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Corporate entrepreneurship strategy: extending the integrative framework through the lens of complexity science

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Abstract Whereas our understanding of corporate entrepreneurship (CE) and corporate entrepreneurship strategy (CES) continues to expand, there has been little theoretical development to support the most extensive framework to date: the integrative model of CES as proposed by Ireland et al. (Entrep Theory Pract 33(1):19–46, 2009). According to the model, CES is built upon the "three foundational elements of an entrepreneurial strategic vision, a pro-entrepreneurship organizational architecture, and entrepreneurial processes and behaviors as exhibited throughout the organization" (Ireland et al. 2009, p. 38). The purpose of this study is to present a broad, overarching theory—complexity science—to examine the key elements and propositions of the CES model. Complexity science—founded on assumptions of interdependent heterogeneous agents and nonlinear interactions, as well as non-deterministic and potentially extreme outcomes—offers established multilevel concepts, theoretical boundary conditions, and methodological guidance for scholars to build and test future studies on CE and CES. Though our complexity perspective draws extensively from conceptual work on complex adaptive systems and agent-based models, we ground our arguments on the empirical ubiquity of power law distributions in all constructs and levels of analysis within the CES model. We conclude with a detailed research agenda, as well as a prescriptive discussion related to theory development, quantitative analysis, and practical applications to guide future studies on CE.

Keywords Complexity science · Corporate entrepreneurship strategy · Entrepreneurship · Growth expectations · Power law distributions · Schemata

JEL Classifications L22 · L26

1 Introduction

The importance of corporate entrepreneurship (CE) to organizational competitiveness is well established in the entrepreneurship, strategic management, and economics literature (c.f., Dess et al. 2003; Fini et al. 2012). CE research had been fragmented until recent conceptual work by Ireland et al. (2009) developed an integrated model of the antecedents, elements, and outcomes of a corporate entrepreneurship strategy (CES) at multiple levels of analysis that subsumed extant frameworks. In so doing, the authors position CE as a distinct organizational strategy, which is driven by two antecedents—the *cognitions of the*

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individuals within the focal firm and the firm's *external environmental conditions*—and three primary elements—an *entrepreneurial strategic vision*, a *pro-entrepreneurship organizational architecture*, and *entrepreneurial processes and behaviors*. All components in the Ireland et al. (2009) model are both individually distinct and collectively exhaustive, which provides scholars with bottom-up conceptualizations of a CES (organizational members to top-level managers to organization to environment) to augment the top down, environmentally driven conceptualizations that abound in the organizational literature.

The Ireland et al. (2009) model's antecedents and elements are proposed to result in specific outcomes, namely enhanced competitive capabilities and strategic repositioning. Whereas the model's framework is rooted in evolutionary thought, Ireland et al. (2009) acknowledge the lack of an overarching theoretical perspective that can be used to support the model's propositions. This is an important problem for the development of collective knowledge about CE and CES. Without theory, research becomes a race of empiricists to "focus energy exclusively on the collection of data," which can be ill-advised and short-sighted in that it "discourage[s] researchers from asking fundamental questions about the assumptions that underpin knowledge and the methods used to acquire knowledge" (Suddaby 2014, p. 408). The purpose of this article is to propose an overarching theoretical perspective—complexity science—to clarify assumptions, identify boundary conditions, and recommend methods to build and test CE- and CES-related theory.

We use a complexity science perspective because it can offer a robust and established theory to understand the relationships among the antecedents, elements, and consequences of a CES, as well as provide methodological guidance for modeling the highly skewed distributions of inputs and outcomes inherent in the study of entrepreneurship. Complexity science focuses on the underlying dynamics that give rise to a broad range of outcomes in all social systems (Anderson 1999). The goal of complexity science is to understand emergence in its most fundamental form in a search for commonalities that apply to all ventures, across multiple orders of magnitude (Gell-Mann 1988). A complex system is composed of heterogeneous agents who create emergent structures that cannot be explained by their individual component parts (Anderson 1999; McKelvey 2004a; Lichtenstein 2011). At its foundation, complexity science seeks to explain the emergence of new order (McKelvey 2004b) where, for example, that "order" could be the creation of entrepreneurial beliefs of individuals, the self-organized entrepreneurial behavior of members within a firm, the firm's exploitation of an entrepreneurial opportunity, or a corporate spin-off. However, since each firm's context is unique, and successful emergence is never guaranteed, complexity science offers inherent assumptions that uniquely align it with CE and CES. Namely, complexity science assumes interdependent heterogeneous agents, potentially nonlinear agent interactions over time, coevolving causality, as well as non-deterministic and potentially extreme outcomes (Schindehutte and Morris 2009; Lichtenstein 2014).

Based on these assumptions, complexity scholars have developed unique concepts and methods to explain and describe the qualitatively novel outcomes of emergent phenomena. Though we identify and integrate multiple complexity approaches throughout the paper—including complex adaptive systems and agent-based modeling—the crux of our analysis centers on the decidedly non-normal distribution of outcomes that manifest within the various components of the Ireland et al. (2009) CES framework. As we seek to demonstrate, these outcomes are nearly all distributed according to a power law. Power law distributions (PLDs) are heavily skewed to the right, where outliers in the fat tail of the distribution influence both the statistical and behavioral properties of the entire population. In the current study, we suggest that PLDs play an important role in theory building and empirical testing related to a CES. In contrast with the traditionally assumed normal (Gaussian) distribution, where events are collapsed around the mean, completely independent, and identically distributed, PLDs identify the infinite variance within data, as well as the fundamental interconnectedness and interdependence of events (Simon 1968; Andriani and McKelvey 2009). Most relevant to our arguments: When PLDs exist, traditional data collection, data analysis, and hypothesis testing may be severely biased because outliers skew the direction, size of effect, and substantive conclusions of relationships among input and outcome constructs (Aguinis et al. 2013).

Our contribution to the CE and CES literature centers on three main points: (1) identifying PLDs within all components of the Ireland et al. (2009) CES model; (2) advising scholars on how PLDs influence both theory and methods related to CES; and (3) using complexity science to provide both theoretical and methodological guidance for future studies on CES. By first identifying extant PLDs within the constructs of the Ireland et al. (2009) model, we provide an empirical foundation for a better shared understanding of CE and, more specifically, generate nuanced insights about CES at multiple units and levels of analysis. For example, O'Boyle and Aguinis (2012) find that all aspects of individual performance are most accurately characterized as PLD, suggesting that organizational member *cognitions*, inherent in opportunity recognition and exploitation abilities (as well as top-level manager *strategic vision*) in the Ireland et al. (2009) model, will be similarly skewed. Zipf (1949) and Barabási et al. (2002; Barabási and Bonabeau 2003; with Song et al. 2010) find PLDs in all patterns of human activity, interaction, and network connectivity, implying that *entrepreneurial processes and behaviors* are likely skewed in a similar manner. Finally, Crawford et al. (2015) find PLDs in all individual- and team-level inputs, in addition to all revenue-, employee-, and growth-based outcomes in entrepreneurship in both the USA and Australia ($N = 12{,}000+$), indicating that organizational level *environmental conditions, organizational architecture,* and *performance outcomes* should be viewed in the context of PLDs when building theory related to the Ireland et al. (2009) model.

We structure our study in the following manner. Section 2 outlines and describes the fundamental underpinnings of CES within the CE literature. Next, Sect. 3 exposes the empirical reality of CE by identifying PLDs within all components of the CES model. We segue into arguments that show how PLDs differ from normal (i.e., Gaussian) distributions, how these differences pose potential hazards for theory development, and why PLDs require unique theory and method to accurately describe the phenomena. In Sect. 4, we make a significant contribution to the literature by presenting the elements of CES within an established theoretical system that can be used to integrate extant assumptions within the existing CE literature. We utilize established complexity science concepts as an outline for future questions that can facilitate what Cornelissen and Durand (2013, p. 154) describe as "a coherent and sustainable program of research." Section 5 concludes the paper with a detailed research agenda, along with a discussion of future theory building, research design, and quantitative analysis to serve as a foundation for building a collective body of knowledge on CES.

