Methodological Brief

A Methodological Guide for Quantitative Analysis of Star Performance in Entrepreneurship

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Abstract

Entrepreneurial performance is often right-skewed and heavy-tailed, yet empirical studies typically focus on average outcomes, assuming normality. Recent research addresses this by examining full performance distributions. We extend this work by introducing an intuitive framework with three distinct characteristics of distributional tails: (a) tail impact, the contribution of star performers relative to the rest; (b) tail extremity, the extent by which the highest performer exceeds the typical performer; and (c) tail frequency, the fraction of performers who are stars. We outline a methodological guide, offer illustrative examples, and provide R code to enrich future investigations of star performance in entrepreneurship.

Keywords

star entrepreneurs, star performers, outliers, right-skewed and heavy-tailed performance distributions, distributional shapes and tail characteristics

Introduction

In many entrepreneurial contexts, a few star performers consistently outperform typical performers (Crawford et al., 2015; Decker et al., 2014; Gala & Schwab, 2024; Shane, 2009). Consequently, the performance distributions for a pool of entrepreneurial individuals, teams, or firms are often right-skewed and heavy-tailed (Crawford, Joo, & Aguinis, 2024; Gala et al., 2024). In other words, when entrepreneurial performance is plotted as a distribution, it is highly asymmetric and has an extended right tail.[1] These distributional characteristics create challenges for entrepreneurship research that seeks to identify drivers of success based on their impact on *average* performance (Dean et al., 2007; Gala & Schwab, 2024). Indeed, average-centric studies not only leave variance unexplained and weaken the robustness of empirical findings but also inhibit the development of evidence-based theories of star performance (Beamish & Hasse, 2022; Gibbert et al., 2021; Ruef &

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Birkhead, 2024). Therefore, it is critical to supplement such studies with studies that capture the full range of performance and explicitly investigate star performance (Clark et al., 2023; Hymer & Smith, 2024).

Beyond entrepreneurship research, scholars have drawn attention to star performers in other organizational contexts (Aguinis & O'Boyle, 2014; Aguinis et al., 2013). These studies have inspired research that adopts a *distributional perspective* (i.e., explicitly investigates the full range and extremity of performance) and introduces methodologies to capture variability in performance (Certo et al., 2024). Crawford, Joo, and Aguinis (2024) compiled a comprehensive list of such studies and distribution-focused methodologies. For specific entrepreneurial contexts, research has identified distributional shapes (e.g., lognormal) that best characterize the observed performance distributions and linked these shapes to specific underlying *generative mechanisms*, that is, the factors and processes that may explain the emergence of star performers (Gala et al., 2024).

Despite these scholarly efforts and methodological advances, most empirical entrepreneurship studies do not explicitly investigate star performers or directly examine performance distributions. Only a few studies report relevant statistics, such as skewness (Gala & Schwab, 2024). Others simply log-transform the outcome variables without explicit theoretical justification or interpretation of effect sizes (Becker et al., 2019; Rönkkö et al., 2022).

Several reasons may explain why scholarly attempts to adopt a distributional perspective in quantitative empirical studies have been impeded. First, this focus on performance distributions is relatively new to entrepreneurship research. Thus, the required analytical frameworks and methodological approaches are not (yet) well-established in entrepreneurship research (Crawford, Joo, & Aguinis, 2024). Second, the traditional distributional properties, such as skewness and kurtosis, do not lend themselves to intuitive examinations of star performance and subsequent interpretation of empirical findings to inform entrepreneurship practice and policy (Berglund et al., 2018). Instead, studies of star performance would benefit from a multifaceted conceptualization and investigation of distributional tails because star performance can manifest in different forms, ranging from a single extreme performer to many different configurations of exceptional performers.

To address these issues, this *methodological brief* introduces an intuitive framework and related analytical guidance for future empirical investigations of star performance. This brief is organized as follows. First, we outline the primary levels of analysis when adopting a distributional perspective. Next, we review the statistical properties commonly used to estimate variability. Then, we introduce three interrelated yet distinct features of distributional tails and ways to operationalize them. We outline how these tail characteristics provide a more comprehensive understanding of star performance, thus enabling a richer interpretation of empirical observations. Finally, we use data for Inc. 5000 companies (2021 edition) to illustrate the application of this framework to capture star performance in entrepreneurship. In Supplemental Appendix 1, we also provide corresponding R code to help scholars apply the introduced framework to their datasets.

The primary contribution of this study is the introduction of a framework and related methodology to capture nuances of performance distributions. The suggested tail characteristics promise new theoretical and empirical insights into star performance in entrepreneurial settings. Table 1 situates this study amidst related research in entrepreneurship. As shown, prior entrepreneurship research that adopted a distribution perspective has ranged from conceptual and inductive qualitative studies to quantitative studies that involve exploratory analyses or hypothesis development and testing. Our contribution is best categorized as "methodological development" that expands the scope of empirical studies to

Table 1. Types of Studies of Performance Distributions and Outliers.

Type of study	Exemplar studies	Independent variable	Mechanism(s) or model(s)	Dependent variable: Star performers	Dependent variable: Performance distributions
Conceptual study	Andriani and McKelvey (2009)	-	Sixteen plausible mechanisms	-	Power laws
	Clark et al. (2023)	-		Research directions	-
Inductive qualitative study	Ruef et al. (2023)	-	Mechanisms of survival and success	Single case	-
Exploratory quantitative study	Booyavi and Crawford (2023)	Gender	-	Stars versus non-stars	Power laws
	Crawford (2013)	-	Agent-based model	-	Power laws
	Crawford et al. (2015), Crawford, Joo, and Aguinis (2024)	-	-	-	Power laws; Multiple distributional shapes
	Crawford Linder, et al. (2024b)	New venture execution strategies	-	Stars versus non-stars	-
	Lu and Dimov (2023)		System dynamics	-	Distributional properties
	Khurana et al. (2023)	Gender		-	Distributional differences
Quantitative hypothesis testing study	Gala et al. (2024)	Domain characteristics	Proportional differentiation	-	Multiple shapes, lognormal parameters
Methodological development study	Aguinis et al. (2013)	-	-	Defining, identifying, and handling outliers	-
	Gala and Schwab (2024)	-	-	Inferring the prevalence of star performers	Inferring distributional properties and shapes
	This study	-	-	**Identifying star performers**	**Examining distributional properties, shapes, and tails**

distributional shapes and tails. Moreover, the proposed tail characteristics—tail impact, tail extremity, and tail frequency—promise nuanced insights into star performance for entrepreneurship theory and practice.

Primary Levels of Analysis When Examining Variability in Entrepreneurial Performance

A distributional perspective on performance explicitly examines the full range of outcomes, not only the mean and standard deviation (*SD*), for a given population of performers. When adopting a distributional perspective, empirical studies of entrepreneurial performance choose from two primary levels of analysis. The first level is that of *performers*, that is, individuals, teams, or ventures whose performance warrants deeper understanding, explanation, and prediction. Here, the focal dependent variable is performance, and studies typically examine how one or more antecedents influence performance (Crawford, Linder, et al., 2024). For example, a study might examine how customer ratings influence the relative performance of sellers in a specific product category on Amazon.com. For this level, a distributional analysis starts by evaluating the variability in performance using statistical techniques, then locates star performers in the distribution, and finally compares them with typical performers. Such studies can use quantile regression or additive nonparametric regression to test whether and how the influence of antecedents differs for star performers versus others (Fox, 2005; Li, 2015). Instead of focusing on predicting average performance or imposing a functional (e.g., linear) form on the relationship between a predictor and performance, these techniques provide flexibility in capturing heterogeneous effects across the distribution and uncovering nonlinear patterns that may be overlooked in average-focused analyses.

The second relevant level of analysis is that of *pools of performers*. Such research shifts the focus of investigation to entire ecologies of performers, such as industries, markets, or product categories, wherein firms compete for survival, growth, and profits (Aldrich & Martinez, 2001). For example, a study might examine how the competitive intensity in a product category on Amazon.com influences the performance distribution for entrepreneurs operating in that category. Thus, the emphasis is on "*many interacting firms in particular selection environment*," and "*it is ultimately the fates of populations that are of concern, not the fates of firms*" (Nelson & Winter, 1982, p. 410). Accordingly, the focal dependent variable can be a distributional property, such as skewness or kurtosis, and related studies examine how antecedents influence key characteristics of performance distributions (Aguinis et al., 2016; Gala et al., 2024).

Statistical Properties to Evaluate Variability in Performance

Any investigation of star performance, regardless of the chosen level of analysis, ought to start with empirical probing of the focal dependent variable: performance. Such examination begins by graphically plotting the performance distribution (Wennberg & Anderson, 2020). Then, a set of established statistical properties should be estimated to develop an initial understanding of the distribution; see Table 2 for a summary. We briefly discuss these properties below.

Table 2. Statistical Measures of Central Tendency and Variability of Performance.

Statistical measure	Key question	Sensitivity to an extremely high value	Type of estimate
Mean	What is the average performance?	High	Unit-based
Median	What is the typical (i.e., most likely) performance?	Low	Unit-based
Mode	What is the most common performance	Low	Unit-based
Minimum	What is the worst performance?	Low	Unit-based
Maximum	What is the best performance?	High	Unit-based
Standard deviation	How much does the performance vary around the mean?	High	Unit-based
Median absolute deviation	How much does the performance vary around the median?	Low	Unit-based
Quantile absolute deviation	How much does the performance vary around the specified quantile?	Low	Unit-based
Coefficient of Variation	How much does the performance vary around the mean?	High	Unitless
Gini coefficient	How unequally distributed is the performance?	Moderate	Unitless
Skewness	How asymmetric is the distribution of performance?	Moderate	Unitless
Kurtosis	How heavy are the tails of the distribution of performance?	High	Unitless

Central Tendency: Mean, Median, and Mode

The first property estimated when examining variability is the central tendency. Research has traditionally used the *mean* of performance to represent the typical performer to test hypotheses about how one or more antecedents influence performance, on average. However, methodologists have highlighted the limitations of the mean as a measure of central tendency for right-skewed and heavy-tailed distributions (Leys et al., 2013). For example, a single extreme value can substantively shift the average value for a distribution (Aguinis et al., 2013). When outliers,[2] or extreme data points, carry disproportionate influence, the *median* is considered a more robust estimate of central tendency than the mean (Hartwig et al., 2020; Wilcox & Keselman, 2003). Furthermore, the mode captures the value that appears most frequently in a distribution. Although less commonly used in entrepreneurship research, the mode can provide insights into identifying clusters of performers, such as a multimodal performance distribution. The relative position of the mean, the median, and the mode offers rudimentary information about the nature of asymmetry of a distribution.

Range: Maximum and Minimum

Next, researchers should examine the maximum and minimum values of performance. The highest observed value of performance represents the best empirical estimate for maximum performance. However, this estimate is often conservative for right-skewed, heavy-tailed distributions and may substantially underestimate the feasible maximum performance (Taleb, 2020). Conversely, when the minimum observed performance is zero, empirical analyses must account for left-censoring, particularly if zeros represent a substantive fraction of performers. For example, removing observations where the value of performance is zero will artificially inflate the estimates of median and mean performance (Hunt & Lerner, 2017).

Variability: SD and Median Absolute Deviation

The *SD* is the most commonly used measure of variability in entrepreneurship research. Because its definition involves deviations from the mean, its estimation is vulnerable to extreme observations because the observed deviations from the mean are squared before averaging. To mitigate this issue, statisticians recommend using variants of the median absolute deviation (MAD), which involves neither squared terms nor averaging and is, therefore, more robust for highly skewed distributions (Rousseeuw & Croux, 1993; Rousseeuw & Hubert, 2011).

Inequality: Coefficient of Variation and Gini Coefficient

A commonly used unitless measure of inequality is the Coefficient of Variation (CoV), estimated as the ratio of the *SD* to the mean (Allison, 1978; Kokko et al., 1999). Because it focuses on the mean as the measure of central tendency, the CoV is also sensitive to extreme observations (Arachchige et al., 2022). Nevertheless, it can be a diagnostic tool to tentatively infer the functional form of performance distributions (Certo et al., 2020; Cirillo, 2013; Gala & Schwab, 2024).

Another measure of inequality frequently used in organizational research is the Gini coefficient, which ranges from 0 to 1 and is *not* centered on the mean (Harrison & Klein, 2007). In contrast to the CoV, which indicates the spread or volatility of univariate data around the mean, the Gini coefficient focuses on the overall inequality by assessing all possible pairs of values in the data. Thus, an extreme observation is more likely to disproportionately increase the CoV, whereas the Gini coefficient is relatively more robust to extreme values. The Gini coefficient has traditionally been used in finance and economics research that examines the influence of factors such as geography or government policy on income and wealth inequality (Oancea & Pirjol, 2019). This statistic has been applied to similar investigations in entrepreneurship research (Xie et al., 2023).

Skewness and Kurtosis

Skewness and kurtosis are the third and fourth moments of a distribution, with skewness reflecting asymmetry and kurtosis reflecting extremity (DeCarlo, 1997; Doane & Seward, 2011). Put simply, skewness indicates whether the data are lopsided, while kurtosis indicates how pronounced the extreme highs and lows are relative to the average. A skewness of 0 indicates a perfectly symmetric distribution, as illustrated in the middle panel of Figure 1. Negative skewness reflects a longer left tail, whereas positive skewness reflects a longer right tail. In entrepreneurial contexts, the distribution of performance—when captured using continuous and positive scales—commonly features right-skew, wherein the mean is substantially greater than the median because extreme observations strongly influence the mean (Gala & Schwab, 2024).

