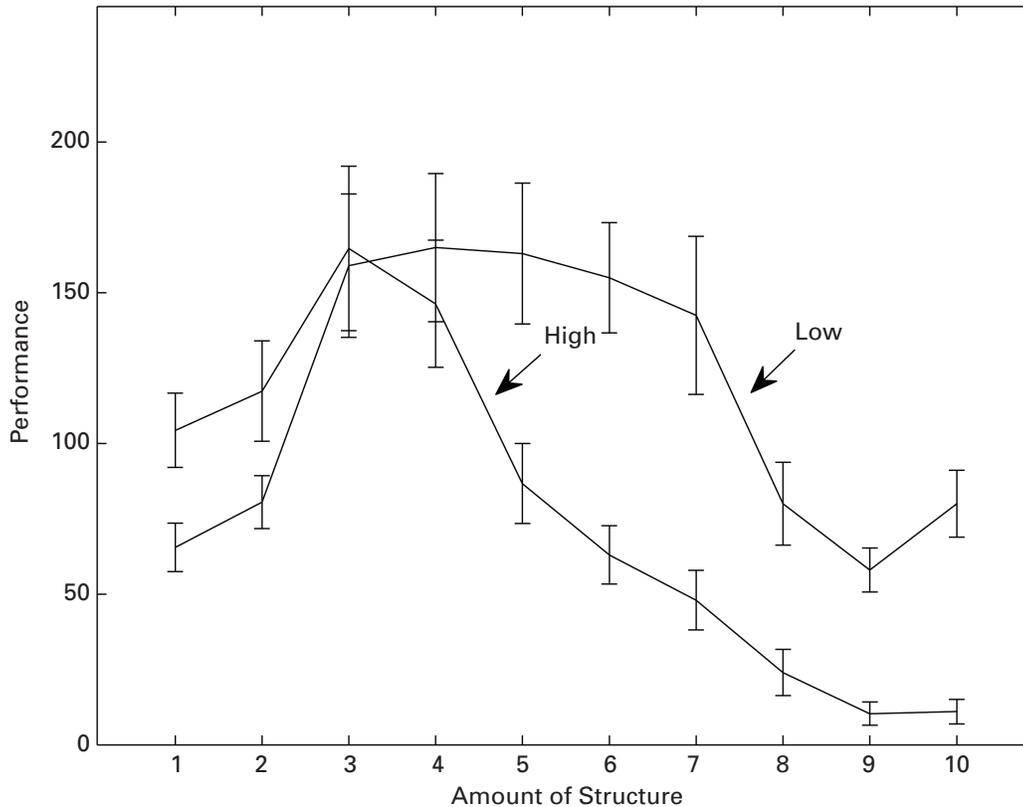


flow of opportunities) on performance by superimposing the results of two representative cases of low and high unpredictability ($U = .72$ and 1). Again, a unimodal, asymmetric relationship, supporting P1a, is found in both environments. But unlike the results for velocity, complexity, and ambiguity, we find a shifting optimum, as predicted by P2, as the optimal amount of structure decreases with higher unpredictability. Thus unpredictability is the environmental dimension that shifts the optimal amount of structure. Moreover, our model offers insight into the logic: the optimal structure decreases with increasing unpredictability because managers are less able to adjust structure to fit the environment when the presence of consistent patterns in the opportunity flow declines. In these environments, managers must rely more on real-time improvised actions and less on structure because there is less pattern in the environment that can be mirrored in organizational structure. This suggests a modified proposition:

Proposition 2a (P2a): As environmental unpredictability increases, the optimal amount of structure decreases.

There are also unexpected findings related to the range of optimal structures. As figure 5 shows, when environments have low unpredictability, the relationship between structure and performance forms a broad plateau. This suggests a forgiving environment in which there is a wide range of optimal structures with roughly the same performance

Figure 5. Effects of increasing environmental unpredictability on performance (over 30 runs).



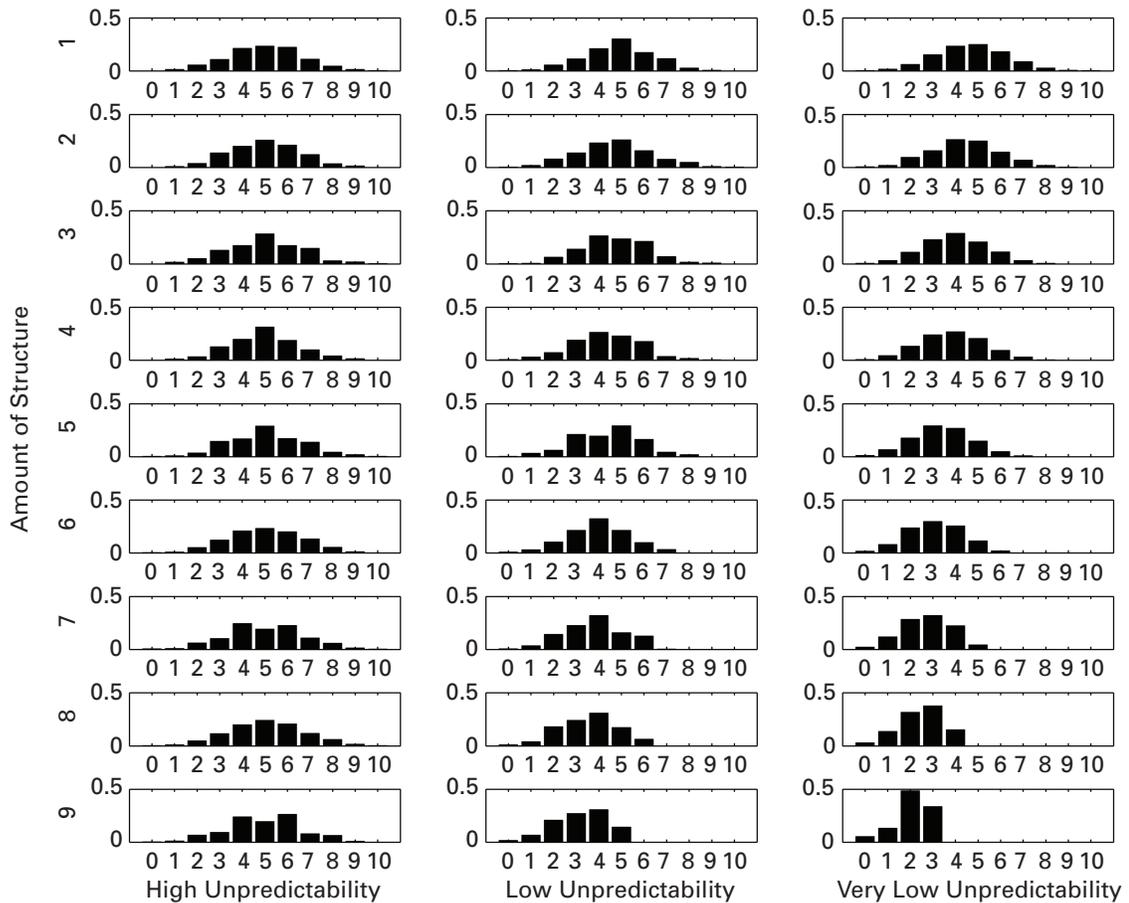
outcomes. In contrast, when environments have high unpredictability, there is an inverted-V relationship between structure and performance. This suggests a punishing environment in which there is a narrow range of optimal structures, such that it is challenging to find the optimal amount of structure, hard to maintain the optimal structure even when perturbations of structure are small, and very low performance when the optimal structure is not achieved. Even small changes in structure have large effects on performance, consistent with an edge of chaos in which only a narrow range of structures leads to superior performance. Thus, in contrast to forgiving low-unpredictability environments, high-unpredictability environments are punishing, with a narrow range of optimal structures.

Analyzing mistakes. Because mistakes are likely to be relevant in a more complete theoretical logic linking structure, performance, and environment, we next examined mistakes. We define a *mistake* as an application of any action (rule-based or improvised) to an opportunity feature that does not match, and *mistake size* as the number of mistakes (i.e., count of mismatches of actions with opportunity features) committed in an attempt to capture an opportunity.

We computed the *frequency distributions of mistake size*, focusing on unpredictability because of its role in shifting the optimal structure. We ran the simulation at multiple unpredictability and structure settings and then tabulated the number of attempts to capture an opportunity for each mistake size.

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Figure 6. Mistake size frequency distributions for varying amount of structure and unpredictability parameters.



As shown in figure 6, we have nine values of structure, from low = 1 to high = 9, down the rows (omitting the value of 10 because it produced undefined endpoint values), and three values of unpredictability—high, low, and very low ($U = 1, .72,$ and $.47$)—across the columns. The sum of each distribution is normalized to 1 for easy comparison across distributions. Each of the resulting 27 distributions is a mini-graph that plots the proportion of attempts to capture opportunities at each mistake size for specific values of unpredictability and structure.

The mistakes analysis sheds light on the theoretical logic for why the range of optimal structures decreases (i.e., from a broad plateau to an inverted-V) as unpredictability increases. First, in low-unpredictability environments (column 2 in figure 6), the analysis indicates that increasing structure reduces the mean mistake size and eliminates large mistakes. These trends are accentuated in environments with very low unpredictability (column 3 in figure 6). The underlying reasoning is as follows. When unpredictability is low, opportunities are more homogeneous and there are recognizable patterns occurring in the opportunities. This predictability allows managers to adjust their structures to more closely fit the opportunities. So a structured action is more likely to be successful for capturing an opportunity. This means that

although increasing structure narrows the range of opportunities that can be addressed, the elimination of large mistakes and the drop in mean mistake size partially offset this disadvantage, such that there is a “mistakes advantage” for structure in less unpredictable environments. This suggests a relatively broad range of successful structures (i.e., plateau) in low-unpredictable environments, as observed in figure 5.