2 Corporate entrepreneurship strategy

In an effort to integrate previous research on CE, Ireland et al. (2009, p. 21) theorized that CES represents "a vision-directed, organization-wide reliance on entrepreneurial behavior that purposefully and continuously rejuvenates the organization and shapes the scope of its operations through the recognition and exploitation of entrepreneurial opportunity." The concept of CES encompasses all of the various firm-level initiatives related to CE that allow companies to recognize and exploit opportunities (Morris et al. 2011). According to the Ireland et al. (2009) framework, CES is built upon the "three foundational elements of an entrepreneurial strategic vision, a pro-entrepreneurship organizational architecture, and entrepreneurial processes and behaviors as exhibited throughout the organization. The absence or weakness of any of these elements would indicate that CE strategy does not exist in a firm." (Ireland et al. 2009, p. 38).

The first core element of CES is a strong organizational commitment to entrepreneurial values, philosophies, and beliefs. When an organization's top-level managers develop and clearly communicate its strategic vision, members of the organization receive the guidance and encouragement that is required to support their entrepreneurial efforts. The second core element of CES is a pro-entrepreneurship architecture, which is reflected in the willingness of an organization to foster and maintain an organizational climate that is conducive to entrepreneurship (e.g., Burgelman 1983, 1984; Covin and Slevin 1991; Hornsby et al. 2009; Kuratko 2009). The third core element of CES is an organizational reliance on entrepreneurial processes and behaviors. Taken together, these three elements embody the core attributes that distinguish an organization that has truly embraced a coordinated strategic approach toward CE from one that has not.

In developing their conceptual model, Ireland et al. (2009) argue that CES is primarily a firm-level construct. However, while CES represents a firm-level strategy, Ireland et al. explicitly outline antecedents at the individual level (individual entrepreneurial cognitions) and environmental level (external environmental conditions) that are likely to influence the core elements of CES. In this context, entrepreneurial cognitions refer to "the knowledge structures that people use to make assessments, judgments, or decisions involving opportunity evaluation, venture creation, and growth" (Mitchell et al. 2002, p. 97). This reinforces the arguments of authors such as Hornsby et al. (2002) and Hornsby et al. (2009), who suggest that individual-level factors influence a firm's CE activities from the bottom up, while authors such as Rosenbusch et al. (2013) argue that environmental factors influence these same activities from the top down. In so doing, the Ireland et al. (2009) framework builds upon earlier conceptualizations of CE (e.g., Covin and Miles 1999) and entrepreneurial orientation (Miller 1983; Covin and Slevin 1989). Consistent with the Ireland et al. (2009) framework, Covin and Miles (1999) argue that specific organizational elements must be present to justify the existence of CE, suggesting that "it is important to emphasize that these forms [of CE] will often concurrently exist in entrepreneurial organizations" (Covin and Miles 1999, p. 51).

Inspired by the arguments of Ireland et al. (2009), and in an effort to bolster future research on CE, in general, and CES, in particular, Sect. 3 below examines the existence of PLDs that are relevant when identifying and assessing the presence of a CES within organizations. In Sect. 4, we identify how the emergence of PLDs fall under the umbrella of complexity science, a theoretical framework that addresses how small differences in initial conditions can, over time and multiple interactions in an environment, lead to extreme differences in outcomes.

3 Power law distribution effects on corporate entrepreneurship strategy

Traditional theory-building and testing efforts in the organizational literature tend to revert to the default assumption that inputs and outcomes are distributed according to a symmetrical and normal (i.e., Gaussian) curve, where some observations are very positive, some are very negative, and the majority congregate around the middle. In this case, the mean and standard deviation can accurately characterize every observation in the population and, since each observation is independent of the other, outliers do not influence any other properties of the distribution. In contrast, PLDs are heavily skewed to the right, with long, heavy tails where outliers influence both the behavioral and statistical properties of all other agents in the population. Though these distributions are ubiquitous in social systems (c.f., Bettencourt et al. 2010), their importance to CE scholars has not been explored. As an example of PLDs, Fig. 1a shows a gray power law curve in contrast with the black outline of the traditional bell curve. Notice that in the PLD, the majority of observations (highest frequency) are of the smallest event size (i.e., the lowest performance) when plotted on linear scales; using log–log scales in Fig. 1b, the tail of a PLD forms a straight line (Simon 1955; Andriani and McKelvey 2009). A power law's emergence is relevant and important in more fully understanding a CES because of the extreme outcomes in the tail of the distribution, represented by the Paretian World in the area to the right of the shaded region in Fig. 1b.

Though somewhat rare, an outcome in the long tail of a PLD—most clearly identified by the largest circle at the bottom right of Fig. 1b—is of disproportionate influence on the entire system. As an example, the small circles in the upper left might represent the 22 million Mom and Pop retail stores in the USA, with one or two employees and less than $100K in annual revenue, while the largest circle in the lower right may represent a company such as Apple, with 80,000 employees and $150B in revenue. In our example, the size of the circle represents both a measure of performance relative to the rest of the population and a measure of influence on the entire system. In such an example, Apple represents an outlier, or "extreme" point, that generates exorbitant output levels that influence both the statistical and behavioral properties of the entire distribution (Aguinis and O'Boyle 2014). Empirically, PLDs have been found in a variety of other phenomena, including the size of global economies (Buldyrev et al. 2003), all firms (Axtell 1999) and all industries (Zanini 2008) in the USA, as well as in industry sectors (Crawford et al. 2015), intellectual capital breakthroughs (Fleming 2007; Singh and Fleming 2010), network structure (Barabási et al. 2002), firm innovations (Poole et al. 2000), competitive performance advantages (Powell 2003), and human performance (O'Boyle and Aguinis

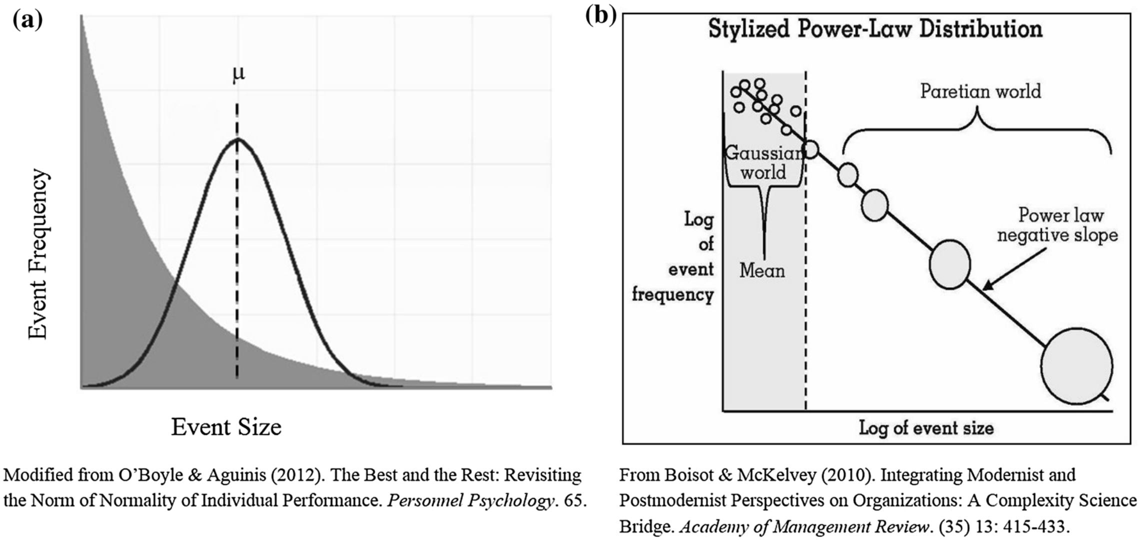

Fig. 1 **a** Contrast of bell-shaped Gaussian distribution with long-tailed power law distribution in *gray* on regular scales; **b** stylized power law distribution on log–log scales

2012). In entrepreneurship, PLDs exist in all resource-, cognition-, action-, and environment-based *input* variables (Crawford et al. 2015) and all revenue- and employee-based growth *outcome* variables in samples of nascent ventures, a cohort of new firms, and the fastest growing companies—a total of more than 12,000 cases—from Australia and the United States (Crawford and McKelvey 2012; Crawford et al. 2014).

