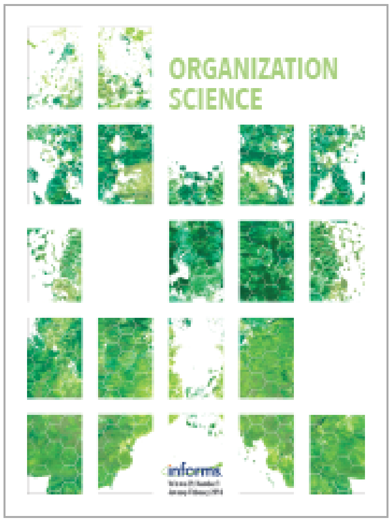

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PERSPECTIVE

Chance Explanations in the Management Sciences

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We propose that random variation should be considered one of the most important explanatory mechanisms in the management sciences. There are good theoretical reasons to expect that chance events strongly impact organizational behavior and outcomes. We argue that models built on random variation can provide parsimonious explanations of several important empirical regularities in strategic management and organizational behavior. The reason is that random variation in a structured system can give rise to systematic patterns at the macro level. Here, we define the concept of a chance explanation; describe the theoretical mechanisms by which random variation generates patterns at the macro level; outline how key empirical regularities in management can be explained by chance models; and discuss the implications of chance models for theoretical integration, empirical testing, and management practice.

Keywords: randomness; luck; chance; theoretical mechanisms; null models
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1. Introduction

Management scholars often consider chance and randomness as a nuisance to be eliminated. Chance may be the null hypothesis, but the null hypothesis is usually only included as a straw man to be rejected (Starbuck 1994). Randomness, according to this conventional view, is due to measurement error or unobserved heterogeneity and should be eliminated through improved measurement or controlled for with proper statistical methods. The main goal is to understand the systematic, i.e., nonrandom, forces that really interest management scholars. Hence attributing an event or pattern to chance and randomness hardly counts as a proper explanation.

We argue instead that theory development that relies on randomness as its first principle can offer a theoretically rich and empirically fruitful paradigm in the management sciences. Random variation offers a parsimonious explanation of several important empirical regularities in management. Random variation deserves to be taken seriously as a theoretical mechanism of considerable generality and with strong empirical support. The purpose of this paper is to develop this argument and promote what could be called “the random school of thought” in the management sciences.

The idea that random variation can explain regularities in organizational behavior is not novel. Several management scholars have stressed that behavior by and within organizations is likely to contain a random element (Aldrich 1979, Barney 1986, Fichman 1999, March 2010, Nelson and Winter 1982, Starbuck 1994) and have examined how models relying on chance variation can explain patterns previously attributed to systematic effects (Alchian 1950, Barney 1997, Denrell 2004, Levinthal 1991, Mancke 1974, March and March 1978, Powell 2003). Yet the theoretical unity and empirical richness of models relying on randomness is seldom appreciated. The reason is, in part, that these contributions are scattered across many different subdisciplines. Even management scholars who believe randomness is important may not be aware of the wide range of chance explanations that exist. Moreover, because the focus is usually on a particular application (such as strategy, career patterns, or organizational learning), the underlying mechanism is not always explicated. As a result, readers are unlikely to appreciate the theoretical unity that exists amid the diverse applications.

Models that demonstrate how an empirical regularity can be explained by random variation also tend to be framed as contributions to statistics: the purpose is to develop a more sophisticated null hypothesis instead of testing theories against a null hypothesis that assumes a zero effect (Schwab et al. 2011). Although such a framing makes the argument easier to sell to skeptics who doubt the importance of chance in management, it also downplays the substantive importance of random variation. As we elaborate in detail later, chance models are often sufficient to explain empirical regularities and the assumption of (nearly) random variation is consistent with empirical data. Thus, the reason we advocate for management scholars to develop explanations based on random variation is very different from why Schwab et al. (2011) advocated naïve hypotheses or "null models." Schwab et al. stated that "naïve hypotheses are not supposed to provide satisfying explanations, but to offer stronger competition than null hypotheses do" (2011, p. 1114). We propose explanations relying on random variation not only because they provide stronger competition but also because they can offer satisfying explanations. Our explanations are satisfying both in the sense that random variation is sufficient to explain the regularity and in the sense that the assumption of (nearly) random variation is often consistent with empirical data.

To many scholars, chance explanations seem less interesting and compelling than "real" explanations that attribute regularities to systematic causal effects. We find this attitude puzzling. If random variation can explain an empirical regularity and if the predictions of such a chance model are empirically validated, isn't this a scientific success story? Chance explanations are, in fact, common in several scientific disciplines. Chance is the core theoretical postulate in statistical approaches to physics (Ruhla and Ruhia 1992)[1] and is central in genetics (Kimura 1984). Models relying on chance variation have become popular in ecology since Hubbell (2001) showed that they could explain several empirical regularities in the distribution of species.

Management scholars view chance explanations as less compelling than other explanations partly because they seem less useful normatively. We believe this attitude is misguided. If an explanation based on random variation is correct, this has several important normative implications. For example, if growth rates are "nearly random" (Geroski 2005), we cannot learn much about the determinants of growth by studying high-growth firms. The bias against chance explanations stems in part from persistent underestimation of the role of random variation. Consistent with the fundamental attribution error (Ross 1977), management scholars have been slow to recognize the importance of random variation and the limits to predictability (Chan et al. 2003, Makridakis and Hibon 2000, Pant and Starbuck 1990).

In this paper we hope to make the case for taking chance explanations seriously in management by (1) defining and defending the concept of a chance explanation, (2) outlining the theoretical mechanisms used in chance explanations to show how randomness at the micro level can give rise to systematic patterns at the macro level, (3) providing an integrated review of how chance models can explain key empirical regularities in the management sciences, and (4) suggesting implications and promising avenues for management research and practice.

2. The Idea of Chance Explanations

A chance explanation can be defined as an explanation that incorporates randomness, conceptualized as unsystematic and unbiased variation, as a key assumption to explain an empirical regularity.

To illustrate the idea of a chance explanation, consider stochastic growth models (Gibrat 1931, Levy 2003, Simon and Bonini 1958), which have been developed to explain the skewed size distribution of firms. Many theories in economics and strategic management attribute size differences to systematic differences in capabilities, costs, management, or strategy. The idea is that productive, cost-effective, innovative, or favorably positioned firms will grow and become large (Hopenhayn 1992, Jovanovic 1982, Nelson and Winter 1982). In contrast, stochastic growth models assume that growth rates are independent of firm attributes, strategy, or management. Specifically, the growth rate of firm i in period t, $g_{i,t}$, is modeled as if it were drawn from a probability distribution identical for all firms and all periods. Hence, no firm is more likely than any other to grow large, and all size differences are caused entirely by the luck of the draw. Nevertheless, such models generate a skewed size distribution.

Stochastic growth models explain the size distribution of firms in the sense that the phenomenon to be explained (the skewed distribution) can be derived from the assumptions of the model (random growth rates). The key explanatory mechanism is random variation combined with the multiplicative nature of growth processes: the size of firm i in period t is equal to its initial size multiplied by the realized growth rates (Gibrat 1931, Sutton 1997). Random variables that interact multiplicatively tend to generate skewed distributions (Kesten 1973) because a single period of decline will have a disproportionate impact. Suppose a firm is equally likely to grow or decline by 50% in any given year. A firm that experiences one year of growth and one year of decline will not return to its initial size but will be 25% below it (since 1.5 times 0.5 is 0.75). Note that the assumption of variability (randomness) in growth rates is central to this explanatory mechanism. A model assuming that all firms grew at the same rate in every period would not produce a skewed size distribution.

