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CUMULATIVE ADVANTAGE: CONDUCTORS AND INSULATORS OF HEAVY-TAILED PRODUCTIVITY DISTRIBUTIONS AND PRODUCTIVITY STARS

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We use the metatheoretical principle of cumulative advantage as a framework to understand the presence of heavy-tailed productivity distributions and productivity stars. We relied on 229 datasets including 633,876 productivity observations collected from approximately 625,000 individuals in occupations including research, entertainment, politics, sports, sales, and manufacturing, among others. We implemented a novel methodological approach developed in the field of physics to assess the precise shape of the productivity distribution rather than relying on a normal versus nonnormal artificial dichotomy. Results indicate that higher levels of multiplicity of productivity, monopolistic productivity, job autonomy, and job complexity (i.e., *conductors* of cumulative advantage) are associated with a higher probability of an underlying power law distribution, whereas lower productivity ceilings (i.e., *insulator* of cumulative advantage) are associated with a lower probability. In addition, higher levels of multiplicity of productivity, monopolistic productivity, and job autonomy were associated with a greater proportion of productivity stars (i.e., productivity distributions with heavier tails), whereas lower productivity ceilings were associated with a

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smaller proportion of productivity stars (i.e., productivity distributions with lighter tails). Results serve as a building block for future theory development and testing efforts aimed at understanding why, when, and how the distribution of individual productivity may follow a non-normal curve—and to what extent. We also discuss implications for organizations and management in terms of the design and implementation of human resource systems (e.g., selection, training, compensation), as well as for individuals interested in becoming productivity stars themselves.

What workers do and the outcomes of their work are key antecedents to critical firm-level results—results that determine the sustainability and very survival of the organization (Boudreau & Ramstad, 2007). In fact, human resource management practices such as staffing and training positively affect a firm's financial results because they improve labor productivity (Kim & Ployhart, 2014). Not surprisingly, then, many theories and practices in organizational behavior and human resource management (OBHRM) and industrial and organizational (I-O) psychology build upon individual performance conceptualized and measured in terms of behaviors (i.e., *how* people do their work) and results (i.e., the *outcomes* of people's work). Evidence of the importance of individual performance is that more articles have been published on this topic than any other in *Journal of Applied Psychology* and *Personnel Psychology* over the past 5 decades (Cascio & Aguinis, 2008a). In addition, the majority of the most influential articles published in *Personnel Psychology* since the inception of the journal have addressed individual performance across a variety of domains such as personnel selection (Barrick & Mount, 1991), leadership (Fleishman, 1953), motivation and work attitudes (Kunin, 1955; Weitz, 1952), and organizational citizenship behavior (Organ & Ryan, 1995), among others (Morgeson, 2011).

The behavior-based and results-based definitions and operationalizations of performance coexist in the literature (DeNisi & Smith, 2014). For example, Campbell (1990), Aguinis (2013), and Beck, Beatty, and Sackett (2014) focused on employee behaviors and actions—particularly those that are relevant to organizational goals. On the other hand, Bernardin and Beatty (1984), Minbashian and Luppino (2014), and O'Boyle and Aguinis (2012) defined and operationalized performance in terms of results. As additional evidence that these definitions coexist in the organizational literature, Viswesvaran and Ones (2000) defined performance as *both* behavior and results as follows: "scalable actions, behavior and outcomes that employees engage in or bring about that are linked with and contribute to organizational goals" (p. 216).

Beck et al. (2014) adopted the behavior-based approach but noted that alternative types of performance indicators that do not conform to a behavior-based definition “may indeed serve many useful organizational and research purposes” (p. 534). In fact, these two approaches to performance are clearly related. For example, an employee that exerts more effort at work (i.e., behavior-based performance) is likely to produce more output (i.e., results-based performance). The empirical evidence shows that these two types of performance are distinct but also related at nontrivial levels (e.g., Beal, Cohen, Burke, & McLendon, 2003; Bommer, Johnson, Rich, Podsakoff, & MacKenzie, 1995).

O’Boyle and Aguinis (2012) and Aguinis and O’Boyle (2014) adopted the results-based definition of performance because “a focus on results rather than behaviors is most appropriate when (a) workers are skilled in the needed behaviors, (b) behaviors and results are obviously related, and (c) there are many ways to do the job right” (Aguinis & O’Boyle, 2014, p. 316). Adopting a similar approach, Minbashian and Luppino (2014) examined the central issue of within-person variability in performance by using the results-based definition (i.e., tennis players’ points won in a match). An additional reason to focus on the results-based conceptual and operational definition of performance is that it plays a central role regarding organizational-level outcomes (Boudreau & Jesuthasan, 2011; Cascio, & Boudreau, 2011). Because of the central role of results-based individual performance to organizational-level outcomes, and given that organizational-level outcomes are central to strategic management studies, improving our understanding of individual performance conceptualized as results has the additional benefit of potentially narrowing the much lamented micro–macro gap in OBHRM, I-O psychology, and the field of management in general (Morgeson, Aguinis, Waldman, & Siegel, 2013).

Like Beck et al. (2014), we see value in both behavior- and results-based operationalizations. Specifically, we see value in the behavior-based approach because knowing how people do their work is necessary to understand processes leading to the output of such work. However, in our study, we focus on the results-based approach for the reasons outlined earlier. Moreover, to minimize confusion, and because Beck et al. (2014, p. 561) noted that the results-based approach is not how job performance “is typically defined” in OBHRM and I-O psychology, in the remainder of our paper we use the term “productivity” instead of “performance.” Note that, although productivity is sometimes defined as a ratio of output per unit of time, in our study we use this term to refer to countable employee output or results.

The Productivity Distribution and Goals of This Study

O'Boyle and Aguinis (2012) conducted five studies involving 198 samples including researchers, entertainers, politicians, and athletes, and results indicated that, overall, the productivity distribution is not normal (i.e., Gaussian) but, rather, it follows a heavy-tailed curve. Such heavy-tailed frequency distributions are described as conforming to a power law; that is, the majority of scores are far to the left of the mean. In contrast to Gaussian distributions, power law distributions are typified by unstable means, (quasi) infinite variance, and a greater proportion of extreme events—what we label "productivity stars."

If the distribution of individual productivity does not follow a normal distribution and, rather, it follows a heavy-tailed curve, then many theories and organizational practices addressing leadership, motivation, organizational commitment, job satisfaction, human capital, attraction-selection-attrition, compensation, teamwork, turnover, agency, and microfoundations of strategy may need to be revisited (Aguinis & O'Boyle, 2014; Crawford, 2012; Groysberg & Lee, 2009). The reason is that most of these theories focus on the "average" employee. In contrast, a heavy-tailed distribution implies that productivity is primarily vested in a small number of workers at the tail of the distribution rather than a large number of workers in the middle. Accordingly, "substantial improvements in average workers may provide little value to the organization as a whole, while very small changes in the performance of an elite worker may determine whether a firm survives or dies" (Aguinis & O'Boyle, 2014, pp. 337–338).

Beck et al. (2014) adopted the behavior-based approach and concluded that performance is normally distributed, but they unequivocally stated that "To be clear, we do not disagree that the variables studied by O'Boyle and Aguinis (2012) had distributions with vast departures from normality" (p. 562). Given Beck et al.'s results in conjunction with those from O'Boyle and Aguinis, there is a need to further our understanding of why, when, and how the distribution of individual productivity follows a heavy-tailed curve—and to what extent. Our paper seeks to provide some answers to this fundamental question by describing the principle of cumulative advantage as a key meta-theoretical generating mechanism that shifts the source of production from being primarily vested in a large group of average workers to a small group of productivity stars, thereby leading to a heavy-tailed rather than a normal distribution. More specifically, we use the metatheoretical principle of cumulative advantage as our conceptual framework to test theory-based predictions regarding *conductors* (i.e., enhancers) and *insulators* (i.e., inhibitors) of heavy-tailed productivity distributions and greater (i.e., heavier tails) or smaller (i.e., lighter tails) proportion of productivity stars.

Our study also makes a methodological contribution that will facilitate future research because testing hypotheses about conditions under which the shape of the distribution differs requires an expansion of how we conceptualize and assess the construct "shape of the productivity distribution." Each of the articles recently published in *Personnel Psychology* refers to distributions as being either normal or nonnormal (Aguinis & O'Boyle, 2014; Beck et al., 2014; O'Boyle & Aguinis, 2012). However, a distribution can range from exactly normal to extremely nonnormal (i.e., very heavy tail). Accordingly, our paper conceptualizes the shape of the productivity distribution as a continuous variable. This expanded conceptualization allows us to assess the extent to which hypothesized conductors and insulators covary with parameter estimate values that describe the shape of the distribution. Specifically, in our study, we aim at understanding the extent to which multiplicity of productivity, monopolistic productivity, job autonomy, job complexity, and productivity ceiling are associated with variations in the shape of the productivity distribution. To do so, we introduce a novel analytic technique that has been developed in the field of physics that is not biased due to information loss incurred in artificially dichotomizing an underlying continuous variable (Aguinis, Pierce, & Culpepper, 2009; Cohen, 1983). Thus, this technique will enable future theory development and testing regarding the presence of heavy-tailed productivity distributions and a greater or smaller proportion of productivity stars.

Next, we describe how cumulative advantage is a general meta-theoretical principle that leads to the presence of a heavy-tailed distribution of individual productivity and a greater proportion of productivity stars. Then, we offer five theory-based hypotheses regarding conductors and insulators of this broad generating principle.

Cumulative Advantage as a Generating Principle for the Emergence of Heavy-Tailed Productivity Distributions and Productivity Stars

Cumulative advantage is a general process by which small initial differences compound to yield large differences (Maillart, Sornette, Spaeth, & Von Krogh, 2008). The most direct analog of cumulative advantage is compound interest, something Albert Einstein is alleged to have once quipped as "the most powerful force in the universe" (Kay, 2008). This power stems from cumulative advantage's ability to offer more opportunities to succeed and from its ability to allow past success to influence the likelihood of future success.

The principle of cumulative advantage is ubiquitous in many scientific fields. For example, Merton (1968) introduced one form of cumulative advantage called The Matthew Effect where initial small advantages in wealth, education, and opportunity over time lead to very large gaps between the "haves" and "have-nots." In theoretical physics, there is common reference to feedback loops that amplify small random events into systematic and complex changes that are best modeled with a heavy-tailed distribution (Gong & van Leeuwen, 2003; Malcai, Biham, & Solomon, 1999; Solomon & Levy, 1996). In other words, small and even random differences grow into chain reactions that yield massive differences, creating systems that are driven not by huge numbers of units (e.g., particles, planets, galaxies) producing average amounts but by small numbers of units producing extraordinary amounts (Souma, 2002). The microeconomics literature also notes how early success in technology innovations leads to a firm's market entrenchment and increasing returns on future innovations (Agarwal & Gort, 2001; Arthur, 1989; Ruttan, 1997). From a macroeconomic perspective, the principle of cumulative advantage has been offered as an explanation for British global competitiveness in the early 20th century (Elbaum, 1990).

The cumulative advantage principle has also been used in the field of econophysics, which applies statistical procedures developed in physics to financial outcomes (Mantegna & Stanley, 2000). Specifically, land ownership (Boghosian, 2012), fluctuations in the price of commodities (Mandelbrot, 1997), and global currency markets (Ohira et al., 2002) all share one thing in common: a heavy-tailed distribution attributed to the cumulative advantage principle. Using the language of Bayesians, econophysicists propose that in complex systems involving nonindependent agents who interact with each other, the distribution of maximal information entropy (i.e., the distribution that best summarizes the data) has a heavy tail and is not normal (Burda, Jurkiewicz, & Nowak, 2003). In short, given the accumulated empirical evidence, a number of scientific fields including natural, biological, and social sciences have elevated the cumulative advantage principle to the status of an axiom—a premise that is so evident that it is accepted as true without controversy (Andriani & McKelvey, 2007, 2009, 2011). Examples are Bradford's Law of journal use, Lotka's Law of research productivity, Pareto's Law of income distribution, and Zipf's Law of word usage (Price, 1976).

The cumulative advantage principle has thus far not played a prominent role in the OBHRM and I-O psychology literatures. In the particular case of individual productivity, cumulative advantage and its compounding effects are often seen as an artifact in need of correction as opposed to a substantive phenomenon worthy of attention (O'Boyle & Aguinis, 2012). However, the opportunity to generate future results is itself influenced by prior productivity (Ceci & Papierno, 2005; Gaston, 1978; Judge, Klinger, & Simon, 2010; Spilerman & Ishida, 1994). Thus, those who find themselves with an initial advantage over others will be offered more opportunities to produce more and better outcomes in the future. Although most personnel selection theories rely on the notion that the most important predictor of future productivity is a job applicant's knowledge, skills, and abilities (KSAs; Schmidt & Hunter, 1998), opportunity to produce also plays a key role in the prediction of future productivity due to the cumulative advantage principle (Merton, 1968).

Once productivity differences exist, additional opportunities to generate results allow such differences, albeit small, to quickly result in the presence of heavy-tailed productivity distributions and a greater proportion of productivity stars than would be realistically possible, from a probability standpoint, by a normal distribution. For example, strategic management studies have concluded that past productivity of larger firms allows them to borrow more and withstand economic downturns (Hall, 1993; Latham, 2009; Ohame, 1989; Srivastava, McInish, Wood, & Capraro, 1997). A similar increased opportunity to produce based on past success has been documented in the field of marketing where firms offering new products will be met with greater opportunities to create results (i.e., customers are willing to try the new product) if past products met customer expectations (Gould, 2002; Podolny, 1993).

Cumulative advantage is also the result of path dependent change where a specific sequence of events "creates unequal propensities for future events" (Glückler, 2007, p. 620). Crawford (2012) argued that, over time, positive feedback from the environment (i.e., success) allows individuals to accumulate intangible resources such as knowledge and absorptive capacity, which can then be leveraged in later interactions. This cumulative advantage not only protects against failure, but it also increases the likelihood of future success. For example, Judge and Hurst (2008) found that initial advantages in career placement yielded much faster career trajectories, and when combined with additional advantages (e.g., education, high core self-evaluations), these trajectories showed even greater evidence of cumulative advantage. Similarly, evidence in the field of sociology suggests that initial workplace success leads to faster promotion rates, compensation, and other relevant work outcomes (e.g., Althauser, 1989; Elman & O'Rand, 2004; Rosenbaum, 1979).

Note that past productivity does not necessarily need to increase KSAs for cumulative advantage to occur. For example, in American football, the best wide receiver on a team does not need to improve his speed, catching ability, or route accuracy to increase the number of receptions and touchdowns. His past results will make the quarterback more likely to pass the ball to him, which will lead to more receptions and touchdowns independent of any increased KSAs. Similarly, early productivity in an academic's career may make other high producing academics more willing to collaborate with her on future research. These collaborations increase the likelihood of publication not only because the quality of work itself may be better but also because the reputation of the researcher might make a journal editor more inclined to accept the paper for publication (Peters & Ceci, 1982). This form of cumulative advantage can be viewed through evolutionary network theory (Glückler, 2007). Networks develop through selection, variation, and retention (Nelson & Winter, 2002). Selection refers to tie formations based on initial success (Venkatraman & Lee, 2004) and is akin to biological fitness in nature or market competitiveness in economics (Knudsen, 2002). Variation is the often-random occurrences of tie formations and breakages (Glückler, 2007) and is akin to ecosystem collapses and market shocks. Both selection and variation establish the initial network, and retention, the final component, addresses the changing nature of the network over time. Retention is important for understanding how cumulative advantage increases the likelihood of future success even independently of increased opportunities to produce and increased KSAs. Retention is the dynamic process by which existing ties facilitate new tie formation through preferential attachment and embedding (Glückler, 2007; Nelson & Winter, 2002). Preferential attachment occurs when Person A's network position makes others seek out a new connection with Person A, thus further embedding them (i.e., increasing their centrality and density) in the network (Barabási & Albert, 1999).