The data points in the tail of the distribution exhibit dynamic properties that are different from those points in the body of the distribution—firms in the tail are the "deviant" cases (Starbuck and Nystrom 1981) that truly *do* things differently. Again, we would suggest that organizations which consistently exhibit a CES over the long run are representative of such outliers. Whereas the midpoints define normal distributions, PLDs are defined by their fat, heavy tails. PLDs permeate all social systems. Andriani and McKelvey (2009) identify these distributions in more than 200 domains of interest, including corporate networks, innovations, and allocation of resources. Extant empirical research shows that when power laws exist, universal underlying dynamics can explain outcomes at one level, as well as helping to explain outcomes at both previous and subsequent levels of analysis; this is called a *scale-free explanation*, where a set of common core constructs can explicate all outcomes in the domain of interest (Rahmandad and Sterman 2008; Andriani and McKelvey 2009). The constructs for these theories are also *scale-invariant*, where all the variables within a construct appear as a PLD, regardless of the measurement (Aguinis and O'Boyle 2014). We posit that the emergence of such PLDs within the antecedents and elements of CES can be effectively studied under the epistemological assumptions of complexity science.

4 Corporate entrepreneurship strategy: a complexity science framework

In this study, we use a complexity science framework to assess the relevance of PLDs in studying and explaining CES. Framed as a paradigm, complexity science can be described as a unique set of principles drawn from rigorous studies of complex systems in natural and computational environments; these principles provide a lens for understanding and explaining the dynamics of emergence, innovation, adaptation, and leadership within and across organizations and management (e.g., Boisot and McKelvey 2010; Lichtenstein 2014). Some of the basic principles include a focus on "agents"—entities that are heterogeneous, interdependent, and interact with the other agents in the system; the adaptive and sometimes nonlinear nature of agent interactions over time; the co-creation and coevolution of agents that are interdependent within their environment; and a recognition that the patterns and properties of emergent entities are neither predictable nor controllable, even given a complete knowledge of every agent's characteristics. Together, these components make up a *complex adaptive system*, where agents are connected, interdependent, and have the potential to produce nonlinear (i.e., extreme) outcomes (Anderson 1999).

For example, complex systems theories explore how "simple rules" for decision-making and action at the micro-level can explain emergence and growth outcomes at the macro-level (Holland 1995; McKelvey 2004b). That is, due to the nested, hierarchical nature of complex systems within complex systems, patterns identified at one level of corporate entrepreneurial activity can be aggregated to higher levels of activity. For example, cognitions at the managerial level may affect strategic behaviors at the organizational level, which in turn may influence competitive patterns at the industry level, and so on. As evidence, Crawford (2012a) found statistically identical distributions of nascent growth expectations and actual outcomes, with the same power law slopes, ~ 1.75, across all levels of organizational emergence, from nascent organizing (in the Panel Study of Entrepreneurial Dynamics) to new firms (in the Kauffman Firm Survey) to the fastest growing private companies in the USA (in the INC 5000).

In all of these systems, activity at the most micro-level of analysis aggregates to higher-order activity, which suggests that outcomes at a macro-level are a result of lower-level aggregation (Stanley et al. 1996; Lewin et al. 1999). Unless a new activity pattern emerges or is imposed by top-down tensions, the higher level aggregate activity will exactly reflect and resemble the scaling pattern of the micro-level pattern. Likewise, each higher level of analysis (order of magnitude) is likely to reflect the same scaling pattern (Andriani and McKelvey 2009). Through this aggregation process, the entire scope of the phenomenon can be driven by the same generative mechanism. Furthermore, due to this similarity, evidence of a power law at one level is an indication that similar dynamics are acting at the preceding level.

Further, as a data point becomes more "extreme" (i.e., more of an outlier), it is more likely to exhibit a stronger influence on the higher level system in which it exists (c.f., Crawford 2012b). That is, outliers become the most important and useful cases for researchers to study. This is wholly consistent with the Ireland et al. (2009) model and helps to augment many of their observations about the path of relationships across different levels of analysis. For example, an employee who thinks "outside the box" and is very vocal in taking his or her ideas for new products to top management is much more likely to wield a disproportionate influence on the entrepreneurial strategic vision supported by top management compared with an employee who always does things "by the book". Likewise, as a firm becomes more and more entrepreneurial in its culture and behaviors, its willingness to embrace frame-breaking strategies begins to exert a stronger influence on the overall industry in which the firm competes. Indeed, as Schumpeter (1942) envisioned, we suggest that outliers drive the process of creative destruction, where the competitive landscape is reshaped, new industries are created, or old industries become extinct.

While firms such as Apple and Google are certainly not the norm in any environment, these firms wield a disproportionate influence on an industry's competitive dynamics. Consistent with the Ireland et al. (2009) model of a CES, the elements of the sub-system (whether the entrepreneurial cognitions of organizational members, the entrepreneurial strategic vision of top-level managers, or the entrepreneurial culture and behaviors of the organization) begin to exert a coevolutionary influence on the elements of the larger system. Though troublesome for theory building, research design, and statistical analysis, power laws can identify the presence of the mechanisms that drive the activity and outcomes of a given phenomenon. In such systems, a specific driver generates order at the most micro-levels; as this order is aggregated into higher levels the generative mechanism cascades "upward" through the system, influencing all subsequent levels. Over time, these influences generate distinctive patterns when viewed from a higher level of analysis.

4.1 Power law distributions as patterns of dynamic interaction

Power law distributions result from a deep, underlying pattern of emergence (Bar-Yam 1997). As Brock (2000, p. 29) describes, "Complexity considers whether these patterns have a property of *universality* about them." Such patterns are called scaling laws

(Gell-Mann 1988) because they are expressed as empirical regularities in specific attributes that apply across many orders of magnitude of a phenomenon—in these cases, when the appearance of a phenomenon is independent of the scale used to measure it, the same causal dynamic is operating at multiple levels (West and Deering 1995; Andriani and McKelvey 2009). How do these distributions emerge?

Drawing from seminal complexity science arguments of autogenesis: an agent's rules that govern interaction drive a recursive, nonlinear process that engages cross-level agents and more emergent systems from the bottom up, eliciting expectations from other "interactants" to select actions based on available information about the meaning of the action and the preferred response (Goffman 1967). Habitual action and interaction cause an individual to make choices based on rules that originate in past experiences and socialization; this is the "deep structure" that links individual action to expected reciprocal action (March and Simon 1958). At intermediate levels of interaction, these rules are inferred, but may not be readily apparent; at higher levels, discernible patterns of "observed structure" emerge (Drazin and Sandelands 1992). The patterns are the visually distinct PLD of outcomes (Simon 1955; Gell-Mann 1988; Andriani and McKelvey 2009). Recent work by Crawford et al. (2014) finds PLDs in all revenue and employee outcomes in entrepreneurship, supporting these seminal conceptualizations of autogenesis.

Complexity science's use of the term "schemata" draws from seminal psychological and sociological treatments, defined by DiMaggio (1997, p. 269) as "knowledge structures that represent objects or events that provide default assumptions about their characteristics, relationships, and entailments under conditions of incomplete information." From a complexity perspective, "agents with schemata" represent an individual's basic cognitive frameworks for achieving expected outcomes, and these schemata drive individual actions and interactions (Anderson 1999). These interactions become recursive and, once they reach some critical threshold, create emergent structures—like innovations or firms—from the bottom up (Drazin and Sandelands 1992). We suggest that these schemata help to explain the dynamics underlying the antecedents (entrepreneurial cognitions and the external environment) and elements (entrepreneurial strategic vision, pro-entrepreneurship architecture, and entrepreneurial processes and behaviors) of a CES. Figure 2 summarizes our core argument that CES revolves around individual schemata—the driver of recursive action and interaction within a system—yet cannot exist without the other components that are present in the ecosystem.