An example of a chance explanation at a very different level of analysis is noise explanations of subadditivity in probability judgments (Bearden et al. 2007, Hilbert 2012). It is an axiom of probability theory that the probability of mutually exclusive events cannot add up to more than one. Individuals asked to evaluate the probabilities of mutually exclusive events, however, often give answers that sum up to more than one (Fischhoff et al. 1978, Fox et al. 1996). Such *subadditivity* in probability judgment has been examined extensively by experimental researchers and has typically been attributed to systematic cognitive bias. For example, it has been argued that events that are "unpacked" and described in vivid details evoke multiple associations and are therefore overestimated (Tversky and Koehler 1994).

An alternative model assuming unbiased but noisy probability judgments provides a more parsimonious explanation (Bearden et al. 2007, Hilbert 2012). Suppose probability judgments are unbiased on average but subject to noise: the estimated probability of an event varies around the correct estimate. Consider the judgments of an individual asked to evaluate the probability of several mutually exclusive events. Because the probabilities of the different events sum to one, the average probability of each event has to be relatively small. For example, if someone is asked to evaluate five events, the average likelihood of these events is 0.2. Because the true probability of the events being evaluated is close to 0, even unbiased but noisy estimates will, on average, lead to overestimation. The reason is a ceiling (or flooring) effect: if the correct probability is 0.2, the event can only be underestimated by at most 0.2 but can be overestimated by a larger magnitude. Note that random variability is key to this explanation. A model assuming unbiased estimates with no variability would not explain subadditivity.

Not all explanations that include random variation should be classified as chance explanations. The evolutionary models developed by Nelson and Winter (1982) include the assumption that the outcome of search is random. Yet differential growth—not random variation—is the key mechanism in most of their models. In contrast, in both chance explanations above, random variability is arguably the *key* assumption used to derive the phenomenon to be explained. For example, the key mechanism that differentiates stochastic growth models from alternative explanations is the assumption of randomness at the level of the growth rate. That growth rates combine multiplicatively is also included in alternative explanations emphasizing persistent firm differences. More generally speaking, all explanations involve numerous assumptions, but not all are essential. Some assumptions specify background knowledge—facts about the world that are well known to most people and common to most explanations. A need for an explanation arises when one cannot see how the regularity to be explained follows from the background knowledge. An explanation adds a piece of knowledge or a principle that, when combined with the background knowledge, makes it possible to derive the phenomenon to be explained (Gardenfors 1988, Hempel and Oppenheim 1948, Runde and de Rond 2010, Van Fraassen 1980). A chance explanation explains a regularity by adding the assumption of random variation and demonstrating how a mechanism involving random variation (such as multiplicative interactions) can be used to derive the regularity in question.

An important feature of the chance explanations we focus on is that they eschew trait-based explanations in favor of the assumptions that all units are, ex ante, identical. Many theories in management explain outcomes as a result of traits that dispose units (firms or individuals) to move in the direction of the outcome to be explained. Large firms have traits (such as productivity or capabilities) that propel them toward large size; small firms have traits that propel them toward small size. People who overestimate low-probability events have a trait (a cognitive bias) that pushes their estimates upward. Chance explanations instead assume unbiased random variation at the unit level and demonstrate how this assumption, combined with the structure of the environment, is sufficient to explain the aggregate movement observed.

Finally, chance explanations do not have to assume that social reality is "essentially" random. We agree that "nothing is really random" and that randomness often is a reflection of human ignorance (de Rond and Thietart 2007, Eagle 2005, Rescher 1995). Randomness is a theoretical postulate, an abstraction introduced by the theorist to capture what he or she believes is essential about the behavior of the units being modeled. A theorist assumes random growth not because she believes this assumption captures everything about how firms work but because she believes that this assumption is sufficient for her purpose. Ex post it may be possible to reconstruct all the detailed events that contributed to a firm's growth, but these details would not add much to the explanation of firm size distributions.

3. Theoretical Mechanisms in Chance Models

Explaining empirical regularities by relying on randomness might seem to be a contradiction in terms. Yet an observed macrolevel pattern can be an expected consequence of randomness at the micro level. In contrast to what unguided intuition might suggest, randomness at the micro level often has systematic aggregate consequences (Feller 1957). A simple example is the central limit theorem, which explains why many quantities are normally distributed. The chance models discussed in the previous section illustrate two additional theoretical mechanisms for how random variation leads to systematic aggregate patterns. Several other mechanisms have been used in chance models in the management literature. Here, we review some of the most important ones. Taken together, these mechanisms provide management theorists with a theoretical toolbox useful for explaining novel empirical regularities.

3.1. Reinforced Random Processes

A key mechanism in many chance models is a reinforcement process that increases the future probability of outcomes that were realized in the past (Pemantle 2007). Such reinforced random processes offer parsimonious explanations of skewed distributions and persistent diversity in outcomes.

The classical illustration is the Pólya (1930) urn model. Imagine an urn with one red ball and one black ball. In each period $t = 1, 2, \ldots$, a ball is drawn at random, it is replaced, and c more balls of the same color are added. Denote the number of red balls after period t by $N_{r,t}$ and the number of black balls by $N_{b,t}$. The probability of drawing a red ball in period t is $(N_{r,t-1} + cI_{r,t-1})/(N_{r,t-1} + N_{b,t-1} + c)$, where $I_{r,t-1} = 1$ if a red ball was drawn in period $t-1$ and $I_{r,t-1} = 0$ if a black ball was drawn in period $t-1$. Thus, the probability of drawing a red ball in the next period is increased if a red ball was drawn in the previous period. After many periods, the proportion of red balls converges to a constant proportion, but what proportion it converges to is a random variable. Thus, different realizations of the same process can generate very different outcomes. If one ball of the same color is added ($c = 1$), the proportion of red balls is equally likely to be any number between 0 and 1 (the proportion is drawn from a uniform distribution). If two or more balls of the same color are added ($c \geq 2$), the proportion of red balls will converge to a value close to 0 or close to 1 (the proportion is drawn from a bimodal distribution).

A wide variety of reinforced random processes proposed in the social sciences can be modeled as extensions of the above urn model (Artur et al. 1983, Pemantle 2007). In particular, preferential attachment processes, in which new alternatives are more likely to link to alternatives with many prior links (Barabási and Albert 1999, Price 1976, Simon 1955), can be viewed as urn models in which new alternatives emerge over time (Berger et al. 2014). Such preferential attachment models offer simple explanations of power law distributions of outcomes.

3.2. Multiplicative Random Processes

Random variables that interact multiplicatively can also generate skewed distributions. Consider $x_t = a_t x_{t-1}$, where $a_t > 0$ is a random variable. Suppose that a_t is symmetrically distributed around 1; i.e., x_{t-1} is equally likely to increase or decrease by a given percentage. For example, suppose that a_t is equally likely to be 0.9 or 1.1. Such a process nevertheless produces a skewed distribution x_t for large values of t. Moreover, the distribution of x_t is more skewed when the variance in the distribution of a_t is higher. The intuition behind these results is that a low value of a_t has a disproportionate impact. The reason is that if x_{t-1} is reduced by 10% (x_{t-1} is multiplied by 0.9), it needs to grow by $1 - 1/0.9 = 11.1\%$ (multiplied by $1.111 > 1.1$) to reach its original size.

Because multiplicative random processes generate skewed distributions, they offer an explanation of diversity in outcomes that does not rely on ex ante differences in the average value of a_t. Moreover, multiplicative random processes can offer simple explanations for why quantities are distributed according to a power law or a log-normal distribution. If there is no lower bound for x_t, then x_t will be approximately log-normally distributed for a large t. If there is a lower bound such that $x_t > 0$, then x_t will be distributed according to a power law (Gabaix 2009).

3.3. Long Leads in Random Walks

Sums of random variables can also have counterintuitive dynamics. In particular, when random variables are added rather than averaged, chance events do not "even out." Rather, bad or good luck can persist for a long time (Feller 1957). To illustrate this, consider a random walk: $x_t = x_{t-1} + e_t$, where e_t is normally distributed with mean 0 and variance 1. If the random walk starts from 0, $x_0 = 0$, and we observe it for 10 periods, how likely is it that the random walk will spend all of the 10 periods above 0? How likely is it that the random walk spends 5 of the 10 periods on the positive side? More generally, let k be the number of periods when $x_t > 0$; i.e., k is the number of periods that the random walk spends on the positive side. What is the distribution of k?