Next, we offer theoretical rationale for each of our hypotheses. Note that each of them addresses conductors (i.e., enhancers) or insulators (i.e., inhibitors) of the metatheoretical principle of cumulative advantage. In addition, our study includes conductors and insulators at different levels of analysis. Specifically, we refer to variables at the occupation level (i.e., multiplicity of productivity and monopolistic productivity) and also job level (i.e., job autonomy, job complexity, and productivity ceiling).

Multiplicity of Productivity

For certain occupations and types of productivity, additional productivity requires fewer resources than past productivity. This is based on the economic concept of marginal costs—the cost of increasing production by one unit (Schumpeter, 1934). For example, if adding a line of automobiles requires the building of a new factory, then the marginal cost is higher than if the new line of cars could be built using an existing factory. We argue that in the same way that marginal costs vary at the macro level of analysis across industries and firms, marginal costs also vary at the individual level of analysis across occupations and measures of productivity.

Given such, the extent to which the context allows productivity stars to keep their marginal costs low will serve as a conductor of cumulative advantage exhibited in that productivity distribution. We refer to this source of cumulative advantage as *multiplicity of productivity*. Multiplicity of productivity is a conductor because it makes it easier to draw on past success to create future success. For example, in terms of time, effort, and resources, the cost associated with a travel agent acquiring a new client is considerably higher than the cost associated with repeat business (Gyte & Phelps, 1989). If productivity is measured as the total number of bookings, then an established travel agent drawing on past productivity (i.e., repeat business) has lower marginal costs than a travel agent just beginning. On the other hand, if productivity is measured instead as the number of new clients, then the reduced ability to draw on past customers should make the marginal costs for established and beginner travel agents more similar. Thus, the differing marginal costs of the two productivity measures will result in differing weights in the tails of their productivity distributions.

In addition, different occupations will demonstrate different marginal costs and, by extension, a differing level of multiplicity of productivity. Consider an assembly line worker. This occupation has near zero multiplicity because past productivity does not necessarily amplify and multiply the likelihood of generating more meaningful outcomes in the future. On the other hand, consider academic researchers. Each additional journal publication has a high marginal cost—particularly, the first few publications in a researcher's career. However, due to increased opportunities to perform (e.g., more time to devote to research due to decreased teaching demands), positive feedback from the environment (e.g., accepted publications), and an increased network of collaborators and resources due to past successes (e.g., better access to data collection opportunities and computing equipment), the marginal cost of each subsequent publication decreases. Moreover, other important indicators of research productivity such as citations have a near zero marginal cost. So, multiplicity of productivity is higher in the work context of academic researchers compared to that of assembly line workers. In short, we offer the following hypothesis:

Hypothesis 1: Multiplicity of productivity will be a conductor of cumulative advantage, such that the end result of higher multiplicity work contexts will be a greater likelihood of a power law distribution and a greater proportion of productivity stars (i.e., heavier tail).

Monopolistic Productivity

Cumulative advantage leading to a heavy-tailed distribution may also be present when the context allows few individuals to disproportionately access resources, such that their productivity inversely relates to the productivity of their coworkers—what we label *monopolistic productivity*. Monopolistic productivity is more likely in jobs characterized by interdependence among workers. The reason is that such interdependence enables processes resulting in domination of resources by few individuals or units. For example, monopolistic productivity at the firm level emerges through a series of interorganizational exchanges such as mergers, acquisitions, and alliances that allow for one firm or a small number of firms to achieve network centrality and dominate the access to resources (Cook, 1977). The result of these interactions is a small number of firms dominating overall output (Boulding, 1966). This same rationale can be extended to the individual level of analysis due to the three reasons we describe next.

First, tournament theory posits that when rewards are based on rank as opposed to absolute output, individuals who possess greater network centrality may be able to leverage their position to discourage competition for top prizes (Connelly, Tihanyi, Crook, & Gangloff, 2014). By discouraging others from competing, stars are able to dominate production and contribute to a heavy-tail distribution. Not only are those at the top able to maintain their exceptional levels of productivity through leveraging of their position power, but signaling theory (Spence, 1973) suggests that productivity stars may use informal means of communication to assert their dominance over nonstars in ways that discourage nonstars from trying to compete directly (Connelly, Certo, Ireland, & Reutzel, 2011; Spence, 2002). Examples of when individuals might draw on their network centrality and information signaling include consultants battling over the most lucrative contracts, surgeons competing for choice rounds and more desirable procedures, and attorneys competing for better positions within the same firm (Galanter & Palay, 1991; Wigham, 1997).

Second, psychological processes may also lead to interdependencies resulting in monopolistic production. For example, contrast effects during the performance appraisal review can influence the evaluation of an average employee immediately following a review of a productivity star (Smither, Reilly, & Buda, 1988). Further, in an organization where there are a large number of unsatisfactory workers, supervisors will increase their overall appraisal of the best workers as well as increase the rewards tied to those ratings (Goodstadt & Kipnis, 1970; Ivancevich, 1983). Similarly, if resources are tied to evaluations, then a star worker's current level of productivity seen through rose-tinted glasses due to previous success (i.e., assimilation effect) may limit the resources available to nonstars (Arvey & Murphy, 1998).

Third, in a zero-sum game fashion, greater amounts of resources given to few individuals mean fewer resources available to the rest. For example, interdependencies are evident in professional sports where the best players demand the most playing time, which limits their teammates' opportunity to produce results—a key process leading to cumulative advantage. In many team sports, the best players can also influence the team's ability to recruit additional players by absorbing a majority of the limited resources (e.g., a salary cap). Moreover, in sports such as basketball, in which athletes play both offense and defense, players hamper the competitors' output. This is an argument common in the labor economics literature: Productivity stars, wittingly or unwittingly, are able to dominate through monopolistic means (e.g., Borghans & Groot, 1998; Franck & Nüesch, 2012). Accordingly, we offer the following hypothesis involving monopolistic productivity as a conductor for cumulative advantage:

> *Hypothesis 2*: Monopolistic productivity will be a conductor of cumulative advantage, such that the end result of higher monopolistic work contexts will be a greater likelihood of a power law distribution and a greater proportion of productivity stars (i.e., heavier tail).

Job Characteristics

Beyond the work context, which are variables conceptualized at a higher level of analysis (i.e., occupation, type of productivity measure), there are features at a lower level of analysis (i.e., the work itself) that can serve as conductors and insulators of the cumulative advantage principle. We focus on three such job characteristics: job autonomy and job complexity as hypothesized conductors and productivity ceiling as a hypothesized insulator.

Job autonomy. Discretion in how an individual is able to accomplish the tasks, duties, and responsibilities of the job may serve as a conductor for cumulative advantage leading to the end result of a heavy-tailed productivity distribution and a greater proportion of productivity stars. Empirically, job autonomy generally has a positive relation with productivity (Humphrey, Nahrgang, & Morgeson, 2007). Job autonomy is an especially salient conductor because it offers high-productivity individuals the flexibility and control over processes that may lead to stratification of individuals' output levels (Kohn & Schooler, 1983). We offer three specific reasons behind this theoretical position.

First, job autonomy provides the discretion that can allow stars to show their creativity and innovation (Ohly & Fritz, 2010) as well as allowing them to more fully utilize their unique competencies (McIver, Lengnick-Hall, Lengnick-Hall, & Ramachandran, 2013). In other words, job autonomy fosters a sense of responsibility to be creative and also enables individuals to experiment in the workplace (Ohly & Fritz, 2010), thereby facilitating the innovation process (Glynn, 1996).

Second, jobs that offer all employees greater autonomy are likely to see stratification in the productivity distribution because stars are better able to leverage available resources (Aguinis & O'Boyle, 2014). For example, high-productivity employees are typically higher in growth needs than their less productive counterparts (Westlund & Hannon, 2008) and, according to the job characteristics model, this should result in a stronger relation between job autonomy and productivity specifically for stars (Hackman & Oldham, 1975). This stronger link between job autonomy and productivity at the upper echelon of the productivity distribution should result in pushing the stars further out and adding heaviness to the tail of the distribution.

Third, job autonomy in a knowledge economy extends beyond the discretion to do one's job independent of managerial oversight. Greater job autonomy allows individuals to make network connections across levels of the organization as well as outside the organization. These cross-level and external ties allow for stronger and larger networks, which are known to enhance success and generate extreme productivity levels (Crawford & LePine, 2013; Oliver & Liebeskind, 1998; Zucker, Darby, & Brewer, 1998). In short, we offer the following hypothesis:

Hypothesis 3: Job autonomy will be a conductor of cumulative advantage, such that the end result of jobs with greater autonomy will be a greater likelihood of a power law distribution and a greater proportion of productivity stars (i.e., heavier tail).

Job complexity. Jobs that are more complex are more mentally demanding, difficult to perform and require higher levels of information processing (Humphrey et al., 2007). We expect that job complexity will be a conductor for cumulative advantage. One reason is that, similar to the rationale for job autonomy, job complexity introduces more variance in worker output (Gerhart, 1988; Hunter, Schmidt, & Judiesch, 1990) such as by requiring greater creativity and decision latitude that allow for extraordinary levels of productivity. For example, a highly complex job such as that of a academic researcher has long been known to demonstrate a heavy-tailed productivity distribution in terms of number of publications as well as citations (Shockley, 1957), as have other prototypically complex jobs that have become so pervasive in today's knowledge economy (e.g., software engineers; Curtis, Sheppard, Milliman, Borst, & Love, 1979; Darcy & Ma, 2005). On the other hand, less complex jobs from the manufacturing sector exhibit little variance in outputs (Schmidt & Hunter, 1983).

In addition, complex jobs also generate more complex output (De Sitter, Den Hertog, & Dankbaarl, 1997). Specifically, resource-based theory, which usually focuses on productivity at the firm and not the individual level of analysis, describes complex output, especially output at the tails of the distribution, as more difficult to imitate and less likely to be substituted by even slightly less productive firms (Barney, Ketchen, & Wright, 2011). In sum, we hypothesize the following:

Hypothesis 4: Job complexity will be a conductor of cumulative advantage, such that the end result of jobs with greater complexity will be a greater likelihood of a power law distribution and a greater proportion of productivity stars (i.e., heavier tail).

Productivity ceiling. Even in highly autonomous and complex jobs, those elite workers who create the heavy tail of the productivity distribution may still experience a maximum cap—what we label a *productivity ceiling*. This productivity ceiling is particularly noticeable for jobs that have a physical and/or time limit component. For example, Pearce, Stevenson, and Perry (1985) provided evidence that certain work outcomes such as safety records have maximum values that prevent further improvement. On the other hand, illustrating a more permeable productivity ceiling, an academic researcher can accumulate a theoretically unlimited number of citations over her career. Accordingly, we expect that jobs that rely mainly on productivity measures that have an inherent ceiling will exhibit distributions with lighter tails.

Even within the same job, certain facets may show different ceilings to productivity. For example, consider the case of call center representatives and several possible measures of productivity such as sales, returns, and number of complaints. All of these productivity measures have different performance ceilings. Phone calls are constrained by a number of factors such as number of rings to an answer, rate of speech, and available leads. Complaints and returns are capped at the number of customer interactions and sales. Alternatively, the amount of revenue may be less constrained by barriers. If, for example, a $1,000 sale takes about the same amount of time as a $100 sale, then revenue exhibits a higher ceiling to productivity.

To date, much of the focus in OBHRM and I-O psychology theory and practice regarding the limits of productivity has been on the lower bound of the distribution, as implemented by personnel selection systems that focus on meeting minimum thresholds across a number of criteria (Cascio & Aguinis, 2011, Chapter 14). During much of the 20th century, the lower bound of productivity was integral to overall production as assembly lines and piecemeal manufacturing could only go as fast as the slowest worker (Buzacott, 2002). However, in the 21st century knowledge economy, the focus seems to be shifting from raising the output of underperformers to removing the obstacles for those who generate the preponderance of output (i.e., productivity stars), and the upper bound of the productivity distribution is now the focus of increased interest. For example, Aguinis and O'Boyle (2014) described a stockbroker who is able to make a sale in 30 minutes but is then bogged down in the paperwork of writing up the sale for an additional 30 minutes. Thus, the productivity ceiling for this broker's number of sales in an 8-hour day is eight. If the organization provided this broker with an assistant to complete her paperwork for each sale, this would double her productivity ceiling to 16. The extent to which a job possesses natural or artificial barriers to productivity will therefore place a limit on the proportion of productivity stars and make it less likely for heavy-tailed distributions to emerge.

As an illustration based on actual productivity data, Grant, Nurmohamed, Ashford, and Dekas (2011) collected information on sales representatives' calls per hour and also revenue per hour. We used Grant et al.'s raw data to create Figure 1. As can be seen in Figure 1's Panel A, the distribution of number of calls made per hour, which has a time-based productivity ceiling, is approximately normal. However, Figure 1's Panel B shows the distribution of revenue made per hour for the same employees, which does not have such an apparent ceiling, and the distribution has a much heavier tail. In sum, we offer the following hypothesis:

Hypothesis 5: Productivity ceiling will be an insulator of cumulative advantage, such that the end result of jobs with lower productivity ceilings will be a smaller likelihood of a power law distribution and a smaller proportion of productivity stars (i.e., lighter tail).

Method

Our hypotheses refer to the relationship between conductors and insulators and the shape of the productivity distribution. Accordingly, testing our hypotheses requires the use of the productivity distribution as the unit of analysis rather than the individual worker. In addition, our hypotheses refer to the end result of the cumulative advantage process. So, an important requirement is that the data be gathered after individuals have interacted with their work environments over time (Burda et al., 2003).