In contrast, in high-unpredictability environments, the mistakes analysis indicates that organizations at all levels of structure are likely to commit multiple mistakes of varying size, including some very large mistakes (column 1 in figure 6). When unpredictability is high, opportunities are very heterogeneous and there is very little pattern in the flow of opportunities. Thus managers cannot adjust their structures to fit environmental opportunities because they do not know what those opportunities will be. The result is mistakes of varying sizes (even large ones) at all levels of structure, including the optimal structure. So there is no “mistakes advantage” for structure that compensates for the loss of flexibility when structure is added. Rather, there is a narrow range of optimal structures, making the tradeoff between efficiency and flexibility more severe in highly unpredictable environments.

Modeling structure and performance. To gain added theoretical insights, we next created a simple mathematical formalization. This model formulates the theoretical logics of efficiency, flexibility, and unpredictability more precisely in terms of specific functional forms (Davis, Eisenhardt, and Bingham, 2007).⁷

Let $e(x)$ and $f(x)$ represent efficiency and flexibility as functions of structure, respectively. Prior researchers have argued that efficiency and flexibility have interdependent, non-substitutable effects on how structure influences performance (Adler, Goldoftas, and Levine, 1999; Gibson and Birkinshaw, 2004) in which the aggregate effect on performance, $A(x)$, is a roughly inverted U-shaped curve of the following form:

$$A(x) = e(x) * f(x). \tag{3}$$

Yet not all $e(x)$ and $f(x)$ functions produce a unimodal $A(x)$ curve and shift the optimal structure, x^* , as unpredictability increases. As shown in the Mathematical Appendix, the requirements for such a curve and shifting optimum put strong constraints on the forms of $e(x)$ and $f(x)$.⁸

Consistent with our mistakes analysis and prior research, we assume that increasing structure increases efficiency—i.e., $e'(x) > 0$ (Brown and Eisenhardt, 1997; Siggelkow, 2001)—such that more structure enables faster, more reliable execution of those opportunities for which the structure is appropriate. But as structure increases, the number of opportunities that fit the structure decreases, and the gains to efficiency of economizing on attention grow more slowly (Donaldson, 2001). So there are likely to be decreasing efficiency returns for added increments of structure that we capture with a logarithmic function of efficiency:

$$e(x) = \ln(x) \tag{4}$$

⁷ This mathematical formalization is not intended to be a formal derivation of our simulation results. Rather, its aim is to build an interpretive model that increases understanding of the theory and enhances confidence in the simulation results. We appreciate the encouragement and guidance of an anonymous reviewer to add this formalization.

⁸ We thank an anonymous reviewer for this formulation and other helpful insights.

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The logarithmic form of $e(x)$ satisfies the important condition that $e'(x) > 0$ because $e'(x) = 1/x > 0$ for $x > 0$ and captures the intuition that efficiency increases, albeit at a declining rate, as structure increases.

Conversely, the literature suggests that flexibility declines as structure increases—i.e., $f'(x) < 0$ (Brown and Eisenhardt, 1997; Miner, Bassoff, and Moorman, 2001). On the one hand, less structure enables organizations to use improvised actions to address more different opportunities. On the other hand, more structure constrains improvised actions, forces more rule-based actions, and limits the heterogeneity of opportunities that can be addressed (Weick, 1993; Baker and Nelson, 2005). Empirical studies of structural inertia have found that this decline in flexibility occurs most dramatically at low levels of structure, at which even small additions of structure can greatly constrain organizational actions (Greve, 1999). This is consistent with the argument that the effect of incremental additions of structure is to eliminate successive fractions of opportunities that could have been flexibly addressed by less structure. This implies that flexibility is rapidly declining and inversely proportional to structure, a relationship that we capture as follows:

$$f(x) = 1/x \quad (5)$$

This function satisfies the important condition that $f'(x) < 0$ because $f'(x) = -1/(x^2) < 0$ for $x > 0$. As described in the Mathematical Appendix, this function is a particularly appropriate choice because it captures the effect of eliminating successive fractions of opportunities with each increment of structure. Finally, because efficiency and flexibility are interdependent and non-substitutable (Gibson and Birkinshaw, 2004), aggregate performance is:

$$A(x) = \ln(x)/x \quad (6)$$

Though other functional forms for efficiency and flexibility may be possible, this $A(x)$ produces a unimodal, asymmetric right relationship between structure and performance that is consistent with our simulation results and theory, as noted in the Mathematical Appendix.⁹

Next, we move to unpredictability. Though researchers have simply argued that flexibility becomes more influential than efficiency as environmental dynamism increases, we show in the Mathematical Appendix that simply increasing flexibility does not shift the optimal structure. Instead, unpredictability, u , has two separate effects on performance that shift the optimum.

First, as unpredictability increases, the heterogeneity of opportunities increases. Organizations with less structure can potentially capture at least some of these more varied opportunities through improvisation. But executing these additional opportunities critically depends on having the greater latitude of action (i.e., flexibility) that less structure provides and so is inversely proportional to structure, $1/x$. Also, though additional opportunities can be addressed, the number of opportunities that can be captured grows increasingly slowly

⁹ We tried other functional forms for efficiency and flexibility, including linear forms, which do not reproduce these results. We chose these two functional forms because they also fit with empirical literature and logical argument. More details are in the Mathematical Appendix.

as unpredictability increases. The reason is that less structure slows down improvisation and takes more attention because the number of opportunity features that must be successfully improvised at once grows. So although there are more opportunities available, the number of additional opportunities that can be successfully captured increases at a decreasing rate. We represent this increasing difficulty with a logarithmic function of unpredictability, $\ln(u)$. Thus we model the added performance improvement that occurs with increasing unpredictability by $\ln(u)/x$. Combining this effect with $A(x)$ changes performance to $A(x) + \ln(u)/x = \ln(x)/x + \ln(u)/x = \ln(ux)/x$.

Second, as unpredictability increases, it becomes more challenging to capture opportunities regardless of whether improvised or rule-based actions are used. Adding structure is ineffective in this environment because there is little predictable pattern in the flow of opportunities that managers can use to adjust their organizational structures to the environment. Subtracting structure is helpful, as noted above, in terms of adding opportunities that can potentially be addressed. But it is also harmful because improvisation is more difficult. Improvisation demands more attention, has more degrees of freedom, and generates many mistakes (including large ones) and so becomes more challenging as unpredictability increases. We represent this overall declining performance with a dampening parameter, $1/u$. Adding this second effect of unpredictability generates a performance function, $P(x,u)$:

$$P(x,u) = 1/u [\ln(ux)/x] = \ln(ux)/ux \quad (7)$$

As noted in the Mathematical Appendix, this function satisfies the conditions for P1a, generating a unimodal, asymmetric right relationship between structure and performance. It also satisfies the conditions for P2a that as unpredictability, u , increases, the optimal structure, $x' = e/u$, decreases. Overall, the mathematical model is consistent with our simulation results and theory.

This mathematical model offers several useful extensions. First, it clarifies the approximate functional forms and rates of change of efficiency and flexibility that contribute to the asymmetry between structure and performance. Performance is asymmetric because efficiency and especially flexibility are changing more rapidly at low structure than at high. When structure is low, even small increments in structure create large increases in efficiency, $\ln(x)$, and large decreases in flexibility, $1/x$. Thus there is a severe tradeoff between efficiency and flexibility. In contrast, when structure is high, performance is much less sensitive to structure. Efficiency improves very gradually with added structure. Flexibility is already so low that increases in structure have little effect. Thus there is only a modest tradeoff between efficiency and flexibility. Overall, having too little structure is particularly risky because efficiency and flexibility are highly sensitive to even small changes in structure when structure is low.

Second, this model clarifies the inverted-V curve and related edge of chaos in highly unpredictable environments. According to prior research, less structure is better in highly dynamic

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environments because flexibility is more advantageous than efficiency. In contrast, a core insight of our model is that neither efficiency nor flexibility works very well in highly unpredictable environments. As expected, extensive structure and so efficiency are ineffective because they are overly rigid. But unexpectedly, improvised actions and so flexibility are not very effective either. With so little structure, improvisation consumes a lot of attention, is fraught with mistakes, and is very slow. As a result, the organization can only capture a few opportunities, and risks falling into an "error catastrophe," in which it lacks enough traction to improvise fast enough to capture opportunities before they disappear. So the optimal structure is a narrow range (i.e., at the edge of chaos) of just enough structure to capture at least a few opportunities.

DISCUSSION AND CONCLUSION

Using computational and mathematical modeling, we added to theory on the fundamental relationships among structure, performance, and environment. As summarized in table 1, our core contribution is a more precise theory of how the locus, asymmetry, and range of optimal structures are grounded in the tradeoff between efficiency and flexibility in differing environments. First, we clarify this tradeoff between flexibility and efficiency. Prior theory focuses on balancing efficiency and flexibility (Tushman and O'Reilly, 1996; Brown and Eisenhardt, 1997; Uzzi, 1997; Rowley, Behrens, and Krackhardt, 2000). In contrast, we find that this tradeoff is more accurately the flexible capture of widely varying opportunities vs. efficient execution of specific opportunities.¹⁰ Less structure opens up the organization to the possibility of addressing a wider range of opportunities that serendipitously occur, but it also hinders the rapid, mistake-free execution of those opportunities. Conversely, more structure enables the efficient execution of particular opportunities that can be anticipated. But too much structure is more than just too rigid. It also narrows the range of possible opportunities, suggesting that structure is most valuable when many similar opportunities are available.