Kurtosis captures the "tailedness" of a distribution (Westfall, 2014). As illustrated in Figure 2, a platykurtic distribution has lighter tails and a flatter peak than a normal distribution, a mesokurtic distribution (like the normal) has moderate tails and peak, and a leptokurtic distribution is sharply peaked with heavy tails, indicating a higher likelihood of

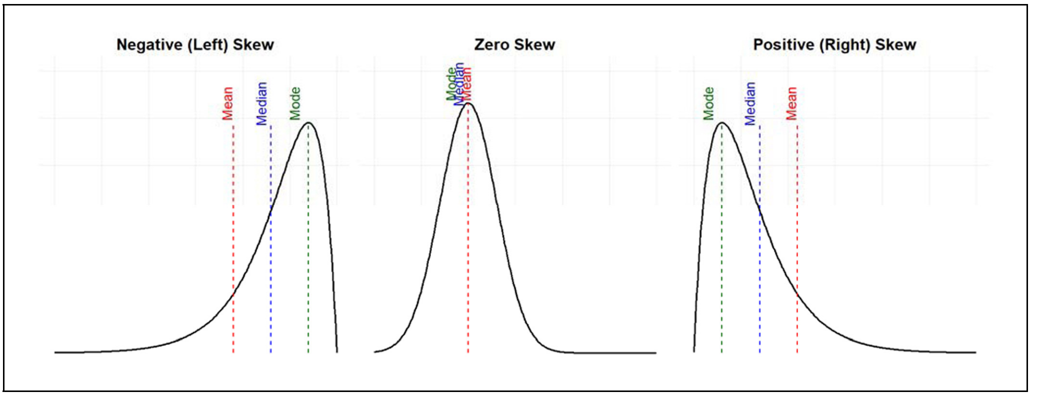

Figure 1. An illustration of positive, zero, and negative skew in distributions.

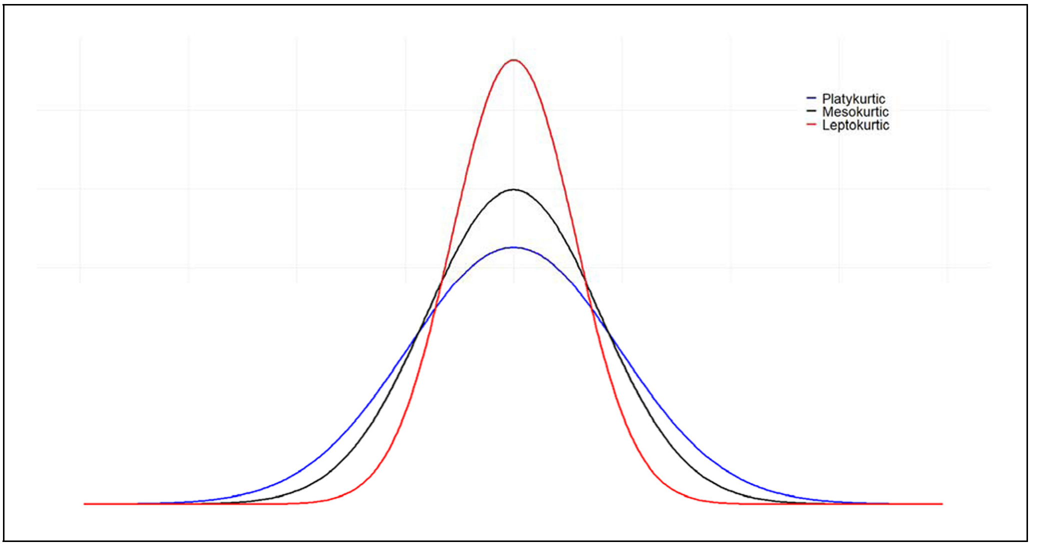

Figure 2. An illustration of varying degrees of kurtosis in distributions.

extreme values. Star performance in entrepreneurship is often characterized by right-skewed and heavy-tailed (i.e., leptokurtic) distributions (Crawford, Joo, & Aguinis, 2024; Crawford et al., 2015).

When evaluating univariate normality, scholars often use skewness > 2 and kurtosis > 7 as heuristic indicators of severe non-normality (West et al., 1995). For example, Gala et al. (2024) report skewness of 16.1 and kurtosis of 358.5 for the distribution of entrepreneurial performance on a digital platform, indicating the prevalence and dominance of star performers. However, statisticians have discussed the challenges in interpreting these abstract statistical properties, which are poor descriptors of overall distributional shapes (Balanda & MacGillivray, 1988; Borroni & De Capitani, 2023; Micceri, 1989). Consequently, these measures provide limited insights into the thickness and extremity of distributional tails (i.e., the presence and relevance of star performers).

Table 3. Equations of Statistical Measures of Central Tendency and Variability.

Statistical measure	Computation	R package::function( )
Mean	$\frac{\sum x_i}{n}$	mean( )
Median	Middle value of ordered data	median( )
Mode	Most frequently occurring value	DescTools::Mode( )
Minimum	$\min(x_1, x_2, \ldots, x_n)$	min( )
Maximum	$\max(x_1, x_2, \ldots, x_n)$	max( )
Standard deviation	$\sqrt{\frac{\sum (x_i - \text{Mean})^2}{n-1}}$	sd( )
Median absolute deviation	$\text{median}(\lvert x_i - \text{Median}\rvert)$	mad( )
Quantile absolute deviation[a]	$Q(\lvert x_i - \text{Median}\rvert)$	qad( )
Coefficient of variation	*SD*/Mean	sd( )/mean( )
Gini coefficient	$\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\lvert x_i - x_j\rvert}{2*n*\text{Mean}}$	DescTools::Gini( )
Skewness[b]	$\frac{\sum (x_i - \text{Mean})}{(n-1)*SD}$	e1071::skewness( )
Kurtosis[c]	$\frac{\sum (x_i - \text{Mean})}{(n-1)*SD}$	e1071::kurtosis( )

Note. n = number of observations; x_i = value in the dataset; *SD* = standard deviation.
[a]See Akinshin (2022) for a detailed explanation.
[b]The R function adds a correction for small sample bias to the equation.
[c]Equation corresponds to type = 1 (regular kurtosis, not excess kurtosis).

Nevertheless, skewness and kurtosis have been used as the focal dependent variable in studies where the level of analysis is a pool of performers (Makino & Chan, 2017). Considering the strengths and limitations of these various statistics, researchers can integrate the insights gained from each measure to develop a rudimentary understanding of star performance in their data. Table 3 provides the relevant equations and corresponding R packages for estimation.

Assumed Distributional Shape and Its Parameters

The important next step in examining variability in performance is to assess the entire distribution directly. Seminal organizational research in this direction typically assumed a specific distribution shape, tested the goodness-of-fit between the observed distribution and this shape, and then estimated the relevant parameters. Often, this shape was the "pure power law," a highly asymmetric distribution characterized by a large number of observations well below the mean and a small number of extreme observations that populate the right tail. For example, Aguinis et al. (2016) and Crawford et al. (2015) used the Kolmogorov-Smirnov statistic to test whether the observed performance distributions matched a power law shape; if yes, they estimated the corresponding critical value ($X_{\min}$) and scaling exponent (alpha). Here, $X_{\min}$ represents the minimum value of performance for which the power law holds, and alpha represents the rate of decline in frequency for high values (Clauset et al., 2009). However, assuming a specific shape, especially a pure power law, has been challenged as potentially inaccurate and, therefore, a threat to the accuracy of findings (Broido & Clauset, 2019; Stumpf & Porter, 2012).

Most Likely Distributional Shape and Its Parameters

The limitations arising from only considering a dichotomy of normal versus power law distributions were overcome by a methodological advance: *distribution pitting*. Specifically, Joo et al. (2017) suggested the use of pairwise comparisons between seven shapes (i.e., normal, Poisson, Weibull, exponential, lognormal, power law, and power law with exponential cutoff) to identify the type of distribution most likely to characterize the observed performance data. Notably, the power law with exponential cutoff exemplifies a combination of two distributions, the pure power law and the exponential, indicating the possibility of fitting more complex shapes to empirically observed performance distributions in entrepreneurship.

Joo et al. (2017) also developed the corresponding R package *Dpit* for distribution pitting, a detailed description of which is available in the appendix of Crawford, Joo, and Aguinis (2024). This technique to identify the most likely distribution shape can guide the choice of distributional parameters to be used as focal dependent variables. For example, Gala et al. (2024) used the *Dpit* package and found that the lognormal shape best characterizes the distribution of entrepreneurial performance for most product domains within a digital platform. Therefore, they used the lognormal scale parameter (mu) as a dependent variable—while controlling for the lognormal shape parameter (sigma)—to test hypotheses about the influence of domain-level antecedents on the distribution of performance.

Figure 3 illustrates some distributional shapes using simulated data and shows how the pure power law is associated with the most extreme cases of star performance. Notably, the *stretched exponential* distribution, essentially the Weibull distribution with a shape parameter of less than one, can arise from multiplicative processes, similar to the lognormal distribution (Laherrere & Sornette, 1998). However, this distribution has "lighter" tails than the lognormal, as indicated by the maximum values.

From Distributional Shapes to Generative Mechanisms

Importantly, identifying a specific functional form, such as lognormal or power law, as the best-fitting shape using a distribution-pitting method does *not* necessarily translate into identifying a specific generative mechanism because multiple mechanisms (e.g., phase transition, self-organized criticality) can engender the same distributional shape (e.g., pure power law) (Andriani & McKelvey, 2009). Moreover, comparisons based on goodness-of-fit or maximum likelihood statistics focus on relative rather than absolute fit, implying that the "best" distribution may still inaccurately represent the data. Right-skewed, heavy-tailed distributions are particularly challenging to distinguish in finite samples, as evidenced by re-examining datasets initially believed to follow a power law distribution (Broido & Clauset, 2019; Stumpf & Porter, 2012). Even when statistical evidence strongly supports a specific functional form, distribution-pitting approaches do not explicitly model or test the causal processes that generate the observed distributions.

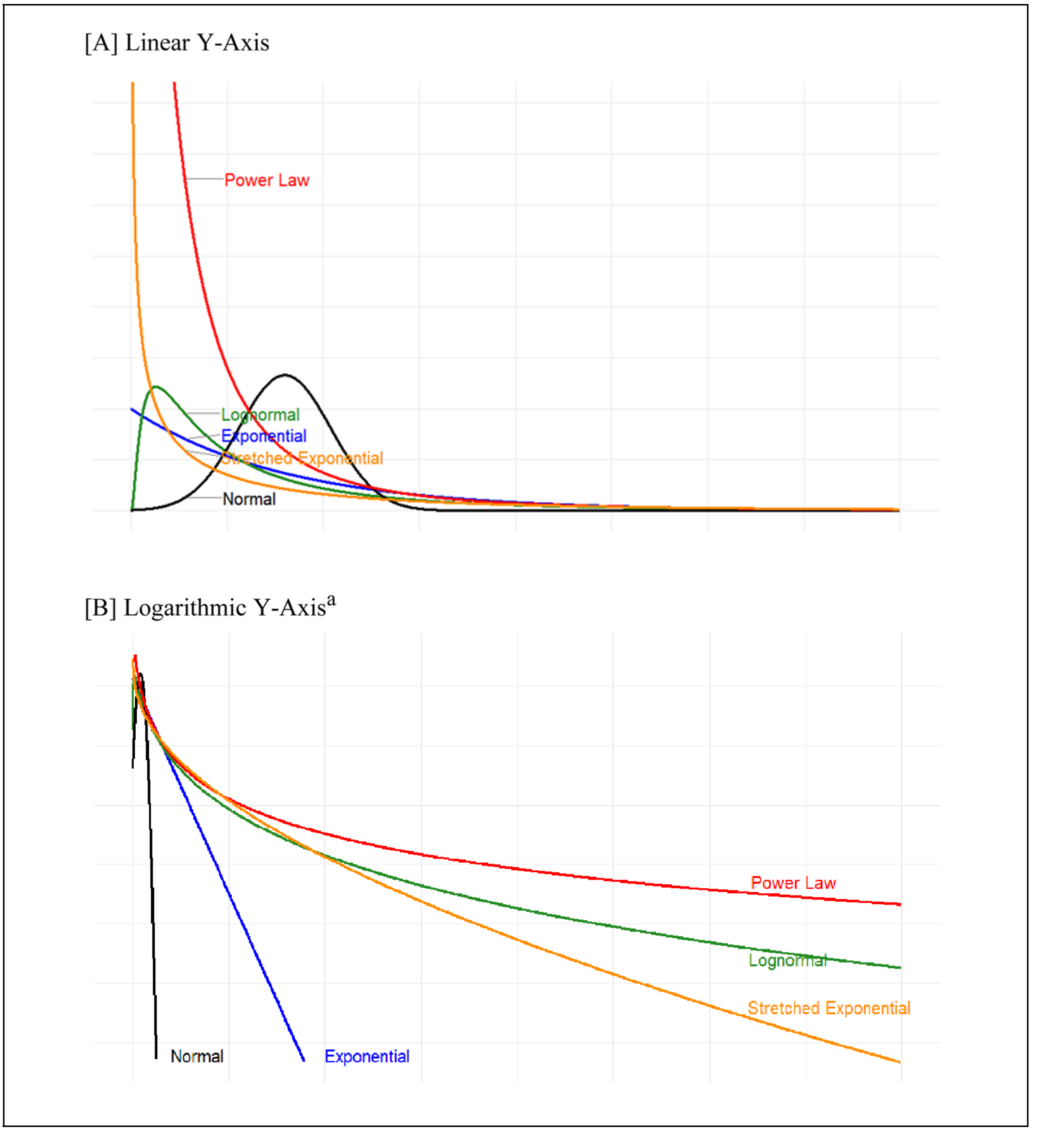

Figure 3. A comparison of distributional shapes using simulated data: (A) Linear Y-axis, (B) Logarithmic Y-axis.[a]

Note. For all distributions, sample size = 10,000, minimum = approximately 0.0, and mean = approximately 2.0. Standard deviation for simulated data: Normal (0.6), Exponential (2.0), Stretched Exponential (3.5), Lognormal (3.3), Power Law (5.4). Maximum for simulated data: Normal (4.6), Exponential (22.3), Stretched Exponential (57.9), Lognormal (83.7), Power Law (197.1). The Exponential (blue) is a straight line of negative slope on semi-log axes.