As an additional consideration, experience and opportunity to perform may be a confounding variable. For example, recently minted PhDs may be constrained to the low end of the productivity distribution in terms of total number of articles published. However, we anticipate differences in terms of number of publications even among new scholars

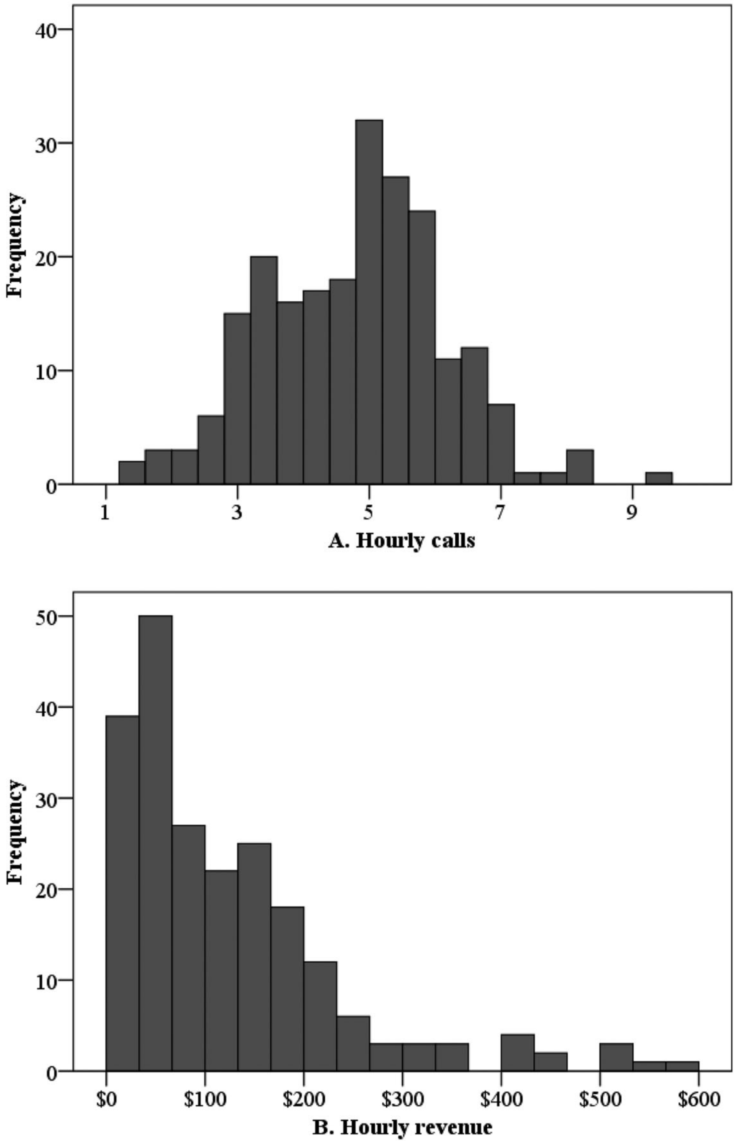

Figure 1: **Productivity Distribution for Call Center Employees ($N = 219$).**

Note. Panel A is the distribution of calls per hour (i.e., lower productivity ceiling), and Panel B is the distribution of revenue per hour (i.e., higher productivity ceiling). Data source: Grant et al. (2011), Study 2.

because, although they have just received their doctorates, the cumulative advantage principle has already produced differences—as documented by Cole and Cole (1973, p. 112) and noted by Merton (1988, p. 615). In fact, Kell, Lubinski, and Benbow (2013) argued that the cumulative advantage process may begin before age 13. So, any decision about establishing a common baseline for the individuals included in a given productivity distribution would necessarily be somewhat arbitrary. Accordingly, our data collection effort did not impose any baselines regarding the precise point in time when the cumulative advantage process actually began (e.g., after the first tenure-track position, after the postdoc experience, after receiving the doctorate, after graduating from college, after graduating from high school). Thus, our datasets include all individuals at all levels of experience for any given distribution to avoid imposing an arbitrary baseline. Further, from an organization's perspective, the amount of productivity of individual workers is the key phenomenon of interest regardless of the tenure of each individual in the organization or profession. Please note that, to address this issue further, the results section includes supplementary analyses addressing the role of experience and its relationship with the presence of a power law compared to normal distributions.

Datasets

We collected as many datasets as possible. This involved a combination of electronic and manual searches and also included several steps such as contacting authors of articles and requesting their data when applicable. First, we wanted to gather productivity distributions including data that were most relevant to OBHRM and I-O psychology research. Accordingly, we focused our initial data collection efforts on articles published in *Journal of Applied Psychology, Academy of Management Journal, Personnel Psychology, Journal of Management,* and *Organizational Behavior and Human Decision Processes.* Specifically, we searched for articles describing productivity distributions.

Second, we used Google Scholar to search for published studies conducted using occupations such as computer programming, customer service (e.g., call centers), sales, and manufacturing for which productivity data are usually made available in the article in the form of a frequency table, histogram, or data plot from which we could reconstruct the raw dataset. This was a broader search compared to the first step, but we decided it was necessary with the goal of gathering as many distributions as possible.

Third, because it is less likely that authors of articles published more than 10 years ago would have access to their raw data, we limited our search to studies published in the past decade. However, during the course of our search, we found that it was relatively common for older studies to report productivity data in the article (e.g., histogram or data plot), so we included older studies that we located that reported their data in one of these forms. For example, we found that some articles/books published in the 1930s to 1960s (and one instance in the 1980s) included either frequency tables or histograms, or plots from which frequency tables could be constructed. Examples of these include Hearnshaw (1937), Lawshe (1948), Maier and Verser (1982), and Stead and Shartle (1940).

Fourth, in addition to electronic searches, we also conducted manual searches using earlier editions of OBHRM and I-O psychology texts. The rationale for this step in the search process was that, as noted, it was then a more common practice to report productivity data either in a frequency table or histogram. As an example of the result of this step, we included data reported by Tiffin and McCormick (1965).

As a result of our search procedures, we were initially able to gather a total of 267 datasets for potential inclusion, each representing a different individual productivity distribution. However, 229 of these 267 distributions were ultimately included in our analysis based on the following criteria. First, some of the datasets included unequally binned productivity categories (Towers, 2012), which did not allow for their inclusion in our analyses. Unequal binning typically appears at the highest category of the scale. For example, a scale using three points may include 1 = *five or fewer* (low), 2 = *between five and 15* (average), and 3 = *16 or more* (above average). In this case, a score of 3 on this scale could obviously refer to 16, 20, or 100 units of output (or any other number larger than 16). The use of such a scale biases the shape of the distribution by "squeezing" the upper tail and not allowing the emergence of what could be an underlying heavy tail (Towers, 2012). Second, some of the datasets did not include a sufficiently large number of observations to conduct the analyses. In such cases, using the maximum likelihood estimation (MLE) procedure we describe later in our paper did not converge on the correct values for the parameters of interest. In the interest of replicability, a detailed table including a list and description of the 38 distributions that were excluded from this study is available from the authors upon request.

Table 1 includes a description of the 229 datasets included in our study as well as the source for each. As can be seen in this table, we included distributions involving several types of occupations, settings, and productivity measures. The total number of observations across the datasets is 633,876. Although each dataset denotes a unique sample for the purposes of our analyses (e.g., different time frames, different productivity operationalizations), some of the datasets are not composed of different individuals. For example, there is overlap between the National Football League (NFL) fumbles and NFL rushing yard samples (i.e., which are

TABLE 1
Description of Datasets Used in this Study

Occupation	Productivity measure and comments
Research	
1. Agriculture	Number of publications in top five field-specific journals, by impact factor, from January 2000 to June 2009
2. Agronomy	
3. Anthropology	
4. Astronomy	
5. Biological psychology	
6. Clinical psychology	
7. Computer science	
8. Criminology	
9. Demography	
10. Dentistry	
11. Dermatology	
12. Developmental psychology	
13. Ecology	
14. Economics	
15. Education	
16. Educational psychology	
17. Environmental science	
18. Ergonomics	
19. Ethics	
20. Ethnic studies	
21. Finance	
22. Forestry	
23. Genetics	
24. History	
25. Hospitality	
26. Industrial relations	
27. International relations	
28. Law	
29. Linguistics	
30. Material sciences	
31. Mathematics	
32. Medical ethics	
33. Parasitology	
34. Pharmacology	
35. Physics	
36. Public administration	
37. Radiology	
38. Rehabilitation	
39. Rheumatology	
40. Robotics	
41. Social psychology	
42. Social work	

continued

TABLE 1 (continued)

Occupation	Productivity measure and comments
43. Sociology	
44. Sports medicine	
45. Statistics	
46. Substance abuse	
47. Thermodynamics	
48. Urban studies	
49. Urology	
50. Veterinary science	
51. Virology	
52. Water science	
53. Women's studies	
54. Zoology	
Entertainment	
55. *AVN* nominations actor	*AVN* nominations across a wide variety of categories counted toward the performance total
56. *AVN* nominations actress	
57. *AVN* nominations actor	
58. *AVN* nominations actress	
59. *AVN* nominations director	
60. Cable ACE nominations actress	Nominees for best actress on cable television
61. Country Music Awards nominations	Ratings for Best Male or Female Vocalist
62. Edgar Allan Poe Awards nominations	Expert rankings in Best Novel category
63. Emmy nominations actor	Nomination to any category, and an artist can obtain multiple nominations in the same year. The nomination process combines a popular vote with volunteer judging panels
64. Emmy nominations actress	
65. Emmy nominations art direction	
66. Emmy nominations casting	
67. Emmy nominations choreography	
68. Emmy nominations cinematography	
69. Emmy nominations direction	
70. Emmy nominations editing	
71. Emmy nominations lighting	
72. Emmy nominations writing	
73. Golden Globe nominations actor	Nomination to any category, and an artist can obtain multiple nominations in the same year. The Hollywood Foreign Press Association rates and votes on the nominees
74. Golden Globe nominations actress	
75. Golden Globe nominations direction	
76. Golden Globe nominations TV actor	

continued

TABLE 1 (continued)

Occupation	Productivity measure and comments
77. Golden Globe nominations TV actress	
78. Grammy nominations	Nomination to any category
79. Man Booker Prize Fiction nominations	Expert rankings in Best Novel category
80. MTV VMA nominations	Fan voting and industry ratings
81. *NYT* Best Seller fiction	Each appearance on the *New York Times* Bestseller list
82. *NYT* Best Seller nonfiction	
83. Oscar nominations actor	Nominations as determined by Academy members using a preferential-voting system for best director and nominees in a primary or supporting acting role
84. Oscar nominations art direction	
85. Oscar nominations direction	
86. Oscar nominations actress	
87. Oscar nominations cinematography	
88. PEN award voting	Nomination in any category (e.g., drama)
89. Pulitzer Prize nominations drama	Selection to finalist for the drama category
90. *Rolling Stone* Top 500 albums	Number of appearances on the Top 500 list as rated by contributors and writers
91. *Rolling Stone* Top 500 songs	
92. Tony nominations actress	Nominations determined by a panel of judges from entertainment industry
93. Tony nominations choreography	
94. Tony nominations actor	
95. Tony nominations director	
96. Actors	Domestic total gross revenue (in millions)
97. Actors	Total number of movies
98. Directors	Domestic total gross revenue (in millions)
99. Directors	Total number of movies
100. Producers	Domestic total gross revenue (in millions)
101. Producers	Total number of movies
102. Cinematographers	Domestic total gross revenue (in millions)
103. Cinematographers	Total number of movies
104. Screenwriters	Domestic total gross revenue (in millions)
105. Screenwriters	Total number of movies
106. Composers	Domestic total gross revenue (in millions)
107. Composers	Total number of movies
Politics	
108. Alabama Legislature	Number of years served by current members of the legislative branch elected between 1969 and 2010
109. Australia House (1969)	
110. Australia House (2009)	

continued

TABLE 1 (continued)

Occupation	Productivity measure and comments
111. Canadian Legislature	
112. Connecticut Legislature	
113. Denmark Parliament	
114. Finland Parliament	
115. Georgia House	
116. Illinois Legislature	
117. Iowa Legislature	
118. Ireland Parliament	
119. Ireland Senate	
120. Kansas House	
121. Kansas Senate	
122. Kentucky Legislature	
123. Louisiana House	
124. Maine Legislature	
125. Maryland Legislature	
126. Massachusetts House	
127. Minnesota House	
128. New York Assembly	
129. New Zealand Legislature	
130. North Carolina Assembly	
131. Nova Scotia Legislature	
132. Oklahoma Legislature	
133. Ontario Legislature	
134. Oregon Legislature	
135. Oregon Senate	
136. Pennsylvania House	
137. Quebec Legislature	
138. South Carolina House	
139. Tasmania Assembly	
140. Tennessee House	
141. UK Parliament	
142. US House	
143. US Senate	
144. Virginia Assembly	
145. Wisconsin Legislature	
Sports	
146. MLB career strikeouts	
147. MLB career HR	
148. MLB career manager wins	
149. NCAA baseball DIV1 HR	
150. NCAA baseball DIV2 HR	
151. NCAA baseball DIV3 HR	
152. NCAA 2008 RB rushing yards	
153. NCAA 2008 WR reception yards	
154. NCAA 2008 TE reception yards	

continued

TABLE 1 (continued)

Occupation	Productivity measure and comments
155. Cricket runs	Top 200 cricketers in runs/wickets
156. Cricket wickets	
157. EPL goals	Number of goals scored
158. NBA coaches career wins	
159. NBA career points	
160. PGA career wins	All-time tournament wins
161. Olympic medals male swim	Gold, silver, or bronze medal across an entire career
162. Olympic medals female swim	
163. Olympic medals male track	
164. Olympic medals female track	
165. Olympic medals male alpine	
166. Olympic medals female alpine	
167. PBA titles	All-time tournament wins
168. NFL career coaches wins	
169. NFL career kick return yards	
170. NFL career TD receptions	
171. NFL career field goals	
172. NFL career sacks	
173. NFL career rushing yards	
174. NFL career passing yards	
175. NHL defender assists	
176. NHL center points	
177. NHL right wing points	
178. NHL left wing points	
179. NHL goalie saves	
180. Tennis grand slams men	Grand Slam tournament wins across an entire career
181. Tennis grand slams women	
182. NCAA basketball 2008 points	Points scored for a single season
183. MLB career errors 1B	Errors assigned for MLB players
184. MLB career errors 2B	
185. MLB career errors 3B	
186. MLB career errors C	
187. MLB career errors OF	
188. MLB career errors SS	
189. EPL yellow cards	
190. NBA fouls 2005 to 2008	
191. NFL RB fumbles	
192. NFL QB interceptions	
193. NHL defender penalty minutes	Penalty minutes received for all NHL players across their careers
194. NHL center penalty minutes	
195. NHL right wing penalty minutes	
196. NHL left wing penalty minutes	
197. NCAA 2008 QB interceptions	Quarterbacks only

continued

TABLE 1 (continued)

Occupation	Productivity measure and comments
Additional Occupations	
198. Bank tellers	Sales in month 1
199. Bank tellers	Sales in month 2
200. Bank tellers	Customer service ratings month 1
201. Bank tellers	Customer service ratings month 2
202. Bank tellers	Customer service ratings month 3
203. Bank tellers	Number of minutes spent idle month 1
204. Bank tellers	Number of minutes spent idle month 2
205. Bank tellers	Number of minutes spent idle month 3
206. Retail sales associates	Sales over 1-month period
207. Call center employees	Hourly revenue over 3-month period
208. Call center employees	Hourly calls over 3-month period
209. Call center employees	Total revenue over 3-month period
210. Fundraising callers	Number of calls over 2-week period
211. Fundraising callers	Revenue over 2-week period
212. Fundraising callers	Calls per hour over 2-week period
213. Call center employees	Number of sales over 7-week period
214. Call center employees	Revenue over 7-week period
215. Paper sorters	Pounds sorted per hour over 2-year period
216. Grocery checkers	Time spent checking
217. Pelt pullers	Number of pelts pulled
218. Curtain and drapery salespeople	Percentage of merchandise returned
219. Casting shop employees	Number of absences
220. Toll-ticket sorters	Number of tickets sorted
221. Typists	Words typed per minute, adjusted for errors
222. Application blank sorters	Errors per thousand blanks
223. Card punch operators	Average number of cards punched per hour
224. Lamp shade sewers	Number sewn
225. Lamp shade sewers	Number sewn
226. Card punch operators	Average number of cards punched per hour
227. Card punch operators	Average number of cards punched per hour
228. Electrical fixture assemblers	Number assembled
229. Wirers	Ratio of production time per unit assembled to standard

Note. *AVN* = *Adult Video News*; ACE = Award for Cable Excellence; MTV = Music Television; VMA = Video Music Awards; *NYT* = *New York Times*; PEN = Poets, Playwrights, Editors, Essayists, and Novelists; UK = United Kingdom; US = United States; MLB = Major League Baseball; HR = home run; NBA = National Basketball Association; NCAA = National Collegiate Athletic Association; QB = quarterback; RB = running back; TE = tight end; WR = wide receiver; TD = touchdown; DIV = division; NHL = National Hockey League; NFL = National Football League; PBA = Professional Bowling Association; PGA = Professional Golf Association; EPL = English Premier League; 1B = first baseman; 2B = second baseman; 3B = third baseman; C = catcher; OF = outfielder; SS = shortstop. Dataset sources: 1–95 and 108–197: O'Boyle and Aguinis (2012); 96–107: Information courtesy of Box Office Mojo (2013); 198–205: Sliter, Sliter, and Jex (2012); 206: Erdogan and Bauer (2009); 207–208: Grant et al. (2011); 209: Grant and Wrzesniewski (2010); 210–212: Grant and Sumanth (2009); 213–214: Grant (2012); 215: Hearnshaw (1937); 216–219: Lawshe (1948); 220–221: Maier and Verser (1982); 222–227: Stead and Shartle (1940); and 228–229: Tiffin and McCormick (1965).

produced by running backs in the NFL). Thus, the total number of distinct individuals included in our study is approximately 625,000.