Second, the relationship between structure and performance is unexpectedly asymmetric: performance gradually fades with too much structure but drops catastrophically with too little. Thus structure and performance do not have an inverted-U relationship, as argued previously (Brown and Eisenhardt, 1997; Gibson and Birkinshaw, 2004; Rothaermel, Hitt, and Jobe, 2006). Rather, efficiency and flexibility are distinct functions that change slowly when structure is high. In contrast, efficiency and especially flexibility change rapidly when structure is low, creating a more acute tradeoff between efficiency and flexibility. The consequential implication is that it is safer to err on the side of too much structure (efficiency) than on the side of too little (flexibility).

Third, our results show that simple rules and other semi-structures are surprisingly robust across multiple environments, in contrast with research arguing that they are best only in highly dynamic environments (Burns and Stalker, 1961; Rowley, Behrens, and Krackhardt, 2000; Eisenhardt and Sull, 2001).¹¹ In predictable environments, there is a broad plateau of optimal structures, and so numerous high-performing

10
We appreciate the advice of an anonymous reviewer to include this more nuanced understanding of the core tradeoff between efficiency and flexibility.

11
We appreciate the suggestion of an anonymous reviewer to consider the robustness of a simple-rules strategy.

Table 1

Comparison of Theoretical Frameworks for Structure-environment-performance Relationships		
Framework feature	Prior	Revised
Core tradeoff	Flexibility vs. efficiency.	Flexible capture of varying opportunities vs. efficient execution of specific opportunities. Relevance of limited attention, mistakes, time delays, and fleeting and varied opportunities.
Structure-performance relationship	Inverted-U. Flexibility and efficiency are opposing, approximately linear processes.	Unimodal, asymmetric right. Attention advantage of increasing structure. Efficiency increases at a decreasing rate; flexibility decreases at decreasing rate.
Major environmental constructs	Environmental dynamism shifts locus of optimal structure.	Unpredictability shifts the locus and range of optimal structure. High velocity raises performance. High complexity lowers performance. High ambiguity lowers performance and broadens the range of optimal structure.
Robustness of simple rules	Necessary in highly dynamic environments.	Simple rules are robust across a wide range of environments. Viable in predictable environments. Necessary in unpredictable environments.
Range of optimal structures	Constant.	In predictable environments, plateau of many optimal structures. In unpredictable environments, inverted-V of a few optimal structures, and selection and exit rules likely crucial.
Edge of chaos	Highly dynamic environments. Inverse power law distribution of mistakes. High managerial energy focused on staying poised at the optimal structure or edge of chaos	Highly unpredictable environments. Many mistakes of varying sizes, including large ones, roughly normal distribution. Mistakes advantage of increasing structure in less unpredictable environments. High managerial energy focused on improvisation, mistake recovery, and staying poised at the optimal structure or edge of chaos.

structures exist. The tension between too much and too little structure is easy to manage in this forgiving environment in which many structures are roughly equivalent. So executives can rely on simple rules, loose coupling, and other semi-structures that favor flexibility (albeit with more attention and mistakes) or elaborate structures with tight coupling that favor efficiency (albeit with a narrower range of opportunities) without sacrificing much performance. For example, executives who need to minimize mistakes (e.g., nuclear power plants, aircraft carriers) can design highly reliable organizations that utilize very extensive structure (Perrow, 1984; Weick and Roberts, 1993) with little performance penalty.

In contrast, in unpredictable environments, there is an inverted-V relationship between structure and performance with only a narrow band of optimal structures. Even minor perturbations in structure can be catastrophic in these punishing environments in which performance is precarious and mistakes can be many, large, and fatal. The tension between too much and too little structure is challenging and crucial to manage. The mistakes advantage of structure vanishes, and improvisation is difficult. Here, only simple rules are high performing. The overall implication is that simple rules and other semi-structures are robust across diverse environments—i.e., they are viable in predictable environments and essential in unpredictable ones.

Underlying the robustness of simple rules across environments are the dynamics of unpredictability that shape the

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locus and range of optimal structure. Prior research has included velocity (Eisenhardt, 1989), complexity (Gavetti, Levinthal, and Rivkin, 2005), and ambiguity (March and Olsen, 1976; Rindova and Kotha, 2001) as major dimensions of environmental dynamism. But though these dimensions have intriguing implications for strategy and performance (see below), only unpredictability influences optimal structure. Underlying this finding is the insight that structure is valuable when there are consistent patterns in the flow of environmental opportunities and when managers have adjusted their structures to match these patterns. But as our simulation suggests, these tuning adjustments need not be exactly accurate. Rather, sometimes matches may occur by chance, and sometimes structure helps just by diminishing the degrees of freedom in mistake-prone improvisation. The key implication is that adding structure when unpredictability decreases can be valuable (or at least not harmful), even when it is not completely clear what exactly that structure should be. Thus our results support a structural explanation for Weick's (1990) well-known observation of the success of a European army in navigating the Alps based on a map of the Pyrenees (see also Gavetti, Levinthal, and Rivkin, 2005).

A particularly intriguing optimum in the structure-performance-environment relationship is simple rules in highly unpredictable environments. Prior researchers have argued that favoring flexibility leads to high performance (Burns and Stalker, 1961; Brown and Eisenhardt, 1998). But though we find that flexibility is helpful, this argument is too simplistic because neither structure nor improvisation is very effective in these environments. As a result, the optimal structure not only diminishes, but its range unexpectedly shrinks from a broad plateau to an inverted-V (i.e., edge of chaos). And more unexpectedly, the number of opportunities that can be successfully executed also drops as improvisation becomes more difficult. A consequential implication is that the content of a high-performing simple-rules strategy will likely focus on capturing a few, high-payoff opportunities—i.e., a small number of rules to quickly select a few “home-run” opportunities and to quickly exit those opportunities when they do not pan out. This implication also helps explain why heuristics that focus on prioritizing and exiting opportunities are particularly high performing in highly dynamic environments (Bingham, Eisenhardt, and Furr, 2007).

Finally, we contribute insights into the edge-of-chaos concept from the complexity sciences (Kauffman, 1993; Carroll and Burton, 2000). Research has defined the edge of chaos as a phase transition between order and disorder (Kauffman, 1993), and it is often described more colorfully with phrases like “snooze, you lose” and “only the paranoid survive” (Brown and Eisenhardt, 1998; Burgelman, 2002). Our contribution is theoretical insights into this intriguing construct and its role within our elaborated theory of structure, performance, and the environment. First, we identify where the edge of chaos is likely to occur: in highly unpredictable environments. In these environments, the relationship between structure and performance is an inverted-V with tipping points on both sides of the optimal structure, consistent with an edge of chaos. Second, we explain why the edge of chaos occurs—when

structure is low, rapidly changing efficiency and flexibility with difficult improvisation create a thin range of optimal structures. Third, we characterize the distribution of mistakes at the edge of chaos—many errors of widely varying size and including some large errors. Managers are likely to experience both small oversights and debilitating miscalculations. Note that we did not find an inverse power law distribution of many small mistakes and few large ones (Bak, 1996). Rather, the distribution is roughly normal. Finally, we provide insight into the energy required to maintain a position at the edge of chaos. Researchers have argued that the edge of chaos is a dissipative equilibrium, an unstable critical point that requires constant energy to maintain (Prigogine and Stengers, 1984). We extend this notion to our focal literatures by clarifying that managerial energy at the edge of chaos centers on real-time improvisation of opportunities, recovery from the inevitable mistakes that will occur, and continuous monitoring of the amount of structure to avoid drift from the optimum.

Toward a Pluralistic View of Strategies

More broadly, our work also contributes to strategy and its mandate to develop theoretical logics explaining variance in firm performance. First, we contribute to the strategic logic of opportunity and the related strategy as simple rules (Eisenhardt and Martin, 2000; Eisenhardt and Sull, 2001). According to the logic of opportunity, firms achieve high performance in dynamic markets by using a few simple rules to guide the capture of opportunities (e.g., Gersick, 1994; Burgelman, 1996; Galunic and Eisenhardt, 2001; Miner, Bassoff, and Moorman, 2001; Rindova and Kotha, 2001; Bingham, Eisenhardt, and Furr, 2007). Our research extends this view with support and insights into the core theoretical logic by clarifying the implications of limited attention, mistakes, and the fleeting and varied nature of opportunities. These dynamics place a premium on using increasingly simple rules to capture increasingly unpredictable opportunities. Thus, like other simulations that provide internal validation of theory (e.g., Sastry, 1997), our simulation helps to sharpen the theory that underlies the strategic logic of opportunity.