[a]We thank an anonymous reviewer for suggesting the addition of this figure.

Table 4 draws on prior literature to present a preliminary mapping of multiple generative mechanisms to specific distributional shapes (Nair et al., 2022). This many-to-one correspondence calls for empirical studies, such as Gala et al. (2024), that move beyond distribution pitting and directly probe the causal processes underlying the right-skewed, heavy-tailed distributions often observed in entrepreneurial contexts.

Table 4. Mapping Distributional Shapes to Plausible Generative Mechanisms.

Distributional shapes	Plausible generative mechanisms	Relevant literature
Normal (Gaussian)	Homogenization, performance constraints, random shocks, and additive interactions between independent factors	Joo et al. (2017), Nair et al. (2022), Sornette (2006)
Exponential (Gamma)	Cumulative advantage with diminishing returns, incremental differentiation (size-dependent growth rate), memoryless processes (constant hazard rate)	Bottazzi and Secchi (2006), Bradley and Aguinis (2023), Joo et al. (2017)
Stretched Exponential (Weibull)	Multiplicative processes with growth constraint, nonconstant hazard rate, preferential attachment with aging or ceiling effects	Dorogovtsev and Mendes (2000), Laherrere and Sornette (1998), Nair et al. (2022)
Lognormal	Positive feedback loops, multiplicative interactions between independent factors, proportional differentiation (size-independent growth rate), and the theory of breakage	Crow and Shimizu (1987), Gala et al. (2024), Joo et al. (2017), Limpert et al. (2001), Mitzenmacher (2004)
Power law (Pareto)	Niche proliferation, path dependence (memory effects), phase transition, preferential attachment, self-organized criticality, *and many others*[a]	Andriani and McKelvey (2009, 2011), Newman (2005), Sethna (2021)
Asymmetric Exponential Power (Subbotin), including Laplace as a special case	Classical competition with growth constraints, heterogeneous competition, investor expectations, luck, and aggregation of micro-shocks	Alfarano and Milaković (2008), dos Santos and Scharfenaker (2019), Mundt and Oh (2019)

[a]See Andriani and McKelvey (2009) for a comprehensive list of plausible generative mechanisms for power law distributions.

Shifting the Focus to Distributional Tails: Identifying Star Performers

The preceding statistical properties provide a starting point for a deeper understanding of performance variability, including initial insights into centrality, dispersion, inequality, lopsidedness, and extremity. These insights serve as a foundation for the next step, which involves examining distributional tails to identify star performers directly. Notably, traditional organizational research focused on *average* performance considers extreme observations as problematic outliers and a "nuisance" to be handled (Sullivan et al., 2021). Related studies use statistical techniques to identify outliers and run analyses to evaluate and control their impact (Aguinis et al., 2013). For example, researchers often use two *SD*s above the mean as a cutoff to identify outliers and then (a) drop these outliers, (b) winsorize the data, or (c) run regression analyses with and without the outliers.

In contrast, researchers focused on star performance treat extreme observations as their primary focus of investigation (Beamish & Hasse, 2022; Downes & Lee, 2023; Ruef & Birkhead, 2024). Star performers are influential observations that affect substantive conclusions and merit explicit investigation (Aguinis et al., 2013). In the extreme, the study of a single star performer has been used to develop theories of entrepreneurial success (Ruef et al., 2023). In "large *N*" studies that adopt a distributional perspective, such "outliers" reside in the right tails of performance distributions. Therefore, we discuss statistical

Table 5. Star Performance Cutoffs in Empirical Studies.

Basis for outlier cutoff	Strength/limitation	Likelihood of identifying too many points as outliers	Empirical examples in management and entrepreneurship research
Mean, standard deviation	Most commonly used in management and entrepreneurship research	Low	Berkhout et al. (2016), Kulich et al. (2011)
Median, median absolute deviation[a]	More robust to extreme values of performance	High	Miron-Spektor et al. (2023), Song et al. (2018)
Power law parameter X_{min}	Assumes that actual performance distribution fits a power law	Low	Booyavi and Crawford (2023), Crawford et al. (2015), Crawford, Linder, et al. (2024)
Interquartile range	Relatively robust to extreme values of performance	High	Arikan and Shenkar (2013), Glaub et al. (2014)
Median, quantile absolute deviation[a]	Provides flexibility in the tradeoff between robustness and efficiency	Low	—
Optimal Trimmed Harrell-Davis Median Estimator, optimal quantile absolute deviation[a]	**Most efficient for right-skewed, heavy-tailed distributions, but sensitive to unpredictably extreme or infinite values**	**Low**	**This study**

[a]See Akinshin (2022, 2024) for a detailed explanation.

approaches that use distributional information to identify star performance. In this primer, we focus on intuitive techniques to help entrepreneurship researchers heed editorial calls to investigate star performance (Crawford et al., 2022; Maula & Stam, 2020). These approaches to identify star performers are summarized in Table 5.

Identifying Star Performers Using Estimates of Central Tendency and Variability

The most common cutoff used to identify star performers for continuous, non-negative measures is *mean + k* standard deviations*, where *k* is typically 2, 2.5, or 3 (Aguinis et al., 2013; Sullivan et al., 2021). As discussed earlier, the mean and *SD* are sensitive to even a single extreme value and, therefore, ill-suited for right-skewed, heavy-tailed distributions of entrepreneurial performance. An alternative cutoff to identify star performers is *median + k*median absolute deviations*, where *k* is typically 2, 2.5, or 3 (Leys et al., 2013). These statistical properties are less vulnerable to extreme values in the data, making the corresponding cutoff more stable in the presence of influential observations. However, they are better suited for symmetric distributions (Rousseeuw & Croux, 1993). Moreover, using them carries the risk of identifying a substantial fraction of data points as extreme because the median is much smaller than the mean for right-skewed, heavy-tailed distributions.

Both the preceding approaches to outlier identification use rules of thumb when choosing a value for "*k*." They also assume symmetric distributions and are sensitive to sample size (Van Selst & Jolicoeur, 1994). However, statisticians have suggested bootstrapping as an alternative to determine this critical threshold for right-skewed, heavy-tailed distributions (Martin & Roberts, 2010). This approach repeatedly resamples the dataset with replacement to create many simulated samples and subsequently computes a distribution for "k." Then, a specific value of "k" is chosen based on a predefined confidence level instead of an arbitrarily fixed value (e.g., $k = 2$, 2.5, or 3).

Identifying Star Performers by Fitting a Power Law

To the extent that the observed distribution of performance fits a power law, the critical value parameter ($X_{\min}$) can serve as a cutoff (Crawford, Linder, et al., 2024; Wales et al., 2025). For example, Booyavi and Crawford (2023) fit a pure power law to performance data from the Panel Study of Entrepreneurial Dynamics (PSED) II dataset and use the distributional parameter $X_{\min}$ to differentiate between star and non-star ventures in their study of how gender influences venture performance. However, this approach is vulnerable to concerns that pure power laws are ill-suited to real-world contexts with finite limits to performance. Instead, the lognormal or a combination of distributions may better characterize the observed data (Broido & Clauset, 2019; Cirillo, 2013; Stumpf & Porter, 2012). Indeed, Crawford, Joo, and Aguinis (2024) use distribution pitting to re-investigate the datasets used in Crawford et al. (2015) and report that the pure power law is unlikely to characterize most measures of entrepreneurial performance.

Identifying Star Performers Using the Interquartile Range

The interquartile range (IQR) is a measure of spread or dispersion, representing the range between the 25th (Quartile 1) and 75th (Quartile 3) percentiles of the data. For performance measures that are continuous and non-negative, data points above $Q3 + k \times IQR$ can be considered star performers, with a typical value of $k = 1.5$ (Rousseeuw & Hubert, 2011). However, the IQR is considered more informative for distributions that are symmetric or moderately skewed (Rousseeuw & Hubert, 2011). Moreover, IQR-based cutoffs often identify too many points as outliers in the case of right-skewed, heavy-tailed distributions, thus diluting the focus on star performers (Sullivan et al., 2021).

Identifying Star Performers Using the Quantile Absolute Deviation

While *SD*-based approaches assume a normal distribution, entrepreneurial performance data often violates this assumption, necessitating more robust alternatives. Given the prevalence of discrete, multimodal, right-skewed, and heavy-tailed distributions across the sciences, statisticians have developed flexible, nonparametric methods to estimate statistical dispersion and variability robustly.

One recent advance in this area is the Quantile Absolute Deviation (QAD) (Wooff & Jamalzadeh, 2013). Conceptually, the QAD generalizes the well-established MAD by allowing the user to choose any quantile of interest as the reference point (Akinshin, 2022). For example, researchers focused on star performers might measure absolute deviations around the 95th percentile instead of the 50th percentile (i.e., the median). Conversely, if researchers are primarily concerned about unpredictably extreme—even infinite—values in the data, they might specify the QAD for the 50% quantile, in other words, the MAD.

However, such concerns are absent in entrepreneurship research because real-world performance is finite.

The flexibility of QAD with respect to the reference point is valuable in controlling the tradeoff between the robustness of a measure of variability (i.e., how sensitive it is to extreme values) and its efficiency (i.e., how precisely it estimates variability) (Pinsky & Klawansky, 2023). Notably, Akinshin (2022) shows that setting the reference quantile at 86.2%—the *Optimal QAD* (OQAD)—maximizes statistical efficiency, setting it at 50% (the MAD) maximizes robustness, and setting it at 68.3%—the *Standard QAD*—yields a balance between robustness and efficiency. Given these advantages of the QAD, we suggest using the *median* and the *QAD* to increase the robustness of outlier cutoffs for right-skewed, heavy-tailed distributions, rather than using conventional cutoffs based on the *SD* or the MAD.

Robust Estimates of Central Tendency and Critical Threshold

We suggest an additional refinement to outlier identification: using the Trimmed Harrell-Davis Median Estimator (THDME) instead of the sample median when defining cutoffs for star performance (Akinshin, 2024). The THDME is a modern, robust estimator of central tendency that improves on the traditional median. Conceptually, it works by estimating the weighted average of all order statistics in the sample rather than simply selecting the middle observation, thus making it more stable and efficient for small samples (Harrell & Davis, 1982). Moreover, the "trimmed" modification to the traditional Harrell-Davis estimator down-weights or discards the most extreme values before applying the weighting, thus making it more robust to extreme observations. This robustness is particularly valuable in entrepreneurship research, where star performance often dominates.

Finally, we suggest using *bootstrapped* values of "k" to determine outlier cutoffs rather than the traditional thumb rules of $k = 2$, 2.5, or 3 (Martin & Roberts, 2010). In this approach, the sampling distribution of the chosen dispersion measure (i.e., QAD) is empirically derived by repeatedly resampling from the observed data, allowing the multiplier "k" to be tailored to the specific shape and tail of the observed distribution. This data-driven method adapts to the actual variability and maintains the appropriate sensitivity for right-skewed, heavy-tailed distributions rather than imposing a generic threshold (e.g., $k = 2$ or 3) grounded in assumptions of normal distributions. Table 5 summarizes the preceding options to identify star performers.

Notably, the proposed QAD-based cutoff for star performance is well-suited for continuous, non-negative measures of performance, such as revenue, employee count, and customer count. However, it is ill-suited for binary performance measures (e.g., venture success or failure), categorical or ordinal performance measures (e.g., revenue < \$1M, revenue between \$1M and \$5M, and revenue > \$5M), and measures based on Likert-like scales.

While using the QAD enhances the precision of identifying star performers, it also reveals a broader analytical challenge: threshold-based measures, when applied to continuous performance distributions, can obscure important facets of the variability in entrepreneurial performance. Addressing this limitation requires moving beyond the "stars versus non-stars" dichotomy to enable a more nuanced differentiation between different types of performance distributions, focusing on differences in their tails.

Three Characteristics of Distributional Tails

In this section, we introduce three interrelated yet distinct characteristics of distributional tails to enhance the interpretability of empirical findings related to star performance. Notably, star performance can manifest in equifinal ways. For example, in some entrepreneurial contexts, one extreme performer may constitute star performance, whereas in others, several exceptional performers may account for the same collective outcome, as illustrated in Figure 4.

Consider the example of a new seller exploring a category on Amazon.com. The maximum performance of incumbent sellers in that category can be an aspirational benchmark for new entrants. The observed extreme performance likely informs resource allocation expectations and decisions about the capital, effort, and time required for extreme success (Dunkelberg et al., 2013). Conversely, for Amazon, the platform owner-operator, extreme performance signifies a seller whose success makes them less dependent on the platform (Cutolo & Kenney, 2021). Arguably, Amazon prefers an oligopoly of several exceptional performers over a monopoly. Similarly, policymakers focused on job creation may prefer a configuration with exceptional performers more dispersed across different regions and industries over a few extreme performers concentrated in only a few regions and industries (Brown et al., 2017).