Measures of Conductors and Insulators

Because the unit of analysis in our study is the distribution, we assigned a score to each of the 229 datasets described in Table 1 with respect to each of the five conductors and insulators included in our hypotheses. Next, we offer a description of the procedures we implemented to gather these data.

Job autonomy and job complexity. We used scores available in O*NET for coding job autonomy (i.e., conductor in Hypothesis 3) and job complexity (i.e., conductor in Hypothesis 4). All of the O*NET variables are scored on a range from a low of 1 to a high of 100. For job autonomy, we averaged the scores for "degree of structured versus unstructured work" and "freedom to make decisions" from the work context domain. These two items reflect the definition of autonomy offered by Morgeson and Humphrey (2006) and had an alpha reliability of .91. For job complexity, we averaged the scores for "processing information" and "analyzing data or information" from the generalized work activity domain, which also reflects the definition of job complexity offered by Morgeson and Humphrey (2006). This two-item scale had an alpha reliability of .90.

Multiplicity of productivity, monopolistic productivity, and productivity ceiling. Collecting data for these three variables involved using coders who assigned scores to each of the 229 distributions. We used three independent scores by implementing the following procedures.

First, we created a coding protocol that included definitions and examples for multiplicity of productivity, monopolistic productivity, and productivity ceiling. This material is essentially the same as the information included in our paper's hypotheses sections but excluding information on the relationship between each variable and the shape of the productivity distribution.

Second, the second and third authors coded a random sample including 30% of the datasets. At the completion of this task, we computed the ICC(2) as an index of interrater agreement, and it was .90 across the three variables. All discrepancies were resolved by a subsequent discussion, and the second author coded the remaining datasets. At the completion of this process, we used a single score for each of the distributions produced by the second author.

Third, we collected an additional and independent set of scores produced by another coder who was blind to our study's content and goal. This coder is a student enrolled in a PhD program in OBHRM and had taken doctoral-level courses in research methods, statistics, and human resource management (including a module on job analysis). She first coded a randomly selected set of 30 distributions regarding each of the three variables. At the completion of this task, she met with the second and third authors to inquire if there were any questions. There were no questions, and she proceeded to code the remaining distributions.

Fourth, we collected a third set of independent scores produced by another coder who was also blind to our study's content and goal. He is a doctoral student enrolled in a PhD program in OBHRM at a different university and state than the previous coder. He first coded a randomly selected set of 30 distributions. At the completion of this task, the first author consulted with him to inquire if there were any questions. There were no questions, and he proceeded to code the remaining distributions.

At the completion of the coding process, we computed reliability across the three sets of codes and three variables using ICC(2) (LeBreton & Senter, 2008). Results were .81 for multiplicity of productivity, .81 for monopolistic productivity, and .77 for productivity ceiling. LeBreton and Senter (2008) recommended that ICC(2) values be between .70 and .85 to justify aggregation because these suggest that a substantial amount of coders' variance (i.e., between 70% and 85%) is systematic as opposed to random. Accordingly, we created an average score based on the three sources of coding for multiplicity of productivity, monopolistic productivity, and productivity ceiling, and we used these three averages in our substantive analyses.

Data-Analytic Approach

A set of values x follows a power law if it fits the following probability distribution (Clauset, Shalizi, & Newman, 2009):

$$p\,(x) \propto x^{-\alpha} \tag{1}$$

where α is the scaling exponent (also called scaling parameter), which is a constant (Maillart & Sornette, 2010). The scaling exponent is calculated using MLE based on running a semiparametric Monte Carlo bootstrap calculation 1,000 times—specifically, the Hill estimator (Hill, 1975). Distributions with a heavy tail are characterized by a slow hyperbolic decay in their tail, and the scaling exponent controls the rate of decay. Note that a difference between Equation 1 and the more familiar exponential function is that, in exponential functions, the exponent is the variable and x is constant. In contrast, in power laws, the exponent is the constant and x is the variable. Because α is expressed as an exponent, as α is closer to unity, the tail of the distribution is heavier. Thus, α values can be used to assess whether the distributions (i.e., proportion of productivity stars)

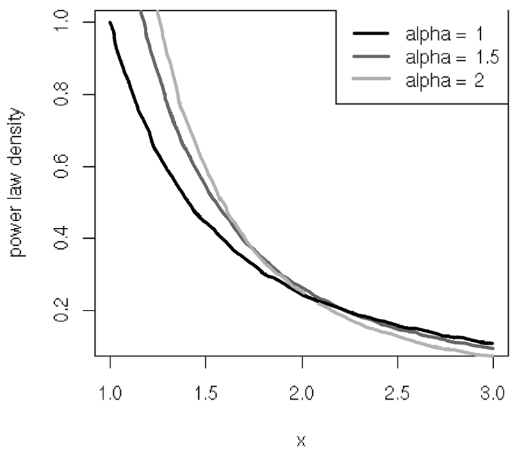

Figure 2: **Power Law Distributions With Different Values for Scaling Parameter α Illustrating That Smaller α Values Are Associated With Distributions With Heavier Tails.**

vary in ways consistent with our hypotheses. For example, a distribution with $\alpha = 1$ has a heavier tail compared to a distribution with $\alpha = 2$, as illustrated in Figure 2.

In addition to the size of the scaling exponent, which indicates the weight of a distribution's tail, we also assessed the extent to which each distribution is likely to conform to a power law with the Kolmogorov–Smirnov goodness-of-fit statistic (K–S test) and its associated *p*-value (Massey, 1951). The K–S test is a nonparametric goodness-of-fit index similar to chi-square. Like the chi-square statistic, smaller K–S values and higher *p*-values indicate better conformity to a power law because the null hypothesis is no absolute deviation between the observed and an underlying power law distribution (Clauset et al., 2009; Maillart et al., 2008; Massey, 1951). Thus, the K–S statistic can be used to assess the probability that there is a power law distribution underlying each empirically obtained distribution.

Note that in much the same way as researchers in OBHRM, I-O psychology, and related fields have loosened the definition of "normally distributed" from a statistical exactitude of skew = 0 and kurtosis = 3, and equal values for the mean, median, mode to a more general approximation, we take the same strategy in how we refer to a "power law distribution." We use the term power law to refer to those heavy-tailed distributions where productivity is clearly dominated by a small group of elites and most individuals in the distribution are far to the left of the mean.

Although results may show a superior fit compared to a normal distribution, distributions may not meet the traditional exactitude of a power law, which implies that the distribution has a never ending tail and infinite variance.

Although the K–S test provides information in support of the presence of a power law for the entire range of scores in a distribution, the fit is generally better for one particular section of the distribution (i.e., tail) compared to the entire range of scores. Accordingly, we also computed x_{min} values, which mark the beginning of the region of the distribution for which power law fit is the best. When the data are continuous, x_{min} offers a lower bound with the following equation:

$$p\left(x\right) = \frac{\alpha - 1}{x_{min}} \left(\frac{x}{x_{min}}\right)^{-\alpha} \quad (2)$$

We used the PLFIT and PLPVA packages in MATLAB 7.10 to calculate the scaling exponent α, K–S statistic and associated p-value, and x_{min} value for each of the 229 distributions. Syntax to conduct these calculations is available at http://tuvalu.santafe.edu/~aaronc/powerlaws/plfit.m and http://tuvalu.santafe.edu/∽aaronc/powerlaws/plpva.m. Note that R code is also available at http://tuvalu.santafe.edu/∽aaronc/powerlaws/plfit.r and http://tuvalu.santafe.edu/∽aaronc/powerlaws/plpva.r to conduct the exact same analyses. In addition, the code provided in http://tuvalu.santafe.edu/∽aaronc/powerlaws/plplot.m creates log–log plots, illustrations of which we include later in our manuscript together with an explanation regarding their interpretation.

Results

Table 2 shows descriptive statistics and correlations among the hypothesized four conductors and one insulator, the scaling parameter (i.e., α), and the K–S goodness-of-fit statistic. Table 3 includes descriptive information for each of the distributions as well as descriptors of the shape of each distribution (i.e., α, K–S statistic and associated p-value, and x_{min}). This table also includes the number of *SD*s included in each variable range, computed as #*SD* = (max – min)/*SD*. Results in Table 3 show that some of the distributions do not include very wide ranges, and it is likely that they include mainly productivity stars (i.e., those in the extreme upper tail of the distribution). For example, the #*SD* value for sample 62 (Edgar Allan Poe Awards nominations) is only 3.86. However, across the 229 samples, the mean #*SD* value is 9.91, the median is 6.98, and the range is 51.60. Thus, taken together, the datasets included in our study cover a wide range of productivity levels.

TABLE 2
Descriptive Statistics and Correlations Among Hypothesized Conductors and Insulators and Productivity Distribution Descriptors

Variable	*Mean*	*SD*	1	2	3	4	5	6
1. Multiplicity of productivity	3.62	1.08	(.81)					
2. Monopolistic productivity	3.82	1.10	.79	(.81)				
3. Job autonomy	78.63	11.62	.32	.45	(.91)			
4. Job complexity	51.77	19.47	–.06	.11	.78	(.90)		
5. Productivity ceiling	2.10	.94	–.52	–.68	–.44	–.11	(.77)	
6. α	3.35	1.46	–.28	–.31	–.22	–.07	.23	
7. K–S statistic	.08	.08	–.50	–.67	–.44	–.15	.72	.26

Note. $n = 229$ datasets except for correlations with job autonomy and job complexity, for which $n = 191$. *SD* = standard deviation; α = scaling parameter for the power law curve (the smaller the value, the heavier the tail of the distribution); K–S statistic = Kolmogorov–Smirnov goodness-of-fit statistic (the smaller the value, the greater the likelihood of the presence of a power law distribution). Variables 1, 2, and 5 range from 1 to 5, and variables 3 and 4 range from 1 to 100. Reliabilities given in the diagonal are ICC(2) for multiplicity of productivity, monopolistic productivity, and productivity ceiling, and internal consistency (alpha) for job autonomy and job complexity. For correlations greater than $|.12|$, $p < .05$ (one-tailed test).

As an additional consideration, Table 3 shows that our study included 54 distributions of researcher productivity (i.e., number of journal articles). Table 3 also shows 38 distributions of politician productivity (i.e., number of years served as elected official in a legislative body), which corresponds to number of elections won. Regarding researchers, publication norms are different across fields. For example, in some fields it is not possible to publish an article in a top-tier journal without receiving a grant and setting up a lab first. In others, publications include numerous coauthors, and yet in other disciplines the typical number of publications is much larger compared to other fields. In addition, the nature of the published articles is different across fields as well—in some fields articles are very short and in others they are much longer. These differences in publication norms across scientific fields are likely to lead to differences in the productivity distributions because, although all of the researcher productivity distributions address "number of journal articles," the nature of the article itself (i.e., the product) seems to be qualitatively different.

Information included in Table 3 provides a way to empirically assess the extent to which the researcher distributions may be about different types of productivity. Support for this idea would be found if the distributions are heterogeneous. On the other hand, all distributions could be treated as different illustrations of a singular type of productivity and possibly combined, if they were homogenous. Table 3 shows that, across the 54 samples of researchers, sample size ranges from 678 to 37,757,

TABLE 3
Productivity Distribution Descriptors for Datasets Used in Present Study

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
Research												
1. Agriculture	25,006	1	1.91	7.26	2.54	1	60	23.21	2	2.55	.02	.00
2. Agronomy	8,923	1	1.42	6.36	1.16	1	26	21.56	2	3.21	.01	.07
3. Anthropology	5,755	1	1.87	4.49	1.95	1	30	14.84	1	2.29	.03	.00
4. Astronomy	13,101	2	3.10	4.11	3.99	1	70	17.29	6	2.87	.05	.00
5. Biological psychology	8,332	1	1.40	6.14	1.11	1	22	18.99	1	2.79	.02	.00
6. Clinical psychology	10,418	1	1.89	10.80	2.38	1	93	38.68	3	2.84	.02	.01
7. Computer science	3,597	1	1.45	5.35	1.11	1	19	16.17	3	3.50	.02	.32
8. Criminology	678	1	1.29	4.16	.77	1	8	9.10	2	3.50	.02	.48
9. Demography	737	1	1.58	15.90	2.91	1	62	20.96	1	2.67	.02	.05
10. Dentistry	12,345	1	2.26	6.54	2.98	1	66	21.80	2	2.54	.03	.00
11. Dermatology	30,531	1	2.25	8.01	3.38	1	93	27.19	2	2.40	.02	.00
12. Developmental psychology	7,303	1	1.75	6.72	1.90	1	45	23.20	2	2.76	.02	.00
13. Ecology	5,730	1	1.71	7.87	1.68	1	50	29.21	4	3.50	.02	.75
14. Economics	3,048	1	1.62	7.14	1.67	1	27	15.53	3	3.13	.02	.25
15. Education	1,201	1	1.26	7.70	.84	1	16	17.92	1	3.14	.01	.05
16. Educational psychology	3,032	1	1.70	5.41	1.55	1	27	16.78	4	3.44	.01	.87
17. Environmental science	2,447	1	1.42	10.74	1.17	1	33	27.36	1	2.73	.03	.00
18. Ergonomics	3,309	1	1.34	5.17	.90	1	16	16.68	2	3.48	.01	.37
19. Ethics	1,073	1	1.65	6.83	1.78	1	26	14.08	2	2.89	.01	.95
20. Ethnic studies	2,003	1	1.47	5.99	1.38	1	17	11.63	2	3.05	.01	.94
21. Finance	3,019	1	2.14	4.69	2.52	1	28	10.71	6	3.26	.04	.06
22. Forestry	12,211	1	1.82	5.66	1.80	1	46	25.05	5	3.50	.03	.10
23. Genetics	16,574	1	1.71	26.42	2.18	1	120	54.56	4	3.35	.02	.19
24. History	6,708	1	1.54	3.33	.97	1	14	13.43	2	3.50	.04	.00