Contrary to unguided intuition, the distribution of k is bimodal: the most likely events are $k = 0$ and $k = 10$. The least likely event is that $k = 5$. That is, the most likely outcome is that the random walk spends all 10 periods on either the positive or the negative side. This is the phenomenon of long leads (Feller 1957). This result does not require that e_t be normally distributed, but it is true for any symmetric random walk (for a precise statement, see Feller 1968, p. 411). To explain the underlying intuition, suppose $x_1 = 1$. What is most likely to happen in the next period: (a) the process remains above 0 ($x_2 > 0$), or (b) the process falls below 0? Because the expected value of e_2 is 0, the process most likely remains above 0. The phenomenon of long leads implies that addition of random variables can explain persistent differences in outcomes. For example, suppose that actor A wins and receives a payoff of 1 in every period in which $x_t > 0$, and actor B wins and receives a payoff of 1 in every period in which $x_t < 0$. If we observe the two actors for 10 periods, the most likely event is that one of the actors wins all of the time.

3.4. First-Passage Times of Random Walks

Random walks with a lower absorbing barrier can offer a simple explanation for why the probability of exit from a system initially increases and then decreases with time spent in the system (Aalen and Gjessing 2001, Lancaster 1972). The main assumption is that exit from the system occurs when a random walk first hits a lower boundary (Redner 2001, Schrödinger 1915). Suppose a random walk starts at $X_0 = c > 0$ and subsequently evolves as $X_t = X_{t-1} + e_t$, where e_t is a normally distributed variable with mean 0 and standard deviation s. The random walk exits the system the first time t at which $X_t < 0$. Let $h(t)$ be the probability that a random walk that has not exited the system in period $t-1$ will do so in period t. If the standard deviation s is sufficiently small compared with the initial position c, $h(t)$ will initially increase with t, but eventually $h(t)$ will start to decrease in t. The intuition for the initial increase is that it takes some time before the process reaches the lower boundary, so it is unlikely to reach it in the first period. The intuition for the eventual decrease in $h(t)$ is the following. In the absence of a lower barrier, the random walks would spread out over time (the variance in X_t would increase with t). If a lower barrier is present, random walks that hit the lower barrier are eliminated. Those that remain are random walks that happen to avoid the lower barrier. Conditional upon survival, these random walks are likely relatively far above the lower barrier. As a result, they are unlikely to hit the lower boundary in the next period.

3.5. Flooring and Ceiling Effects

Constraints that imply that a random variable has to be above or below a barrier imply that even symmetric random variables will generate skewed outcome distributions. This was the mechanism in the chance model for subadditivity: overestimation was more likely than underestimation in the presence of a lower barrier. Similarly, constraining random walks to be above or below a barrier generates systematic trends (Gould 1988). Consider a random walk that starts at $X_0 = c$. Whenever $X_t > 0$, X_t is equally likely to increase or decrease by 1. Whenever $X_t = 0$, X_t is equally likely to increase by 1 or stay at 0. Such a random walk bounded by a lower barrier generates an upward trend: $E[X_t]$ is increasing in t. An upper barrier generates a downward trend.

3.6. Regression to the Mean

Independent random variables can give rise to systematic trends because of regression to the mean. Suppose $X_1 = u + Z_1$ and $X_2 = u + Z_2$, where Z_1 and Z_2 are independent and identically distributed random variables. The expected difference $E[X_1 - X_2]$, is 0, but if we only observe X_2 when X_1 is unusually large ($X_1 > E[X_1]$), the expected difference, $E[X_2 - X_1 \mid X_1 > E[X_1]]$, is negative. More generally, extreme values of random variables are likely to be followed by values closer to the average, hence the term "regression to the mean."[2] The intuition is that extreme events are unlikely to be repeated. Regression to the mean can offer parsimonious explanations of what appear to be causal effects. For example, suppose X_1 and X_2 are firm performances in two consecutive periods. Any intervention that occurs when X_1 is unusually low will be associated with a performance increase (Cohen and March 1974). Asymmetries in the extent to which regression to the mean operates or is observed can generate other patterns (Denrell 2005, Hogarth and Karelaia 2012). For example, low values of X_1 may not be observed because of selection. As a result, $E[X_2 - X_1]$ will be negative in the selected sample.

3.7. Noise in Selection Systems and Systems Driven by Extremes

Unsystematic noise can generate systematic effects in systems subject to selection. Consider a selection system in which only actors with performance above a threshold survive, $P_{i,t} > c$. Suppose the performance of actor i in period t is normally distributed, with mean u_i and variance v_i. The expected performance in period 1 of the actors that survived in period 1, $E[P_{i,1} \mid P_{i,1} > c]$, is increasing in v_i (Denrell 2003). The intuition is that actors with higher variability in performance are more likely to achieve very high and very low performance, but only the upper tail matters for survivors.

More generally, unsystematic noise has a systematic effect on the outcome of systems driven by extremes. Consider a system that selects the alternative i with the highest observed realization. The random variable Y_i ($i = 1, \ldots, N$) is normally distributed with mean 0 and variance v_i. The probability that alternative i is selected is an increasing function of v_i. The intuition is that random variables drawn from distributions with higher variances are more likely to generate extreme realizations. The implication is that any variable, such as sample size, that systematically influences the variance of a random variable will have a systematic effect in systems driven by extremes. For example, consider three samples of random variables: $X_1, X_2, \ldots, X_N$, $Y_1, Y_2, \ldots, Y_M$, and $Z_1, Z_2, \ldots, Z_K$. Suppose all random variables are independently normally distributed with mean 0 and variance 1. Which sample is likely to have the highest average? The answer is the sample with the smallest number of observations (Wainer and Zwerling 2006). The reason is that the variability of an average declines with the number of observations. By contrast, suppose we ask, which sample is most likely to contain the largest observation of all? The answer: the sample with the largest sample size. The reason is that a larger sample is likely to contain more extreme outcomes.

4. Empirical Regularities Explained by Chance Models

By combining the theoretical mechanisms outlined above, chance models can provide parsimonious explanations of a wide range of empirical regularities in management. Here, we review how chance models based on the above theoretical mechanisms have been used to explain important empirical regularities in different subfields in the management sciences. The review is summarized in Table 1.

4.1. Strategic Management

Firm size and profitability are typically explained by firm strategy, resources, or other firm attributes or by industry attributes. At the same time, empirical studies of the variability in firm performance and growth show that a large part of the variance in these variables is unexplained and cannot be attributed to firm or industry effects (Coad 2009, McGahan and Porter 2002). This finding suggests that chance models could provide an alternative basis for explanations in strategic management. Chance models have also been proposed for important empirical regularities in strategic management.

4.1.1. Firm Growth Rate and Size Distribution. Stochastic growth models offer parsimonious explanations of the firm size distribution. These models assume that growth rates are independent of firm characteristics and dominated by unsystematic random variation. Consistent with these models, empirical studies show that the mean growth rate is independent of size (Bottazzi and Secchi 2006). Moreover, the idea that unsystematic variation dominates firm growth is well supported empirically in the sense that the variance explained by systematic factors is small (Coad 2009, Davidsson 2006, Geroski 2005). Nevertheless, two empirical findings are inconsistent with the assumption that firm growth is the result of small independent shocks. First, the observed growth rate distribution is fat tailed: very high and very low growth rates are much more common empirically than what would be expected if growth rates were normally distributed (Stanley et al. 1996). If aggregate firm growth is the result of small independent shocks, the central limit theorem suggests that aggregate growth rate should be normally distributed. Second, the variance of firm growth declines with size (Stanley et al. 1996).