4.2 Antecedents of CES: individual schemata as entrepreneurial cognitions

An individual's schemata represent the set of cognitive heuristics which drive decision-making and behavior based on their expectations for future outcomes (Anderson 1999; Labianca et al. 2005). As an agent interacts with the environment over time, feedback regulates these expectations. When agents receive feedback, it generates *more* interactions: Positive feedback generates more of the *same types* of interactions, whereas negative feedback generates more of *different types* of interactions (Stacey 1995; Förster et al. 2001). Consistent with previous research, the key tenant of these arguments is that feedback spirals promote action and generate distinct patterns of thought, behavior, and interactions with potential stakeholders (Baron and Ensley 2006; McMullen and Shepherd 2006; Lichtenstein et al. 2007; Grégoire et al. 2010).

In particular, schemata—whether embodied through the entrepreneurial cognitions of an employee or the entrepreneurial strategic vision of a top-level manager—allow an organization to identify salient opportunities (Shane and Venkataraman 2000) and to actively create potential markets for products that do not yet exist (Sarasvathy 2001). Expectations about future outcomes provide the impetus and motivation to pursue and/or enact a new opportunity (Chiles et al. 2010). Thus, individual-level expectations drive action and interactions toward the pursuit of a specific opportunity (McMullen et al. 2007; Lomi et al. 2010). Although schemata are affected by feedback from the environment, prior studies show that they are endogenous, "deep cognitive structures" (Grégoire et al. 2010) that are relatively stable over time (McGraw et al. 2003; Aldrich and Ruef 2006), oftentimes even after disconfirming evidence.

Such individual schemata are inherent in entrepreneurial cognitions, which are the basis for transforming opportunities into organizational advantage, as they drive both present and future interactions

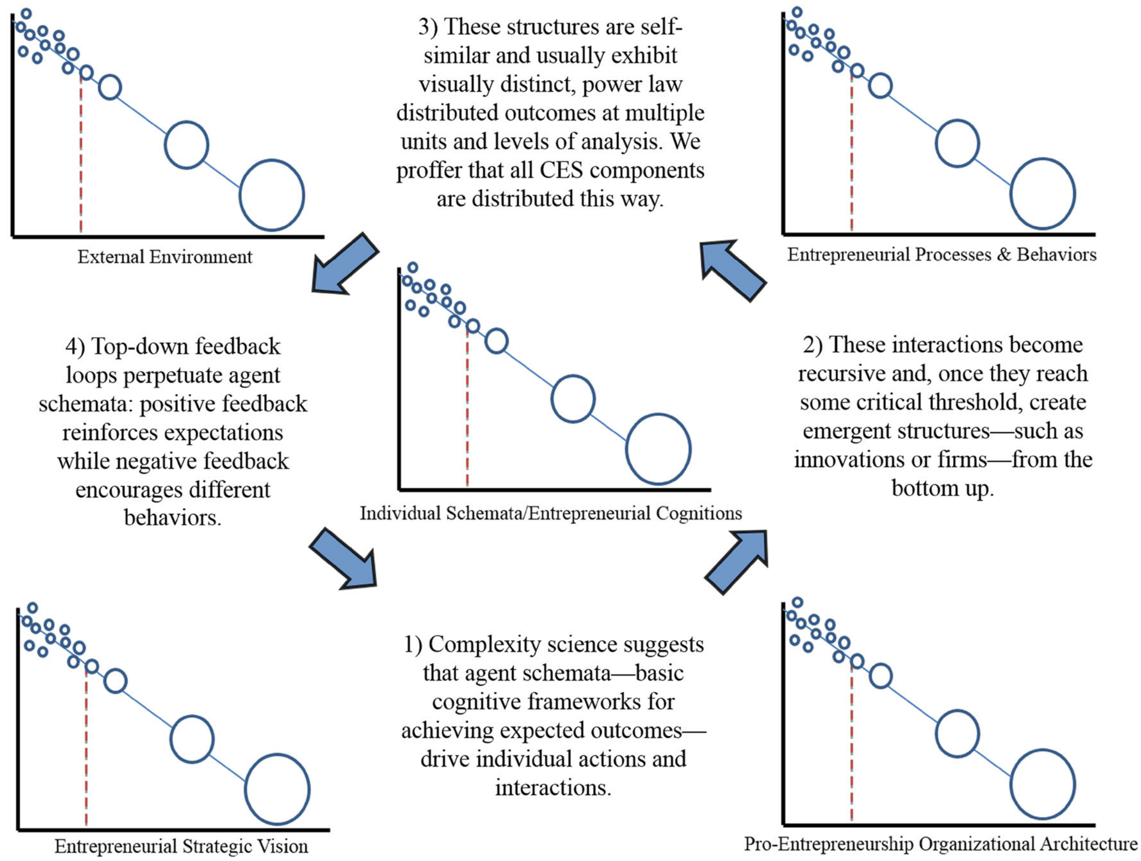

Fig. 2 Complexity science perspective on the power law distributions of each component within the CES framework

with customers, suppliers, investors and other stakeholders (DeKinder and Kohli 2008). For example, just as individual schemata determine perceptions of opportunities (Alvarez and Barney 2007), they also direct the pattern of interactions by an entrepreneur that leads to legitimacy of the firm (Delmar and Shane 2004). Further, customers use these interactions to construct expected value of the firm's offering and its potential outcomes (Gartner et al. 1992; Vargo and Lusch 2008). Likewise, a founder's expectations about the company's future growth, and the explicit or implicit expression of that intent to stakeholders, influence the perceived value and potential of the firm (Wiklund and Shepherd 2003). Although feedback from potential stakeholders about the value of the firm may depend on external conditions and current resource endowments, these factors are generally subservient to the endogenous perceptions and actions of entrepreneurial individuals (Winter et al. 2007). The schemata employed and acted upon by these entrepreneurial individuals serve as the foundation and lifeblood of a CES within organizations.

4.3 Antecedents of CES: the schemata inherent in external environmental conditions

The external environment encompasses the population dynamics that influence, and are influenced by, the elements of a CES. These dynamics are top-down tensions on the system and include selection forces from both competitive intensity and resource munificence (Anderson 1999). A complexity science perspective views an environment as the potential top-down influence on a system as well as the resources available to the population of agents within that system (Anderson 1999; McKelvey 2004b). *Environments*, therefore, can be conceptualized by the intensity of competition (i.e., potential top-down selection forces) and the quality and quantity of resources (i.e., competitive intensity and resource munificence) in the immediate location (Amburgey and Rao 1996; Baum et al. 2001). In these environments, "selection forces operate on the *outcomes* of actions, not their intended results" (Aldrich and Ruef 2006, p. 83); regardless of inter-firm expectations, these forces provide a feedback loop that influences the relative innovativeness of opportunities that individuals within an organization recognize, exploit, or create.

At the macro-level, stakeholders provide feedback to firms by purchasing products or by investing (or selling) in a company's stock. All of these stakeholders *expect* progress from organizations. Progress could come in the form of efficiency or effectiveness, with the same product delivered faster or cheaper, or with new products that provide more functionality or a higher quality experience; in the same way, investors expect greater or more stable returns. These expectations cascade down through the value chain, where the largest companies and buying groups push manufacturers, suppliers, and distributors for increased progress (Axtell 1999; Zanini 2008). This push—in the form of larger purchasing contracts, for example—usually favors those firms that already have some kind of initial advantage in endowments (e.g., human, social, intellectual, or financial capital), resulting in additional skewed distributions in these sub-systems (Poole et al. 2000; Kohli and Sah 2006). Thus, an expectation for growth becomes the dominant logic of the entire system (Bettis and Wong 2003; Miller and Lin 2010).