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SDs*	x_{min}	α	K–S	*p*
25. Hospitality	1,684	1	1.38	3.99	1.00	1	9	8.01	1	2.84	.01	.00
26. Industrial relations	1,504	1	1.34	4.01	.83	1	10	10.78	2	3.50	.02	.49
27. International relations	1,483	1	1.65	10.93	3.09	1	50	15.86	1	2.66	.01	.05
28. Law	1,350	1	1.55	3.89	1.24	1	13	9.68	2	3.03	.03	.03
29. Linguistics	3,600	1	1.73	5.99	1.78	1	28	15.18	5	3.50	.02	.86
30. Material sciences	24,723	1	1.76	11.52	2.42	1	85	34.69	3	2.80	.01	.01
31. Mathematics	3,972	1	1.45	4.86	1.02	1	15	13.68	2	3.50	.01	.30
32. Medical ethics	2,928	1	1.92	13.67	3.21	1	98	30.24	1	2.36	.02	.00
33. Parasitology	11,667	1	1.78	9.85	2.12	1	57	26.37	7	3.47	.02	.68
34. Pharmacology	11,654	1	1.54	7.98	1.68	1	39	22.57	1	2.65	.01	.00
35. Physics	1,373	1	1.18	8.74	.73	1	12	15.07	1	3.49	.01	.05
36. Public administration	3,473	1	1.73	5.52	1.73	1	30	16.78	4	3.25	.02	.66
37. Radiology	27,146	1	2.25	6.19	2.88	1	93	31.99	5	2.91	.04	.00
38. Rehabilitation	5,661	1	1.50	11.11	1.52	1	46	29.59	2	3.08	.01	.27
39. Rheumatology	6,665	1	1.48	5.33	1.25	1	18	13.65	2	3.13	.01	.08
40. Robotics	5,021	1	1.92	5.24	2.17	1	31	13.83	2	2.64	.02	.00
41. Social psychology	4,425	1	2.35	4.58	3.04	1	42	13.48	2	2.31	.04	.00
42. Social work	2,357	1	1.45	5.25	1.16	1	17	13.81	3	3.45	.02	.59
43. Sociology	2,417	1	1.81	3.34	1.49	1	14	8.70	4	3.50	.03	.40
44. Sports medicine	16,412	1	1.79	8.44	2.08	1	70	33.13	3	2.86	.02	.00
45. Statistics	10,679	1	2.08	6.22	2.52	1	54	21.04	4	2.93	.02	.00
46. Substance abuse	9,513	1	1.78	5.84	1.95	1	39	19.53	2	2.69	.02	.00
47. Thermodynamics	9,856	1	2.45	5.41	3.31	1	62	18.42	12	3.50	.04	.07
48. Urban studies	3,548	1	1.33	4.58	.83	1	13	14.38	2	3.50	.02	.16
49. Urology	37,757	1	2.24	6.02	2.92	1	58	19.54	12	3.50	.02	.18
50. Veterinary science	31,224	1	1.90	6.19	2.13	1	51	23.47	8	3.50	.02	.36
51. Virology	17,480	1	1.68	8.45	1.73	1	72	41.06	4	3.23	.03	.00

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
52. Water science	25,757	1	2.43	7.08	3.79	1	94	24.53	5	2.62	.03	.00
53. Women's studies	2,982	1	1.26	18.95	1.00	1	38	37.01	1	3.15	.02	.00
54. Zoology	14,789	1	1.46	5.03	1.13	1	21	17.73	3	3.50	.02	.04
Entertainment												
55. *AVN* nom. actor	132	1	1.83	2.00	1.36	1	7	4.42	2	2.87	.08	.04
56. *AVN* nom. actress	245	1	1.77	2.47	1.38	1	9	5.81	1	2.28	.07	.00
57. *AVN* nom. actor	135	1	1.82	3.14	1.66	1	11	6.02	2	2.75	.05	.32
58. *AVN* nom. actress	302	1	1.82	2.98	1.50	1	12	7.32	3	3.29	.04	.72
59. *AVN* nom. director	108	1	1.52	4.20	1.20	1	10	7.48	2	3.24	.01	.98
60. Cable ACE nom. actress	104	1	1.21	3.18	.59	1	4	5.12	1	3.27	.01	.74
61. Country Music Awards nom.	106	1	1.84	3.21	1.49	1	11	6.69	2	2.97	.04	.63
62. Edgar Allen Poe Awards nom.	121	10.45	15.07	1.41	10.39	6.40	46.51	3.86	10	2.71	.14	.00
63. Emmy nom. actor	685	2	2.86	2.49	2.74	1	21	7.30	6	3.50	.06	.33
64. Emmy nom. actress	442	2	2.49	2.45	2.33	1	17	6.86	4	3.11	.07	.04
65. Emmy nom. art direction	866	1	1.82	7.40	2.37	1	36	14.76	1	2.38	.02	.02
66. Emmy nom. casting	193	1	2.16	2.89	2.01	1	14	6.47	2	2.55	.06	.12
67. Emmy nom. choreography	127	1	1.71	3.23	1.54	1	11	6.48	1	2.40	.04	.11
68. Emmy nom. cinematography	588	1	1.68	4.33	1.43	1	18	11.90	1	2.39	.04	.00
69. Emmy nom. direction	395	1	1.95	4.96	2.07	1	24	11.12	2	2.65	.03	.30
70. Emmy nom. editing	942	1	1.89	3.53	1.77	1	17	9.03	5	3.50	.05	.15
71. Emmy nom. lighting	131	1	3.02	2.91	3.55	1	24	6.47	3	2.43	.08	.12

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
72. Emmy nom. writing	1,457	1	2.46	3.51	2.72	1	29	10.28	1	2.01	.06	.00
73. Golden Globe nom. actor	392	1	2.07	3.45	2.02	1	17	7.93	1	2.14	.07	.00
74. Golden Globe nom. actress	415	1	2.05	3.68	2.06	1	21	9.70	1	2.17	.04	.00
75. Golden Globe nom. direction	156	1	1.94	2.14	1.53	1	10	5.89	1	2.16	.06	.00
76. Golden Globe nom. TV actor	375	1	2.12	2.41	1.78	1	12	6.17	3	3.06	.07	.04
77. Golden Globe nom. TV actress	354	1	2.19	2.03	1.79	1	12	6.14	4	3.50	.05	.50
78. Grammy nom.	3,313	1	2.02	6.81	2.78	1	56	19.77	1	2.27	.02	.00
79. Man Booker Prize Fiction nom.	283	1	1.35	3.22	.84	1	6	5.96	1	2.85	.02	.07
80. MTV VMA nom.	561	2	3.98	4.68	5.58	1	68	12.02	13	3.50	.05	.91
81. *NYT* Best Seller fiction	222	1	2.42	4.73	3.85	1	30	7.53	1	2.16	.01	.93
82. *NYT* Best Seller nonfiction	419	1	1.19	7.34	.65	1	10	13.84	1	3.40	.01	.23
83. Oscar nom. actor	421	1	1.84	3.35	1.62	1	15	8.62	1	2.26	.06	.00
84. Oscar nom. art direction	531	1	2.64	4.75	3.75	1	36	9.33	2	2.28	.05	.04
85. Oscar nom. direction	199	1	1.97	2.46	1.60	1	12	6.86	1	2.14	.07	.00
86. Oscar nom. actress	432	1	1.80	2.87	1.50	1	12	7.31	1	2.28	.05	.00
87. Oscar nom. cinematography	159	1	1.91	2.74	1.56	1	12	7.06	1	2.19	.05	.00
88. PEN award voting	125	10.54	14.47	2.20	11.45	6	71	5.66	24	3.50	.07	.81
89. Pulitzer Prize nom. drama	121	1	1.26	3.91	.75	1	6	6.66	1	3.11	.01	.73
90. *Rolling Stone* Top 500 albums	261	1	1.90	3.09	1.52	1	11	6.60	3	3.45	.05	.43
91. *Rolling Stone* Top 500 songs	247	1	2.02	5.24	2.19	1	23	10.06	4	3.31	.05	.44

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
92. Tony nom. actress	583	1	1.59	3.09	1.18	1	10	7.62	1	2.46	.05	.00
93. Tony nom. choreography	108	1	2.10	2.24	2.10	1	11	4.77	1	2.17	.04	.27
94. Tony nom. actor	642	1	1.43	2.88	.94	1	8	7.48	1	2.68	.03	.00
95. Tony nom. director	237	1	1.86	3.82	1.70	1	16	8.82	1	2.25	.04	.02
96. Actors total revenue	695	637.9	828.43	1.29	711.26	.04	4,073.30	5.73	1,512	4.59	.06	.15
97. Actors number of movies	695	15	17.30	.85	12.45	1	70	5.54	23	3.50	.10	.00
98. Directors total revenue	704	95.2	233.25	3.80	353.03	.00	4,155.90	11.77	569	3.25	.07	.08
99. Directors number of movies	704	3	4.82	2.39	4.51	1	40	8.65	8	3.40	.08	.01
100. Producers total revenue	627	208.4	510.06	3.18	806.42	.01	6,468.20	8.02	1,198	3.04	.08	.05
101. Producers number of movies	627	4	8.63	3.10	11.96	1	81	6.69	17	2.90	.06	.25
102. Cinema. total revenue	66	392.35	556.43	1.25	541.84	.50	2,106.10	3.89	374	2.35	.14	.01
103. Cinema. number of movies	66	14	15.12	.80	9.82	1	48	4.78	16	3.50	.09	.66
104. Screenwriters total revenue	744	112.7	242.57	3.41	372.03	.00	3,379.80	9.08	359	2.64	.06	.06
105. Screenwriters number of movies	744	3	4.00	2.91	3.88	1	40	10.05	7	3.50	.04	.65
106. Composers total revenue	137	385	1,102.76	2.75	1,696.91	1	9,446.10	5.57	1,313	2.52	.09	.32
107. Composers number of movies	137	13	23.12	1.54	25.21	1	109	4.28	14	2.07	.13	.00

continued

TABLE 3 (continued)

Dataset	n	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	p
Politics												
108. Alabama Legislature	104	10	11.43	1.01	8.47	1	35	4.01	19	3.50	.20	.03
109. Australia House (1969)	128	9	11.26	.63	8.42	1	38	4.51	14	3.50	.16	.00
110. Australia House (2009)	153	9	10.46	.83	6.84	2	37	5.12	12	3.50	.12	.02
111. Canadian Legislature	4,059	2	2.65	1.58	1.87	1	16	8.01	4	3.50	.07	.00
112. Connecticut Legislature	151	8	9.89	.64	6.31	2	30	4.60	6	2.39	.18	.00
113. Denmark Parliament	177	8	10.41	1.15	7.39	1	38	5.00	14	3.50	.15	.01
114. Finland Parliament	199	6	9.39	1.18	7.74	2	34	4.13	13	3.50	.14	.02
115. Georgia House	179	3	4.80	1.51	3.89	1	17	4.12	6	3.24	.08	.17
116. Illinois Legislature	118	9	9.96	.78	6.48	1	31	4.63	7	2.74	.16	.00
117. Iowa Legislature	100	6	6.74	.97	4.89	1	22	4.30	6	3.05	.08	.18
118. Ireland Parliament	1,147	3	3.99	1.29	3.15	1	17	5.07	6	3.50	.08	.00
119. Ireland Senate	716	2	2.40	1.75	1.95	1	13	6.14	4	3.50	.08	.01
120. Kansas House	5,675	2	2.72	3.17	2.94	1	32	10.53	8	3.50	.05	.02
121. Kansas Senate	1,209	3	4.01	2.71	3.34	1	26	7.48	8	3.50	.06	.18
122. Kentucky Legislature	100	4	5.06	1.10	4.04	1	18	4.21	8	3.50	.11	.24
123. Louisiana House	3,468	1	1.93	5.67	1.97	1	39	19.32	6	3.50	.03	.62
124. Maine Legislature	153	2	2.58	3.72	2.06	1	18	8.25	3	3.50	.07	.25
125. Maryland Legislature	141	6	9.42	1.25	7.63	1	36	4.59	13	3.50	.15	.02
126. Massachusetts House	160	9	9.82	.80	6.88	1	34	4.79	13	3.50	.13	.02
127. Minnesota House	134	3	4.31	1.96	3.66	1	19	4.91	6	3.20	.07	.53

continued

TABLE 3 (continued)

Dataset	n	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	p
128. New York Assembly	148	9	11.61	.93	8.94	1	39	4.25	17	3.50	.13	.05
129. New Zealand Legislature	122	4	8.05	1.01	7.49	1	28	3.60	10	3.27	.17	.00
130. North Carolina Assembly	124	4	4.70	1.34	3.38	1	17	4.73	4	2.83	.09	.05
131. Nova Scotia Legislature	414	3	3.01	1.40	1.26	2	9	5.55	2	2.80	.10	.00
132. Oklahoma Legislature	101	5	4.70	.69	2.67	1	13	4.49	5	3.50	.17	.00
133. Ontario Legislature	1,879	4	4.56	1.58	3.30	1	24	6.98	6	3.50	.13	.00
134. Oregon Legislature	377	4	4.47	1.76	3.81	1	22	5.51	8	3.50	.07	.25
135. Oregon Senate	161	4	5.45	1.59	4.44	1	27	5.85	9	3.50	.10	.23
136. Pennsylvania House	200	7	10.76	1.02	9.18	1	37	3.92	17	3.50	.13	.02
137. Quebec Legislature	399	3	3.52	1.12	2.40	1	11	4.16	5	3.50	.11	.00
138. South Carolina House	124	7	8.23	.97	6.44	1	31	4.66	11	3.50	.10	.28
139. Tasmania Assembly	542	2	3.11	1.46	2.35	1	15	5.95	5	3.50	.08	.03
140. Tennessee House	99	4	5.22	1.32	4.10	1	19	4.39	7	3.50	.08	.62
141. UK Parliament	7,214	3	3.41	1.44	2.59	1	23	8.49	5	3.50	.10	.00
142. US House	8,976	2	3.42	2.13	3.23	1	27	8.05	7	3.50	.08	.00
143. US Senate	1,840	6	9.14	1.58	7.79	1	50	6.29	17	3.50	.10	.00
144. Virginia Assembly	99	9	11.09	1.53	8.26	1	49	5.81	16	3.50	.13	.08
145. Wisconsin Legislature	99	6	8.11	1.77	6.99	1	39	5.44	15	3.50	.12	.53
Sports												
146. MLB career strikeouts	1,001	926	1,103.16	2.63	563.22	586	5,714	9.10	1,028	3.50	.05	.00
147. MLB career HR	1,004	132	174.00	1.88	109.44	75	762	6.28	224	3.50	.06	.01
148. MLB career manager wins	646	121	301.02	2.80	450.90	1	3,731	8.27	1,028	3.50	.07	.59

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
149. NCAA baseball DIV1 HR	548	11	11.57	1.50	3.76	8	28	5.32	8	3.50	.07	.00
150. NCAA baseball DIV2 HR	383	9	10.26	1.63	3.66	7	29	6.02	7	3.50	.08	.00
151. NCAA baseball DIV3 HR	424	6	7.27	2.18	2.91	5	26	7.23	5	3.45	.05	.01
152. NCAA 2008 RB rushing yards	529	236	407.56	1.47	444.68	1	2,208	4.96	837	3.50	.11	.01
153. NCAA 2008 WR receiving yards	798	201	299.09	1.43	294.03	13	1,538	5.19	542	3.50	.08	.02
154. NCAA 2008 TE receiving yards	297	82	146.84	2.67	190.73	1	1,329	6.96	194	2.74	.08	.19
155. Cricket runs	252	3,452.5	4,279.48	1.37	2,205.77	2001	1,2773	4.88	6,741	6.10	.07	.74
156. Cricket wickets	150	160.5	201.55	2.20	117.84	99	773	5.72	208	3.50	.06	.73
157. EPL goals	1,521	4	10.89	4.88	19.72	1	260	13.13	34	2.86	.06	.24
158. NBA coaches career wins	258	79	183.15	2.68	263.73	1	1,806	6.84	260	2.66	.10	.10
159. NBA career points	3,932	664.5	2,670.91	2.60	4,308.44	1	3,8387	8.91	9,710	3.50	.07	.00
160. PGA career wins	200	10	14.05	2.77	12.62	5	82	6.10	11	2.66	.06	.17
161. Olympic medals male swim	654	1	1.78	2.94	1.38	1	11	7.24	3	3.50	.06	.08
162. Olympic medals female swim	538	1	1.75	2.83	1.39	1	10	6.48	3	3.50	.03	.78
163. Olympic medals male track	981	1	1.34	2.93	.76	1	7	7.94	2	3.50	.04	.09
164. Olympic medals female track	437	1	1.45	2.97	.94	1	8	7.46	1	2.63	.04	.00
165. Olympic medals male alpine	167	1	1.46	3.37	.94	1	8	7.48	2	3.50	.02	.90

continued

TABLE 3 (continued)