Recent models have shown that simple extensions of the basic stochastic growth model can accommodate these empirical findings. Bottazzi and Secchi (2003) showed that a modified stochastic growth model, in which a reinforced random process regulates the number of growth shocks a firm is subject to, can explain the empirically observed growth rate distribution. They assume that growth shocks occur when a firm tries to exploit an opportunity (which can result in either growth or decline). They propose that the number of growth shocks a firm is subject to during a year is the result of a preferential attachment process: firms that have captured many opportunities so far are more likely to capture the next opportunity. This process can explain the empirically observed Laplace distribution of the growth rate.

Sutton (2002) showed that a model of random assignment of subunit sizes can explain the association between size and the variance of the growth rate found in empirical studies. Consider a firm with size $s = 10$ (units are in millions of sales). How many independent subunits does such a firm consist of and what are their sizes? Sutton assumed that every partition of 10 is equally likely. Partitions of 10 include $\{9, 1\}$ as well as $\{4, 3, 3\}$, etc. Sutton showed that the assumption of random partitions implies that the variance of the growth rate declines with size in a way that replicates the pattern found empirically. Bottazzi and Secchi (2006) provided microfoundations to Sutton's model by demonstrating how stochastic processes regulating diversification efforts within firms can generate the empirically observed size-variance dependency. They showed that both a reinforced random process (in which diversification by a firm increases the rate of future diversification) and a branching process (in which subunits can give rise to further subunits) generate a distribution of subunits compatible with the observed size-variance association.

Later literature has built on these ideas and developed integrated models. For example, Fu et al. (2005), Riccaboni et al. (2008), and Growiec et al. (2008) showed that a model that includes a preferential attachment process that determines the subunit a new product is assigned to can explain the firm size distribution, the distribution of the growth rate, and the relation between size and the standard deviation of growth.

4.1.2. Firm Size and Profitability. Why is market share associated with profitability? This association is usually explained by theories of monopoly power, economies of scale, or superior efficiency. Mancke (1974) showed that a chance model could offer a simple interpretation of the evidence. The basic idea is that companies that stumbled on products with high demand would both be profitable and grow large. His chance model predicts that changes in profitability should not be correlated with firm size—a prediction for which he finds support.

4.1.3. Performance Persistence. The question of what explains performance persistence is central to strategic management. Why do some firms continue to

Table 1 A Summary of Chance Models in Subfields of Management

Empirical regularity	Remarks	Main theoretical mechanism[a]
Strategic management		
Firm growth	A stochastic growth model in which random events are multiplied can explain a skewed distribution of firm sizes and market share without assuming a priori firm differences (Gibrat 1931).	§3.2: Multiplicative random processes
	A modified stochastic growth model in which a reinforced random process regulates the number of growth shocks a firm is subject to can explain the empirically observed tent-shaped growth rate distribution (Bottazzi and Secchi 2003).	§3.1: Reinforced random processes
	A model of random assignment of subunit sizes can explain the observed negative association between firm size and the variance in growth (Sutton 2002, Bottazzi and Secchi 2006).	Random divisions; §3.1: reinforced random processes
Firm profitability and size	Companies that stumbled on products with high demand would be both profitable and grow large without assuming economies of scale (Mancke 1974).	Common random shocks
Performance persistence	Long leads in random walks explain sustained differences in performances without assuming any a priori differences among firms (Denrell 2004).	§3.3: Long leads in random walks
	A modified random walk model, which assumes that firms differ in how frequently their resources change but not in their initial level of resources or the expected change in resources, provides a good fit to empirical data on performance persistence (Henderson et al. 2012).	Random walk with a semi-Markov structure
Performance and risk taking	Heterogeneity in variability implies that high- and low-performing firms likely have high variance in future performances even if past performance does not influence future risk taking (Denrell 2008).	§3.7: Noise in selection systems and systems driven by extremes
Organizational ecology		
Density dependence	A reflected random walk plus selection bias can explain why the exit rate is a U-shaped function of density and why the entry rate is an inverted U-shaped function of density without referring to legitimacy and competition (Denrell and Kovács 2008).	§3.5: Flooring and ceiling effects
Age dependence in failure rates	A random walk with an absorbing lower barrier can explain why the probability of failure initially increases with and then decreases with age without assuming a learning effect or differences in skills among firms (Levinthal 1991).	§3.4: First-passage times of random walks
The Red Queen effect	Increased variability in performance triggered by competition can explain why intense competition is associated with increased survival and growth rates for the surviving firms (Barnett 2008, Denrell 2003, Denrell and Shapira 2009).	§3.7: Noise in selection systems and systems driven by extremes
Organization theory		
Popularity distributions	Randomness plus rich-get-richer social processes can explain the skewed distributions of popularity without assuming any a priori differences among the objects (Barabási and Albert 1999, Simon 1955).	§3.1: Reinforced random processes
Fads in management practices	A practice can diffuse widely among firms even if the performances of practices are random and firms base their imitation decisions on observed performance. The reason is that a practice adopted by many is more likely to be associated with the highest level of performance, because extreme values are more likely in large samples (Strang and Macy 2001).	§3.1: Reinforced random processes
Superstitious learning and diversity in practices	Even if practices do not differ in success probabilities, firms may learn to adopt different practices. The reason is that increasing the probability of repeating actions associated with success leads to superstitious learning (Lave and March 1975).	§3.1: Reinforced random processes
The S-shaped diffusion curve	Random encounters can explain the S-shaped diffusion curve without assuming that conformity varies with the number of adopters (Lave and March 1975).	Random encounters
Career dynamics	A chance model that posits that career advance or dismissal depends on imperfect performance sampling can explain how turnover varies with experience (March and March 1978, Romanow 1984).	§3.4: First-passage times of random walks

Table 1 (cont'd)

Empirical regularity	Remarks	Main theoretical mechanism[a]
Judgment and decision making		
Entrepreneurial overconfidence	More extreme demand forecasts will likely be followed by less extreme outcomes. But if only entrepreneurs who entered are studied, overestimation will appear to be more common than underestimation, because the ones who underestimate demand are unlikely to enter the market (Hogarth and Karelaia 2012).	§3.6: Regression to the mean and selection
In-group bias	Because people avoid others of whom they have a negative impression, negative impressions tend to persist. Negative impressions are more likely to change and regress upward for people in the in-group whom one is likely to meet irrespective of one's impression of them (Denrell 2005).	§3.6: Regression to the mean and biased encounters
Biases in probability estimates	The difficulty of questions that turned out to be easy to answer will likely have been overestimated. The difficulty of questions that turned out to be hard to answer will likely have been underestimated (Juslin et al. 2000).	§3.6: Regression to the mean
	People's probabilistic judgments may be accurate on average but are subject to noise. Because of a ceiling effect—the estimated probability must be at least 0—the average estimate is biased upward for low probability events (Bearden et al. 2007).	§3.5: Flooring and ceiling effects

[a]We refer to the mechanisms introduced in §3 whenever a direct match is possible.

have high profitability? Persistent profitability has been attributed to industry characteristics (Porter 1980, Waring 1996) as well as to persistent differences in resources and capabilities (Barney 1991, Demsetz 1973). Stochastic processes can offer an alternative explanation. Denrell (2004) argued that the phenomenon of long leads in random walks—the fact that a random walk starting from zero will stay on either the positive or the negative side for a considerable period—can offer a parsimonious explanation for performance persistence. He showed that performance persistence is the expected outcome of a chance model in which the resources of firms are subject to a random walk. In such a model, the most likely event is that a group of firms with high and sustained performance exists, as well as a group with low and sustained performance. Sutton (2007) similarly showed that "durations of leadership" can be expected to be long if market share follows a random walk. Building on Singer and Spilerman (1973–1974), Henderson et al. (2012) proposed a modified random walk model that fits the empirical data on performance persistence better. In their modified model, there is a random waiting period before the next random variable is added to the random walk and firms differ in the average waiting time. By adding heterogeneity in "stickiness" (the tendency to stay at a given performance level), their model can account for additional persistence in performance without having to assume heterogeneity in firm averages.