The extensive literature on firm growth provides further insights into the tail extremity of performance distributions (Coad, 2009; Coad et al., 2024; Davidsson & Wiklund, 2013). For example, an analysis of U.K. ventures revealed that "*it is the 7th or 8th decile of the growth distribution that has the highest survival chance*" (Coad et al., 2020, p. 1). Paradoxically, being an extreme success in scaling a venture tends to adversely impact the odds of profitability and survival, even though better performance is positively associated, on average, with higher survival rates (Ben-Hafaïedh & Hamelin, 2023; Freel & Gordon, 2022). Furthermore, prior research has discussed the often substantial role of chance, luck, and randomness as performance becomes extreme. In other words, extreme performance may *not* necessarily indicate extreme ability or skill (Denrell & Liu, 2012; Henderson et al., 2012; Liu & De Rond, 2016). Instead, luck and chance may transmute randomness at the micro level to systematic patterns at the macro level, calling into question trait-based explanations of extreme performance (Denrell et al., 2015; Denrell & Liu, 2021). In sum, there is a need for a more nuanced understanding of the odds and extremity of star performance in entrepreneurial settings.

Tail Impact, Tail Extremity, and Tail Frequency

To enhance the identification and interpretation of the nuances of star performance, we propose three interrelated yet distinct metrics: *tail impact*, *tail extremity*, and *tail frequency*. Tail impact quantifies the proportional contribution of star performers vis-à-vis the aggregate performance within the distribution, that is, across all performers in a given industry, market, or product category. Tail extremity quantifies the magnitude of deviation of the most extreme observation from the distribution's central tendency, that is, the extent to which the highest performer exceeds the typical performer. Tail frequency captures the number of star performers relative to the overall number of performers. Because tail impact helps answer "*Does star performance matter*," it carries primacy over tail extremity and tail frequency, which together help answer "*In what way does star performance matter*." Table 6 summarizes the conceptualization and operationalization of these novel tail characteristics.

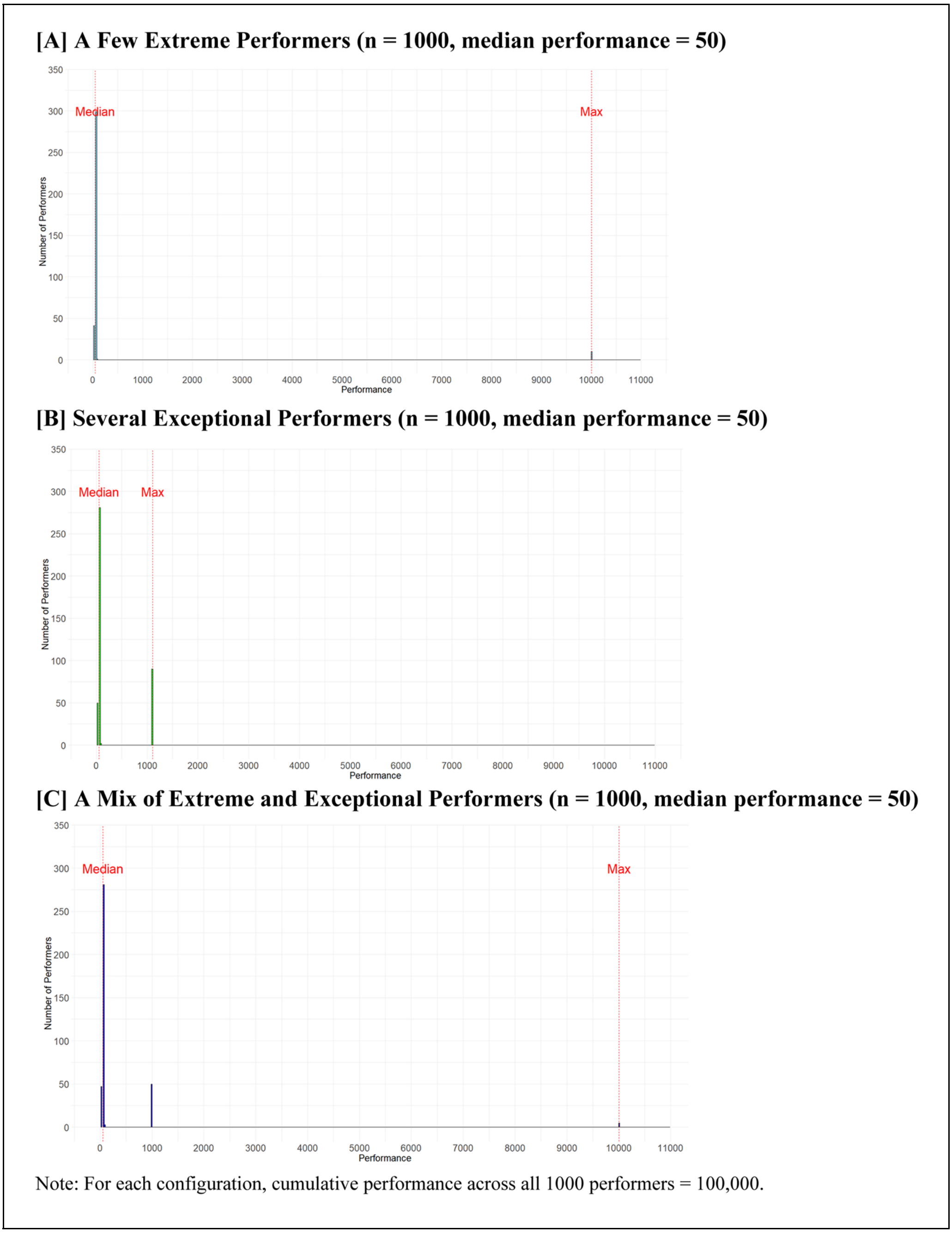

Figure 4. Illustrative configurations of star performance: (A) A few extreme performers ($n = 1{,}000$, median performance = 50). (B) Several exceptional performers ($n = 1{,}000$, median performance = 50). (C) A mix of extreme and exceptional performers ($n = 1{,}000$, median performance = 50).
Note. For each configuration, cumulative performance across all 1,000 performers = 100,000.

Table 6. Characteristics of Distributional Tails.

Tail characteristic	Key question	Operationalization	Computation
Tail impact	Collectively, how impactful are star performers vis-à-vis the pool of performers?	Cumulative performance of star performers as a proportion of the aggregate performance across all performers in the pool	$\frac{\sum_{i \in stars} P_i}{\sum_{j \in all} P_j}$
Tail extremity	To what extent does the most extreme performer outperform the typical performer?	Maximum value of performance relative to the typical value of performance of the pool	max(P)/median(P)
Tail frequency	What is the proportion of star performers in a pool of performers?	Number of star performers as a fraction of all performers in the pool	$N_{\text{stars}}/N_{\text{all}}$

Note. P_i = performance of performer *i;* N_{all} = number of performers; N_{stars} = number of star performers.

Tail Impact

The combined contribution of star performers to the cumulative outcome of a pool of performers indicates how *impactful* these star performers are in a specific entrepreneurial context. For example, if the cumulative annual revenue of all sellers in an Amazon category is $100 million, of which the star performers collectively account for $60 million, the tail impact for that category is 60%. By making tail impact a *percentage* measure, we can compare the relative contribution of star performers across industries, markets, product categories, or regions. Indeed, the collective revenue or profit share of star performers in a given industry provides important information about star performance not only to new entrants but also to incumbents or investors contemplating new investments (Cochrane, 2005).

Tail Extremity

The maximum value of performance is of substantive interest to entrepreneurs seeking *extreme* success as well as to investors, policymakers, researchers, and other stakeholders (Nystrom et al., 2010). Here, the focus is on the observed maximum performance. Without a theoretical upper bound, the best evidence-based estimate for maximum performance is the observed highest performance in the focal industry, market, or product category. Comparing performance maxima across "pools of performers" benefits from normalization (Micceri, 1989; Morrison & Tobias, 1965). Therefore, we propose the ratio of the maximum value ("the best") to the median value ("the rest") of performance as a *normalized* measure of tail extremity. This scale-independent measure of extremity enables comparisons across industries, markets, product categories, et cetera.

Tail Frequency

The number of star performers indicates how *frequently* the performers in a given context exceed the threshold for star performance. We measure tail frequency as the *proportion* of star performers among a pool of performers. For example, if the performance for 50 out of all 1,000 entrepreneurs operating in a category exceeds the cutoff for star performance, the

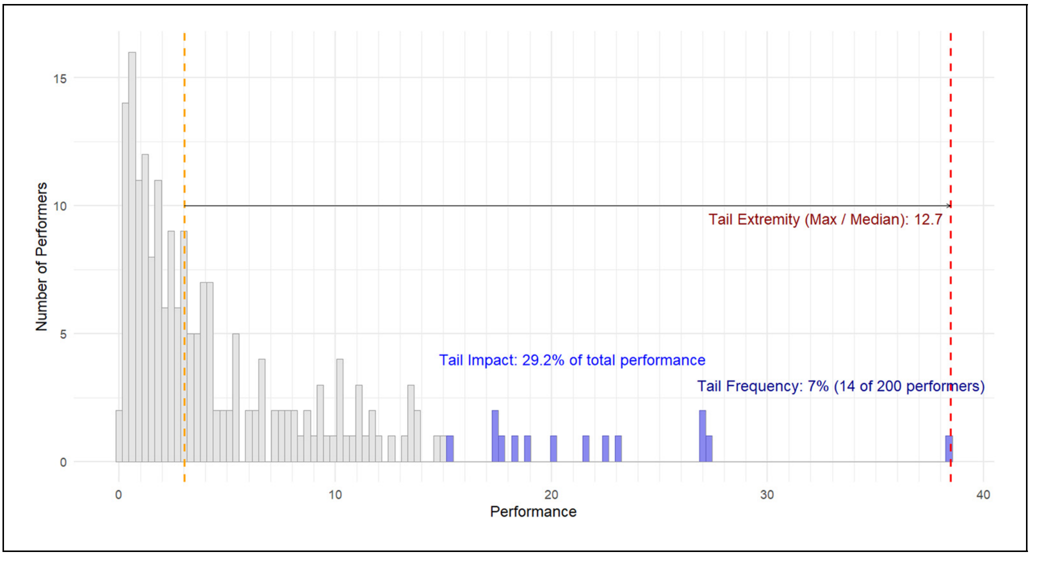

Figure 5. An illustration of tail impact, extremity, and frequency.
Note. Simulated data with $n = 200$ and lognormal distribution (mu = 1, sigma = 1.2).

tail frequency for that category is 5%. This normalized operationalization of tail frequency enables comparisons across different categories, industries, or markets. Hence, this measure helps ambitious competitors assess their odds of stellar performance when making market entry and exit decisions (Cassar, 2010). Similarly, it allows investors of risk capital—for whom star performers often drive portfolio returns—to better estimate the odds of their portfolio companies achieving exceptional performance (Mason & Harrison, 2002). Finally, the number of star performers helps assess the competitive intensity among them.

Figure 5 illustrates tail impact, extremity, and frequency using a simulated dataset with 200 performers, of which 14 are star performers (tail frequency = 7%). These star performers collectively capture approximately 29% of the cumulative performance across all 200 performers (tail impact = 29%). Thus, tail impact captures the tail area relative to the overall area in Figure 5, independent of how it is distributed along the *X*-axis (performance) and the *Y*-axis (number of performers). The best performer outperforms the typical performer by approximately 13-fold (tail extremity of 13). Together, these tail characteristics and their operationalization represent a substantive addition to the methodological framework for investigating star performance in entrepreneurship.

Envisioned Role of Tail Characteristics

We suggest that the tail characteristics introduced above can play an important role as interrelated dependent variables in future studies of entrepreneurial performance. Unlike traditional statistical analyses of outliers, which typically assess the sensitivity of average-focused results to extreme values (Aguinis et al., 2013), these tail characteristics draw explicit attention to extreme values in the distribution. In doing so, they encourage and enable researchers to study the antecedents and mechanisms of star performance. Furthermore, unlike organizational research on star performers (O'Boyle & Götz, 2025), which often dichotomizes individuals into stars and non-stars, the tail characteristics account for multiple facets of star performance.

The combined application of tail impact, extremity, and frequency promises a more nuanced capturing of star performance. Moreover, analytical techniques such as seemingly unrelated regression can factor in the inherent correlations between these tail characteristics (Fiebig, 2001; Zellner, 1962). Finally, the scale-independent operationalization of these tail metrics allows for systematically comparing contextual influences on star performance. For example, researchers can examine how industry characteristics affect the prevalence and importance of star performance by comparing the respective tail characteristics. Finally, the intuitiveness of these tail characteristics promises to enhance the interpretation of effect sizes for policy and practice in studies of star performance (Connelly et al., 2010).

Toward a Multifaceted Distributional Perspective to Enrich Empirical Research

The preceding sections juxtapose established univariate distributional properties with the three newly introduced tail characteristics. Together, they can serve as valuable tools for empirical studies of star performance. Because this paper focuses on right-skewed, heavy-tailed distributions, we expect moderate-to-high pairwise correlations between various distributional properties. For example, research suggests skewness is often highly correlated with kurtosis, even though they are, respectively, the third and fourth moments of the distribution (Cristelli et al., 2012). Similarly, we expect tail frequency and tail impact to be consistently correlated because they both capture the thickness of distributional tails.