Dataset	n	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	p
166. Olympic medals female alpine	148	1	1.64	1.89	.98	1	6	5.12	2	3.45	.07	.10
167. PBA titles	310	2	4.95	3.05	6.70	1	45	6.56	10	2.99	.07	.48
168. NFL career coaches wins	413	13	31.25	2.82	46.64	1	328	7.01	111	3.50	.07	.86
169. NFL career kick return yards	250	2,714.5	3,238.43	2.79	1,698.95	1,802	1,4014	7.19	4,353	4.62	.08	.09
170. NFL career TD receptions	253	46	50.92	2.73	20.59	31	197	8.06	39	3.50	.08	.00
171. NFL career field goals	252	70.5	110.61	1.50	108.69	12	565	5.09	200	3.50	.08	.48
172. NFL career sacks	251	51	59.67	2.00	28.43	32	200	5.91	51	3.50	.05	.39
173. NFL career rushing yards	250	4,648	5,611.01	1.91	2708.46	3,176	18,355	5.60	3,351	3.19	.06	.01
174. NFL career passing yards	250	14,418	16,897.24	1.19	11,431.06	4,347	65,127	5.32	26,258	5.15	.06	.79
175. NHL defender assists	1,533	44	107.12	3.38	165.48	1	1,579	9.54	307	3.33	.06	.18
176. NHL center points	1,213	58	191.55	2.82	300.87	1	2,857	9.49	497	3.27	.06	.17
177. NHL right wing points	1,073	46	162.36	2.44	246.82	1	1,850	7.49	573	3.50	.09	.03
178. NHL left wing points	1,102	40.5	141.81	2.33	210.36	1	1,394	6.62	398	3.50	.07	.15
179. NHL goalie saves	392	1,385.5	3,497.99	1.89	4,848.02	2	24,279	5.01	9,712	3.50	.11	.11
180. Tennis grand slams men	146	2	2.94	1.97	2.80	1	15	5.00	2	2.19	.09	.00
181. Tennis grand slams women	110	2	3.68	2.73	4.37	1	24	5.27	5	2.80	.08	.34

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
182. NCAA basketball 2008 points	100	589.5	615.21	1.74	75.02	542	916	4.99	575	3.50	.42	.00
183. MLB career errors 1B	5,933	4	5.66	1.85	5.75	1	41	6.95	12	3.50	.06	.00
184. MLB career errors 2B	6,400	5	8.05	1.86	8.74	1	64	7.20	18	3.50	.07	.00
185. MLB career errors 3B	7,099	4	8.01	1.79	8.55	1	86	9.95	17	3.50	.08	.00
186. MLB career errors C	6,276	4	5.46	1.86	4.73	1	41	8.46	9	3.50	.04	.00
187. MLB career errors OF	13,721	3	4.27	1.78	3.81	1	36	9.19	8	3.50	.06	.00
188. MLB career errors SS	6,456	6	11.98	1.77	13.55	1	98	7.16	25	3.50	.07	.00
189. EPL yellow cards	1,876	5	9.78	2.43	12.26	1	89	7.18	28	3.50	.07	.02
190. NBA fouls 2005 to 2008	433	5	8.84	2.34	10.33	1	85	8.13	6	2.15	.10	.00
191. NFL RB fumbles	251	48	55.28	1.87	23.19	33	161	5.52	49	3.50	.07	.03
192. NFL QB interceptions	253	86	102.74	1.11	60.76	36	310	4.51	122	3.50	.11	.01
193. NHL defender penalty minutes	1,505	180	368.67	2.01	460.31	2	3,381	7.34	599	2.92	.10	.00
194. NHL center penalty minutes	1,129	79	216.84	3.10	329.99	2	3,565	10.80	327	2.58	.08	.00
195. NHL right wing penalty minutes	1,015	111	288.89	3.15	466.39	2	3,515	7.53	480	2.53	.07	.01
196. NHL left wing penalty minutes	1,053	108	286.61	3.05	449.41	2	3,966	8.82	1,121	3.50	.08	.22
197. NCAA 2008 QB interceptions	202	6	7.02	.74	4.61	1	23	4.78	7	3.15	.12	.00
Additional Occupations												
198. Bank tellers	75	1.8	1.73	.10	.77	.20	3.20	3.88	2	6.13	.13	.06
199. Bank tellers	75	1.8	1.63	.10	.69	.40	3.20	4.07	2	7.33	.16	.00
200. Bank tellers	75	90	89.44	–.46	6.03	75	100	4.14	75	3.50	.47	.00

continued

TABLE 3 (continued)

Dataset	n	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	p
201. Bank tellers	75	89	88.91	–.32	6.85	73	100	3.94	73	3.50	.44	.00
202. Bank tellers	75	91	89.91	–.44	6.29	74	100	4.13	74	3.50	.46	.00
203. Bank tellers	75	136	142.67	1.15	30.81	99	250	4.90	99	3.50	.17	.00
204. Bank tellers	75	146	151.80	.51	40.06	70	250	4.49	115	3.50	.14	.00
205. Bank tellers	75	142	144.96	.51	30.22	97	240	4.73	102	3.50	.17	.00
206. Retail sales associates	244	360.22	321.99	–.78	150.61	0	843.16	5.60	454	11.50	.10	.25
207. Call center employees	219	85.32	124.19	1.78	112.18	6.67	572.06	5.04	174	3.46	.08	.28
208. Call center employees	219	4.93	4.79	.02	1.37	1.29	9.27	5.85	6	11.60	.06	.91
209. Call center employees	86	1650	3,153.70	1.29	3,453.93	50	13,270	3.83	10,950	19.20	.17	.34
210. Fundraising callers	57	107	97.88	–.31	54.46	0	232	4.26	98	3.50	.21	.00
211. Fundraising callers	101	1070	2,329.36	3.00	3,456.88	45	21,500	6.21	820	1.85	.12	.00
212. Fundraising callers	80	1.5	8.26	3.70	15.95	0	103	6.46	8	2.38	.08	.66
213. Call center employees	71	93	130.89	1.04	115.83	2	434	3.73	137	2.98	.13	.21
214. Call center employees	71	7,969	10,357.11	1.26	9,521.57	300	44,640	4.66	9508	2.76	.11	.14
215. Paper sorters	18	86	86.56	–.12	9.98	66	106	4.01	66	3.50	.32	.01
216. Grocery checkers	46	375	360.87	.62	75.21	225	575	4.65	275	3.50	.23	.00
217. Pelt pullers	13	150	156.15	.30	28.73	110	210	3.48	110	3.50	.27	.10
218. Curtain and drapery salespeople	18	12	10.39	.52	4.65	3	22	4.08	13	3.50	.33	.32

continued

TABLE 3 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	*p*
219. Casting shop employees	152	1	2.30	1.18	2.51	0	10	3.98	4	3.26	.10	.14
220. Toll-ticket sorters	13	1150	1,226.38	.63	409.00	610	2,098	3.64	910	3.50	.14	.93
221. Typists	43	45	42.81	–.73	13.45	10	63	3.94	35	3.50	.25	.00
222. Application blank sorters	98	4.5	5.17	1.80	2.66	1.50	16.50	5.64	9	4.81	.18	.25
223. Card punch operators	62	66.5	68.42	.96	20.33	31.50	136.50	5.17	60	5.51	.20	.00
224. Lamp shade sewers	18	21	23.00	.25	7.23	13	35	3.04	17	3.50	.16	.33
225. Lamp shade sewers	19	41	43.21	.27	5.41	35	51	2.96	35	3.50	.37	.00
226. Card punch operators	113	220	226.72	.95	29.89	165	341	5.89	176	3.50	.30	.00
227. Card punch operators	121	187	193.00	.12	31.40	110	275	5.25	143	3.50	.22	.00
228. Electrical fixtures assemblers	40	70	70.50	.60	14.13	40	110	4.95	60	3.50	.31	.00
229. Wirers	35	60	67.71	.83	18.00	40	120	4.44	50	3.50	.27	.00

Note. *n* = sample size; Med = median; *SD* = standard deviation; Min = score with the smallest value (minimum); Max = score with the largest value (maximum); #*SD*s = number of standard deviations included in the range of the distribution; x_{min} = the lower bound value in the distribution above which the power law fits best; α = scaling exponent (i.e., parameter) of the power law curve (the lower the value, the heavier the tail of the distribution); K–S = Kolmogorov–Smirnov goodness-of-fit statistic (the lower the value, the higher the probability of an underlying power law distribution); *p* = statistical significance for the K–S statistic (the higher the value, the better the fit with an underlying power law distribution); nom. = nominations; cinema. = cinematographer; *AVN* = *Adult Video News*; ACE = Award for Cable Excellence; MTV = Music Television; VMA = Video Music Awards; *NYT* = *New York Times*; PEN = Poets, Playwrights, Editors, Essayists, and Novelists; UK = United Kingdom; US = United States; MLB = Major League Baseball; HR = home run; NBA = National Basketball Association; NCAA = National Collegiate Athletic Association; QB = quarterback; RB = running back; TE = tight end; WR = wide receiver; TD = touchdown; DIV = division; NHL = National Hockey League; NFL = National Football League; PBA = Professional Bowling Association; PGA = Professional Golf Association; EPL = English Premier League; 1B = first baseman; 2B = second baseman; 3B = third baseman; C = catcher; OF = outfielder; SS = shortstop. Total *N* = 633,876 observations based on approximately 625,000 individuals.

the mean number of publications ranges from 1.18 to 3.10, the *SD* for the number of publications ranges from .73 to 3.99, and the #*SD*s for the number of publications ranges from 8.01 to 54.56. Taken together, these results suggest that although these 54 distributions all refer to number of journal publications, the type of productivity captured by these distributions seems to differ across academic fields. Thus, we treated each of the 54 distributions as a separate data point in our analyses.

Similarly, regarding the 38 distributions involving politicians, running for office in the U.S. Senate seems to be qualitatively different from running for office in the Tasmanian (Australia) Legislature given the number and type of constituents involved, issues involved in running for office, and budgetary issues regarding campaigning. For example, the estimated average cost to win a U.S. Senate campaign is about $10.5 million, whereas the cost to win a U.S. House campaign is "only" $1.7 million (Knowles, 2013). Table 3 shows that, across the 38 samples of politicians, sample size ranges from 99 to 8,976, the mean number of years served ranges from 1.93 to 11.61, the *SD* for the number of years served ranges from 1.26 to 9.18, and the #*SD*s for the number of years served ranges from 3.60 to 19.32. These results indicate that, although these 38 distributions refer to politicians and number of years served (corresponding to number of elections won), the type of productivity captured by these distributions seem to differ across legislative bodies around the world. Accordingly, we included these 38 distributions and treated each as a separate data point in our analyses.

For illustrative purposes, Figure 3 includes log–log plots for a selected set of our datasets. The observed data are represented by the circles, and the fitted estimator is indicated with a solid line. The absolute value of the slope of this line approximates the scaling parameter α (Mandelbrot, 2008). Thus, in these graphs, the more the data follow a slowly downward-sloping straight line (i.e., the less steep the negative slope), the heavier the tail of the distribution—as indicated by a smaller scaling exponent α (Clauset et al., 2009; Maillart, Sornette, Frei, Duebendorfer, & Saichev, 2011). Prior to the availability of the more precise fitting procedures that we used in our paper, distributions were considered to follow a power law if the data as shown in Figure 3 generally follow a slowly downward-sloping straight line when plotted on log–log scales (Clauset et al., 2009).

Figure 4 includes histograms for the same illustrative datasets included in Figure 3 using the original scores (i.e., no log transformation). Figure 4 illustrates that, as alpha decreases, the distributions have a greater proportion of productivity stars (i.e., heavier tails). For example, Figure 4's panel F shows the distribution for fundraisers, which has a heavy tail and alpha of 1.85. On the other hand, Figure 4's panel H (years served in the U.S. Senate) has an alpha of 3.50. Both distributions conform to a

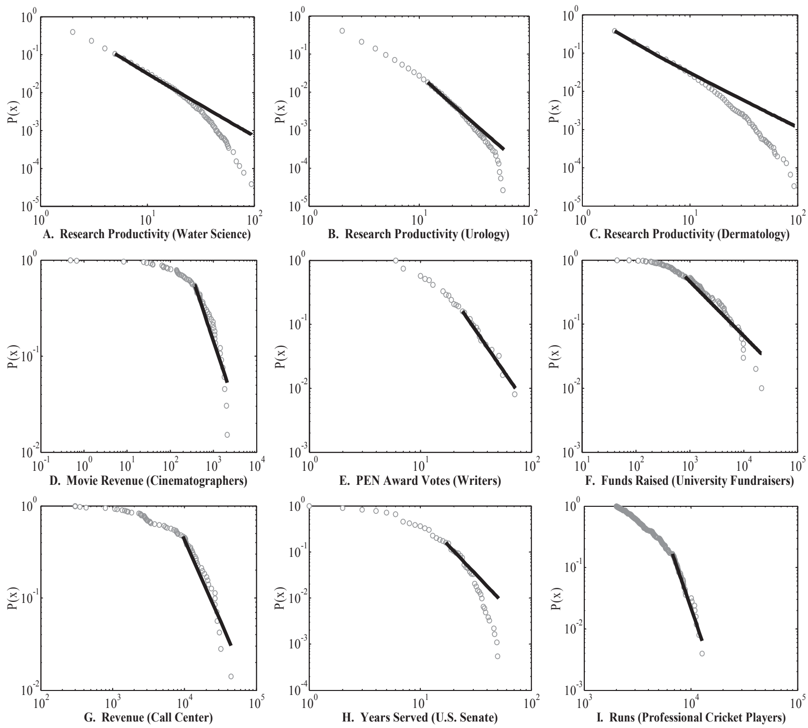

Figure 3: **Log–Log Plots for Illustrative Datasets Used in This Study.**

Note. The observed data are represented by the circles, and the fitted maximum likelihood estimator is indicated with a solid line. Using the same numbering of datasets as in Tables 1 and 3, Panel A corresponds to dataset 52, B to 49, C to 11, D to 102, E to 88, F to 211, G to 214, H to 143, and I to 155. The scaling exponents α (i.e., absolute values of the slopes of the maximum likelihood estimate of the power law) are as follows: A = 2.62; B = 3.50; C = 2.40; D = 2.35; E = 3.50; F = 1.85; G = 2.76; H = 3.50; and I = 6.10.

power law, but the smaller exponent indicates the distribution containing a greater proportion of productivity stars (i.e., heavier tail).