4.1.4. Performance and Risk Taking. Following Bowman (1980), a subfield of strategic management has tried to explain the association between firm risk and return. Firms with an average return on assets far above or far below the industry average tend to have a more variable return on assets than firms with a return on assets close to the industry average (Fiegenbaum 1990). A common explanation of this finding is that managers have context-dependent risk preferences (Kahneman and Tversky 1979, March and Shapira 1992). A chance model that only assumes differences in variability offers an alternative explanation (Denrell 2008). Suppose the performance of firm i in period t is a random draw from a normal distribution with mean u and standard deviation s. Moreover, u and s are random variables. This simple chance model is sufficient to explain the empirical regularity: firms with a large value of s—i.e., those that happened to draw a performance level from a more variable distribution—will be more likely to have an average performance far from the mean. The mechanism is that variability makes extreme outcomes more likely.

4.1.5. Comment. Chance models in strategic management assume that firm outcomes such as size and profitability can be modeled as the aggregate result of independent and identically distributed shocks. In growth models, a new shock is multiplied with the prior outcome (size). The assumption is that a new shock can magnify or reduce the impact of all prior shocks. In performance models based on random walks, a shock is added to past performance, implying that a new shock does not interact with or change the impact of past shocks. Because shocks are multiplied or added, and not averaged, both growth and performance models generate persistent diversity in outcomes (size and profitability). Models that relax the assumption that all firms are subject to the same number of shocks can explain more detailed aspects of the data. For example, the distribution of the growth rate and the association between size and the variance of the growth rate can be explained by chance models that model the assignment of shocks between and within firms. Performance models that include heterogeneity in stickiness and in the variance of performance similarly relax the assumption that all firms are equally likely, in every period, to be subject to a performance shock.

4.2. Organizational Ecology

In contrast to strategic management, organizational ecology does not assume that the fate of firms is in the hands of managers. The role of chance events is more readily acknowledged. Nevertheless, to explain empirical regularities, organizational ecology predominantly relies on firm traits and social processes such as legitimation and competition. Chance models can offer alternative interpretations of some of the key findings.

4.2.1. Density Dependence. Studies in organizational ecology show that both entry and exit rates are nonmonotonic functions of density (Carroll and Hannan 2000). The explanation offered by organizational ecologists emphasizes legitimacy and competition. Denrell and Kovács (2008) showed that a model based on random walks could offer an alternative explanation of nonmonotonic density dependence. Their model does not assume density dependence. Rather, density evolves according to a reflected random walk. In each period, density is equally likely to increase or decrease by one firm (except at a density of 0, where density is equally likely to stay at 0 or increase by 1). The other assumption is that only industries where density reached a high level are examined. The idea is that researchers selectively sample populations: because of data availability, they are much more likely to study large populations and much less likely to study small populations. They show that this simple chance model also generates nonmonotonic density dependence.

4.2.2. Age Dependence in Failure Rates. Why does the probability of failure (i.e., bankruptcy or exit from an industry) initially increase with age and then decrease with age? Explanations of this regularity in organization theory have typically attributed it to changes in organizational skills, perhaps from learning. A different explanation emphasizes preexisting and unchanging heterogeneity in organizational viability combined with selection (Vaupel et al. 1979). Explanations that emphasize learning or preexisting heterogeneity, however, are not consistent with the initial increase in the failure rate. Levinthal (1991) noted that the initial increase and eventual decrease could be explained by the first-passage properties of a random walk. His model assumes that organizational "capital" follows a random walk: the organizational capital C in period t is the organizational capital in period $t-1$ plus a random shock: $C_t = C_{t-1} + e_t$ (formally, his model assumes that organizational capital follows a continuous-time Brownian motion). The model incorporates random variation in organizational capital as a result of demand shocks or the activities of competitors. The key assumption is that random variation is added up (and thus not averaged out). Organizational capital starts at some positive level. An organization exits the industry whenever its organizational capital hits a lower boundary.

Levinthal (1991) showed that his model can explain both the initial increase and eventual decrease in the hazard rate of failure. The intuition is the same as that outlined in §3.4. Random variation in organizational capital is key to Levinthal's model. Random variation implies that heterogeneity "emerges stochastically over time" (Levinthal 1991, p. 401). As a result, it is not necessary to postulate initial heterogeneity. Moreover, the assumption of random variability in organizational capital is crucial to generate the pattern to be explained. In the absence of random variation in organizational capital, the other assumptions (capital is added up, selection operates on organizational capital, organizations start with a positive endowment) are not sufficient to generate a hazard rate that initially increases and then decreases.

4.2.3. The Red Queen Effect. Studies show that organizations exposed to more competition subsequently become more viable than organizations exposed to less competition (Barnett 1997, Barnett and Hansen 1996). Barnett (2008) argued that competition makes organizations more viable partly because competition triggers organizational learning. Barnett also suggested that a chance model, in which exposure to competition only impacts the variance of viability, can offer an alternative account (Barnett 2008, p. 58; Denrell 2003). Suppose the performance of organization i in period t is normally distributed with mean u_i and variance v. An organization that is subject to competition gets a shock to its viability: $u_i' = u_i + z$, where z is drawn from a normal distribution with mean 0 and variance k. Competition has no systematic effect on average viability in this model. Rather, organizations are triggered to take action by competition, but the outcome of such an action is difficult to foresee and can both increase and decrease viability. A firm is subject to competition with probability q. Finally, a firm fails if its performance in any period is below c. The model implies that exposure to competition will be positively associated with viability. The mechanism is that unsystematic noise has systematic effects in selection systems: $E[u \mid p > c]$ is higher when u is drawn from a normal distribution with higher variance.

4.2.4. Comment. The models demonstrate how randomness at the micro level, combined with selection, is sufficient to explain prominent empirical regularities. In all cases the selection biases were well known—organizational ecologists were well aware that firms and even industries fail—but the consequences of such selection biases were not fully appreciated. The models operate at different levels of aggregation (industry versus firm), but it would seem feasible to develop an integrated model in which density is the result of entry and exits modeled as stochastic processes (Klepper and Thompson 2006). Explicitly modeling linkages between industries (via consumer budget constraints and diversification choices by firms) could help explain stylized industry patterns.

4.3. Organizational Theory

Chance models have been developed in several subfields in organization theory, including career dynamics (March and March 1977, 1978; Romanow 1984). Here, our focus is on theories of how management practices spread. Organization theorists have traditionally argued that practices become widespread because they help organizations coordinate and control activities efficiently (Chandler 1962, Williamson 1975). Institutional theorists proposed that legitimacy also drives diffusion. Chance models add to this debate by showing how several empirical regularities in diffusion processes can be the outcome of a random process in which all practices are equally likely to become popular ex ante.

4.3.1. Popularity Distributions. Reinforced random processes can help explain why distributions of popularity are often skewed and distributed according to a power law (Barabási and Albert 1999, Simon 1955). The key assumption is a rich-gets-richer dynamic in which actors with many connections tend to get more connections. Nodes that happen to have more connections will attract more new connections and become hubs in a network where most nodes have only a small number of connections. An alternative explanation of skewed distributions in outcomes is that "fitness" or "quality" follows a skewed distribution (Bianconi and Barabási 2001). For example, researchers differ in individual traits that can explain part of the difference in productivity and citations (Simonton 1999). An explanation relying on reinforcement offers a superior account in settings when it is not sensible to assume that the distribution of such traits is highly skewed. For example, many individual traits are approximately normally distributed, which implies that large differences in traits are very unlikely (Hamlen 1991, Simonton 1999).