Despite this partial overlap, each distributional property promises to capture unique information about the presence, prevalence, and relevance of star performance. Hence, reporting *all* the aforementioned statistical properties promises to enhance the rigor of related quantitative studies (Brinkerink, 2023; Maula & Stam, 2020). For example, in studies with *performers* as the primary level of analysis, high tail impact may indicate the need for testing hypotheses using quantile regression instead of Ordinary Least Squares (OLS) regression (Koenker, 2017; Kolokas et al., 2022). Moreover, longitudinal changes in skewness, kurtosis, or tail characteristics can inform the development of process theories of when, how, and why star entrepreneurs dynamically emerge from an initial pool of aspirants (Davidsson & Gruenhagen, 2021; Sternad & Mödritscher, 2022).

Similarly, in studies with *pools of performers* as the primary level of analysis, the pattern of correlations between tail frequency and extremity may reveal the influence of contextual factors on star performance in product categories, industries, or markets. Accordingly, researchers should try to gain a holistic understanding of their focal dependent variable, entrepreneurial performance, by conducting multifaceted empirical investigations, looking for anomalies and counterintuitive patterns, and using visualizations (Schwab, 2018; Wennberg & Anderson, 2020). Uncovering nuances and patterns in performance distributions will guide future research design and analytic strategies, thus enhancing theory-method compatibility (Anderson et al., 2019; Linder et al., 2023).

Summary of the Analytical Framework

Table 7 compares the framework introduced herein, which focuses on star performance, with traditional approaches, largely focused on average performance. Furthermore, Table 8 summarizes the key concepts and terms relevant to this study. Together, these

Table 7. Focus of Study and Relevant Analytical Techniques for Probing Performance.

Focus of study		Descriptive statistics	QCA	Goodness-of-fit statistics	Distribution pitting	Framework outlined in this study	Exemplar outputs
Average performance		✓				✓	Mean, *SD*
Median performance		✓				✓	Median, IQR
Performance configurations			✓				Sufficiency/necessary patterns
Performance distributions	Presumed distributional shape[a]			✓			Chi-square, K-S statistics; Distributional shape parameters
	Most likely distributional shape(s)				✓	✓	Likelihood ratios; Distributional shape parameters
	Distributional tails (i.e., star performers)					✓	Distributional tail characteristics (impact, extremity, and frequency)

Note. *SD* = standard deviation; IQR = interquartile range; K-S = Kolmogorov-Smirnov; QCA = Qualitative Comparative Analysis.
[a]This approach involves assuming a specific distributional shape (e.g., power law), estimating goodness-of-fit statistics (e.g., K-S statistic) to check whether the observed distribution fits the assumed shape, and, if so, estimating corresponding shape parameters (e.g., alpha, X_{min}).

Table 8. Summary of Key Concepts and Terms.

Key concept/term	Definition/explanation
Distributions	Statistical representations that describe how a set of observations is spread across a range of possible outcomes.
Distributional perspective	An analytical approach that focuses on the full spread of observations, rather than just the average, to better understand variability and extremes.
Distributional shapes	Specific forms (e.g., lognormal) exhibited by a frequency distribution that describe how observations are concentrated or dispersed.
Distributional tails	The extreme ends of a distribution, representing observations far above or below the central tendency of data.
Exceptional performers	Star performers whose performance exceeds that of most of the pool of performers, but who may not be the highest performers.
Extreme performers	Star performers whose performance is the absolute highest in the pool of performers.
Generative mechanism	The factors and processes that produce the observed performance distribution, plausibly explaining how its shape and tail(s) arise.
Outliers	Observations whose values deviate substantially from the bulk of the data, thus lying in the distributional tails.
Performers	Specific individuals, teams, or ventures with performance outcomes.
Performance distributions	Statistical distributions representing the variability in performance among a pool of performers.
Pool of performers	A relatively homogeneous group of individuals, teams, or ventures (e.g., within an industry or a market) used to investigate their performance.
Right-skewed distributions	Asymmetric distributions in which most observations cluster at lower values, but a small number extend the tail to the right.
Right-skewed, heavy-tailed performance distributions	Asymmetric distributions where the right tail is not only extended but also has one or more extremely large values.
Star performers	Performers whose outcomes lie in the upper tail of the performance distribution and substantially exceed typical performance levels.
Star performance	A phenomenon in which one or a small number of performers within a pool of performers achieve outcomes situated in the right tail of the performance distribution, thus exerting disproportionate influence on aggregate outcomes.
Tail impact	The aggregate contribution of star performers relative to the total performance across the pool of performers.
Tail extremity	The magnitude by which the performance of the best (i.e., most extreme) performer exceeds that of a typical performer.
Tail frequency	The proportion of performers classified as stars relative to the total pool of performers.

tables summarize the methodology developed in the preceding sections. However, a comprehensive understanding of the suggested framework requires actively engaging with its constituent analytical steps. Accordingly, the following section applies the methodology to a real-world dataset, enabling readers to observe how the tail characteristics can yield nuanced and valuable insights into star performance.

Illustrative Application of the Methodological Framework

We apply the suggested framework to the (a) annual revenue and (b) employee counts of the firms that were featured in the 2021 edition of *Inc*. Magazine (Inc., 2021). For annual

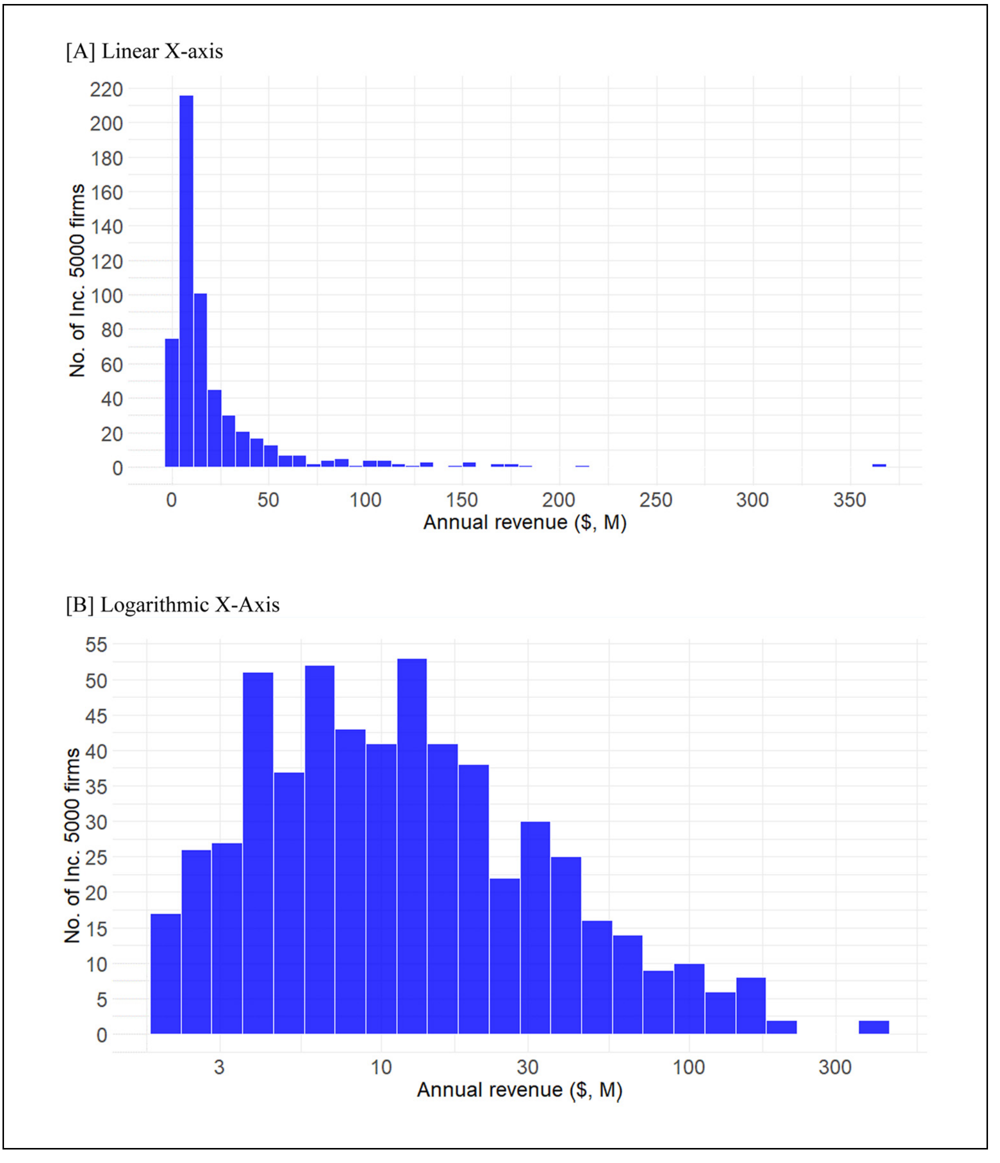

Figure 6. Annual revenue distribution (Inc. 5000, 2021 edition, Software industry). $n = 570$ firms.

revenue, we investigate: performance distribution within a single industry and performance distributions across multiple industries. Notably, the Inc. 5000 sample is self-selected because privately held U.S. firms voluntarily apply to be featured in *Inc*. Magazine. This process likely introduces left-censoring in the sample because slower-growing companies remain under-represented or absent from the sample. Consequently, distributional properties such as skewness and tail extremity may be underestimated to a degree, relative to analyses of *all* privately held firms in the United States. This limitation highlights the importance of recognizing and reporting context-specific features and sample biases to inform the interpretation of data and empirical analyses (Schwab & Starbuck, 2017).

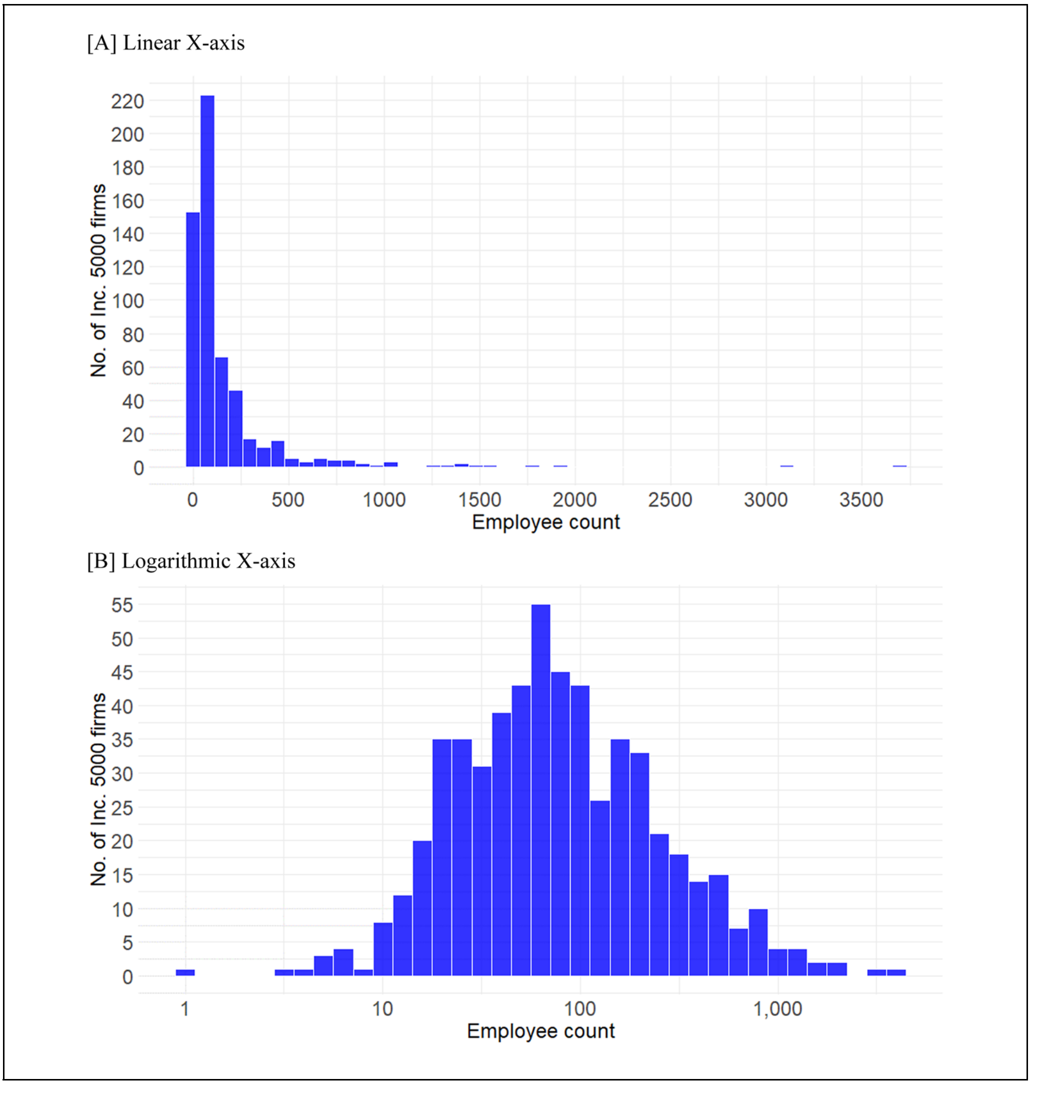

Figure 7. Employee count distribution (Inc. 5000, 2021 edition, Software industry). $n = 570$ firms.