Combined, external environmental conditions create opposing tensions on firms: An abundance of perceived resources pulls firms into the market, while preexisting firms—or other selection forces—have the potential to select out emerging organizational forms. Whereas most firms that exhibit a CES are likely started by a founder with aggressive growth intentions, the expectations for growth are likely to be equally as high (or higher) from the top down when compared to independent ventures. From the top down, franchisors, venture capitalists, investment bankers, fund managers, and shareholders push for continual growth (Amit et al. 1990, 2000). If expectations for growth and individual schemata drive entrepreneurial activity from the bottom up, as we have already discussed, then what happens when firms operate in environments where top-down expectations are even higher? When an independent founder controls the vision and interaction of a company, she can get feedback from the environment to regulate her expectations of what is possible and what is not, thereby adjusting interactions inside and outside the firm. Aggressive top-down expectations can potentially make the firm's interactions more chaotic by forcing it to search for novel ways to achieve growth.

In sum, complexity science suggests that patterns of interaction are endogenously generated by individuals and firms, and at the same time the marketplace exogenously provides feedback as to the relative value of the new firm's offering. Together, these interactions exhibit coevolving bottom-up and top-down causality, as originally posited for organization science by Lewin et al. (1999) and for entrepreneurship by McKelvey (2004a)—this is consistent with the relationships proposed in the Ireland et al. (2009) model. Based on the complexity science analysis above: The potential nonlinear influences caused by differing expectations for growth from multiple stakeholders in the *antecedents* of CES will also influence the *elements* of CES: entrepreneurial strategic vision, pro-entrepreneurship organizational architecture, and entrepreneurial processes and behaviors. We discuss these in turn.

4.4 Elements of CES: influence of schemata on entrepreneurial strategic vision

As individual entrepreneurial cognitions become aggregated, they start to influence the strategic properties of the entire organization. At the level of top managers, the attributes of an entrepreneurial strategic vision are likely to be influenced by individual schemata and cognitions, and in turn to influence the emergence of PLDs at adjacent levels through pro-entrepreneurship organizational architecture and entrepreneurial behaviors and processes. As noted, if several interdependent organizational components or behaviors appear as skewed distributions across several units of analysis, research by Komolgorov (1933) and Simon (1968) suggest that these are fractal structures with one mechanism driving interactions among other generating mechanisms and, subsequently, result in similar outcome patterns. Thus, based on a scale-free theory, expectations should also influence the components of a system. Beyond expectations, what other generating mechanisms could exist in CE? First, since outcomes are PLD, any mechanism that generates it should be similarly skewed. This suggests that each input construct/variable must have the potential for nonlinearity in the tail of the distribution. Second, as Sutton (2002) notes, the mechanisms should have subtle forms of correlation between the units that comprise a system. Ergo, given the hierarchical nature of complex systems, each construct should have the potential for scalability, a foundation upon which additional components can be built.

Following a complexity science perspective, outcomes will also be a result of an organization's initial conditions—its endowment of resources and expectations for future growth. If these initial conditions are beyond some minimal threshold, it has the potential to interact with an entrepreneurial strategic vision at multiple levels and possibly cause an extreme outcome. An entrepreneurial strategic vision "represents a commitment to innovation and entrepreneurial processes and behavior that is expressed as the organization's philosophical modus operandi" (Ireland et al. 2009, p. 26). From a complexity perspective, the most important point is that expectations inherent in the entrepreneurial strategic vision drive outcomes (Chiles et al. 2010). So, if expectations are low, there is no incentive, motivation, or desire to build up the venture endowments which provide the opportunity to scale; if expectations are low, then there is little chance of any type of cascading influence across levels of the organization.

Using a complexity view and scale-free theory, we suggest that an entrepreneurial strategic vision recursively interacts with a firm's resource endowments and the individual schemata of employees and top-level managers as a means of understanding where one *is* compared to where one has been and to some envisioned outcome of where one wants to *be*. This view is consistent with behavioral theory (Cyert and March 1963), the strategic behavior view (Ansoff 1987), and strategic reference point theory (Shinkle 2012). We identify this now to establish a theoretical baseline to further describe the interactions among individual schemata and pro-entrepreneurship organizational architecture, as well as individual schemata and entrepreneurial processes and behaviors. The important connection between expectations and entrepreneurial outcomes is underlined by researchers examining the link between individual-level cognitions and processes and macro-level outcomes (e.g., Lomi et al. 2010). For example, Lomi et al.'s (2010) system dynamics model suggests that a founder's expectations for future resource availability plays a vital role in venture creation as well as in the overall density and carrying capacity of the market. They show how small changes in micro-level expectations qualitatively (and nonlinearly) influence macro-level outcomes, supporting the claim that an entrepreneurial strategic vision leads to other organizational elements and outcomes.

Thus, if a top manager's expectations are within a *normal* distribution of outcomes—i.e., similar to 95 % of other firms—they will likely lead to actions similar to the majority of individuals in the population and, unable to differentiate from everyone else, be subject to normal, random fluctuations of the market. Similarly, without an entrepreneurial strategic vision, it would be difficult for the organization to differentiate itself from the myriad other competing ventures. In contrast, when expectations for outcomes are novel, there is a greater potential for nonlinearity. Chiles et al. (2010, p. 467) call these "expectations of an imagined future." As an empirical example of this, Zott and Huy (2007) find that entrepreneurs who perform symbolic actions (e.g., actions conveying an envisioned state that is different than what stakeholders can readily see) are able to procure resources like investors, employees, associates, or customers in greater quantity and quality than those who do not perform such actions. Thus, expectations beyond the normal outcomes can produce cascading nonlinear effects that have the potential to drive entrepreneurial behavior and to pull in exogenous resources.

Executives, boards of directors, shareholders, and the highest performing corporations also have expectations about how their company should be growing, and these expectations often have extreme effects. For example, tensions are generated among managers when a Board of Directors fires a CEO when the firm is not growing as expected (Khanin et al. 2009). Similarly, incongruent expectations between levels (i.e., workers and managers) about personal growth lead to nonlinear effects that are both positive and negative (Toegel et al. 2013). Most important to the discussion here is that an entrepreneurial strategic vision plays a major role at multiple levels. When an entrepreneurial strategic vision is present, individuals do not want to miss any opportunities (discovered or created) in the environment, and exhibit a heightened state of global awareness (Scholer and Higgins 2010). Expectations have been shown to link micro-level, pre-organizing stage activities to macro-level outcomes in a systems dynamics model (Lomi et al. 2010), where the authors found that slight changes in the expectation variable had nonlinear effects on outcomes, suggesting that small, consistent differences in entrepreneurial strategic vision can disproportionately influence the other elements of a CES.

4.5 Elements of CES: influence of schemata on pro-entrepreneurship organizational architecture

The Ireland et al. (2009) model highlights resources as a primary component of pro-entrepreneurial organizational architecture. Resources can include assets, firm characteristics, knowledge, skills, and capabilities (Wernerfelt 1984), and the resource-based view (RBV) assumes information asymmetries, where an organization may possess different stocks of knowledge relative to other firms in the industry. RBV further suggests that this knowledge can be a source of performance differentials among firms in an industry (Barney 1991). As well, these resources influence the processing abilities of individuals who have specific stocks of knowledge and provides increased capacity to accurately filter, assimilate, and transform new information into sources of performance differentials (Cohen and Levinthal 1990; Mahoney and Pandian 1992).

We highlight the value of resources in the context of pro-entrepreneurship architecture in that—when coupled with complexity science and power law perspectives—outliers may be less prone to experiencing the liabilities of newness and smallness (Stinchcombe 1965) that traditionally hamper the growth efforts of most ventures. In essence, outliers already possess novel endowments (e.g., human, social, intellectual, or financial capital) that provide competitive advantages that permeate the culture of the firm. An endowment is any resource that an organization possesses endogenously or has access to exogenously (Shane and Stuart 2002). These resource endowments provide the initial inputs for a venture, enabling engagement in the market, and serve as the foundation of pro-entrepreneurship architecture. Such architecture represents "cultural norms favoring entrepreneurial behavior" (Ireland et al. 2009, p. 27). When these actions leverage the firm's resources (i.e., when there is an alignment between engagement and endowments), superior performance can result (Ndofor et al. 2011). Marketplace advantages, however, are derived not simply from the resources alone, but from the connections among those resources (Florin et al. 2003) and the ensuing utilization of these resources to support the organization's culture. To follow, we build upon the RBV to first identify how resources could be a source of advantage in a market and then explain how empirical PLDs and expectations for future outcomes might drive a CES. As discussed earlier, outliers in the tail of a PLD are rare, with orders of magnitude greater than the average, and have a disproportionate influence on the statistical and behavioral properties of other observations in the population. If firm resources (e.g., capital endowments, human experience, knowledge, ability) are PLD, then firms with attributes in the tail have the potential to recognize, exploit, or—most importantly—create opportunities that other firms cannot.