Second, we contribute insights into the boundary conditions of several strategic logics. In positioning logic, executives achieve high performance by building tightly linked activity systems in valuable strategic positions, such as low cost or high differentiation (Porter, 1985; Rivkin, 2000). Our findings add to this view by clarifying that such high-structure strategies are effective in predictable markets. Further, our findings contribute to a deeper understanding of why tightly linked activity systems are high performing in such predictable markets—i.e., while fewer opportunities may fit these highly structured strategies, their tightly linked activity systems produce both few and small mistakes. Therefore they efficiently execute a flow of similar opportunities. In addition, given that there are many possible high-performing structures in predictable markets (i.e., a plateau relationship between structure and performance), our findings indicate why executives can achieve good performance with many alternative strategies. These numerous optimal strategic alternatives help to explain why multiple differentiated positions are often

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viable in predictable markets (Porter, 1985). Finally, our findings clarify why, once achieved, competitive advantage gained through positioning is relatively robust to environmental and structural perturbations, creating a foundation for sustainable competitive advantage and superior performance.

By contrast, in opportunity logic, executives achieve high performance by using a few simple rules or heuristics to capture varied opportunities (Eisenhardt and Sull, 2001; Bingham and Eisenhardt, 2008). Our findings contribute to this view by indicating that low-structure opportunity logic is particularly essential in unpredictable markets, while positioning logic is most effective in predictable markets, thereby sketching a boundary condition between these strategic logics. Our findings further contribute a subtle insight into the precarious nature of competitive advantage (D'Aveni, 1994; Lenox, Rockart, and Lewin, 2006). Though prior researchers have argued that firms should seek a series of short-term, competitive advantages in dynamic environments (Roberts and Amit, 2003; Chen et al., 2009), our results indicate that competitive advantage in these environments is unstable and its duration unforeseeable (but not necessarily short-term). Overall, this suggests that firms with a strategic logic of opportunity are threatened by internal collapse—i.e., they can fail as a result of having too much or too little structure and not just as a result of external competition. This potential for internal collapse offers an alternative explanation of intra-industry performance heterogeneity that differs from path dependent and competitive explanations (McGahan and Porter, 1997; Bowman and Helfat, 2001). Thus a key insight is that the managerial challenges of finding and maintaining optimal structure at the edge of chaos may contribute to heterogeneous firm performance within dynamic industries.

A Richer View of Environments

Our work also contributes to a better understanding of distinct environments. Prior research tends to focus on single environmental dimensions or mix several dimensions together. The result is an imprecise understanding of different environments. In contrast, we highlighted four distinct, widely used environmental dynamism dimensions (i.e., velocity, complexity, ambiguity, and unpredictability) and developed their unique implications for strategy and performance. We covered unpredictability above and now turn to the remaining three dimensions.

High-velocity environments are particularly attractive. Because they are opportunity-rich, managers can be selective and so choose many, high-payoff opportunities. In addition, this finding offers further insight into why rapid executive actions and processes such as fast strategic decision making (Eisenhardt, 1989) and fast product innovation (Eisenhardt and Tabrizi, 1995) are so effective in high-velocity environments. In these opportunity-rich environments, there are likely to be many high-payoff opportunities. By acting quickly, executives can secure a larger number of these superior payoffs for a longer time and so achieve high performance. In contrast, by acting slowly, executives are likely to secure fewer opportunities and to exploit them for less time, leading to low performance.

The attractiveness of high-velocity environments may also explain why the Internet era (with its high velocity of opportunities) had a surprisingly low failure rate. Although many firms died, the death rate was unusually low when compared with the total number of foundings (Goldfarb, Kirsch, and Miller, 2007). Overall, we found that high-velocity environments are attractive for achieving high performance.

In contrast, complex environments are particularly unattractive. In highly complex environments, opportunities have many features that executives must execute correctly. Thus these opportunities are challenging to capture, and performance is correspondingly low. This finding extends prior research by helping to explain why firms in complex environments such as biotechnology (Owen-Smith and Powell, 2003) and "green" power (Sine, Mitsuhashi, and Kirsch, 2006) often perform poorly even when their executives have high domain expertise. In these technically and institutionally complex environments, executives must achieve success in many areas (e.g., technical, manufacturing, safety, regulatory, marketing) to capture an opportunity. When organizations fail to capture some opportunities, attention is wasted that could have been used to address other opportunities. Thus organizations in complex environments can address relatively few opportunities and are likely to have a low probability of success when they do. Overall, we find that high-complexity environments are unattractive for gaining high performance.

Our findings for environmental ambiguity are especially intriguing. When ambiguity is high, executives are unable to perceive opportunities accurately and have a wide range of reasonably optimal structures that produce roughly equivalent, albeit mediocre, performance. By contrast, when ambiguity is low, the range of optimal structures narrows and so favors executives who are able to locate and maintain optimal structure. Thus performance at the optimal structure improves because executives can more accurately perceive opportunities and so more precisely match structure to them.

These insights contribute to understanding effective institutional entrepreneurship in nascent markets. Research indicates that entrepreneurs in these highly ambiguous markets often excel when they shape industry structure to their advantage (Rao, 1994; Rindova and Fombrun, 1999; Santos and Eisenhardt, 2009). For example, entrepreneurs succeed when they form portfolios of relationships that shape the industry structure to gain a central network position (Ozcan and Eisenhardt, 2008) or when they use analogies to provide some unique insight into the opportunity structure of these novel markets that improves opportunity capture (Gavetti, Levinthal, and Rivkin, 2005).¹² We add to institutional entrepreneurship by revealing that these actions are successful attempts to reduce ambiguity and so increase the possibility of very high performance. Thus successful entrepreneurs seek to change nascent markets from games of luck with likely mediocre performance in which the optimal structure is easy to find (high ambiguity) to games of skill with potentially high performance in which the optimal structure is challenging to find (low ambiguity).

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We appreciate the observation of an anonymous reviewer that unique insight into the opportunity structure can potentially provide large returns in highly ambiguous environments. This observation suggests that these managers could use such insights (e.g., as derived from analogies) to lower ambiguity. We use this interpretation as part of our explanation of the behavior of successful executives in highly ambiguous markets, including nascent markets. In addition, this reviewer also noted that such unique insights might also be effective in highly unpredictable environments. Here, also, analogies may be a concrete example of the kind of unique insights to which this reviewer referred.

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Adaptation in Entrepreneurial vs. Established Organizations

Finally, our work contributes to organization theory. At the heart of our research is the core tradeoff between flexibility and efficiency in dynamic environments. Less structure enables the flexible capture of serendipitous opportunities. But with too much improvisation, the organization runs the risk of incoherence, confusion, and drift. More structure enables tight focus on the efficient execution of expected opportunities. With too much structure, however, the organization runs the risk of stagnation and misalignment with fresh opportunities. The essence of flexibility is thus the messy capture of the unexpected, while the essence of efficiency is the smooth execution of the anticipated.

Our contribution is the insight that this core efficiency-flexibility tradeoff affects types of organizations differently. For entrepreneurial organizations that typically have little structure, the challenge in any environment is the same: to gain enough structure before failure ensues. Legitimation and competition, of course, affect performance. But the key insight here is that sufficient structure is also essential. Without sufficient structure, it is impossible to improvise effectively and so to capture opportunities. Thus the well-known liability of newness may mask a liability of too little structure.

In contrast, for established organizations that often have extensive structure, such as roles, rules, and linkages among units, the imperative varies in different environments. If the environment is predictable, this structure can be high performing because it can take advantage of consistent patterns in the environment that can be mirrored in structure. The number and size of mistakes decreases with more structure in predictable environments, and only modest executive attention is needed to retain an optimal amount of structure. Organizations can gain a stable equilibrium that is robust to structural and environmental changes.

But as the environment becomes unpredictable or executives diversify into unpredictable environments, our findings indicate major challenges for established organizations. One is obviously to decrease the amount of structure. But a second, subtler challenge is the need for a dramatically altered mindset. This mindset entails vigilantly managing the amount of structure (not just its content), improvising to capture fresh opportunities, and quickly rebounding from mistakes—all at the edge of chaos, where firms can at best capture only a few opportunities and gain an unstable or dissipative equilibrium. Simply put, managing in unpredictable environments is different, harder, and more precarious than in predictable environments. Overall, the irony of adaptation is that, as it becomes more crucial for organizations to adapt, it also becomes more challenging to do so. Thus the well-known liability of senescence may be as much a cognitive phenomenon as an age phenomenon.

We began by noting that diverse literatures emphasized that balancing between too much and too little structure is essential for high performance in dynamic environments. This

consonance led us to explore the theoretical logic of efficiency versus flexibility underlying fundamental relationships at the heart of the science of organization. By incorporating limits on attention, time delays, the inevitability of mistakes, and the fleeting and heterogeneous nature of opportunities, we construct a more precise theory that links structure, performance, and environment. This theoretical framework reveals the surprisingly wide applicability of a simple-rules strategy and semi-structures, an asymmetry that favors more structure, and demanding managerial challenges at the edge of chaos. Overall, we spotlight a research agenda that places complexity sciences reasoning at the nexus of organizational studies, network sociology, and competitive strategy.