4.3.2. Fads in Management Practices. What explains faddish trajectories in which interest in a management practice initially increases but subsequently falls? Management scholars and sociologists have put forward a variety of explanations, emphasizing conformity, the desire to be seen as a fashion leader, and the importance of distinguishing oneself from the competition (Abrahamson 1991, Abrahamson and Fairchild 1999, Haunschild and Miner 1997). Strang and Macy (2001, Experiment 1) showed that a chance model, focusing on imitation of exceptional performance, could also generate faddish trajectories. The key mechanism in their model is that the largest observed outcome is likely to come from a large rather than a small sample. Suppose there are two practices, A and B. Firm performance is random and independent of what practice a firm adopts. With probability q, a firm imitates the practice of the firm with the highest observed performance in the current period. Suppose more firms adopt practice A than B. Because there are more firms using practice A, the firm with the highest performance is more likely a firm with practice A. More firms will imitate A, and A will likely be the most common practice also in next period. Imitation of extremes thus ensures that dominant practices likely remain dominant. This self-reinforcing dynamic breaks down when a firm using practice B randomly achieves the highest performance and other firms start imitating practice B.

4.3.3. Superstitious Learning and Diversity in Practices. Despite the tendencies of firms to imitate each other, there is wide variation in the practices firms use. What explains this diversity? It is possible that different firms benefit from different practices or that diversity reflects incomplete diffusion. Lave and March (1975) suggested a different explanation that emphasizes superstitious learning in a benign world where all practices are equally good. A reinforced random process is the key mechanism in their model of superstitious learning (see also Arthur 1993). Whenever a practice is used and success happens, a firm becomes more likely to use this practice. If the probability of success is high, firms are likely to continue with the practice they initially tried. If the positive feedback loop is strong, the outcome is diversity in adoption: each firm repeatedly uses the practice it started with, but firms differ in which practice they use.

4.3.4. The S-Shaped Diffusion Curve. One of the most well-known empirical regularities in studies of diffusion is the S-shaped diffusion curve. Several different explanations have been proposed, focusing on heterogeneity in adoption timing, externalities in adoption, and pressures to conform that vary with the number of adopters (Rogers 1995). A simple chance model that emphasizes random encounters can also reproduce the S-shaped diffusion curve without making any assumptions about how conformity varies with the number of adopters (Lave and March 1975). Suppose a nonadopter adopts with some probability whenever she meets an adopter. If two people are chosen to meet at random, the probability that a nonadopter meets an adopter is $2(1-p)p$, where p is the proportion of adopters. This probability initially increases in p (because nonadopters are more likely to encounter an adopter when p is large) but eventually decreases in p (because eventually there are few nonadopters).

4.3.5. Comment. All of the above models assume that popularity is driven mainly by endogenous processes rather than by stable differences in the attractiveness of the practices. Ex ante all practices are equally likely to become popular and generate successful outcomes. Differences in popularity are the result of a stochastic process operating in a social landscape in which past popularity impacts exposure, the probability of observing extreme values, and the probability of contact with nonadopters. It would be useful to develop an integrated model that incorporates each of the above mechanisms and explains not only the skewed distribution of popularity but also when faddish trajectories emerge instead of the typical S-shaped curve and when convergence to one (or a few) practice occurs instead of divergence caused by superstitious learning.

4.4. Judgment and Decision Making

Research in organizational behavior has been much influenced by studies on judgment and decision making, in particular the findings of Tversky and Kahneman (1974). The emphasis is on how biased and irrational choices can be explained by systematic cognitive biases. Recently, however, psychologists have realized that random variation combined with sample biases can provide a unified account for several classical behavioral biases (Fiedler 2000, Hilbert 2012). Examples of biases that have been reinterpreted—in addition to subadditivity, which was discussed in §2—include the following.

4.4.1. Entrepreneurial Overconfidence. Entrepreneurs overestimate their chances of success and the demand for their products (Busenitz and Barney 1997, Cooper et al. 1988). Cognitive biases could explain this, but so can a model of unbiased but noisy judgments if combined with self-selection (Hogarth and Karelaia 2012). Suppose entrepreneurs decide whether to enter a market based on a noisy signal of demand. Entrepreneurs who believe demand will be very high will be more likely to enter a market than entrepreneurs who believe demand will be low. Because of regression to the mean, very high demand forecasts will likely be followed by less extreme outcomes. Similarly, a very low demand forecast will be followed by less extreme outcomes. If judgments are unbiased, overestimation will be as likely as underestimation among all entrepreneurs. But if only entrepreneurs who entered are studied, overestimation will appear to be more common than underestimation because the ones who underestimate demand are unlikely to enter the market.

4.4.2. In-Group Bias. Why do people have more favorable impressions of those in their in-group? Social psychologists have attributed this to cognitive biases and stereotypes. Denrell (2005) showed that a model of unbiased impressions and sequential sampling can offer an alternative account. The key mechanism is asymmetric regression to the mean as a result of avoidance of people one has a negative impression of. If individual A has a negative impression of B, A is unlikely to interact with B and change his or her impression, eliminating the possibility of regressing upward to the mean. If B is a friend of A's friends, however, A may nevertheless meet B again, potentially regressing upward to the mean. As a result, A's negative impression might change, which might not have happened if B was not part of A's social network. In general, this mechanism implies that systematic differences in interaction patterns will produce systematic differences in impressions.

4.4.3. Biases in Probability Estimates. People tend to overestimate the frequency of rare events and underestimate the frequency of commonly occurring events (Fischhoff et al. 1977). The regularity has been attributed to systematic cognitive biases, such as availability, but it could also result from unbiased but noisy judgments (Hilbert 2012). Suppose judgments (J) are imperfectly correlated with the true answers (A). If we know that the random variable A is high, then J is likely lower because of regression to the mean. Similarly, if we know that A is low, then J is likely higher. The "hard–easy effect" in overconfidence studies can be explained in the same way (Erev et al. 1994, Juslin et al. 2000). People are especially overconfident with difficult questions, whereas they are less overconfident—even underconfident—with easy questions. Because of regression to the mean, a model of unbiased but noisy judgments reproduces such a hard–easy effect. The intuition is that the difficulty of questions that turned out to be easy to answer will likely have been overestimated. Similarly, the difficulty of questions that turned out to be hard will likely have been underestimated.

4.4.4. Comment. The same model of unbiased but noisy judgments can explain all the above cognitive biases as well as subadditivity. In this model, biased judgments occur because environmental constraints, such as flooring effects (e.g., subadditivity) or asymmetries in the extent to which regression to the mean is possible (overconfidence, in-group bias). Hilbert (2012) reviewed a range of cognitive biases that can be similarly explained and shows how each of these biases can be formally derived from one common model. Chen and Risen (2010) showed how a similar model can explain the finding that people reevaluate their chosen alternative more positively.

5. Implications for Management Research

Given the empirical support for random variation and the wide range of phenomena that has been explained by models relying on random variation, we believe that chance explanations deserve a more prominent role in management theory. When a management scholar tries to explain an empirical regularity, it makes sense to start the search for an explanation by developing a model relying on random variation.

5.1. How Can Chance Models Be Developed Theoretically?

If management scholars would take random variation seriously, what are the implications for theory building? How can researchers who are interested in developing chance models proceed?

First, a researcher can apply the above mechanisms to explain empirical regularities in other areas of management. There are opportunities for such intellectual arbitrage in any area of management research where an empirical pattern exists that the above chance mechanisms can generate. Consider, for example, research on the causes of organizational change. A common finding is that organizations performing below their aspiration level are more likely to engage in risky changes (Greve 1998, 2003). To explain this pattern, theorists have argued that low performance changes risk preferences and triggers search (Cyert and March 1963, Greve 2003). How could a chance model produce this regularity? The empirical finding, viewed abstractly, is that extreme performance (performance far below or above the aspiration level) is associated with instability (risky change). Because extreme performance is more likely for organizations with high variability in performance (see §3.7), this formulation suggests a chance model in which firms differ in reliability and reliability impacts both the variance in performance and the probability of risky change. In this chance model, change probabilities are constant and do not increase as a result of low (or high) performance. Nevertheless, this model generates the empirical pattern that extreme performance (a result of high variance in performance) is associated with change (from a high chance propensity).