Often, top-down constraints on an individual in a system (i.e., environmental conditions, organizational architecture) force the distribution of outcomes to look more Gaussian than Paretian. Yet, the new competitive landscape calls for the other extreme—managers and firms that support and embrace entrepreneurial processes and behaviors. Therefore, consistent with the propositions outlined by Ireland et al. (2009), the structure, culture, and reward systems of a firm—inherent elements of a pro-entrepreneurial organizational architecture—must be in alignment with the individual schemata of employees and the entrepreneurial strategic vision of top-level managers in order to fully support such entrepreneurial processes and behaviors.

4.6 Elements of CES: influence of schemata on entrepreneurial processes and behaviors

Individual schemata, and their ensuing influence on entrepreneurial strategic vision and pro-entrepreneurship organizational architecture, facilitate the organizational recognition and exploitation of opportunities through which firm-level entrepreneurial processes and behaviors manifest (Ireland et al. 2009). When organizations attempt to discover, evaluate, and exploit opportunities, internal and external conditions have a significant influence on innovative ability. At multiple levels, the environment selects out novel possibilities, and reduces the opportunity for firms to be innovative. Many evolutionary theorists suggest that the ability to adapt to the external environment is critical aspect of survival (c.f., Aldrich and Ruef 2006). Yet, individual learning is a large component of an individual's adaptability and, by extension, a firm's dynamic capability (Zahra et al. 2006). Research demonstrates that the ability of an organization to learn is directly related to the amount of specific knowledge already possessed by individuals within the organization. This collective ability is known as a firm's absorptive capacity (Cohen and Levinthal 1990). Often, opportunities for new innovative ventures require an individual to have specific stocks of knowledge before he or she recognizes it; without "deep structural knowledge" of the opportunity, the entrepreneur (and, thus, the firm) will probably not be able to evaluate it or exploit it (Grégoire et al. 2010).

The knowledge and ability of individuals and organizations to recognize new opportunities is highly path-dependent (Ronstadt 1988), suggesting that organizations that do not have individuals with the prerequisite knowledge need to learn how to acquire it. In dynamic environments, when resources are limited and time is valuable, it is often less costly and faster to simply look for another opportunity than to try to learn how to exploit an existing opportunity. Finally, Shane (2000) finds that most opportunities are recognized when entrepreneurs or firms have prior knowledge of customers, knowledge of markets, and knowledge of how to solve customer problems. Thus, if innovative opportunities emerge, but the entrepreneur (or firm) does not have the prior knowledge, he or she will not be able to discover it. Knowledge, however, is not normally distributed.

Most important to our argument here is that human performance is power law distributed. As recent empirical findings by O'Boyle and Aguinis (2012) and conceptual work by Aguinis and O'Boyle (2014) suggest, those with endowments (e.g., experience, as measured by human capital or social capital) in the tail of the distribution produce a disproportionate amount of a firm's total output. Since experience is power law distributed, then specific domain knowledge is also likely to be PLD. If that is the case, then the basic cognitive frameworks for recognizing, creating, or exploiting opportunities within a firm will be concentrated within a small group of elite performers.

Taken together, as shown in Fig. 2, we suggest that individual schemata and cognitions drive a CES from the bottom up. These schemata influence the entrepreneurial strategic vision of top-level managers, and in turn entrepreneurial strategic vision influences a pro-entrepreneurship organizational architecture and firm-level entrepreneurial processes and behaviors. As addressed in the preceding sections, PLDs are likely to influence each of the individual components of CES and, next, we discuss the implications of these arguments.

5 Discussion and conclusions

The primary objective of the current study is to enhance future theory building and empirical testing related to CE by drawing upon complexity science and power laws to more fully understand and extend the relationships outlined in the CES framework proposed by Ireland et al. (2009). CE occurs in a world of extreme outcomes, large events, and inputs that cannot be effectively characterized by a normal curve. Our focal argument suggests that outliers in the tail of the distribution—regardless of the phenomena measured—are *different* than others in the population and have a disproportionate influence on the statistical and behavioral properties of others within a system. We provide a foundation for building a collective body of knowledge on CES and contribute to the Ireland et al. (2009) model by identifying where PLDs exist within each element outlined in the model, as well as how individual schemata and expectations for future growth drive the emergence of power laws from both the top down and bottom up.

Given the importance of CE as a primary source of industry innovation and national economic progress, understanding the mechanisms and effects of a CES is of vital interest. Despite theoretical arguments from founder psychology (Haynie and Shepherd 2009), the RBV (Alvarez and Busenitz 2001; Barney 1991), opportunity discovery (Eckhardt and Shane 2003; Shane and Venkataraman 2000), and population ecology (Aldrich and Ruef 2006), which posit individual-, firm-, and environmental-level constructs as the primary drivers of performance differentials among organizations, each suffers from ceteris paribus assumptions that do not fully represent the empirical reality in which these firms are embedded. And, each is not able to capture the entirety of a CES. More specifically, each theory assumes that all aspects within the respective system—whether the number of organizational forms in the environment, the quality and quantity of opportunities therein, the resource endowments of firms, or the cognitive and behavioral properties of individuals in those firms—either remain equal or are homogeneous. As empirical reality attests, this is almost never the case. In addition, each theory is tested with statistical techniques founded on assumptions of independent observations and normal distributions of inputs and outcomes (c.f., Andriani and McKelvey 2009).

Based on the assumptions of interdependent heterogeneous agents, nonlinear interactions, indeterminism, and potentially infinite variance of outcomes, complexity science has the potential to integrate the extant CE literature while offering a more dynamic, coevolutionary, and empirically accurate account of the antecedents and consequences of a CES. In an effort to guide future research studies related to CES, we have included Table 1 that positions a variety of complexity science approaches within the structure of the Ireland et al. (2009) framework. Specifically, we outline nine specific complexity science approaches and link them to particular CES-based research concepts; we use these approaches and CES links to formulate future research questions that could be tested with complexity science concepts and methods.

A complexity science perspective offers theoretical and methodological guidance in modeling the inherent nonlinear outcomes of CE. Often, complexity scholars shy away from causal inference and ex ante prediction of emergent entities like new firms based on the theory's non-deterministic and nonlinear assumptions—there are simply too many unknowns and too high a probability for extreme events (like those in the tail of PLDs) that can influence outcomes. Instead, complexity scholars traditionally build theory inductively and prefer the "thick descriptions" of firms portrayed in multiple case studies (c.f., Eisenhardt et al. 2010; Eisenhardt 1989; Eisenhardt and Graebner 2007), emergent narratives (c.f., Lichtenstein et al. 2007; Lichtenstein 2011, 2014), or computer simulations (c.f., Siggelkow and Rivkin 2005; Rivkin and Siggelkow 2007) where historical contingencies, agent interactions and interdependencies, and multilevel feedback loops can be understood over time. For the development of generalizable scientific knowledge, however, these descriptions are often metaphorical and lack methodological replicability or theoretical falsifiability. Table 1 explicates *complex adaptive systems*, *power law distributions*, and *fractals and scale-free theory* as complexity science concepts that can be used to build theory about CE and CES; *self-organized criticality* and *preferential attachment* frameworks can be used as extant reference for describing the processes by which PLDs emerge; and *agent-based modeling, systems dynamics*, *genetic algorithms*, and *NKC Fitness Landscapes* are simulation techniques that can model potentially nonlinear relationships among constructs without relying on the assumptions of normality inherent in Gaussian methods.