REFERENCES

- Adler, P. S., B. Goldoftas, and D. I. Levine**
1999 "Flexibility versus efficiency? A case study of model changeovers in the Toyota production system." *Organization Science*, 10: 43–68.
- Amabile, T.**
1996 *Creativity in Context*. Boulder, CO: Westview Press.
- Anderson, P.**
1999 "Complexity theory and organization science." *Organization Science*, 10: 216–232.
- Bak, P.**
1996 *How Nature Works: The Science of Self-organized Criticality*. New York: Springer-Verlag.
- Baker, T., and R. E. Nelson**
2005 "Creating something from nothing: Resource construction through entrepreneurial bricolage." *Administrative Science Quarterly*, 50: 329–366.
- Baligh, H. H.**
2006 *Organization Structures: Theory and Design, Analysis and Prescription*. New York: Springer.
- Baum, J. A. C., T. Calabrese, and B. R. Silverman**
2000 "Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology." *Strategic Management Journal*, 21: 267–294.
- Bigley, G., and K. Roberts**
2001 "Structuring temporary systems for high reliability." *Academy of Management Journal*, 44: 1281–1300.
- Bingham, C. B., and K. M. Eisenhardt**
2008 "Position, leverage, and opportunity: A typology of strategic logics linking resources with competitive advantage." *Managerial and Decision Economics*, 29: 241–256.
- Bingham, C. B., K. M. Eisenhardt, and J. P. Davis**
2009 "Opening the black box: What firms explicitly learn from their process experiences." Working paper, University of North Carolina at Chapel Hill, Kenan-Flagler Business School.
- Bingham, C. B., K. M. Eisenhardt, and N. R. Furr**
2007 "What makes a process a capability? Heuristics, strategy, and effective capture of opportunities." *Strategic Entrepreneurship Journal*, 1: 27–47.
- Bowman, E., and C. E. Helfat**
2001 "Does corporate strategy matter?" *Strategic Management Journal*, 22: 1–23.
- Bradach, J. L.**
1997 "Using the plural form in the management of restaurant chains." *Administrative Science Quarterly*, 42: 276–304.
- Brown, S. L., and K. M. Eisenhardt**
1997 "The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations." *Administrative Science Quarterly*, 42: 1–34.
- 1998 *Competing on the Edge: Strategy as Structured Chaos*. Boston: Harvard Business School Press.
- Burgelman, R. A.**
1994 "Fading memories: A process theory of strategic business exit in dynamic environments." *Administrative Science Quarterly*, 39: 24–56.
- 1996 "A process model of strategic business exit: Implications for an evolutionary theory of strategy." *Strategic Management Journal*, 17: 193–214.
- 2002 "Strategy as vector and the inertia of coevolutionary lock-in." *Administrative Science Quarterly*, 47: 325–357.
- Burns, T., and G. M. Stalker**
1961 *The Management of Innovation*. London: Tavistock.
- Burton, R. M., and B. Obel**
1995 "The validity of computational models in organization science: From model realism to purpose of the model." *Computational and Mathematical Organization Theory*, 1: 57–72.
- Carroll, G. R., and J. R. Harrison**
1998 "Organizational demography and culture: Insights from a formal model and simulation." *Administrative Science Quarterly*, 43: 637–667.
- Carroll, T., and R. Burton**
2000 "Organizations and complexity: Searching for the edge of chaos." *Computational and Mathematical Organization Theory*, 6: 319–337.
- Chen, E. L., R. Katila, R. M. McDonald, and K. M. Eisenhardt**
2009 "All the right moves: Competitive interaction, temporary advantage, and firm performance." Stanford Technology Ventures Program Working Paper.
- Cinlar, E.**
1975 *Introduction to Stochastic Processes*. Englewood Cliffs, NJ: Prentice-Hall.
- Cohen, M. D., J. G. March, and J. P. Olsen**
1972 "A garbage can model of organizational choice." *Administrative Science Quarterly*, 17: 1–25.
- Cover, T., and J. Thomas**
1991 *Elements of Information Theory*. New York: Wiley.
- Cyert, R. M., and J. G. March**
1963 *A Behavioral Theory of the Firm*. Englewood Cliffs, NJ: Prentice-Hall.

Optimal Structure

- D'Aveni, R. A.**
1994 *Hypercompetition: Managing the Dynamics of Strategic Maneuvering*. New York: Free Press.
- Daft, R. L.**
1992 *Organization Theory and Design*, 4th ed. St. Paul, MN: West Publishing.
- Davis, J. P.**
2008 "Rotating leadership and symbiotic organization: Relationship processes in the context of collaborative innovation." Working paper, MIT Sloan School of Management.
2009 "Organizing bridge dynamics: Pruning and pairing processes in innovative interorganizational relationships." Working paper, MIT Sloan School of Management.
- Davis, J. P., K. M. Eisenhardt, and C. B. Bingham**
2007 "Developing theory through simulation methods." *Academy of Management Review*, 32: 480-499.
- Dess, G., and D. Beard**
1984 "Dimensions of organizational task environments." *Administrative Science Quarterly*, 29: 52-73.
- Donaldson, L.**
2001 *The Contingency Theory of Organization*. Thousand Oaks, CA: Sage.
- Eisenhardt, K. M.**
1989 "Making fast strategic decisions in high-velocity environments." *Academy of Management Journal*, 32: 543-576.
- Eisenhardt, K. M., and M. M. Bhatia**
2001 "Organizational complexity and computation." In J. A. C. Baum (ed.), *Companion to Organizations*. Oxford: Blackwell.
- Eisenhardt, K. M., and J. A. Martin**
2000 "Dynamic capabilities: What are they?" *Strategic Management Journal*, 21: 1105-1121.
- Eisenhardt, K. M., and D. Sull**
2001 "Strategy as simple rules." *Harvard Business Review*, 79 (January-February): 107-116.
- Eisenhardt, K. M., and B. Tabrizi**
1995 "Accelerating adaptive processes: Product innovation in the global computer industry." *Administrative Science Quarterly*, 40: 84-110.
- Feldman, M. S., and B. T. Pentland**
2003 "Reconceptualizing organizational routines as a source of flexibility and change." *Administrative Science Quarterly*, 48: 94-118.
- Finkelstein, S.**
2003 *Why Smart Executives Fail*. New York: Portfolio.
- Fleming, L., O. Sorenson, and J. Rivkin**
2006 "Complexity, networks, and knowledge flow." *Research Policy*, 35: 994-1017.
- Galbraith, J.**
1973 *Designing Complex Organizations*. Reading, MA: Addison-Wesley.
- Galunic, D. C., and K. M. Eisenhardt**
2001 "Architectural innovation and modular corporate forms." *Academy of Management Journal*, 44: 1229-1250.
- Garud, R., and S. Jain**
1996 "The embeddedness of technology systems." In J. A. C. Baum and J. E. Dutton (eds.), *Advances in Strategic Management*, 13: 389-408. Greenwich, CT: JAI Press.
- Gavetti, G., D. Levinthal, and J. W. Rivkin**
2005 "Strategy making in novel and complex worlds: The power of analogy." *Strategic Management Journal*, 26: 691-712.
- Gell-Mann, M.**
1994 *The Quark and the Jaguar: Adventures in the Simple and the Complex*. New York: W.H. Freeman.
- Gersick, C. J. G.**
1994 "Pacing strategic change: The case of a new venture." *Academy of Management Journal*, 37: 9-45.
- Gibson, C., and J. Birkinshaw**
2004 "The antecedents, consequences and mediating role of organizational ambidexterity." *Academy of Management Journal*, 47: 209-226.
- Gilbert, C.**
2005 "Unbundling the structure of inertia: Resource vs routine rigidity." *Academy of Management Journal*, 48: 741-763.
- Glynn, P., and W. Whitt**
1992 "The asymptotic efficiency of simulation estimators." *Operations Research*, 40: 505-520.
- Goldfarb, B., D. A. Kirsch, and D. Miller**
2007 "Was there too little entry during the dot com era?" *Journal of Financial Economics*, 86: 100-144.
- Granovetter, M.**
1985 "Economic action and social structure: The problem of embeddedness." *American Journal of Sociology*, 91: 481-510.
- Greve, H. R.**
1999 "The effect of core change on performance: Inertia and regression toward the mean." *Administrative Science Quarterly*, 44: 590-614.
- Hansen, M. T.**
1999 "The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits." *Administrative Science Quarterly*, 44: 82-111.
- Hargadon, A., and R. I. Sutton**
1997 "Technology brokering and innovation in a product development firm." *Administrative Science Quarterly*, 42: 716-749.
- Hatch, M. J.**
1998 "Jazz as a metaphor for organizing in the 21st century." *Organization Science*, 9: 556-557.
- Hayek, F. A.**
1945 "The use of knowledge in society." *American Economic Review*, 35: 519-530.
- Hill, C. W. L., and F. T. Rothaermel**
2003 "The performance of incumbent firms in the face of radical technological innovation." *Academy of Management Review*, 28: 257-274.
- Kalos, M., and P. Whitlock**
1986 *Monte Carlo Methods*, vol. 1: Basics. New York: Wiley-Interscience.
- Katila, R., and G. Ahuja**
2002 "Something old, something new: A longitudinal study of search behavior and new product introduction." *Academy of Management Journal*, 45: 1183-1194.
- Kauffman, S.**
1989 "Adaptation on rugged fitness landscapes." In E. Stein (ed.), *Lectures in the Science of Complexity*: 517-618. Reading, MA: Addison-Wesley.
1993 *The Origins of Order*. New York: Oxford University Press.