Hypothesis Tests

Our hypotheses refer to the relationship of conductors and insulator with (a) the probability of an underlying power law distribution and (b) greater or smaller proportion of productivity stars (i.e., heavier or lighter distribution tail). We correlated scores for conductors and insulator with K–S statistic values, which represent the probability that a distribution conforms to a power law, and we correlated scores for conductors and insulator with scaling exponent α values, which indicate

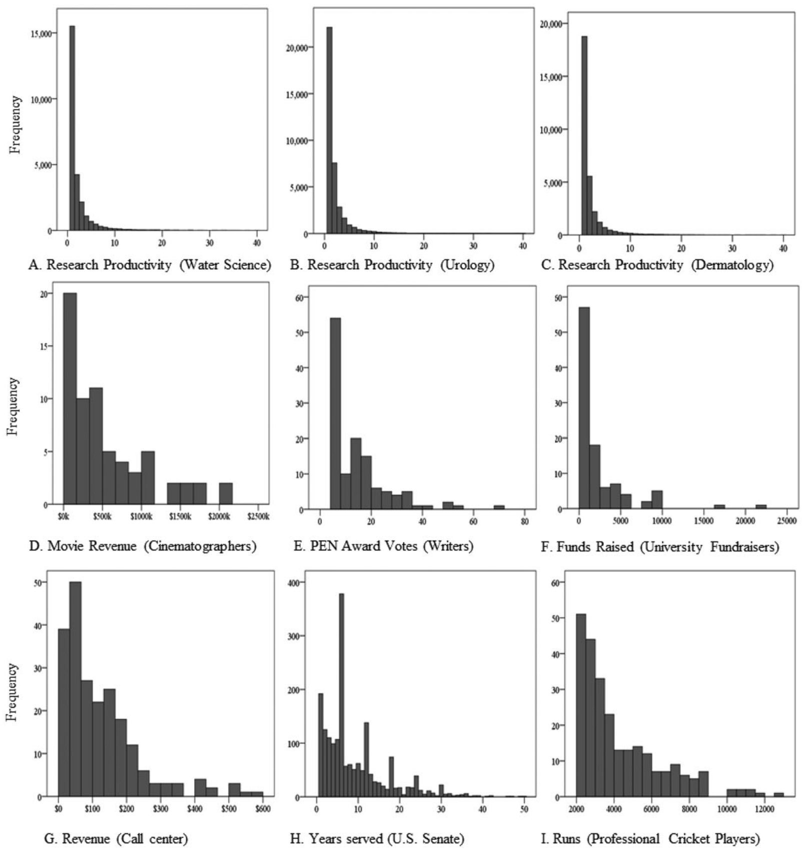

Figure 4: **Frequency Distributions for the Same Illustrative Datasets Included in Figure 3.**

Note. Using the same numbering of datasets as in Tables 1 and 3: Panel A corresponds to dataset 52, B to 49, C to 11, D to 102, E to 88, F to 211, G to 214, H to 143, and I to 155.

greater or smaller proportions of productivity stars. Note that a statistically significant *negative* correlation suggests the presence of a conductor because smaller K–S statistic and smaller α values are indicators of greater possibility of an underlying power law distribution and a heavier distribution tail, respectively. In contrast, because lower productivity ceilings were assigned higher scores in the coding process, a statistically positive correlation suggests the presence of an insulator.

Hypothesis 1 predicted that greater multiplicity of productivity would be associated with a higher probability of a power law distribution and a greater proportion of productivity stars. As shown in Table 2, the correlations between multiplicity of productivity and the K–S statistic ($r = -.50$) and α ($r = -.28$) were statistically significant ($p < .05$), thus providing support for Hypothesis 1. Hypothesis 2 predicted that monopolistic productivity would also be associated with a higher probability of a power law distribution and a greater proportion of productivity stars. The correlations with the K–S statistic ($r = -.67$) and α ($r = -.31$) were statistically significant, also providing support for Hypothesis 2. Hypotheses 3 and 4 predicted that jobs with higher autonomy and complexity would be associated with a higher probability of a power law distribution and a greater proportion of productivity stars. We tested these hypotheses with a smaller sample size of 191 distributions because O*NET does not include information on the degree of job autonomy or complexity for the job "politician." In support of Hypothesis 3, which addressed job autonomy, the correlations between job autonomy and the K–S statistic ($r = -.44$) and α ($r = -.22$) were statistically significant. Regarding Hypothesis 4, which addressed job complexity, the correlation with the K–S statistic ($r = -.15$) was statistically significant, and the correlation with α ($r = -.07$) was in the predicted direction but not statistically significant ($p = .17$). Thus, these results provided support regarding the likelihood of an underlying power law curve but not for the relationship between job complexity and greater proportion of productivity stars. Finally, Hypothesis 5 predicted that jobs that are characterized by a lower productivity ceiling will be associated with a lower probability of an underlying power law distribution and a smaller proportion of productivity stars. In support of this hypothesis, correlations of productivity ceiling with the K–S statistic ($r = .72$) and α ($r = .23$) were statistically significant.

In sum, results provided support for each of the hypotheses about conductors and insulator of heavy-tailed distributions and proportion of productivity stars, except for the relationship between job complexity and greater proportion of productivity stars. Although the results indicated that greater job complexity is associated with a greater probability of an underlying power law distribution, we did not find sufficient support for job complexity as a conductor for a greater proportion of productivity stars.

Supplementary Analyses: The Role of Experience

An anonymous reviewer rightfully noted that our datasets included individuals with different levels of experience. Thus, this reviewer noted that "by pooling individuals brand new to the field with those with decades of experience, a heavy tail would emerge with or without cumulative advantage." To address this issue, it is necessary to consider the role of experience explicitly and the extent to which experience may affect the shape of the resulting distributions. Thus, as supplementary analyses, we collected two additional types of data.

First, we examined distributions involving NCAA football player productivity *within class*—thereby holding experience constant. Specifically, we examined distributions for various types of productivity measures (e.g., touchdown passes for quarterbacks, number of yards for running backs) separately for freshmen, sophomores, juniors, and seniors. Results are included in Table 4, and the mean value for the exponent alpha across these 34 distributions is 3.23.

Second, in a complementary approach to considering the role of experience explicitly, we examined NCAA football and NFL player productivity by implementing the residual procedure used by Hambrick and Quigley (2014). Specifically, we regressed various types of productivity measures on (a) class for NCAA datasets and (b) age for NFL datasets. Then, we examined the shape of the distributions of the residual scores, which partial out the effect of experience. Results are included in Table 5, and the mean value for the exponent alpha cross these 18 distributions is 4.54.

Next, we also computed the mean alpha value across the 229 distributions in Table 3, and this value is 3.36. To examine whether the shape of the distributions vary across the three sets of samples, we computed 95% CIs around each mean alpha value, and results indicated almost complete overlap: Table 3: 3.17 to 3.54; Table 4: 3.10 to 3.36; and Table 5: 3.07 to 6.01. In summary, the supplementary analyses and results, which are based on productivity scores that take into account experience explicitly, led to similar results in terms of the shape of the distributions.

Discussion

The presence of nonnormal productivity distributions and productivity stars has the potential to change the lens through which we view many theories in OBHRM, I-O psychology, and related fields—as well as practices. Recently published work has concluded that power law productivity distributions are quite pervasive (Aguinis & O'Boyle, 2014; O'Boyle & Aguinis, 2012). Moreover, despite Beck et al.'s (2014) concern that the O'Boyle and Aguinis (2012) study did not use behavior-based measures of performance, Beck and colleagues did not dispute the accuracy of the conclusions reached by O'Boyle and Aguinis and noted that they "do not disagree that the variables studied by O'Boyle and Aguinis (2012) had distributions with vast departures from normality" (Beck et al., 2014, p. 562).

Given these empirical results, the next step in this line of research is to determine the extent to which individual productivity may follow a nonnormal distribution—and when this happens. Conducting research to address this issue would lead to more precise theories about productivity

TABLE 4

Supplementary Analyses: 2013 NCAA Football Player Productivity Distribution Descriptors by Class, Position, and Productivity Measure

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	#*SD*s	x_{min}	α	K–S	*p*
Freshman												
Quarterback interceptions	21	9	8.48	-.03	3.30	2	15	3.94	7	3.50	.13	.47
Quarterback passing touchdowns	21	11	13.67	1.53	8.52	3	40	4.34	8	2.69	.11	.63
Quarterback passing yards	21	1,776	2,008.38	.87	846.82	1,071	4,057	3.53	1,602	3.50	.13	.84
Running back rushing touchdowns	33	4	4.91	1.19	2.82	1	14	4.61	4	3.01	.12	.17
Running back rushing yards	33	508	563.79	.66	202.87	334	1,026	3.41	443	3.50	.14	.35
Tight end receiving yards	5	409	392.40	–.99	42.41	321	427	2.50	321	3.50	.49	.13
Wide receiver receiving touchdowns	31	3	3.23	.52	2.14	0	7	3.27	3	2.79	.17	.03
Wide receiver receiving yards	31	463	514.84	1.60	194.65	316	1,174	4.41	410	3.50	.13	.36
Sophomore												
Quarterback interceptions	29	8	8.31	.19	3.81	1	16	3.94	7	3.48	.13	.27
Quarterback passing touchdowns	29	12	14.93	1.04	7.79	5	37	4.11	8	2.53	.11	.30
Quarterback passing yards	29	1,871	2,073.62	.72	840.60	1,033	4,114	3.67	1,198	2.93	.15	.10
Running back rushing touchdowns	64	6	6.84	1.95	5.09	0	31	6.09	6	3.12	.09	.30
Running back rushing yards	64	626.5	716.52	1.24	336.33	339	1,741	4.17	661	3.50	.10	.57
Tight end receiving yards	6	362.5	448.50	.87	174.77	312	748	2.49	343	3.50	.26	.69
Wide receiver receiving touchdowns	69	4	4.96	2.25	3.82	1	24	6.01	4	2.74	.11	.06
Wide receiver receiving yards	69	587	614.04	1.49	268.52	307	1,718	5.25	567	3.50	.13	.12
Junior												
Quarterback interceptions	37	9	8.43	.73	4.20	1	22	5.00	9	3.50	.17	.08

continued

TABLE 4 (continued)

Dataset	*n*	Med	*Mean*	Skew	*SD*	Min	Max	#*SD*s	x_{min}	α	K–S	*p*
Quarterback passing touchdowns	37	18	18.95	.47	9.19	4	39	3.81	18	3.50	.13	.39
Quarterback passing yards	37	2,419	2,514.14	.38	1,086.71	1,103	4,662	3.28	2,094	3.50	.17	.15
Running back rushing touchdowns	78	6	7.03	1.12	4.85	1	23	4.54	8	3.47	.12	.19
Running back rushing yards	78	619.5	740.56	1.38	364.08	338	1,885	4.25	497	3.05	.11	.03
Tight end receiving touchdowns	21	4	3.86	.03	2.15	0	8	3.72	4	3.50	.13	.47
Tight end receiving yards	21	454	519.14	2.37	238.37	311	1,352	4.37	340	3.50	.15	.43
Wide receiver receiving touchdowns	121	4	4.82	.89	3.61	0	16	4.43	7	3.50	.10	.32
Wide receiver receiving yards	121	608	686.20	1.00	321.08	311	1,730	4.42	534	3.33	.10	.07
Senior												
Quarterback interceptions	47	8	9.04	.32	2.60	5	14	3.46	7	3.50	.14	.06
Quarterback passing touchdowns	47	17	18.40	1.08	8.75	6	50	5.03	19	3.50	.16	.04
Quarterback passing yards	47	2,516	2,560.57	.32	868.46	1,011	5,082	4.69	1,995	3.50	.17	.03
Running back rushing touchdowns	67	6	7.09	.66	4.91	0	21	4.28	5	2.42	.15	.00
Running back rushing yards	67	574	767.54	1.11	416.85	343	2,177	4.40	343	2.48	.12	.01
Tight end receiving touchdowns	11	4	4.64	2.21	3.64	2	15	3.57	3	2.78	.11	.71
Tight end receiving yards	11	423	472.09	1.00	152.47	313	821	3.33	313	3.50	.13	.94
Wide receiver receiving touchdowns	109	4	4.85	.73	3.06	0	15	4.91	6	3.50	.11	.09
Wide receiver receiving yards	109	583	649.13	.69	279.10	308	1,477	4.19	308	2.52	.14	.00

Note. n = sample size; med = median; SD = standard deviation; min = score with the smallest value (minimum); max = score with the largest value (maximum); #*SD*s = number of standard deviations included in the range of the distribution; x_{min} = the lower bound value in the distribution above which the power law fits best; α = scaling exponent (i.e., parameter) of the power law curve (the lower the value, the heavier the tail of the distribution); K–S = Kolmogorov–Smirnov goodness-of-fit statistic (the lower the value, the higher the probability of an underlying power law distribution); p = statistical significance for the K–S statistic (the higher the value, the better the fit with an underlying power law distribution); NCAA = National Collegiate Athletic Association. Our dataset initially also included sophomore tight end receiving touchdowns and freshman tight end receiving touchdowns, but analyses did not converge due to small sample size (i.e., $n = 5$ and $n = 6$, respectively). All data acquired from http://stats.ncaa.org.

TABLE 5

Supplementary Analyses: 2013 NCAA Football and NFL Player Productivity Distribution Descriptors Using Residual Scores Accounting for Class (NCAA) and Age (NFL)

Dataset	n	Med	*Mean*	skew	*SD*	Min	Max	# *SD*s	x_{min}	α	K–S	p
NCAA												
Quarterback interceptions	134	–.07	.00	.39	3.45	–7.83	13.34	6.15	5.17	5.45	.10	.94
Quarterback touchdowns	134	–1.99	.00	.97	8.60	–13.36	30.89	5.15	13.64	4.93	.12	.61
Quarterback passing yards	134	–160.22	.00	.55	919.12	–1,587.22	2,483.78	4.43	1,480.54	6.08	.13	.52
Running back rushing touchdowns	244	–.86	.00	1.32	4.70	–7.35	24.64	6.80	10.65	5.05	.09	.97
Running back rushing yards	244	–115.50	.00	1.28	355.09	–439.69	1,394.31	5.16	338.31	2.87	.11	.04
Tight end touchdowns	43	–.50	.00	1.91	2.40	–4.01	10.50	6.06	1.97	3.02	.14	.80
Tight end yards	43	–43.28	.00	2.55	193.88	–199.87	866.33	5.50	64.13	2.04	.16	.44
Wide receiver receiving touchdowns	330	–.73	.00	1.34	3.38	–5.03	19.57	7.28	2.57	2.82	.12	.00
Wide receiver receiving yards	330	–58.77	.00	1.08	287.78	–372.42	1,108.17	5.14	252.58	2.82	.12	.00
NFL												
Quarterback interceptions	85	–1.32	.00	1.06	6.46	–7.95	19.78	4.29	3.78	2.47	.14	.10
Quarterback passing touchdowns	85	–3.80	.00	.93	11.08	–19.54	36.41	5.05	16.03	5.40	.10	.86
Quarterback passing yards	85	–507.32	.00	.52	1,574.58	–2,706.58	3,439.25	3.90	2,702.25	15.22	.11	.96
Wide receiver receiving yards	458	–136.66	.00	1.59	333.03	–417.73	1,420.19	5.52	426.13	3.08	.12	.01
Running back rushing yards	307	–140.97	.00	2.17	306.10	–213.24	1,412.31	5.31	465.86	3.18	.14	.02
Defensive sacks	390	–1.02	.00	1.92	3.01	–3.49	16.09	6.50	6.83	5.39	.12	.31
Field goals	34	.12	.00	–1.05	7.97	–23.38	12.62	4.51	7.62	5.39	.22	.29
Fumbles	307	–.81	.00	1.87	2.35	–3.28	10.46	5.84	4.19	3.84	.13	.12
Kick return yards	195	–115.63	.00	2.48	251.11	–183.01	1,257.37	5.74	258.75	2.68	.11	.31

Note. n = sample size; Med = median; *SD* = standard deviation; Min = score with the smallest value (minimum); Max = score with the largest value (maximum); #*SD*s = number of standard deviations included in the range of the distribution; x_{min} = the lower bound value in the distribution above which the power law fits best; α = scaling exponent (i.e., parameter) of the power law curve (the lower the value, the heavier the tail of the distribution); K–S = Kolmogorov–Smirnov goodness-of-fit statistic (the lower the value, the higher the probability of an underlying power law distribution); p = statistical significance for the K–S statistic (the higher the value, the better the fit with an underlying power law distribution); NCAA = National Collegiate Athletic Association; NFL = National Football League. College (NCAA) data acquired from http://stats.ncaa.org/. Professional (NFL) data acquired from http://pro-football-reference.com.

stars, their pervasiveness, and factors associated with a precise shape of the productivity distribution—and would go beyond a conclusion that a distribution is simply normal or nonnormal. As noted by Van Maanen, Sørenson, and Mitchell (2007), however, increasing the precision of our theories necessitates more precise measurement tools. In fact, it is not possible to develop more precise theories without more precise methodological approaches (Edwards & Berry, 2010). Accordingly, to study and predict the distribution of individual productivity and proportion of productivity stars, there is a need to use measurement tools that assess the precise shape of the productivity distribution. Only such precision would allow for tests of hypotheses and theories about factors associated with different distribution shapes.