This is why, in the following sections, we draw significantly from complexity scholars Boisot and McKelvey's (2010) notion of scalable abduction—scientific knowledge development where falsifiable causal inference is built according to the "best scalable explanation." A scalable explanation is one that can provide the most accurate description of the relationships among constructs at every level and unit of analysis within the theory's boundary conditions, given a micro-level understanding of agent interactions and a macro-level understanding of aggregated outcomes. Thus, scalable abduction can help to explain the bottom-up emergence of agents at the organizational member, management, and organization levels of analysis inherent in inductive studies, as well as to explain the top-down influence of the antecedents, elements, and consequences of CES derived from deductive studies. Abductive models (like agent-based simulations) are then used for demonstration, replication, and falsifiability of how micro-level interactions emerge into empirically validated higher level, power law distributed outcomes. Scalable abduction is particularly relevant to power law distributed phenomena. In the following sections, we explicate power law influences on future CE theory building, research design, and quantitative analyses while providing prescriptive suggestions to enhance collective CE research and conclude with some theoretical and practical implications of our study.

5.1 Power law influences on CE theory development

In our complex, interconnected society, outcomes do not exist on a seven-point sliding scale, fitting neatly into a box that must be described using the average as a

Table 1 Complexity science approaches and future research questions for studies on corporate entrepreneurship (CE) and CE strategy

Complexity science approaches	Research concepts related to CE and CE strategy	Future research questions
Complex adaptive systems How do a system's initial endowments, expectations, and environments influence its potential outcomes?	Entrepreneurial cognitions Entrepreneurial behavior Strategic repositioning Competitive advantage Leadership	Through which entrepreneurial processes can a CE strategy most effectively reposition a company in the industry? How will open-source products influence the entrepreneurial cognitions, processes, and behaviors of organizational members? What are the performance effects of virtual work teams on established firms or new firms? Will those effects differ in dynamic environments? Are those effects dependent on initial conditions?
Agent-based models How do individual-level interactions and interdependencies influence aggregate-level outcomes? How do micro-level behaviors generate macro-level outcomes?	External conditions Competitive capability Firm structure and performance Individual cognitions Behavioral strategies Human resources	When and how do changes in firm-level competitive capability influence the intensity of industry-level competition? How do organizational members' behavioral self-regulation influence survivability and growth in corporate ventures? How do changing levels of technological change and competitive intensity influence a CE strategy? How do demographic shifts affect entrepreneurial behavior in the organization? How does this affect human resource policies? How do alternative business models impact economies of scale and legitimization effects on innovative (or imitative) business models?
Power laws How do distributions of event frequency and size affect the interactions among agents? How do power law distributions emerge?	Competitive intensity Organizational architecture Reward systems Human resource management Technological change Opportunity recognition Opportunity exploitation	What mechanisms drive the empirically observed power law distributions of both inputs and outcomes in CE and CES? How can reward systems compensate outliers without alienating "normal" members? How do power laws exhibited in samples of nascent entrepreneurs influence the annual rate of new venture failure? Do they influence the stylized fact that internal ventures rarely meet expectations? Are the cognitive or behavioral processes to recognize or exploit opportunities differ between outliers and "normal" employees? How do differences in corporate strategy influence customer satisfaction and the potential for sustained competitive advantage?
Fractals and scale-free theory Which common events at a micro-level analysis can be extrapolated out to less frequent, more extreme events at the macro-level?	Product-market fragmentation Product-market emergence Innovation Alliance formation New product development	How do different types of strategic repositioning influence competitive intensity and technological change in the environment? Which behavioral strategies of new venture founders can serve as "initiating events" that have the potential to emerge into extreme outcomes? What types of entrepreneurial behaviors most effectively generate individual creativity and corporate innovation? Do the effects differ on team productivity? How do top-down expectations for growth influence corporate performance?

Table 1 continued

Complexity science approaches	Research concepts related to CE and CE strategy	Future research questions
Self-organized criticality Which repeated patterns across scales reveal an underlying "cause" that simplifies explanation and analysis? At what critical point do agent interactions produce nonlinear outcomes?	Internal venture creation Organizational change Organizational culture Innovation and creativity Leadership Behavioral strategies Decision-making	When is a top-down strategic vision detrimental to individual members' cognitions and subsequent corporate performance? Which organizational process generate the dynamic structuring that support innovation and creativity? How does a strategic vision affect interactions and outcomes at different levels of analysis (e.g., individual, dyad, group, organization, interorganizational, and cross-society)? How can corporate entrepreneurs most effectively discern which independent small events are likely to become scalable? What are the defining characteristics of extreme events? What CES constructs are most likely to exhibit criticality?
Preferential attachment Differences in which initial conditions are most influential on outcome variance?	Cultural influences on organizational behavior Group dynamics Leadership Network formation	How do differences in initial resource endowments influence the potential growth of startup ventures? What types of cultural differences most influence the variability of firm outcomes in established industries? in emerging markets? Can changing corporate leadership really change corporate culture? How do differences in alliance networks influence the distribution of merger and aquisition outcomes?
System dynamics How and why does unexpected behavior occur in complex systems? Which leverage points exist that can cause unintended effects?	Individual cognitions Public policy Process improvement Strategy Organizational restructuring	What are the implications of governmental funding policies on the startup rate and profitability of new businesses? Of existing firms? What are the regional conditions necessary to foster a cluster of highly innovative environmentally focused firms? How are industry-level processes intertwined with organizational processes to generate novel outcomes, like strategic repositioning or a firm's market capitalization in the tail of the distribution?
Genetic algorithm How do shared traits among agents create complex patterns and structures over time? How do team dynamics influence the scope and depth of search for new opportunities?	Organizational learning Innovation and change Resources/capabilities Networks analysis Individual decision-making Team decision-making Resource optimization	How do managerial intentions and actions change over time, and how are they reinterpreted by various stakeholders and organizational levels over time? How do individuals form, nurture, and dissolve external entrepreneurial networks in intensely competitive environments? What composition of individual learning rates and information processing styles optimize team performance teams in entrepreneurial organizations?
NKC fitness landscapes How do different environments influence performance?	External conditions Technological change Product-market emergence Product-market fragmentation	Under what environmental conditions might a CE strategy lead to decreased performance? How will global climate change influence the formation and execution of a CE strategy? How can leaders most effectively deal with issues arising from economic shifts accompanying green organizing and green firms?

benchmark. As O'Boyle and Aguinis (2012) put forth: "Quite simply, if performance is not normally distributed, theories that directly or indirectly build upon individual job performance and its prediction may need to be revisited"—this is particularly relevant for CE, where the creation of new order (e.g., a spin-off) is most likely generated with one individual's cognitive orientation and subsequent action. Additionally, as Andriani and McKelvey (2009, p. 1063) suggest, "The analysis is faulty, if not totally meaningless, if the sampling of outliers is insufficient…" and "…no statistical finding should be accepted into organization science if it gains significance via some assumption device by which extreme events and (nearly) infinite variance are ignored." These arguments provide the impetus for our research.

When it is likely that empirical observations are influenced by power law effects, theory-building efforts should reflect their presence. PLDs are called "scale-free" distributions because they look the same regardless of the scale used to measure them. In these distributions, the relationships among the size of the events are *fractal*—they have self-similar behavioral patterns and physical characteristics, where the small appears similar to the big, and individual sub-parts look the same as the whole (Mandelbrot 1963; West and Deering 1995). Hence, theory development requires knowledge about the whole system and about the underlying emergence of all the sub-systems. When power laws are present, theories to explain them are scale-free. *Scale-free theories* provide an explanation for outcomes at one level of analysis and should also explain inputs and outcomes at preceding levels. Therefore, at lower levels of analysis, CE scholars need to understand the interactions among individual and organizational levels and develop simulation models that can replicate these interactions and, subsequently, demonstrate how the model's emergent outcomes are consistent with aggregated empirical data.