- Kirzner, I.**
1997 "Entrepreneurial discovery and the competitive market process: An Austrian approach." *Journal of Economic Literature*, 35: 60–85.
- Langton, C.**
1992 "Life at the edge of chaos." In C. Langton, J. Farmer, S. Rasmussen, and C. Taylor (eds.), *Artificial Life II: Santa Fe Institute Studies in the Sciences of Complexity*, 10: 41–91. Santa Fe: Addison-Wesley.
- Lave, C., and J. G. March**
1975 *An Introduction to Models in the Social Sciences*. New York: Harper and Row.
- Law, A. M., and D. W. Kelton**
1991 *Simulation Modeling and Analysis*, 2d ed. New York: McGraw-Hill.
- Lawrence, P. R., and J. W. Lorsch**
1967 *Organization and Environment: Managing Differentiation and Integration*. Boston: Harvard University Press.
- Lenox, M. J., S. Rockart, and A. Lewin**
2006 "Interdependency, competition, and the distribution of firm and industry profits." *Management Science*, 52: 757–772.
- March, J. G.**
1991 "Exploration and exploitation in organizational learning." *Organization Science*, 2: 71–87.
- March, J. G., and J. P. Olsen**
1976 *Ambiguity and Choice in Organizations*. Bergen: Universitetsforlaget.
- March, J. G., M. Schultz, and X. Zhou**
2000 *Dynamics of Rules*. Stanford, CA: Stanford University Press.
- March, J. G., and H. Simon**
1958 *Organizations*. New York: Wiley.
- Martin, J. A., and K. Eisenhardt**
2010 "Rewiring: Cross-business-unit collaborations and performance in multi-business organizations." *Academy of Management Journal* (forthcoming).
- McGahan, A. M., and M. E. Porter**
1997 "How much does industry matter, really?" *Strategic Management Journal*, 18: 15–30.
- Miller, D., and P. H. Friesen**
1980 "Momentum and revolution in organizational adaptation." *Academy of Management Journal*, 23: 591–614.
- Miner, A. S., P. Bassoff, and C. Moorman**
2001 "Organizational improvisation and learning: A field study." *Administrative Science Quarterly*, 46: 304–337.
- Mintzberg, H.**
1979 *The Structuring of Organizations*. Englewood Cliffs, NJ: Prentice-Hall.
- Mintzberg, H., and A. McHugh**
1985 "Strategy formation in an adhocracy." *Administrative Science Quarterly*, 30: 160–197.
- Moorman, C., and A. S. Miner**
1998 "Organizational improvisation and organizational memory." *Academy of Management Review*, 23: 698–723.
- Nelson, R. R., and S. G. Winter**
1982 *An Evolutionary Theory of Economic Change*. Cambridge, MA: Belknap Press of Harvard University Press.
- Ocasio, W.**
1997 "Towards an attention-based view of the firm." *Strategic Management Journal*, 18: 187–206.
- Okhuysen, G. A., and K. M. Eisenhardt**
2002 "Integrating knowledge in groups: How formal interventions enable flexibility." *Organization Science*, 13: 370–386.
- Owen-Smith, J., and W. W. Powell**
2003 "Knowledge networks as channels and conduits: The effects of spillovers in the Boston biotechnology community." *Organization Science*, 15: 5–21.
- Ozcan, C. P., and K. M. Eisenhardt**
2009 "Origin of alliance portfolios: Entrepreneurs, network strategies, and firm performance." *Academy of Management Journal*, 52: 246–279.
- Perlow, L. A., G. A. Okhuysen, and N. Repenning**
2002 "The speed trap: Exploring the relationship between decision making and temporal context." *Academy of Management Journal*, 45: 931–955.
- Perrow, C.**
1984 *Normal Accidents: Living with High-risk Technologies*. New York: Basic Books.
- Pisano, G. P.**
1994 "Knowledge, integration, and the locus of learning: An empirical analysis of process development." *Strategic Management Journal*, 15: 85–100.
- Porter, M. E.**
1985 *Competitive Advantage: Creating and Sustaining Superior Performance*. New York: Free Press.
- Prigogine, I., and I. Stengers**
1984 *Order Out of Chaos: Man's New Dialog with Nature*. New York: Shambhala.
- Pugh, D., D. Hickson, C. Hinings, K. Macdonald, C. Turner, and T. Lupton**
1963 "A conceptual scheme for organizational analysis." *Administrative Science Quarterly*, 8: 289–315.
- Rao, H.**
1994 "The social construction of reputation: Certification contests, legitimation, and the survival of organizations in the American automobile industry: 1895–1912." *Strategic Management Journal*, 15: 29–44.
- Reynolds, C. W.**
1987 "Flocks, herds, and schools: A distributed behavioral model, in computer graphics." *SIG-GRAPH '87*, 21(4): 25–34.
- Rindova, V., and C. Fombrun**
1999 "Constructing competitive advantage: The role of firm-constituent interactions." *Strategic Management Journal*, 20: 691–710.
- Rindova, V., and S. Kotha**
2001 "Continuous morphing: Competing through dynamic capabilities, form, and function." *Academy of Management Journal*, 44: 1263–1280.
- Rivkin, J. W.**
2000 "Imitation of complex strategies." *Management Science*, 46: 824–844.
- Rivkin, J. W., and N. Siggelkow**
2003 "Balancing search and stability: Interdependencies among elements of organizational design." *Management Science*, 49: 290–311.
- Roberts, P. W.**
1999 "Product innovation, product-market competition and persistent profitability in the U.S. pharmaceutical industry." *Strategic Management Journal*, 20: 655–670.
- Roberts, P. W., and R. Amit**
2003 "The dynamics of capability development: The case of Australian retail banking." *Organization Science*, 14: 107–122.

Optimal Structure

- Rothaermel, F. T., M. Hitt, and L. Jobe**
2006 "Balancing vertical integration and strategic outsourcing: Effects on product portfolios, new product success, and firm performance." *Strategic Management Journal*, 27: 1033–1056.
- Rowley, T. J., D. Behrens, and D. Krackhardt**
2000 "Redundant governance structures: An analysis of structural and relational embeddedness in the steel and semiconductor industries." *Strategic Management Journal*, 21: 369–386.
- Rudolph, J., and N. Repenning**
2002 "Disaster dynamics: Understanding the role of quantity in organizational collapse." *Administrative Science Quarterly*, 47: 1–30.
- Santos, F. M., and K. M. Eisenhardt**
2009 "Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields." *Academy of Management Journal*, 52: 643–671.
- Sastry, M. A.**
1997 "Problems and paradoxes in a model of punctuated organizational change." *Administrative Science Quarterly*, 42: 237–275.
- Schilling, M. A., and H. K. Steensma**
2001 "The use of modular organizational forms: An industry-level analysis." *Academy of Management Journal*, 44: 1149–1168.
- Schoonhoven, C. B., and E. Romanelli, eds.**
2001 *The Entrepreneurship Dynamic: Origins of Entrepreneurship and the Evolution of Industries*. Stanford, CA: Stanford University Press.
- Scott, W. R.**
2003 *Organizations: Rational, Natural and Open Systems*, 5th ed. Upper Saddle River, NJ: Prentice Hall.
- Shane, S.**
2000 "Prior knowledge and the discovery of entrepreneurial opportunities." *Organization Science*, 11: 448–469.
- Siggelkow, N.**
2001 "Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne." *Academy of Management Journal*, 44: 838–857.
- Simon, H. A.**
1962 "The architecture of complexity." *Proceedings of the American Philosophical Society*, 106: 467–482.
- Sine, W. D., H. A. Haveman, and P. S. Tolbert**
2005 "Risky business? Entrepreneurship in the new independent-power sector." *Administrative Science Quarterly*, 50: 200–232.
- Sine, W. D., H. Mitsuhashi, and D. A. Kirsch**
2006 "Revisiting Burns and Stalker: Formal structure and new venture performance in emerging economic sectors." *Academy of Management Journal*, 49: 121–132.
- Sipser, M.**
1997 *Introduction to the Theory of Computation*. Boston: PWS Publishing.
- Strogatz, S.**
2001 *Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering*. Cambridge, MA: Perseus Books Group.
- Thompson, J. D.**
1967 *Organizations in Action*. New York: McGraw-Hill.
- Tripsas, M.**
1997 "Surviving radical technological change through dynamic capability: Evidence from the typesetter industry." *Industrial and Corporate Change*, 6: 341–377.
- Tushman, M., and R. Katz**
1980 "External communication and project performance: An investigation into the role of gatekeepers." *Management Science*, 26: 1071–1085.
- Tushman, M., and C. A. O'Reilly, III**
1996 "Ambidextrous organizations: Managing evolutionary and revolutionary change." *California Management Review*, 38 (summer): 8–30.
- Tyre, M. J., and W. J. Orlikowski**
1994 "Windows of opportunity: Temporal patterns of technological adaptation in organizations." *Organization Science*, 5: 98–118.
- Uzzi, B.**
1997 "Social structure and competition in interfirm networks: The paradox of embeddedness." *Administrative Science Quarterly*, 42: 36–67.
- Weber, M.**
1946 *From Max Weber: Essays in Sociology*. H. H. Gerth and C. W. Mills, eds. and trans. New York: Oxford University Press.
- Weick, K. E.**
1976 "Educational organizations as loosely coupled systems." *Administrative Science Quarterly*, 21: 1–19.
1990 "Catastrophic myths in organizations." In A. S. Huff (ed.), *Mapping Strategic Thought*: 1–10. New York: Wiley.
1993 "The collapse of sensemaking in organizations: The Mann Gulch disaster." *Administrative Science Quarterly*, 38: 628–652.
1996 "Drop your tools: An allegory for organizational studies." *Administrative Science Quarterly*, 41: 301–313.
1998 "Improvisation as a mindset." *Organization Science*, 9: 543–555.
- Weick, K. E., and K. H. Roberts**
1993 "Collective minds in organizations: Heedful interrelating on flight decks." *Administrative Science Quarterly*, 38: 357–381.
- Williams, C., and W. Mitchell**
2004 "Focusing firm evolution: The impact of information infrastructure on market entry by U.S. telecommunications companies, 1984–1998." *Management Science*, 50: 1561–1575.
- Zott, C.**
2003 "Dynamic capabilities and the emergence of intra-industry differential firm performance: Insights from a simulation study." *Strategic Management Journal*, 24: 97–125.