Performance Distribution Within an Industry

First, we estimate statistical properties and tail characteristics for firms in the *software* industry, which is the most frequently represented industry on the Inc. 5000 list. Here, the unit of analysis is the firm, and we seek to understand the distribution of firm performance in this industry. Figures 6 and 7 show that the distributions of annual revenue and employee count for these firms are right-skewed and heavy-tailed, consistent with past research (Crawford, Joo, & Aguinis, 2024). The bottom panels of these figures show the same distributions using a logarithmic scale, instead of a linear scale, for the *X*-axis.

Applying the *Dpit* package, we identify the power law with exponential cutoff and the Poisson shapes as the most likely distribution shapes for the distribution of annual revenue,

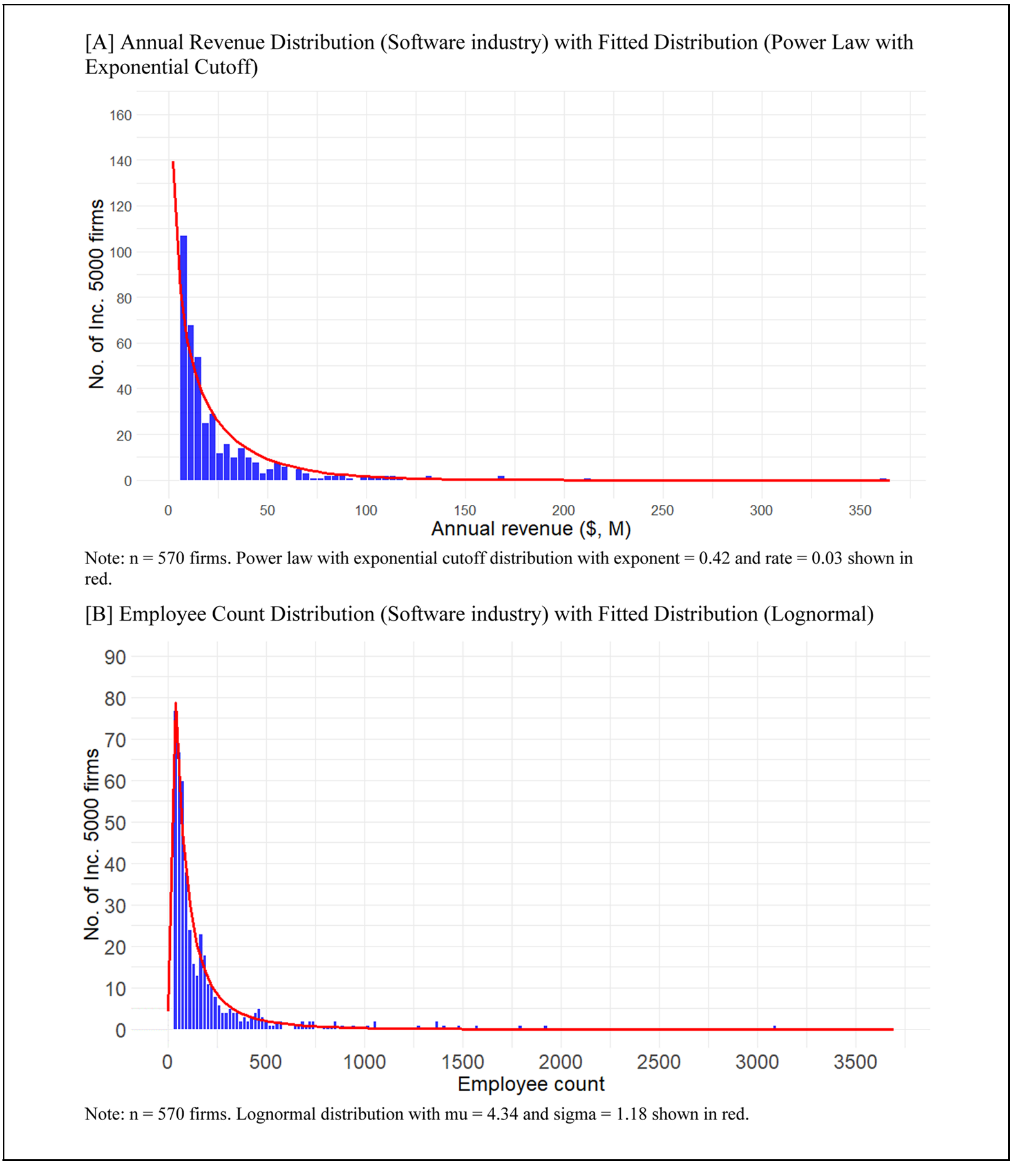

Figure 8. Most likely shapes for observed performance distributions (Inc. 5000, 2021 edition, Software industry).

as shown in the top panel of Figure 8. Further, we identify the lognormal as the best-fitting shape for the distribution of employee count, as shown in the bottom panel of Figure 8.

These shape-related findings firmly establish the asymmetry and non-normality of the overall distribution. For more nuanced insights into star performers, Table 9 provides specific statistical measures and tail characteristics for annual revenue and employee count in the software industry. Notably, the MAD is significantly smaller than the *SD*, and the QAD offers a middle ground for such distributions. The CoV and Gini coefficient indicate

Table 9. Distributional Properties, Shapes, and Tail Characteristics for Venture Performance (Inc. 5000, 2021 edition, Software Industry).

Statistical property/tail characteristic	Estimate for annual revenue ($, million)	Estimate for employee count
Mean	22.7	163.5
Median	10.4	70
Mode	NA	18
Minimum	2.0	1
Maximum	364.8	3,696
Standard Deviation	36.4	305.7
Median Absolute Deviation	9.4	68.2
Quantile Absolute Deviation	30.5	200.3
Coefficient of Variation	1.6	1.9
Gini coefficient	0.6	0.6
Skewness	4.6	5.9
Kurtosis	30.4	50.2
Power law parameters	N/A[a]	X_{min} = 149 Alpha = 2.3
Lognormal parameters	Mu: 2.5 Sigma: 1.1	Mu: 4.3 Sigma: 1.2
Likely shape(s) using distribution pitting	Power law with exponential cutoff, Poisson	Lognormal
Tail impact[b]	61.2%	61.2%
Tail extremity	35.0	53.0
Tail frequency[b]	17.4%	15.6%

Note. n = 570. OTHDME is the Optimal Trimmed Harrell-Davis Median Estimator; OQAD is the Optimal Quantile Absolute Deviation.
[a]The distribution could *not* be fitted to a power law.
[b]Star performance cutoff = OTHDME + bootstrapped_critical_value × OQAD.

high levels of inequality. In addition, high levels of skewness and kurtosis are observed (Westfall, 2014).

Notably, star performers collectively capture over 61% of cumulative performance across all firms in the industry. Furthermore, the best performing firm in the software industry has *35 times* the revenue of the typical (median) performer. The tail extremity for employee count is even higher at 53. Finally, for performance measured as annual revenue, 17% (99 out of 570) of firms in the software industry are identified as star performers using the THDME and QAD to determine outlier cutoffs.

Performance Distribution Across Industries

The Inc. 5000 list includes firms from a variety of industries (Inc., 2021). This classification allows us to examine how the distribution of performance for these private firms varies across industries. We filtered out industries with fewer than 15 firms due to concerns about the reliability of estimates. The final sample comprised 4,986 companies across 26 industries. Here, we focus on annual revenue as the measure of performance. In the three-dimensional plot in Figure 9, each of the 26 points represents the tail impact, extremity, and frequency for the respective industry. As shown in Table 10, tail impact ranges from approximately 39% to 91%, tail extremity from 10 to 710, and tail frequency from 7% to 17%. Figure 9 illustrates how some industries (e.g., IT Systems Development) have very

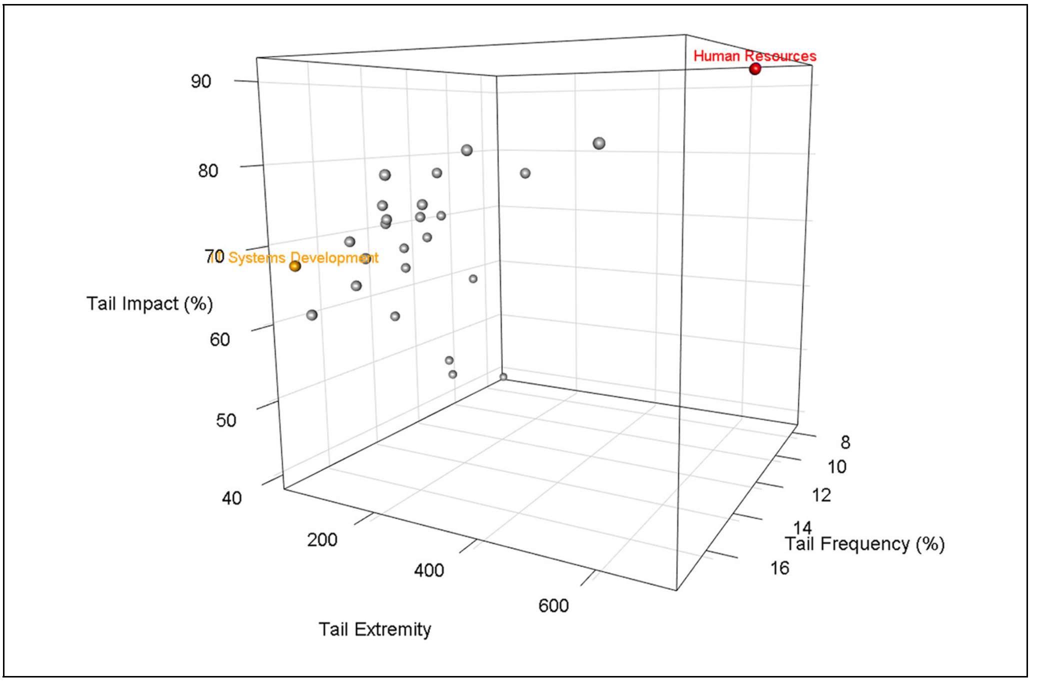

Figure 9. Tail characteristics for annual revenue distributions (Inc. 5000, 2021 edition).
Note. $n = 26$ industries; see Table 10 for each industry's sample size and tail characteristics.

high tail frequency (17.7%), whereas others (e.g., Human Resources) have very high tail extremity (712.0).

Next, we examine the correlations between unitless estimates of variability, such as CoV, Gini coefficient, skewness, and kurtosis, and the three tail characteristics. The CoV, Gini coefficient, skewness, and kurtosis are highly intercorrelated ($r > .6$), indicating overlap in the information they provide, as shown in Figure 10. Tail frequency is uncorrelated with tail extremity and only moderately correlated ($r = .45$) with tail impact. Together, these characteristics enable a multifaceted perspective of industry-specific star performance. While any of the aforementioned statistical properties, such as skewness and kurtosis, can serve as focal dependent variables in hypothesis testing and robustness analyses, using the newly introduced tail characteristics promises more fine-grained studies of star performance and findings that are easier to interpret for researchers and practitioners.

Finally, Figure 11 shows the distribution of annual revenue for firms in two industries, namely "Education" and "IT Systems Development." Both distributions are noticeably right-skewed and heavy-tailed, and both industries have a similar tail impact and magnitude of revenue for the highest performer. However, the former (latter) has a relatively higher tail extremity (tail frequency) combined with a relatively lower tail frequency (extremity). These industries may substantively differ in the key factors that drive the odds and extremity of star performance. When industry and market characteristics likely play a critical role in the emergence of star performance, studies must prioritize the development of context-specific theories designed for rigorous empirical testing (Shepherd & Wiklund, 2009; Shepherd et al., 2019).

Table 10. Industry-Wise Tail Characteristics for Distributions of Annual Revenue (Inc. 5000, 2021 Edition).

No.	Industry	No. of firms (n)	Tail impact (%)	Tail extremity	Tail frequency (%)
1	Human Resources	102	91	712	13
2	Security	69	91	691	12
3	Government Services	181	83	529	15
4	Construction	286	81	302	15
5	Real Estate	207	79	303	14
6	Financial Services	297	79	176	16
7	Retail	171	79	158	15
8	Health	370	74	179	15
9	Business Products & Services	550	74	100	15
10	Logistics & Transportation	176	72	126	14
11	IT Management	256	72	105	15
12	Manufacturing	177	71	72	15
13	Food & Beverage	145	70	56	16
14	Consumer Products & Services	335	68	106	16
15	Education	82	68	74	10
16	Insurance	78	68	69	13
17	IT Systems Development	164	68	48	18
18	Media	31	66	16	13
19	Advertising & Marketing	414	64	71	16
20	Environmental Services	46	64	26	13
21	Software	570	61	34	17
22	Energy	61	59	39	10
23	Telecommunications	88	57	27	14
24	Engineering	65	46	14	11
25	Computer Hardware	38	44	10	11
26	Travel & Hospitality	27	39	10	7

Extending the Proposed Methodology to Left Tails of Performance Distributions

So far, we have focused on performance measures such as annual revenue and employee counts that are not only continuous but also always positive. In other words, we have focused on right-skewed distributions and, thus, the *right* tails of such distributions. In this section, we extend the conceptual framework to performance measures such as return on assets (RoA) and net income, which can also take on negative values. Thus, we apply tail impact, extremity, and frequency to characterize the *left* tails of performance distributions.