Second, theoretical work is needed to formalize chance models, examine their scope conditions, and derive their implications. Theorists have only examined a few chance models in detail, including stochastic growth models and preferential attachment models. For many chance models, scope conditions and robustness properties have not been established. This is an opportunity for analytical or simulation-based work. Consider, for example, the random walk model of age dependence (Levinthal 1991) that generates an initially increasing but eventually decreasing hazard rate. Does this pattern remain if we modify the assumptions about how organizational capital is accumulated (e.g., past organizational capital may decay)? The work of Aalen (1995) and Aalen and Gjessing (2004) provides a good starting point for addressing these questions, but their models need to be adjusted to accommodate realistic assumptions about, for example, competition. Or consider chance models of persistence performance relying on the phenomenon of long leads (Denrell 2004). How are the conclusions of such models altered if one modifies the assumptions about how firms interact and how shocks are accumulated?

Third, theoretical work is needed to integrate different mechanisms within a common theoretical framework. In the area of judgment and decision making, Hilbert (2012) showed how a model of unbiased noisy estimation could explain several regularities in judgment previously attributed to cognitive biases. He developed a formal model from which all regularities could be derived. Can a similar unifying formal framework be developed to explain regularities in strategic management and organization theory? An integrated model of growth, performance, and survival does seem feasible. Chance models of growth and performance assume that aggregate outcomes are the result of independent shocks. Similarly, survival models based on random walks assume that exit occurs as a result of accumulation of unfavorable shocks. A model that assumes that organizations are subject to shocks that impact growth, performance, and organizational capital could integrate all these models. The challenge in developing such a model is how to effectively deal with the fact that a particular shock may have differential impacts on different outcomes (e.g., growth may not be profitable—in fact, the correlation between profitability and growth is close to zero; see Bottazzi et al. 2010). An ambitious goal for an integrated model is to explain not only the qualitative empirical patterns but also the quantitative findings (e.g., the correlation between performance in consecutive periods, the exponent in the power law distribution for firm size).

Fourth, theoretical work is needed to examine how chance interacts with trait-based differences. Most of the chance models we reviewed assume that actors do not differ in traits that dispose units (firms or individuals) to move in the direction of the outcome to be explained. For example, stochastic growth models do not assume that firms differ in their average growth rates. Adding trait-based differences can sometimes significantly change the results of the model, not only quantitatively (i.e., chance matters less when actors differ in traits) but also qualitatively. For example, it is well known that increasing returns can amplify initial chance events and lead to unpredictability (Arthur 1989). If actors differ in quality, however, increasing returns can lead to less unpredictability in the sense that the correlation between quality and performance is higher when increasing returns are present. The reason is that increasing returns may amplify initial quality differences (Lynn et al. 2009). Or consider chance models that reproduce the empirically observed Pareto distribution of wealth. These models assume that actors do not differ in investment talent. A skeptic might argue that an even better fit to data could be obtained by adding such differences. On the contrary, Levy and Levy (2003) showed that models that include differences in mean returns cannot reproduce the empirically observed distribution of wealth.

Finally, the so-called paradox of skill (Mauboussin 2012) illustrates how changes in the distribution of traits can have counterintuitive implications for the impact of chance. If people become more skilled through selection and sorting, chance may become more and not less important. If only sufficiently skilled people remain, the variance in skill is reduced. Unless variability resulting from chance events is also reduced, the proportion of variance in performance from chance will increase (March and March 1977).

5.2. How Can Chance Models Be Tested?

Explanations relying on randomness might seem unfalsifiable: one could always claim that something was caused by chance, but how could such a statement ever be tested? To answer this question, it is important to note that chance models often make more rigorous and detailed empirical predictions than other theories relying on systematic variations. For instance, theories in management typically make point predictions about the sign of a coefficient in a regression ("We theorize that the effect of x on y is positive…"). Theories postulating randomness at the micro level, on the other hand, make predictions about the distribution of outcomes, allowing more opportunities for the theory to be falsified (Coleman 1964). For example, many early tests of stochastic growth models examined whether the size distribution predicted by the model fit the empirical firm size distribution (Simon and Bonini 1958).

Moreover, simple tests are sometimes sufficient to distinguish theories relying on randomness from alternative explanations. For example, stochastic models of firm size distributions predict that growth rates in distinct periods should be uncorrelated; many other theories imply a positive correlation.[3] Or consider the chance model of subadditivity introduced above. This model predicts that the median error in probability estimates is 0, whereas explanations relying on cognitive bias that assume a systematic tendency for overestimation predict that the median error in probability estimates is positive. The two competing theoretical accounts can be distinguished by examining the median rather than the average probability estimate (Bearden et al. 2007).[4] In a similar vein, Gould (1988) showed how using medians rather than means can distinguish a chance model of the increase in complexity—which relies on a flooring effect—from alternative accounts.

In addition, a careful examination of distinct predictions from chance explanations can often suggest useful empirical tests (Stinchcombe 1968). For instance, a random walk model of persistent profitability implies that profitability growth in distinct periods is uncorrelated (Denrell 2004). As another example, a chance model of density dependence can be distinguished from alternative accounts by examining the effect of density on mortality and entry rates using only periods after the maximum density has been reached (Denrell and Kovács 2008).

More broadly, how should management researchers incorporate the possibility of chance explanations into their own research? This depends on one's research goals with respect to randomness versus systematic variation. Consider first management researchers who are focused on systematic nonrandom causal explanations. To identify any systematic effect, such researchers need to acknowledge and correctly model randomness. In particular, the mechanisms and models we have discussed suggest that it is often inappropriate to assume that chance effects average out. Rather, chance events are reinforced or accumulate. The implication is that t-tests cannot be applied to, for example, comparing durations of market leadership (Denrell 2004, Sutton 2007). To correctly estimate the impact of a variable, researchers need to embed this variable in an appropriate chance model, such as a random walk. For example, only by embedding a learning process in random walk can the effect of learning on age dependence in exit rates be accurately identified (Le Mens et al. 2011).

Recent growth and performance models also suggest that it is important to avoid simplistic models of the error terms that assume homogeneity in variability and stickiness across all firms and industries. Consistent with this, Scott (2009) showed that adding heterogeneity in the extent to which performance shocks persist substantially changes conclusions about the existence of sustained performance. Once heterogeneity in persistence (i.e., heterogeneity in an autoregressive model) is included, there is hardly any evidence for firm differences in average profitability. Finally, using a Bayesian approach, researchers can also examine not only whether systematic firm differences *exist* but also how *large* such differences are. Levinthal (1991), for example, used a Bayesian approach to examine the role of systematic firm differences in the drift (i.e., relative fitness) and the variability (i.e., uncertainty) of a random walk. He found that there is evidence of both types of heterogeneity, but firms differ mainly in variability.

Consider next researchers who are interested in testing the empirical implications of chance models. Chance models can help such researchers direct attention to new aspects of data and to novel research questions. First, chance models suggest that empirical regularities can be found at a more aggregate level. In particular, the shape of the distribution of outcomes (e.g., growth, size) may be similar across areas (firms, universities, nations). An important empirical task is to collect data about the distribution of outcomes across a wide range of applications. Comparisons of such data across fields have often inspired theorists to develop universally applicable chance models instead of detailed field-specific explanations (Powell 2003, Simon 1955).

Second, chance models imply that mechanisms such as reinforcing random processes are responsible for what appear as systematic patterns. An important task for researchers is to uncover these mechanisms and study their impact. Consider, for example, research on the so-called relative age effect in sports (Musch and Grondin 2001). In many sports, children train and compete with other children in their age group based on the month when they are born. Empirical studies have consistently found that performance among athletes in adulthood is higher for individuals who were among the oldest in their age group. Because they are older and stronger, their performance is initially higher, and because of this they may be regarded as more talented and will be more likely to receive extra attention and resources. In this case, an initial chance event (birth date) is amplified by positive feedback and leads to substantial and persistent differences in performance.