TECHNICAL APPENDIX: Operationalization and Initialization of Opportunities

Each opportunity is composed of a 10-element vector of perceived features composed of either 1s or 0s (i.e., a bit string), a 10-element actual features vector, and a randomly selected payoff value. The feature vectors are produced by an algorithm that randomly assigns each element either a 1 or 0. The probability of selecting a 1 or 0 is determined by the unpredictability parameter. The perceived features vector differs from the actual features vector by a proportion of elements as set by the environmental ambiguity parameter. The exact elements that differ are randomly chosen. The payoff is drawn from a normal distribution with $\mu = 30$ and $\sigma^2 = 5$, although sensitivity analyses showed that the results do not depend on these values. Moreover, we assume that unexecuted opportunities stay in the environment for a random amount of time drawn from a normal distribution with $\mu = 20$ and $\sigma^2 = 5$; sensitivity analyses showed that the results do not depend on these values either.

Operationalization, Initialization, and Use of Rules

We initialized the rule structure in the computer program in a similar way as for the opportunities. The rules are initialized as 10-element vectors but with ?s (elements that can be improvised) scattered throughout a string of 1s and 0s. Thus the amount of structure is operationalized by the number of 1s and 0s. Similar to the structure of opportunities, the probability of selecting a 1 or 0 is determined by the unpredictability parameter. Thus our computational model reflects that managers can adjust their structures to fit consistent patterns in the flow of opportunities if such patterns exist, consistent with empirical evidence. Also, as in actual organizations, there is typically an approximate fit but often not an exact one. Thus the probability of getting a 1 or 0 is the same in both the rules and opportunities and is determined by the unpredictability parameter. This assumption could be relaxed in future work to explore the impact of misfit between environmental unpredictability and organizational structure, for example, in attempting to understand better the role of learning to fit structure to environmental patterns.

The exact placement of 1s, 0s, and ?s is randomly assigned. For example, if a rule's amount of structure is set to 6, then 0?0?1?01?0 or any other permutation could result as long as four ?s were assigned. After initialization of both rules and opportunities, all available opportunities (both those that recently flowed into the environment and those not yet captured but still in the pool of opportunities) can be captured in each time step.

Rules are used to capture opportunities by combining rule-based and improvised (described below) actions that produce a 10-element bit string (e.g., 0111100110). These bits are compared with each opportunity bit string (e.g., 0110101010). An opportunity is captured and its payoff is gained when the number of actions that correctly match the opportunity's features is greater than the value of environmental complexity.

Improvisation and Attention

A key feature of our model is the *improvisation* of action. Some actions are rule-based and some are improvised. When a rule (e.g., 0?1?10???) is applied to a given opportunity, the organization follows the rule for each element as specified by a 0 or a 1. These are the rule-based actions. In addition, the organization randomly improvises a 0 or 1 action for each ? placeholder with a $p = .5$ likelihood of each outcome. Overall, this process produces a set of actions (e.g., 0111100110 in which the 2nd, 4th, 7th, 8th, and 9th actions are improvised) that can be compared with a given opportunity (e.g., 0110101010). When enough of the actions match the opportunity features as specified by the environmental complexity parameter, the opportunity is captured and the organization gains the opportunity's payoff. When an insufficient number of actions match the opportunity features, the opportunity remains in the environment to be potentially captured using other actions. Depending on the attention available (see below), the organization continues to try to capture an opportunity using improvisation again and in future time steps until it disappears from the environment at a randomly determined time, as described above.

In general, our operationalization of improvisation is consistent with existing research showing that improvisation involves real-time action and that improvised action is not always correct (Weick, 1993, 1998; Miner, Bassoff, and Moorman, 2001). As in actual organizations, only some improvised actions are correct. We also found that different amounts of attention and ratios of rule-based to improvised attention did not qualitatively change the

Optimal Structure

results. As a manipulation check, we also checked that the total number of mistakes decreased with increasing structure as expected. We confirmed that, because decreasing structure increases the organization's capacity to improvise flexibly with a larger number of opportunities that potentially fit, there are more mistakes. This result is similar for different improvisation probabilities. We also conducted an analysis of mistakes in figure 6 that normalizes the total number of mistakes to compare these distributions across the mini-graphs, as described in the text. Overall, our approach is a conservative one that nonetheless captures the fundamental features of improvisation—i.e., improvising requires more attention than following rules and is not always accurate. Our modeling of improvisation thus offers a reasonable abstraction of the actual process that is appropriate for our research question and the objectives of simulation models (Burton and Obel, 1995).

Another key feature of the model is attention. As in actual organizations, we assumed that the organization has a finite amount of attention. In particular, the organization has a fixed attention budget. In each time step, the attention budget is decremented for each application of rules to opportunities, each rule-based action, and each improvised action. Consistent with research on improvisation (Weick, 1993; Miner, Bassoff, and Moorman, 2001) and the use of rules (Cyert and March, 1963), we assumed that an improvised action takes more attention than simply checking whether a rule matches an opportunity or a rule-based action, because improvisation has enhanced demands for real-time sensemaking and the convergence of figuring out actions and executing them (Weick, 1993; Miner, Bassoff, and Moorman, 2001). Thus we set the attention required to check the match of a rule with an opportunity or take a rule-based action at 1 unit of attention and each improvised action at 10 units of attention. Though we chose 10 as a representative value, our sensitivity analyses indicated that the findings are robust to a broad range of variations in the amount of attention that an improvised action requires. In general, the robustness of our findings to a broad range of variations in attention suggests that a more discriminate improvisation process (i.e., one requiring more attention or more improvisational skill) is likely to yield qualitatively similar results. Similarly, sensitivity analysis indicated that our findings are qualitatively robust to different orderings for addressing opportunities. So although we address opportunities by their performance payoffs, other orders (such as random) qualitatively produce the same results. In any given time step, the attention budget is decremented until the attention budget is depleted or the time step ends. Action stops if the attention budget is completely depleted. It is then replenished at the beginning of each new time step. We set the attention budget to 2800 attention units. Sensitivity analyses that varied the attention budget showed that increasing this budget increases the number of opportunities that can be executed in a given time step, as expected, but that these variations (above a minimal threshold) do not produce qualitatively different findings. Therefore we chose this representative value for our simulation runs. Finally, in any given time step, rules are checked against opportunities for a match, and rule-based and improvised actions are taken as long as attention is still available.

Performance and Error Constructs in Monte Carlo Experiments

We used standard Monte Carlo techniques (Law and Kelton, 1991). Each experiment consists of 30 or 50 simulation runs. We selected $n = 30$ as the number of simulation runs for all experiments, except those on the basic relationship between structure and performance, because exploratory analyses revealed that values of n greater than 30 yielded insignificantly small incremental gains on reliability. We used $n = 50$ for the basic relationship between the amount of structure and performance because the larger range of structure values adds precision to our illustration of this relationship. The results of these simulation experiments are graphed consistently across figures 1–5: each point represents the results for one simulation experiment, including the mean performance (Y-axis) computed across all simulation runs for a given amount of structure (X-axis). A curve is then interpolated between the mean performance values by connecting the points with a straight line.

As in all stochastic processes and related phenomena (regardless of whether empirical or simulated), the results of experiments may typically vary across simulation runs even when the construct parameter values are fixed (Law and Kelton, 1991). Therefore we computed not only the mean performance for a given experiment but also its variability in terms of error variances. We then plotted both a performance mean for each value of the amount of structure and associated "error bar" confidence intervals, which indicate the

variability of each result, a standard graphical method used in Monte Carlo outputs (Kalos and Whitlock, 1986). We computed the length of the error bar as the square root of the error variance of each experiment over the number of trials (i.e., simulation runs) of these experiments. These error bars provide an intuitive and visual display of the confidence intervals surrounding a result. As a rule of thumb, if the mean of one result is contained within the error bars of another result, then the two are not significantly different. For example, this implies that the peak performance can be generated by a range of optimal structural values. These structural values can be characterized by their own range intervals (e.g., 3–6) and medians (e.g., 4.5).

Comparing medians is necessary when optimal structure is a range of values. For instance, to assess the shifting optimum in P2, we compared median structures when the optimum was a range of values. P2 is confirmed when these median optimal structures differ. In addition, to assess asymmetry, we compared the slope of the line from the median optimal structure to the endpoint on the left side to the slope of the line from optimal structure to the endpoint on the right side. Curves are asymmetric right when the absolute value of the right slope is lower than the left slope.