Distributions of performance measures such as RoA have *both* left and right tails, corresponding to extreme negative and positive values, respectively. Prior research—primarily by economics scholars—has shown that such performance outcomes often follow "double exponential" (i.e., tent-shaped) distributions (Bottazzi & Secchi, 2006, 2011; Mundt et al., 2016). This research stream has identified the Laplace and Subbotin distributions as the best-fitting shapes for such outcomes (Mundt et al., 2020; Scharfenaker & Semieniuk, 2017; Vidal-Tomás et al., 2022). Moreover, a recent study has found that a mixture (specifically, the product) of two distributions, normal and lognormal, best fits the observed data of 20-year long-term profit for publicly listed firms in the United States, Germany, and the United Kingdom (Wibbens, 2024).

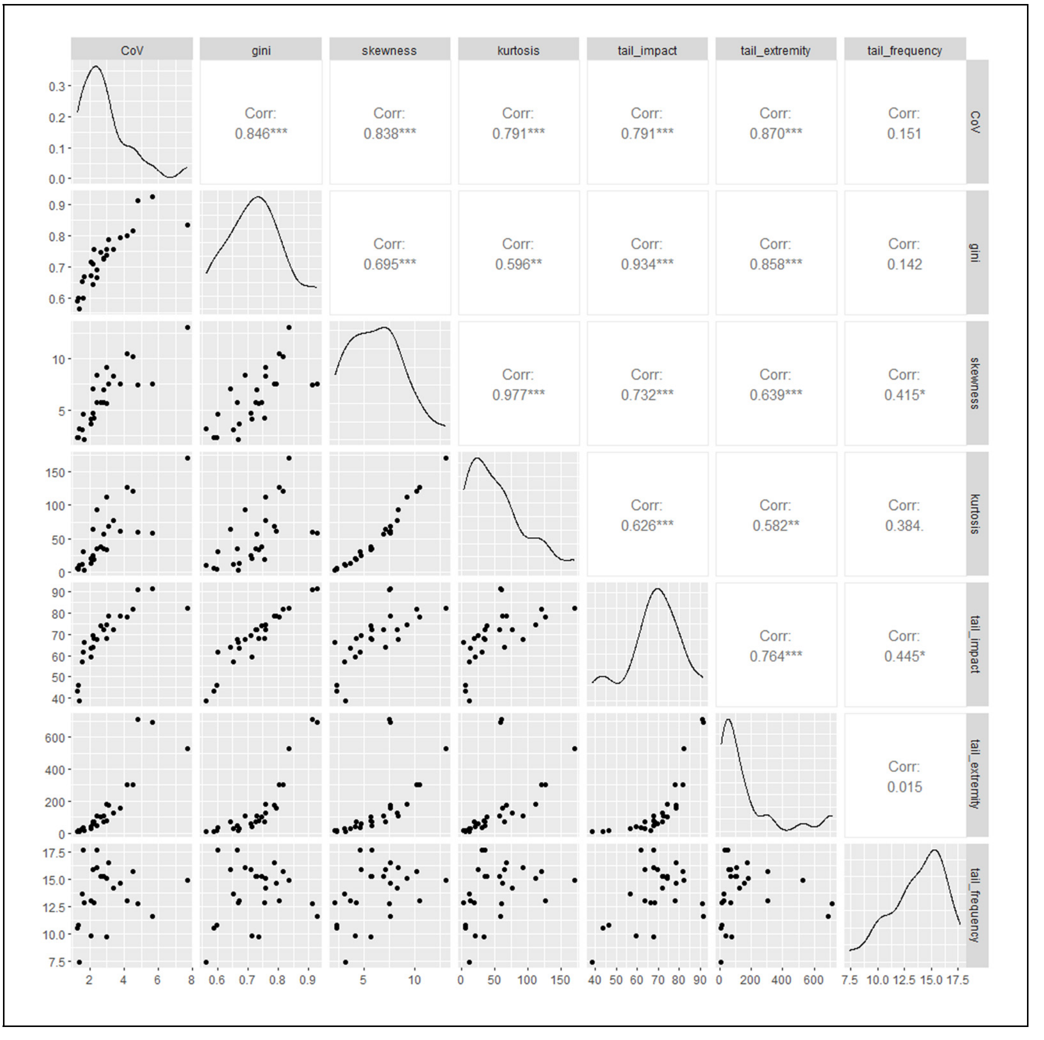

Figure 10. Correlations between measures of variability of annual revenue (Inc. 5000, 2021 edition, 26 industries).

Note. $n = 26$ industries. Graphs on the diagonal represent the distribution of the respective variability estimates across industries. Graphs on the lower triangle represent the pairwise scatterplot for two variability estimates across industries.

When examining the mechanisms that engender the above shapes, researchers have suggested classical competition, firm diversification strategies, and technological or regulatory shocks as plausible explanations for "double exponential" distributions (Alfarano & Milaković, 2008; dos Santos & Scharfenaker, 2019). In addition, firm entry and exit dynamics may help explain why asymmetric distributions with "fatter" left tails than right tails tend to evolve into nearly symmetric distributions over time (Mundt & Oh, 2019). To illustrate how the introduced framework applies to *both* tails, we first replicate the "tent-shaped" distributions for RoA for firms publicly listed in the United States. Figure 12

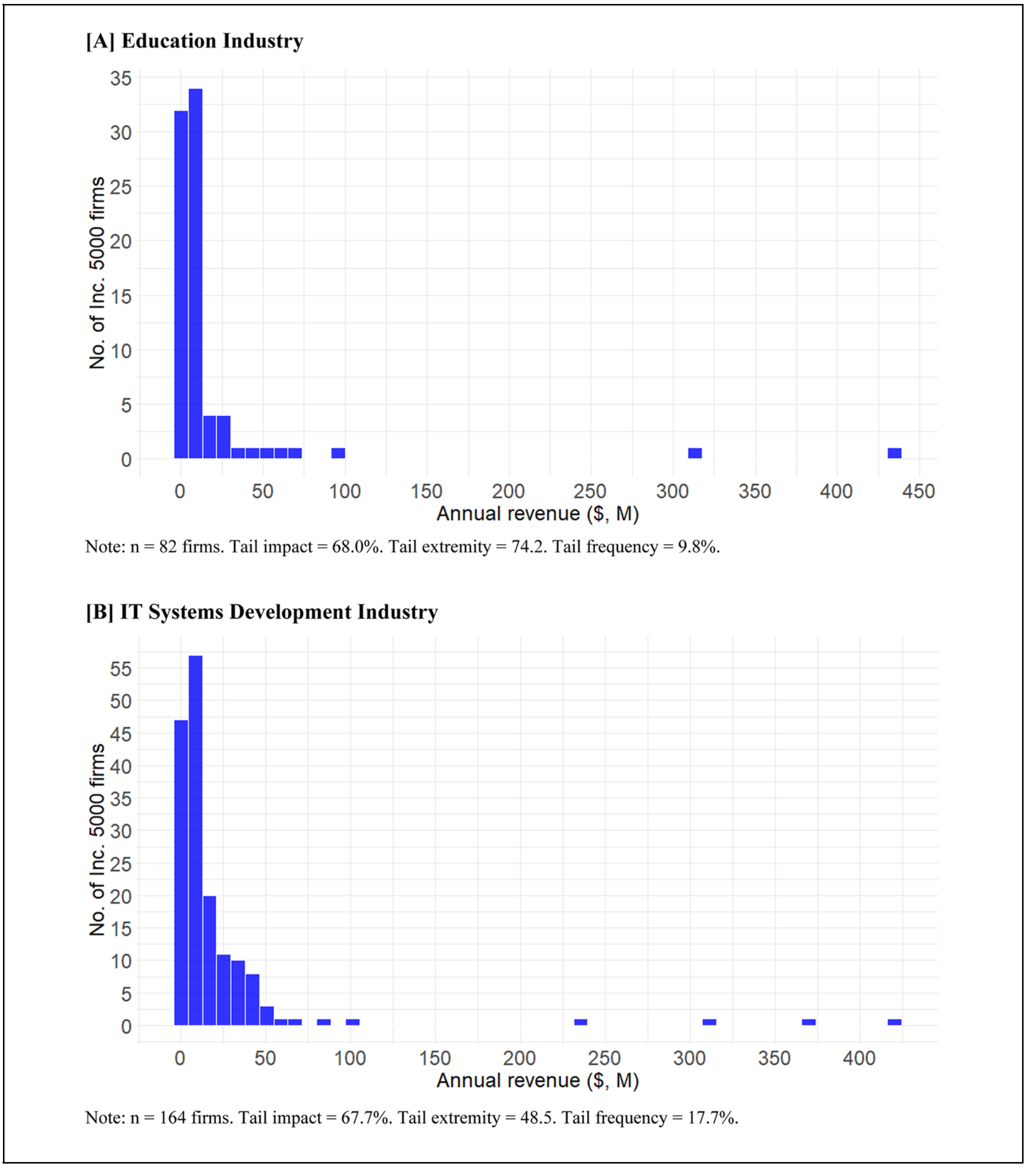

Figure 11. Comparing annual revenue distributions of two industries (Inc. 5000, 2021 edition).

shows that the right tail is longer than the left tail for RoA, potentially reflecting the forced exit of the worst-performing firms.

Next, we separately compute left-tail and right-tail characteristics for RoA. We find that tail extremity and frequency are negatively correlated[3] (r = −.39** for left tail, r = −.32* for right tail), while tail extremity and impact are positively correlated (r = .67*** for left tail, r = .69** for right tail). Tail frequency and impact are also positively correlated (r = .30 for left tail, r = .20 for right tail). Figure 13 shows the corresponding three-

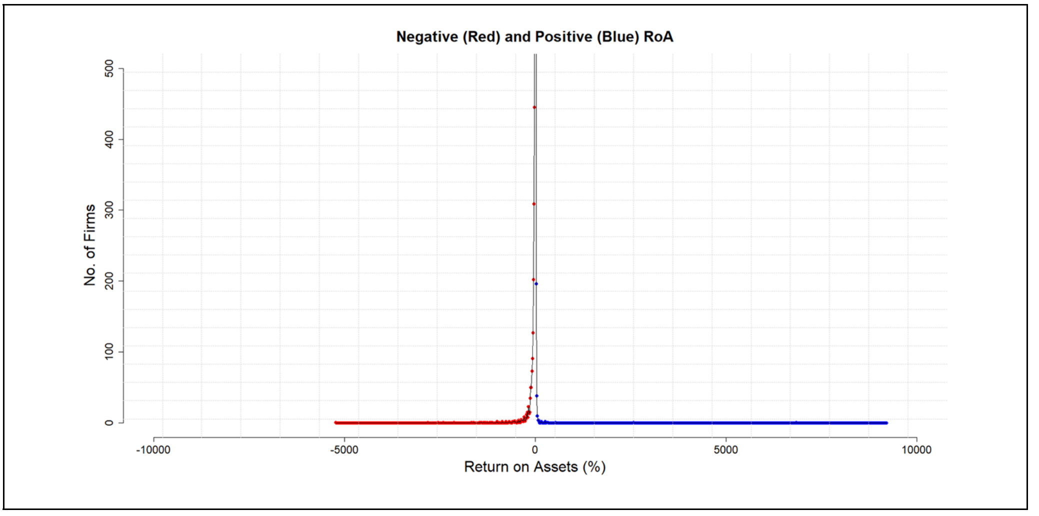

Figure 12. Return on Assets distribution for publicly listed firms in the United States.
Note. n = 41 industries; *m* = 15 to 325 firms per industry.

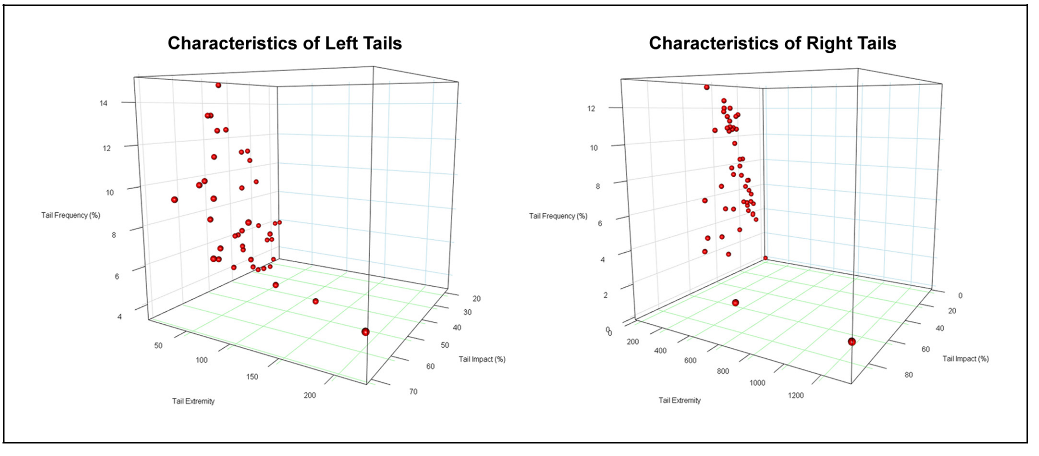

Figure 13. Left and right tail characteristics of return on assets for publicly listed firms in the United States.
Note. n = 41 industries; *m* = 15 to 325 firms per industry.

dimensional plot. These correlations for RoA are consistent with those observed for revenue (i.e., for distributions of non-negative performance measures).

In sum, the suggested tail characteristics are relevant and applicable to the left tails of performance distributions. Importantly, they can be used to compare left and right tails, for example, in studies that examine how generative mechanisms for extreme "winners" differ from those for extreme "losers" (Mundt et al., 2022; Turetsky, 2018).