Our study makes a contribution to our understanding of when the distribution of individual productivity is more likely to follow a power law curve and, concomitantly, a greater proportion of productivity stars is likely to be observed (i.e., distributions with heavier tails). We proposed that the principle of cumulative advantage, which is often considered to be an axiom in a wide range of scientific fields such as economics, physics, and finance, among others, serves as an explanation for the presence of heavy-tailed productivity distributions in OBHRM and applied psychology. Specifically, we hypothesized five different factors that serve as conductors (i.e., enhancers) or insulators (i.e., inhibitors) of the proportion of star performers and heavy-tailed distributions. As recently noted by Ford, Hollenbeck, and Ryan (2014), in addition to a person's characteristics, "work behavior also is influenced by the features or structures surrounding work—task, technologies, climate, culture, and other context features that combine and recombine over time to affect work behavior" (p. 4). Our results show that features and structures surrounding work including multiplicity of productivity, monopolistic productivity, job autonomy, and job complexity (i.e., conductors) are associated with greater conformity to an underlying power law distribution, whereas lower productivity ceilings (i.e., insulator) are associated with less conformity to an underlying power law distribution. In addition, higher levels of multiplicity of productivity, monopolistic productivity, and job autonomy were associated with a greater proportion of productivity stars (i.e., productivity distributions with heavier tails), whereas lower productivity ceilings were associated with a smaller proportion of productivity stars (i.e., productivity distributions with lighter tails).

Before we discuss the implications of our study, we offer two case studies that illustrate our general results regarding the presence of power law distributions and productivity stars. First, at the close of the 2013–2014 National Hockey League regular season, 570 skaters played in at least half of the games (National Hockey League, 2014). The mean number of goals per player was 10.86, and the standard deviation was 8.76. Under a normal curve, the likelihood of scoring 37 or more goals (3 standard deviations above the mean) is approximately 1 in a 1,000 ($p = .0013$). Thus, with 570 skaters, we should see this feat completed every couple of seasons. Instead, six players did this in the 2013–2014 season alone. Furthermore, under a normality assumption, the probability of Alex Ovechkin's 51 goals in the regular season was .000002. With 570 players on the ice, this should occur approximately once every 800 years. Instead, Steven Stamkos scored 60 goals in the previous full 82 game season (something that should occur about once every 175,000 seasons). Professional hockey players may be considered an exception given that they are an elite set of workers. So, as a second case, consider data on the productivity of 219 sales representatives reported by Grant et al. (2011). The mean revenue was $124.19/hour, and the standard deviation was $112.18. Based on a normal distribution, only 1 in a 1,000 employees should generate more than $461/hour in revenue. Instead, five of the 219 sales representatives exceeded $500/hour, 20 times more frequent than that predicted under a normal distribution. The top sales representative generated $572.06/hour; in a normal distribution, this has a probability of occurring of .00003, or 1 in 30,562. These examples illustrate the presence of productivity stars who, under an assumed normal distribution, should simply not exist. In other words, a normal distribution renders them effectively impossible—yet, our results show that these productivity stars are observed quite frequently across types of occupations, jobs, and productivity measures.

Implications for Theory and Future Research

A meta-theoretical principle transcends specific topics or domains of study and describes and predicts phenomena in more abstract terms and at a higher level than specific theories (e.g., Blumberg & Pringle, 1982; Richter, 1986). Accordingly, the value of a meta-theoretical principle lies in its ability to account for empirical observations across a wide variety of contexts and situations (Pierce & Aguinis, 2013).

Our results offer a building block for future theory development and testing efforts regarding the shape of the productivity distribution and the proportion of productivity stars. Our study illustrates the usefulness of using cumulative advantage as a metatheoretical principle to derive hypotheses about particular conductors and insulators. Specifically, features of the work context including multiplicity of productivity and monopolistic productivity serve as conductors of heavy-tailed distributions and contribute to the emergence of a greater proportion of productivity stars. Job autonomy, a feature of work itself, also serves as a conductor. On the other hand, another job characteristic—productivity ceiling—serves as an insulator. Admittedly, we assessed four potential conductors and one insulator only. However, cumulative advantage can be used to derive additional hypotheses. For example, to what extent do features of an individual's network serve as conductors? Particularly dense networks may reduce the ability of stars to dominate production over newcomers and incumbents alike via information asymmetry (Morrison, 2002). Other network features such as status and size may also serve to affect the overall productivity distribution (Inkpen & Tsang, 2005). More generally, contexts and jobs that involve interdependence among individual workers, ongoing interactions, past productivity leading to more opportunities to produce in the future, and, overall, past success influencing future success are likely to be associated with power law rather than normal distributions and a greater proportion of productivity stars (Schroeder, 1991; Vasconcelos, 2004).

In addition, our results suggest a broad research agenda for the future with the goal of gaining a more comprehensive understanding of conductors and insulators as well as their relative importance in various types of contexts. For example, we found that the conducting effect of monopolistic productivity on the probability of an underlying power law ($r = -.67$) was as strong as that of the insulating effect of productivity ceiling ($r = .72$). On the other hand, job complexity had a smaller conducting effect on the probability of an underlying power law ($r = -.15$). What are the factors that make certain conductors and insulators particularly strong? One element that could influence the strength of conductors and insulators is the operationalization of productivity. As we discussed previously, we adopted a results-based definition of productivity. The literature on job characteristics suggests that job autonomy, job complexity, and interdependence are all positively related to subjectively rated performance (i.e., measures of behavior; Humphrey et al., 2007), but there is a need to determine whether the conductors and insulator we identified also relate to power law emergence when productivity is operationalized as behavior. In addition, looking to the future, our results and the cumulative advantage principle can be used in combination with other established conceptualizations, such as resources-based theory, to build more comprehensive theories of productivity that address not only individual but also firm-level productivity.

Related to the presence of conductors and insulators as well as their relative importance in various types of contexts is the question: What leads to early success? As noted earlier, Kell et al. (2013) argued that the cumulative advantage process may begin before age 13. A related question is: When can KSAs compensate for early opportunity to perform? For example, in the specific domain of scientific research, there are some academics who have had slow starts (i.e., no publications upon graduating) yet have become stars—as well as the converse.

Our study also has implications for future research aimed at understanding conditions under which heavy-tailed distributions and productivity stars emerge—and also when they may tend to disappear. Specifically, using the more precise model fitting procedure used in our work, which conceptualizes the shape of the productivity distribution as a continuous underlying construct, will allow for precise tests of hypotheses—regardless of whether hypotheses involve conductors, insulators, other types of predictors, or outcomes of various distribution shapes. For example, to what extent does hiring stars lead to a contagion effect whereby stars' productivity improve their colleague's performance (e.g., Oettl, 2012)? Can stars transport their high level of productivity to other contexts that may differ regarding the presence of conductors and insulators (e.g., Groysberg, Lee, & Nanda, 2008)? Is the presence of too many stars (e.g., an extremely heavy-tailed distribution) associated with negative outcomes at the group or firm levels of analysis (e.g., Groysberg, Polzer, & Elfenbein, 2010)? What are the insulators that may actually nullify and even reverse the effects of conductors and turn heavy-tailed distributions into normal or pseudo normal distributions (e.g., Azoulay, Zivin, & Wang, 2010; Oldroyd, & Morris, 2012)? Does the turnover of productivity stars offer an early sign that can be used to predict future organizational decline (Bedeian & Armenakis, 1998)? Using the novel methodological approach described in our paper allows us to seek empirically based answers for these and many other questions, which are simply not possible to answer by limiting the measurement of the shape of the productivity distribution to an artificial dichotomization of normal versus nonnormal, as has been done in this area of research to date.

In addition to the implications for theory and research about the productivity distribution and productivity stars, our study also has implications for a number of more specific research domains. First, consider personnel selection research. Cascio and Aguinis (2008b) concluded that changes in the nature of work and organizations in the 21st century including the rise of the Internet, increased globalization, and the weakening of organizational hierarchies have placed a plateau in terms of our ability to make accurate predictions about individual productivity. Using the cumulative advantage metatheoretical principle, many of the changes in the nature of work discussed by Cascio and Aguinis (2008b) can be conceptualized as conductors. For example, the Internet, globalization, and flatter organizational structures all allow for more frequent interactions as well as allowing small initial differences to turn into large differences faster. Our study suggests a research agenda in the particular domain of personnel psychology to attempt to understand how the principle of cumulative advantage, combined with the increased impact of conductors, may increase the proportion of productivity stars. In turn, this understanding may lead to the development of novel predictors of productivity that place individuals within particular contexts—what Cascio and Aguinis (2008b) labeled "*in situ* performance."

As a second specific research domain, consider the area of training and development. Transfer of training is considered one of the most important predictors of posttraining productivity improvement (Blume, Ford, Baldwin, & Huang, 2010). Research in this domain has focused on individual characteristics that may predict future productivity improvements—most notably, general mental abilities. Our study suggests a novel research agenda for future training and development research addressing questions such as: What are the conductors and insulators of the process in which initial, pretraining differences in productivity amplify into subsequent, posttraining differences in productivity for various trainees?

Implications for Practice

Recognition of the principle of cumulative advantage has the potential to change the lens through which managers and other organizational decision makers view productivity at work. Building on the notion of in situ productivity mentioned earlier (Cascio & Aguinis, 2008b), opportunity to perform, network position, and other factors serve as conductors or insulators of cumulative advantage and, therefore, lead to productivity differentials among employees. Thus, the design, implementation, and evaluation of outcomes of mentoring programs, training and development interventions, and motivation systems, including compensation and rewards, aimed at improving productivity need to consider how they are likely affected by various conductors and insulators.

Another implication for organizations and managers is the need to understand the extent to which productivity differentials translate into value-added differentials (Aguinis & O'Boyle, 2014). For example, the scaling exponent for Emmy nominations for the writing category is similar to the exponent for Emmy nominations for cinematography. From the perspective of a Hollywood studio, is it more valuable to attract and retain star writers or cinematographers? Both distributions include a similar proportion of productivity stars, but the value added of their productivity for the organization may not be the same. Given such, a studio may choose to allocate more resources to attract and retain writing stars if they add more value to the studio compared to cinematography stars. Regardless of the particular strategic decision, becoming aware of the shape of the productivity distribution, and not assuming normality, is a necessary first step before such decisions can be made.

Our study also has implications for personnel selection practices. As mentioned earlier, most personnel selection theories rely on the notion that the most important predictor of future productivity is a job applicant's KSAs. This might be the case because, in selection contexts, information about past productivity is frequently unreliable or impossible to obtain. As noted by an anonymous reviewer, it is a well-known truism, particularly among personnel selection practitioners, that "the best predictor of future performance is past performance." This motto is consistent with an underlying cumulative advantage principle, albeit it is not often mentioned or acknowledged explicitly. Thus, our study that uses cumulative advantage as the conceptual framework provides further support to this longstanding, yet often implicit, belief that seems to guide selection decisions frequently.

The presence of nonnormal productivity distributions also has implications for compensation practices. In particular, pay dispersion may be seen as more acceptable and fair to employees if they are aware that the distribution has a heavy tail (i.e., a large proportion of productivity stars). Thus, it may be beneficial to share information on the shape of the productivity distribution with various organizational members. However, if the compensation system does not offer additional rewards to productivity stars, productivity information may lead to dissatisfaction among those individuals who are the top producers—possibly leading to a decrease in their productivity or even departure from the organization. Thus, it is important to consider the anticipated consequences of making information on productivity distributions available.

Our results also have implications for individuals who may be interested in becoming productivity stars. First, the existence of insulators such as productivity ceilings will prevent these individuals from achieving their goal. On the other hand, organizational contexts and jobs where conductors are present are more likely to allow those individuals to become productivity stars. Thus, it is important to consider the fact that certain work and organizational contexts are more conducive than others in terms of allowing an individual to realize his or her dream of becoming a productivity star. Second, the emergence of productivity stars is affected not only by work and organizational contexts and the characteristics of jobs but also other issues such as opportunity to produce. So, individuals interested in becoming productivity stars need to be constantly alert regarding new and more opportunities—for example, by establishing social networks and gathering information from the environment. In short, achieving productivity stardom will not depend only on one's job-specific KSAs.

Limitations

An important boundary condition for our conclusions is that our conceptualization and operational definition of performance is based exclusively on results. There is an empirically documented nontrivial relationship between performance defined as behavior and performance defined as results for individuals (Bommer et al., 1995) as well as for teams (e.g., Beal et al., 2003). Nevertheless, our results are not directly informative regarding the shape of the distribution when performance is not defined in terms of results.

Another limitation of our study relates to the nature of our research design. Cumulative advantage is a general process by which small initial differences compound to yield large differences over time. Moreover, cumulative advantage may unfold over long periods of time. For example, although market analysts such as Warren Buffett are synonymous with the word "star," it took many years of accumulated wealth and knowledge in the investment business before he possessed the star power to shift markets and bail out entire corporations such as Goldman Sachs and Mars/Wrigley (Das, 2013). Within our own data, we see examples such as movie actors, directors, and producers who operate in an industry with a heavy-tailed productivity distribution. This is because, referring back to our own results, the movie business is high on monopolistic production, multiplicity of productivity, job autonomy, and job complexity—and has little ceiling to productivity. For example, Tom Hanks produces (i.e., funds) many of his own movies. He is able to do so because his past performance has generated personal wealth, and he has demonstrated an ability to do a job with high complexity quite well. His star power also allows him to work as much as he likes and dictate terms such as time spent on set and number of takes, thus allowing both more opportunities to act (multiplicity of performance and high productivity ceiling) and greater discretion in what movies he will act in and how the character will be portrayed (job autonomy). Note that the cumulative advantage that Tom Hanks has was not present until the last 10 to 15 years. For more than a decade, Tom Hanks worked primarily in television and made-for-TV movies.

We pause to note that although Warren Buffett and Tom Hanks are unquestionably at the far tail of the productivity distribution, our results show that they are not alone. The number of academics, collegiate and professional athletes, movie directors and producers, writers, musicians, politicians, retail and call center employees, electricians, and grocery checkers who can be classified as productivity stars far exceeds the frequency predicted using a Gaussian curve. But, our research design did not capture the process of cumulative advantage as it unfolded over time.

However, what our data show is the end result of the cumulative advantage process: distributions in which a small minority of individuals accounts for a disproportionate amount of the output.

Concluding Remarks

Individual productivity is a central domain of research and practice in OBHRM, I-O psychology, and many other fields. The principle of cumulative advantage, which is pervasive in so many scientific fields, can be used as a metatheoretical and foundational framework to understand the presence of productivity stars and distributions that deviate from normality. Our identification of four conductors and an insulator of cumulative advantage can be used as a building block for a research agenda aimed at understanding when, why, and how heavy-tailed distributions and productivity stars are more likely to emerge. This research agenda will be facilitated by the use of the more precise procedure that we used in our paper to assess the shape of the productivity distribution. This research agenda can also serve as a conduit to address more specific questions in research domains also directly related to individual productivity such as personnel selection, training and development, and compensation, among others. Ultimately, a greater theoretical understanding of the presence of productivity stars and heavy-tailed productivity distributions is likely to lead to more effective organizational practices linking individual and firm-level productivity.

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