Sensitivity Analyses

We performed extensive sensitivity analyses for all of the structure/performance relationships reported in the Results section, thoroughly exploring the parameter space to discover if a given finding remained when construct values (i.e., parameters) were varied. To ensure the robustness of the results, we not only varied the amount of structure measure, but also secondary constructs such as the environmental dynamism dimensions. We chose the specific values for presentation because they represent extreme values of a parameter or the midpoint values between already tested values, as appropriate. Thus we explored the parameter space in a very fine-grained way. We paid special attention to exploring the full range of the environmental dimension values—velocity, complexity, ambiguity, and unpredictability. Because velocity (λ) is unbounded in a Poisson distribution, but actual organizations are both cognitively and resource bounded, we placed an upper bound on λ at the value for which the number of opportunities is an order of magnitude greater than the organization could capture in any time step. We then thoroughly explored velocity at a variety of parameter values, including 0, .4, .6, .8, 1.2, 1.4, 1.6, 1.8, 2.0, 2.2, 2.4, 2.6, 2.8, 3, 4, and 5. All results are consistent with figure 2. We also explored complexity, which ranges from 0 to 1, with a variety of parameter values, including 0, .2, .3, .4, .5, .6, .7, .8, .85, and .9. All results are consistent with those in figure 3. We tested ambiguity, which ranges from 0 to 1, with a variety of parameter values, including 0, .1, .2, .25, .3, .4, .6, .8, and 1.0. All results are consistent with those in figure 4. Unpredictability ranges from 0 to 1 in our tests. We tested the sensitivity of the unpredictability results with a variety of parameter values for the proportion of 1s, including 0, .1, .2, .3, .4, .5, .6, .7, .8, .9, and 1.0. All results are consistent with those in figure 5.

MATHEMATICAL APPENDIX

The mathematical formalization that we constructed sheds light on the logic underlying P1a, P2a, and the varying range of optimal structures from our simulation experiments. In this appendix, we perform some of the mathematical operations that underlie this logic. We are especially grateful to an anonymous reviewer who encouraged our building this interpretive model and developing this line of thinking.

Though the literature is mostly silent about the specific functional forms underlying the relationship between structure and performance, there is consensus that flexibility and efficiency are inversely interdependent and have non-substitutable effects on how structure influences performance (e.g., Gibson and Birkinshaw, 2004). Let x be the amount of organizational structure. We begin by representing the aggregate effect of structure on performance by $A(x) = f(x) * e(x)$, where $f(x)$ and $e(x)$ are the non-negative functions of flexibility and efficiency. Broadly, the literature suggests that efficiency increases and flexibility decreases as the amount of structure increases, respectively: $f'(x) < 0$, $e'(x) > 0$.

This representation allows us to demonstrate that not all flexibility and efficiency functions generate a unimodal curve, as predicted in P1a. Specifically, for a unimodal curve to exist, we require that $[A'(x) > 0 \text{ for } x < x']$ and $[A'(x) < 0 \text{ for } x > x']$, where x' is the optimal amount of structure (i.e., at the performance “peak”).

Optimal Structure

Applying the chain rule [$A'(x) = (e(x)*f'(x)) + (e'(x)*f(x))$] and the absolute value equation [$-f'(x) = |f'(x)|$ when $f'(x) < 0$] yields these two important conditions for unimodal functions of the type $A(x) = f(x)*e(x)$:

$$\begin{aligned} |f'(x)| < f(x)*e'(x)/e(x) \text{ for } x < x' & \quad (1) \text{ and} \\ e'(x) < |f'(x)|*e(x)/f(x) \text{ for } x > x' & \quad (2). \end{aligned}$$

These constraints on the two underlying functions, $f(x)$ and $e(x)$, are necessary to predict a unimodal relationship.

In addition, we can show that the argument that the shifting optimum predicted in P2a is generated because of the increasing importance of flexibility is not correct. Let $a > 0$ represent the importance of flexibility in $A(x) = a*f(x)*e(x)$. Then, applying the chain rule again yields $A'(x) = a[f(x)*e'(x) + f'(x)*e(x)]$. Inspecting this $A'(x)$ reveals that simply increasing the importance of flexibility by increasing the coefficient a does not affect the position of the optimum given that the critical point of $A'(x)$ is independent of a .

Instead, logical argument and empirical literature suggest functional forms that do satisfy the conditions underlying P1a and P2a. For instance, the literature suggests an increasing function of structure for efficiency such that $e'(x) > 0$. Examining the impact of adding a marginal amount of structure sheds further light on the shape of $e(x)$. One possibility is that each incremental application of structure generates a constant improvement, $e'(x) = c$, where c is a constant. But a constant improvement is unlikely over the full range of x . Instead, it is more likely that increasing structure has a diminishing marginal effect on efficiency. A marginal improvement in efficiency, d_e , is derived from a smaller set of opportunities and a smaller efficiency gain from economizing on attention. Thus the marginal improvement in efficiency, d_e , derived from applying a marginal amount of structure d_x is inversely dependent on the base level of structure, x , suggesting an inversely proportional relationship: $d_e \propto d_x/x$ where $x > 0$. Integrating yields a logarithmic efficiency function:

$$e(x) = \ln(x)$$

which satisfies $e'(x) > 0$ as $e'(x) = 1/x > 0$ when $x > 0$. Moreover, this logarithmic efficiency function has the important property of being unbounded—increasing structure always increases efficiency, although at a diminishing rate.

By contrast, empirical literature and logical argument suggest decreasing flexibility as a function of structure such that $f'(x) < 0$. Flexibility involves using improvisation to capture a variety of opportunities that could not be captured by structure-based actions alone. Logic suggests that adding structure eliminates successive fractions of opportunities, and so the amount of structure is inversely proportional to the fraction of opportunities that could have been captured with improvisation. Thus it is most rapidly decreasing at low structure, an argument that is also consistent with empirical evidence (Greve, 1999). This suggests the following function:

$$f(x) = 1/x$$

which satisfies $f'(x) < 0$ as $f'(x) = -1/(x^2) < 0$ when $x > 0$. In our rule-based model, a simple interpretation of the effect of increasing structure on flexible opportunity execution is to decrease the pool of opportunities available to improvisational execution by successive fractions for each addition of structure. That is, flexibility is the product of these fractional losses of opportunities at each level of structure, n : $f(x) = \prod [1 - (1/n)] = \prod [(n-1)/n] = (x-1)!/x! = 1/x$. A natural interpretation, then, is that increasing structure quickly eliminates opportunities from the pool of opportunities available for improvised actions. This modeling of flexibility also has the important property of approaching a limit of 0 as structure increases.

Returning to an objective for this mathematical formalization, it can be shown that these functional forms are consistent with P1a:

$$\text{Let } A(x) = f(x)*e(x) = \ln(x)/x.$$

Recall that for $A(x)$ to be unimodal, it is required that

$$\begin{aligned} |f'(x)| < f(x)*e'(x)/e(x) \text{ for } x < x' & \quad (1) \text{ and} \\ e'(x) < |f'(x)|*e(x)/f(x) \text{ for } x > x' & \quad (2). \end{aligned}$$

Substituting $f(x)$, $e(x)$, $f'(x)$, and $e'(x)$ into $A'(x) = [e(x)*f'(x)] + [e'(x)*f(x)]$ generates $A'(x) = (1 - \ln(x))/(x^2)$, while letting $A'(x) = 0$ yields $x' = e$ as the optimum.

Substituting $f(x) = 1/x$ and $e(x) = \ln(x)$ into the inequalities above also reveals that these functions satisfy the conditions for P1a. For example, after reducing the equations, we find the following true inequalities:

$$\begin{aligned} 1 < \ln(x) & \text{ for } x < x' & (1) \text{ and} \\ 1 > \ln(x) & \text{ for } x > x' & (2). \end{aligned}$$

These functions produce a unimodal, asymmetric right curve as predicted by P1a.

It can also be shown that these basic functional shapes are consistent with P2a as well. Consider unpredictability, the key dimension of environmental dynamism underlying the logic in P2a. An important insight is that unpredictability, u , shapes both flexibility and efficiency by affecting how firms use structure to execute opportunities in two ways. One effect of increasing unpredictability is that some additional opportunities can occasionally be captured in a more unpredictable stream of heterogeneous opportunities. But this increment varies inversely with the amount of structure— $1/x$ —and grows increasingly slowly with increasing unpredictability— $\ln(u)$ —because opportunity capture becomes increasingly difficult at lower levels of structure, both of which we represent with $\ln(u)/x$. Combining this with $A(x)$ changes the performance function: $A(x) + \ln(u)/x = \ln(x)/x + \ln(u)/x = \ln(ux)/x$. Another important effect of unpredictability is to reduce the effectiveness of both structure and improvisation, which is represented as a simple dampening parameter reducing the magnitude of performance, $1/u$, which can be applied to the performance equation above: $(1/u) * \ln(ux)/x$. Although there are potentially many ways to represent these effects, the resulting model is a simple one that nonetheless captures the dual effects of unpredictability, u :

$$P(x,u) = \ln(ux)/ux, \text{ where } u > 0.$$

This modification of $A(x)$ to include unpredictability, u , retains its key properties. For instance, $P(x,u)$ also satisfies the conditions for P1a. Differentiating yields $P'(x,u) = [1 - \ln(ux)]/ux^2$ and setting $P'(x,u) = 0$ yields $x' = e/u$.

Deriving the conditions again yields

$$\begin{aligned} 1 > \ln(ux) & \text{ for } x < e/u & (1) \text{ and} \\ 1 < \ln(ux) & \text{ for } x > e/u & (2) \end{aligned}$$

which are true for $u > 0$.

Turning back to P2a, this model is consistent with a shifting optimum because $x' = e/u$ depends on u . Consistent with P2a, as u increases, x' decreases. Moreover, this $P(x,u)$ also shares other important features of our simulation findings, such as the unimodal, asymmetric right shape and the shift from a broad plateau to a sharp inverted-V (i.e., edge of chaos) as unpredictability increases.