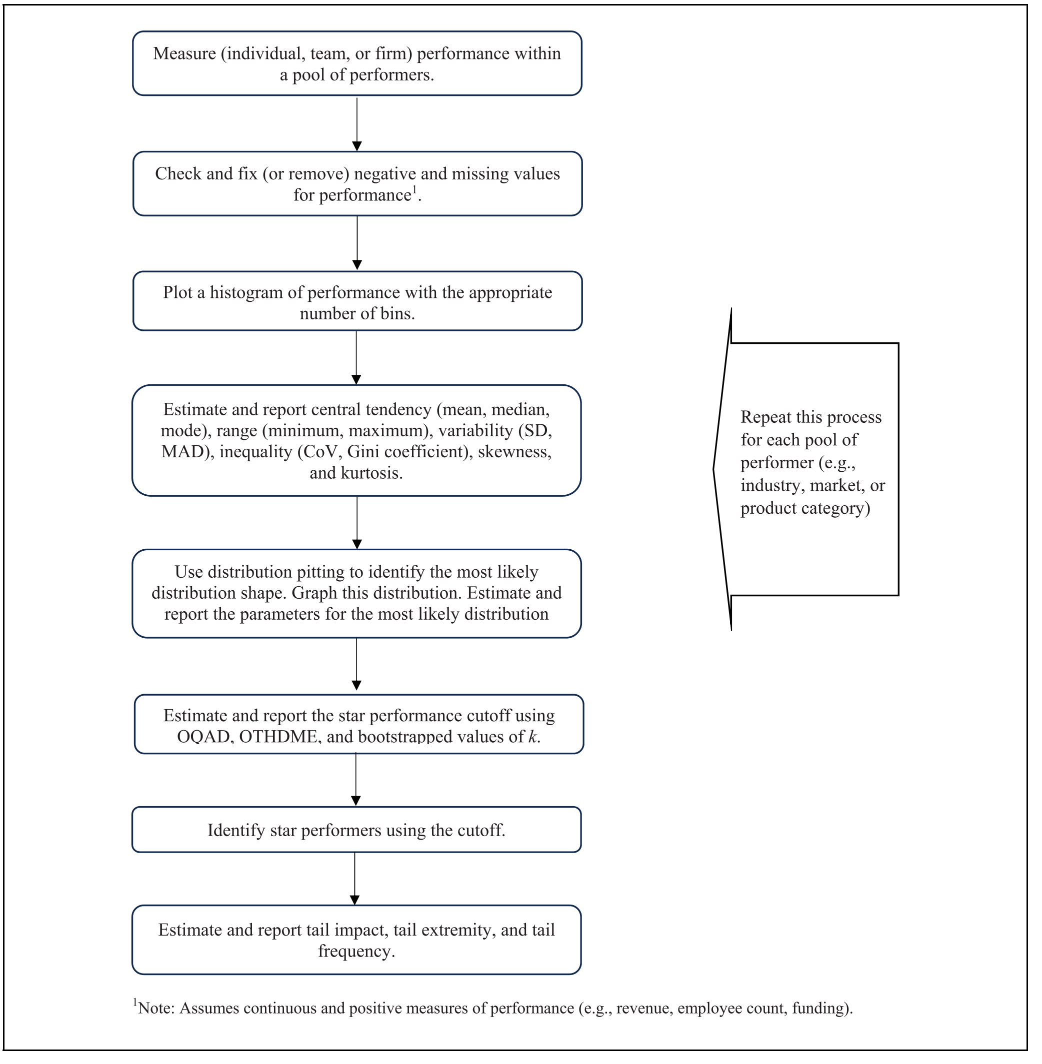

Figure 14. Workflow for systematic evaluation of star performance in entrepreneurship.

Discussion

This methodological primer seeks to support explicit and fine-grained investigations of star performance in entrepreneurship. Figure 14 outlines the suggested workflow for such studies. We show how a combination of various statistical properties can enrich the understanding of variability in performance. Further, we introduce tail impact, tail extremity, and tail frequency as additional properties for such investigations. These novel tail properties not only promise to reveal additional nuances of star performance but are also easier to translate into implications for entrepreneurship research, practice, and policy.

Table 11. Alternative Methodologies to Investigate Performance in Entrepreneurship Research.

Method	Purpose	Focus: IV	Focus: Mechanism	Focus: DV	R package::function()
Goodness-of-fit statistics (e.g., Chi-square statistic)	Examine fit to a specific distributional shape	-	-	✓	ks.test( ) nortest::ad.test( ) fitdistrplus::fitdist( )
Heuristic plots (e.g., moment-ratio plot) Maximum likelihood estimation	Infer the most likely distributional shape	-	-	✓	
Maximum likelihood estimation Bootstrap Analysis	Examine fit to a specific distributional shape	-	-	✓	*poweRlaw* for power law *MASS:: fitdistr( )* for lognormal *AEP::fitaep( )* for AEP
Distribution pitting	Identify the most likely distributional shape from a predefined set	-	-	✓	*Dpit::Dpit( )*
This study	**Comprehensively probe the DV (performance) to inform further empirical analyses**	-	-	✓	**See R code in Appendix 1**
Fuzzy or Crisp Set Qualitative Comparative Analysis	Explore relationships between antecedents and performance	✓	-	✓	*QCA*
Semi or nonparametric regression	Test hypotheses about antecedents of performance while accounting for right-skew and heavy tails	✓	-	✓	*mgcv::gam( )*
Quantile regression	Test hypotheses about how the influence of antecedents changes along the performance distribution	✓	-	✓	*quantreg::rq( )*
Agent-based modeling, system dynamics	Use simulations to explore the emergence of distributions and outliers	✓	✓	✓	

Note. See Clark et al. (2023) and Crawford, Joo, and Aguinis (2024) for exemplar studies that use the above methodologies.

Implications for Research

As Table 11 indicates, this study enriches the portfolio of methodologies by expanding the focus from distributional properties and shapes to specific characteristics of distributional tails. The findings that emerge upon applying the suggested methodology will likely stimulate research exploring predictors and mechanisms associated with star performance.

For example, analyses at the level of "pools of performers" may reveal unique configurations of tail characteristics. Specifically, a single extreme performer may account for the entire star performance (tail impact) in some industries, whereas a larger pool of star performers may account for the same collective outcome in other industries. Such patterns carry important implications for resource allocation decisions by entrepreneurs, the more ambitious of whom may prefer to compete in industries with higher extremity of success despite lower odds of success, whereas the more conservative entrepreneurs may prefer less extreme outcomes (Dunkelberg et al., 2013; Wiklund et al., 2003).

Moreover, the introduced tail characteristics (i.e., impact, extremity, and frequency) can serve as focal dependent variables in future studies investigating the emergence of star performance (O'Boyle & Götz, 2025). In addition to characteristics of entrepreneurs and their ventures, industry- and market-level antecedents deserve systematic examination for their impact on the tails of performance distributions and, in turn, how star performers change the industries and markets in which they operate. Unlike abstract statistical properties such as skewness and kurtosis, tail characteristics are more intuitive to interpret and relevant for entrepreneurship practice and policy.

In addition, empirical patterns in tail characteristics should be combined with conjectures and hunches about star performance to support abductive theorizing (Sætre & Van de Ven, 2021). Surprising patterns thus uncovered may highlight the need to reevaluate study designs (e.g., collect population-level data instead of random samples) and use non-traditional methods, such as quantile regression, for hypothesis testing. Thus, the introduced methodological framework promises a valuable stepping stone to develop and test theories about star entrepreneurs (Shepherd & Wiklund, 2009; Shepherd et al., 2019).

Finally, for researchers who seek to investigate star performance in entrepreneurship, we suggest using the sample R code provided in Supplemental Appendix 1 to examine the variability in such performance. The first step can involve using the publicly available Comprehensive Australian Study of Entrepreneurial Emergence dataset to test the R code and gain familiarity with its generated outputs. Next, scholars can use other datasets that include data for entrepreneurial performance and that have been used in prior research. These include the Inc. 5000 list (U.S. and Europe editions), the Kauffman Firm Survey, and Waves 1 and 2 of the PSED (Crawford, Joo, & Aguinis, 2024; Crawford et al., 2015).

Implications for Practice

The methodological framework developed in this study has several important implications for entrepreneurship practitioners and policymakers. For entrepreneurs, the prospect of star performance often underpins entrepreneurial intent, motivation, and action (Cassar, 2010; Hogarth & Karelaia, 2012). Applying the framework to their industry of interest, entrepreneurs can use *tail impact* to understand how much star performers contribute to aggregate industry performance, *tail extremity* to benchmark the magnitude of the best outcome relative to the most likely outcomes, and *tail frequency* to estimate their odds of becoming a star performer in the industry. For example, when targeting the "IT Systems Development" industry, growth-oriented entrepreneurs in the United States can use the distributional properties and tail characteristics for the corresponding Inc. 5000 firms to realistically gauge their chances of achieving star performance (Fan et al., 2021). Situating themselves within the performance distribution can help entrepreneurs better align their resource assessments and investments with their opportunity costs and goals (Dunkelberg et al., 2013). While many entrepreneurs ostensibly target the extreme right of the performance distribution, their capabilities and expectations can constrain their success (Crawford et al., 2015). Entrepreneurial decision-making can therefore juxtapose tail frequency against tail extremity, thus acknowledging the tension between the likelihood and magnitude of star performance.

For venture investors and acquirers, the methodological framework developed in this study can provide actionable insights into potential risks and rewards for their investment portfolios. For example, historical data for the tail extremity can signal upper bounds for performance. Similarly, venture capital and private equity funds can assess the historical tradeoff between tail extremity and tail frequency when choosing or evaluating a target industry for investments. Thus, decisions to reward (penalize) an entrepreneur for exceptional (poor) outcomes can be informed by a careful evaluation of the likely odds and extremity of star performance (Davidsson, 2021; Davidsson et al., 2020). Moreover, when appraising investment failures, an explicit focus on distributional tails promises a deeper understanding of the role of skill versus chance, randomness, or serendipity in driving venture outcomes (Denrell & Liu, 2012, 2021).

Entrepreneurship educators can integrate the proposed methodological framework into their pedagogy to help students recognize and overcome an implicit bias toward average performance (Gala et al., 2023). Educators can foster data-driven understanding of star performance in entrepreneurial contexts by guiding students to apply the analytical workflow summarized in Figure 14 to publicly available datasets.

Implications for Policy

For public policy focused on entrepreneurship, the introduced framework underscores the limitations of relying solely on the number of ventures or average performance as benchmarks. Formal evaluations of pro-entrepreneurship initiatives indicate that targeting entrepreneurs based on past average performance—rather than future marginal performance—can induce policy failure (Brown et al., 2017; Parker, 2005). Failing to recognize and account for the substantial variance in performance may therefore impede policy success (Parker, 2007; Shane, 2009). Further, consistent evidence of idiosyncrasy and randomness in firm growth (Coad, 2009; Delmar et al., 2003) suggests that policymakers should shift from a focus on individual firms to a broader, distributional perspective targeting pools of firms, some of which will emerge as star performers.

Because a small number of star performers often generate the bulk of societal benefits, such as innovation and job creation (Acs et al., 2016), policymakers can use *tail impact* to guide the design of initiatives that support entrepreneurial endeavors. Policies can be dynamically adjusted to support star performers until they become self-sustaining, while reallocating resources from underperformers toward emerging stars. Similarly, policymakers can use *tail extremity* to evaluate the extent to which a single firm drives the targeted outcomes; the risks associated with the overreliance on such extreme performers can be mitigated through diversification and safeguards.

Limitations and Future Research

Because this brief prioritizes intuitiveness and ease of adoption for entrepreneurship researchers interested in evaluating star performers, it excludes some complex statistical techniques for outlier detection (Aggarwal, 2017). Further, this study focuses on univariate analyses; future research can extend this primer to detecting and evaluating multivariate outliers (Leys et al., 2019). This primer can also be extended to performance anomalies (extreme patterns), which differ from performance outliers (extreme data points) and hence may merit a different methodological framework (Ruef & Birkhead, 2024).

In addition, we call for extensive use of visualization techniques to not only effectively communicate the nature of variability in entrepreneurial performance but also to evaluate the emergence of star performers over time (Healy & Moody, 2014; Schwab, 2018; Schwab et al., 2025; Wennberg & Anderson, 2020). For example, paired with statistical analysis of longitudinal data, animated performance distributions can help researchers visualize the emergence of star performers from an initial pool of aspirants.

Finally, we call for methodological guidance to support explicit empirical investigation of the underlying processes that engender star performance in entrepreneurship. One promising avenue involves computational models and simulations because they can lend rich insights into generative mechanisms that engender different types of skewed performance distributions (Vancouver et al., 2016). Another promising methodological approach is abduction, wherein scholars iterate between (a) exploratory quantitative analyses to discover empirical patterns and (b) literature reviews to identify plausible explanations and propose better theories for the emergence of star performance (Sætre & Van de Ven, 2021).

Conclusion

This methodological primer provides a valuable framework for empirical studies that go beyond the prevalent focus on average performance by explicitly examining star performance through a distributional perspective. The statistical properties and tail characteristics outlined in this analytical guide enable researchers to undertake much-needed investigations of the antecedents, emergence, and implications of star performance. In sum, we seek to motivate research that builds evidence-based theories to explain and predict the substantial performance variability often observed in entrepreneurial settings.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. For continuous and positive measures of performance, such as revenue, employee count, and funding.
2. We use the term outliers when discussing generic statistical properties and analytical techniques. We use the term star performers when discussing actual distributions of entrepreneurial performance. We conceptually map star performers to influential outliers (Aguinis et al., 2013).
3. Spearman correlation coefficient. $*p < .05$; $**p < .01$; $***p < .001$.

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