5.2 Studying interactions and aggregations

From a complexity science perspective, innovations—the *sine non qua* of CE—do not originate solely from the firm, per se. Instead, innovations are emergent structures that are the result of individual agent interactions. And, as we noted earlier, these interactions are driven by schemata. Thus, to understand innovation, scholars need to study the schemata and interactions of individuals within a firm. One such technique to do so is experience sampling methodology (ESM), where subjects use computerized devices to report their personal thoughts, feelings, and behaviors in whatever context they are in. Uy et al. (2010) outline a protocol for ESM studies that collects data on interactions between individuals, and subsequently report different patterns of interactions—including how opportunity recognition, opportunity exploitation, and subsequent innovations emerge.

Corporate entrepreneurship scholars can more clearly focus research efforts by identifying PLDs and outliers in several components of the CES model. Based on extant research, it is likely that PLDs are prevalent when assessing firm-level entrepreneurial orientation (which is subsumed within the CES framework), and the expected future outcomes inherent within an entrepreneurial strategic vision. For example, Short et al. (2010) employed computer-aided text analysis (CATA) to validate the construct of entrepreneurial orientation. CATA could be used to identify the relative novelty of organizational members' expected future outcomes and then identify the relative fit of those expectations with top-level managers' vision via non-linear correlation analysis (like Kendall's Tau or Spearman's Rho). Similarly, scholars can capture entrepreneurial activities at multiple levels using conjoint analysis (Shepherd 2011). A conjoint analysis to test theory about CE and CES could, for example, collect data related to within-firm entrepreneurial decision-making about tasks such as product development or corporate acquisitions by decomposing the decision processes into underlying structures. Subsequent analyses can link these individual processes to different aggregated components at higher levels of analysis, such as structure or culture within an organizational, or external environmental conditions. Indeed, novel methods like these may open up interesting future avenues for CE and CES research.[1]

5.3 Power law influences on CE research design and quantitative analyses

A power law perspective can lend insight to developing better CE and CES research designs. As suggested

[1] We would like to thank an anonymous reviewer for offering this suggestion.

by Fleming (2007) regarding the long tail of innovations, the number of (1) new product inductions, (2) new business introductions, and (3) firm acquisitions is likely to be power law distributed. More importantly, Ireland et al. (2009) outline these three measures for identifying firms with a CES. Based on our framework, then, after sampling a population of firms that may exhibit CES, conducting nonparametric maximum likelihood estimations for fit with a PLDs (as specified in Clauset et al. 2009), CE scholars can identify a more precise cutoff of where in the distribution the power law tail begins—the critical threshold, mathematically calculated as $x_{\min}$—and then categorize which firms exhibit a CES (those above the threshold) and firms which do not (those below the threshold).

In these distributions, the mean is unstable and variance is nearly infinite; no single observation accurately characterizes the average of the system. Using Gaussian methods to study firms in a population does not actually measure performance; instead, it constrains our understanding of the relative power of the highest performing firms. Traditional robustness techniques bury the most important variance in the data, even though this variance provides executives with a more realistic measure of a firm's relative performance. When scholars perpetuate the practice of deleting or manipulating outliers to achieve statistical significance, their findings run the risk of be irrelevant to practicing managers.

Schoonhoven (1981) proffers that the assumption of linear relationships is often "misplaced" and that all empirical analyses should be tested for nonlinear effects. More recent work by Aguinis et al. (2013) identifies dozens more data-analytic problems caused by the outliers inherent in power laws. Kreiser et al. (2013) found that innovativeness, proactiveness, and risk-taking components of entrepreneurial orientation have nonlinear influences on performance, further validating our arguments that a complexity science perspective is particularly well-suited perspective for future studies on CE and CES.

Consistent with complexity science's view of building theory abductively, Fioretti (2013) suggests using agent-based simulations with non- or semi-parametric parameters to model how micro-level interactions generate emergent (and PLD) aggregate outcomes. Using models like this, scholars can integrate the findings from entrepreneurial process and behavior studies, as we describe in Sect. 5.2, and then demonstrate—through computational modeling—how these interactions emerge into aggregated outcomes at different levels of analysis. These techniques model different strategies and simulate the probabilistic interactions and subsequent outcomes among firms within a simulated virtual environment. In all cases, research must begin with assumptions that accurately reflect empirical reality, with interdependent observations as the null hypothesis unless proven otherwise. Gaussian methods and assumptions should only be used if the null is rejected (Aguinis et al. 2013). This can be beneficial for scholars attempting *any* kind of statistical analysis on variables that may be skewed.

5.4 Managerial implications

Drawing upon a complexity science perspective of schemata and power laws provides additional insights on such practical CE applications as corporate change, innovation, and employee compensation systems. First, a complexity science perspective is founded on the historical contingencies of a company, where its initial conditions at time "t" play a significant role in making decisions and changes at time "$t + 1$" (Anderson 1999). As we suggest, schemata are relatively stable and difficult to alter over time, even with disconfirming evidence that an existing schema may be incorrect. Therefore, it would take significant effort, interactions, and resources to make radical changes, such as those required in the adoption of pro-entrepreneurial cognitions. If a firm does not start with pro-entrepreneurial cognitions, it will be exceedingly difficult to incorporate a CES—in fact, it is very rare to see a company successfully change its entire mindset like this. We would advise firms wishing to adopt a CES as a means of innovating and capturing new opportunities to do so via corporate venturing. The acquisition of smaller firms with structurally diverse knowledge-specific resources and similar expectations for growth is likely to be more successful than attempting massive internal change.

Additionally, a power law framework is consistent with Fleming (2007), who suggests that breakthrough innovations are *least* likely to occur when there are barriers to collaboration and not enough interaction among the internal and external networks of developers. Thus, our arguments suggest that firms wanting to incorporate a CES should integrate more open innovation technologies, which reduce traditional constraints on the transfer of firm-specific intellectual capital.

Finally, as Crawford et al. (2015) demonstrate in a four-sample study of more than 12,000 firms at different stages of emergence, all measures of human-, social-, intellectual-, and financial capital in entrepreneurship are PLD, as are a founder's expectations for future growth. Individual employees who are outliers in these distributions are likely to do things or think in a manner that is qualitatively different than individuals who are not in the tail of the distribution. Those who are in the tail produce a disproportionate amount of a firm's output. The Crawford et al. (2015) study suggests that outliers perpetuate superior performance because their human and social capital endowments provide them a greater propensity to: (1) expect their future outcomes to be in the tail of the distribution; (2) have the greatest ability to recognize, create, and exploit opportunities; and (3) possess endowments that are beyond some critical threshold and can influence emergent outcomes at a higher level of analysis (i.e., the organization). For practitioners, this suggests that recruiting and retaining star employees is of vital concern; if recruiters are unable to select candidates based on previous experience or organizational fit, then the practice of hiring those who expect the most novel outcomes is likely to be an effective selection criterion.

5.5 Conclusion

In conclusion, we have provided specific theory building and empirical recommendations related to the elements explicated in the Ireland et al. (2009) model that may be useful in answering some of the insightful research questions posed by those authors; the research questions that we pose in Table 1 are intended to enhance the potential utility of the CES model. In so doing, our study provides two additional insights to theory and practice. First, by identifying that almost all inputs and outputs related to CES are highly skewed, we pinpoint the structural resources that organizations can leverage to scale upwards into an extreme outcome. Second, the nonlinearity of resource endowments provides an explanation for why there are oftentimes inconclusive interpretations related to the role of CE in new venture performance and why a theory of growth appears to be so elusive (Leitch et al. 2010). Traditional Gaussian statistical methods which assume normal distributions have been suggested to produce substantively incorrect conclusions and misspecified theories when used on PLD data (Aguinis et al. 2013)—we posit this is likely to be the case with the majority of CE-related phenomena. By examining CES in the context of PLDs and complexity science, we hope to facilitate and uncover a variety of fruitful research avenues related to the antecedents, elements, and consequences of a CES.

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