6. The Role of Management

The assumption of randomness might seem inconsistent with the notion of management. Managers put in a lot of effort to guide organizations to superior outcomes; they hardly toss a coin to decide what to do. Nevertheless, the idea that chance explanations leave no role for management is clearly incorrect. Chance models are, in fact, compatible with effortful managers who carry out deliberate actions. First, managerial actions do not always have the effects managers intended. The outcome of carefully planned behavior will appear to be random if choices are based on inaccurate forecasts or if implementation is weakly coupled with the intentions of managers. Second, competition between skilled managers who all try to find superior alternatives can lead to random outcomes. In the financial markets, Samuelson (1965) showed how competition between skilled and rational actors in financial markets leads to randomly fluctuating asset prices, because current prices reflect all available information and only change when unexpected events occur. A similar mechanism underlies Barney's (1986) argument that in efficient strategic factor markets, profitability is ultimately traced to unexpected price changes and thus luck. Randomness in outcomes, according to these arguments, is the result of skilled and effortful managerial actions.

If randomness is a useful abstraction and systematic factors explain only a small portion of the variance, doesn't it follow that a passive approach to management—akin to dart throwing or indexing in financial markets—is motivated? For example, if growth rates are nearly random, why should firms bother with identifying high-growth markets? Would not a passive approach, in which firms dispense with market research, do equally well? The answer to this question depends on how strongly one believes in the importance of randomness. Three different approaches can be distinguished.

6.1. Weak and Semistrong Approaches

The *weak* approach assumes that randomness is important but that it reflects ignorance and significant systematic factors hiding beneath the surface can be identified. Understanding how randomness operates improves firms' chances of identifying profit opportunities. Because only a few firms have the capabilities required to identify systematic opportunities, randomness remains a useful description at the aggregate level. The *semistrong* approach assumes that the only reason systematic factors remain is the presence of naïve firms that underestimate the role of randomness. Profit opportunities exist for the (few) firms that accurately understand the role of randomness.

Under the weak and semistrong form approaches, there is a clear role for management to profit from a superior understanding of randomness. Although it is not the purpose of the paper to exhaustively speculate on all possible profit strategies based on a better understanding of randomness, we elaborate briefly on a few of them here.

First, understanding the role of randomness enables managers and policymakers to understand that what appears to be systematic effects is a result of random processes. Identifying such spurious effects can help managers avoid investment in ineffective approaches. For example, stochastic growth models are highly relevant to policymakers because they imply that policies that support high-growth firms are likely ineffective, since high growth is unpredictable and does not persist (Coad et al. 2014). More generally speaking, to identify useful managerial interventions, randomness needs to be properly understood and modeled. For this reason, all of the above mechanisms and models are useful because they help to identify systematic effects.

Second, managers need to understand that valued outcomes may be less predictable than what managers might believe. Recognizing such unpredictability is useful because—as numerous management scholars have stressed—managing in an unpredictable environment dictates a shift from commitment to flexibility and adaptability (Mintzberg 1990). In an unpredictable environment, managers should hedge against uncertainty by relying on a diversified portfolio of companies and adopting a real option approach (Raynor 2007). Managers should explore currently unattractive options that may turn out to be useful in the future (March 1991). Rather than betting big on a small number of options, managers should increase the number of small bets (Mauboussin 2012) to better understand causality and better prepare for future eventualities. In the extreme case of "black swans," where future payoffs are complex and outcomes are extreme, Taleb (2007) cautioned against having a prior or model of events because errors in such models inevitably cause bad results. Chance explanations are thus useful because they help managers recognize the unmanageable and unpredictable.

Third, understanding the underlying theoretical mechanisms of randomness can help managers understand how, when, and where randomness matters. Such understanding can improve decisions about resource allocation (March 1994). For example, understanding how social influence operates and how it reinforces the impact of past lucky breaks can help managers devise marketing strategies (Watts and Hasker 2006). Even if initial product success is largely random, managers can promote demand by managing social influence for the products that happen to take off. For instance, social influence can be enhanced through the use of viral or big-seed marketing (Watts and Peretti 2007), which encourages users to share it with and forward it to their friends or peers. Furthermore, in an unpredictable environment managers should avoid trying to design the intrinsically best product and focus instead on creating a portfolio of products in response to real-time consumer or market feedback (Watts and Peretti 2007). Keys to success in an increasingly unpredictable market place are (a) increasing the number of small bets, (b) investing in the real time capture of market feedback (e.g., in chat rooms, blogs, search engines), and (c) building flexibility into the firm operations (e.g., supply chain, contracts, marketing budgets).

Finally, a superior understanding of randomness can help managers identify when high performance indicates skill or luck. Unpredictability generally implies that high performance is at best a weak signal of skill, but managers who understand the mechanisms by which randomness impacts outcomes can go beyond this truism. For example, when increasing returns or social influence can significantly reinforce initial lucky breaks, higher performance may not be a signal of higher skill. Rather, exceptional performance can be an indication of lower skill than moderately high performance (Denrell and Liu 2012). The mechanism is that exceptional performance requires a lucky break combined with strong social influence. Or consider evaluation of forecasters. An accurate prediction about an extreme event (such as the mortgage loan crisis or the Internet bubble) may indicate inferior rather than superior foresight (Denrell and Fang 2010). The mechanism is that forecasters who frequently make bold predictions are more likely to predict extreme events. Forecasters who often make bold predictions, however, are likely to be those who overreact to weak signals. Rewarding these "prophets" or betting on their subsequent predictions is likely to lead to disappointment.

6.2. Strong Approaches

A third, *strong* approach to randomness assumes that no systematic factors exist. According to this view, randomness does not reflect our ignorance. Rather, competitive processes imply a limit to predictability. Although deviations from randomness may occasionally appear, chasing such deviations is usually a waste of time and resources. A passive approach, in which firms avoid spending resources on selecting superior markets and products, is recommended because it saves money. Such a passive approach does not imply slacking off: there are surely ways to fail in business by being lazy even if there are no rules for riches.

To base strategy on the strong version of randomness may seem paradoxical, but given the successes of passive investment strategies, it would be premature to exclude this possibility. After all, the biggest donation to a business school—to the University of Chicago Booth School of Business—came from an investment firm manager, David Booth, who based his investment strategy on indexing and other insights from efficient market theory. It is true, of course, that if all firms took a passive approach and no firms researched market opportunities, then there would be profit opportunities for firms taking an active approach, and systematic factors would then presumably explain more of the variation in growth rates (Grossman and Stiglitz 1980). Thus, the strong approach to randomness is—similar to many other approaches to management and investing—self-defeating if applied on a large scale. Nevertheless, it may offer a profitable niche for some firms.

To conclude, assuming randomness at the micro level to explain empirical regularities in organization theory or strategy does not deny that managers take deliberate intentional action. Neither is the role of management in chance explanations necessarily restricted to passive approaches such as "do nothing" or "do anything." Rather, recognizing the importance of randomness and luck can be a crucial first step in formulating useful prescriptions for managers. At the same time, there can be scope for firms that abandon the attempt to predict high-growth areas and take a less active approach to strategy. More theoretical and empirical research is needed to evaluate the best way to manage in a world governed, to a large extent, by randomness.

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Endnotes

[1]Interestingly, the statistical approach to social science was a forerunner to the statistical approach in physics (Ball 2002): James Clerk Maxwell was inspired to develop his statistical approach to gases after having read about applications of the central limit theorem to society.

[2]For analyses of the class of distributions for which regression to the mean holds, see Chambers and Healy (2012), Samuels (1991), and Schmittlein (1989).

[3]Empirically, the correlation between growth rates in consecutive periods is not exactly zero but is very small and often negative (Bottazzi et al. 2002, Coad 2007), which seems inconsistent with the view that persistent firm differences in productivity drive firm growth (Nelson and Winter 1982).

[4]Reanalyses of past studies show that when medians are used instead of means, there is still evidence for subadditivity, but the magnitude of the effect is much smaller (Bearden et al. 2007).

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