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Students' assumptions of Entrepreneurs' performance: The paradox of excess entry and missed opportunity

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ABSTRACT

Most variables in entrepreneurship are not distributed normally. Instead, they are characterized by positive skew and heavy tails featuring influential outliers. Yet, this fundamental asymmetry in entrepreneurial endeavors is rarely discussed in entrepreneurship education, which often oscillates between highlighting everyday entrepreneurs and high-growth 'unicorn' startups while overlooking the distributional context for these extremes. Therefore, this paper explores whether students accurately comprehend the non-normality that pervades entrepreneurship. We conducted two studies wherein undergraduate business students at a large, public university in the Midwest US estimated entrepreneurial performance. We elicited students' estimates of the range of performance exhibited by entrepreneurs using a real-world vignette and performance data for an online learning platform. By providing empirical evidence that students may carry largely *in*accurate assumptions of performance distributions, this paper highlights the paradoxical risks of excess entrepreneurial entry on the one hand and missed opportunity on the other.

1. Introduction

Entrepreneurship has rapidly emerged as a mainstream field for academic research and education. In recognition of the inherently practical nature of entrepreneurial endeavors, universities are proactively educating future founders (Landström et al., 2022). The past two decades have witnessed a remarkable surge in entrepreneurship course offerings, particularly at the undergraduate level (Kuratko, 2005; Nabi et al., 2017). In the US alone, over half a million students take entrepreneurship courses each year (Kauffman Foundation, 2019). Some large public universities have made such introductory courses mandatory or enabled students across all majors to pursue a minor in entrepreneurship. The incessant rise of technology startups – centered on the Silicon Valley model – has played a prominent role in this phenomenon (Kuckertz et al., 2023). Indeed, entrepreneurship educators often use founders of unicorns (ventures whose valuation exceeds one billion dollars and are outliers among their cohort) as role models for innovation, funding, hyper-scaling, monetization, and exits.

However, this uptrend in entrepreneurship education has largely missed a key aspect of new ventures – the inherently skewed nature of venture outcomes. In other words, entrepreneurship is often characterized by extreme performers (i.e., outliers) and a large

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majority of under-performers (Fried and Tauer, 2015). Emerging research has shown that not only are entrepreneurial output variables, such as revenues and profits, highly skewed but so are input variables, such as the number of employees and financial capital (Crawford et al., 2015; Khurana et al., 2023). This paradox of entrepreneurial activities and outcomes has been the subject of vigorous scholarly debate. Some scholars have called for a greater celebration and examination of small businesses and 'everyday' entrepreneurs (Welter et al., 2017), while others have – rather provocatively – argued in favor of a sharp focus on high-performing venture-funded startups, and against a broad promotion of entrepreneurship via public policy or institutions (Shane, 2009).

Unfortunately, this polarizing approach does not paint a comprehensive picture of the substantial variance in performance outcomes. A narrow focus on unicorns may imperil budding entrepreneurs by creating a distorted 'rosy' view of their prospects (Kuckertz et al., 2020), given the high odds of venture failure particularly for novice entrepreneurs (Azoulay et al., 2020). Conversely, anchoring students' expectations to everyday entrepreneurship may fail to inspire them toward the incredible potential of innovations in science, technology, and business models. Arguably, entrepreneurship students deserve richer insights into venture performance beyond the dichotomy of the 'expected' outcome – often adverse or mundane – and the 'extreme' outcome, i.e., unicorns (Kuckertz et al., 2023). Therefore, we explore the following question: *To what extent do students carry accurate assumptions about the distribution of entrepreneurial performance?*

Answering this question is important because a lopsided view of entrepreneurship might overly dampen or detrimentally fuel students' emerging passion for entrepreneurship. Notably, undergraduate students are (a) cognitively malleable yet representative of the broader population (Kardes, 1996; Lucas, 2003; Sears, 1986), (b) often encouraged to cultivate an entrepreneurial mindset, and (c) likely to face a career choice between wage employment and self-employment (Berkhout et al., 2016). Therefore, inducing among students an accurate appreciation of the distribution of entrepreneurial outcomes is crucial to the broader mission of entrepreneurship education (Kuckertz, 2021).

2. Distribution of entrepreneurial performance

Research suggests that inputs and outputs in entrepreneurship are dominated by outliers (Crawford et al., 2014, 2015). For example, the mean exit value for a startup is approximately $5.8 million largely due to a few billion-dollar acquisitions, whereas the median exit value is less than $500,000 (Hall and Woodward, 2010). This inherent incongruity of entrepreneurial activities and outcomes – where the average is neither informative nor representative – has been theorized to arise from a combination of luck, path-dependence, self-reinforcing mechanisms, and winner-take-all effects (Crawford et al., 2015; Morgan and Sisak, 2013). Moreover, such *non-normal* distributions of revenues, resources, and other key variables are likely to exacerbate in digital entrepreneurship and innovation (Berger et al., 2021), which represent an increasing share of the global economy (Nicholson, 2020).

Absent personal experience with entrepreneurial endeavors or a detailed exploration of a specific, third-person opportunity (Shepherd et al., 2007), students may assume that entrepreneurial performance is normally distributed (Dean et al., 2007). Instead, research has shown that the distributions of entrepreneurship variables are consistently positively skewed and heavy-tailed (Crawford et al., 2015; Delmar et al., 2022). These distributions are illustrated in Fig. 1, wherein the X axis represents the extent of performance, and the Y axis represents the corresponding probability.

Over-optimism, particularly among nascent entrepreneurs, about expected outcomes can result in excess entry due to an overestimation of the likelihood or odds of success (Cassar, 2010). Paradoxically, students who assume that entrepreneurial performance is normally distributed may also underestimate the extremity of entrepreneurial performance by ignoring the heavy tails, i.e., performance outliers, found in most contexts (Crawford et al., 2015). As illustrated in Fig. 2 (where the X axis represents the extent of performance, and the Y axis represents the corresponding probability), such inadvertent pessimism can result in a lowering of entrepreneurial intention and, therefore, missed opportunities (Baron, 1998; Hogarth and Karelaia, 2012).

Moreover, repeated exposure to success stories may inadvertently create an assumption of a negatively skewed distribution among students. Here, entrepreneurship education centered on case studies featuring prominent entrepreneurs may induce among students

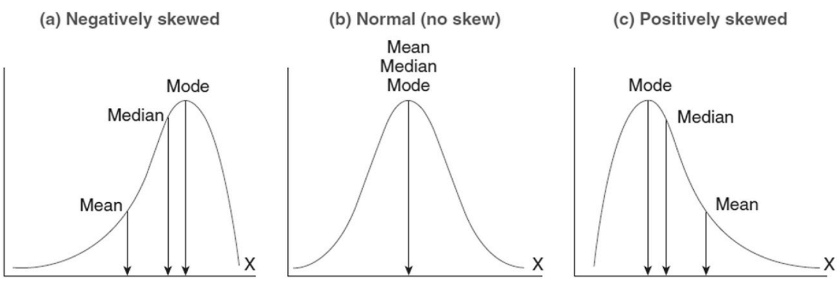

Fig. 1. Normal versus skewed distributions.

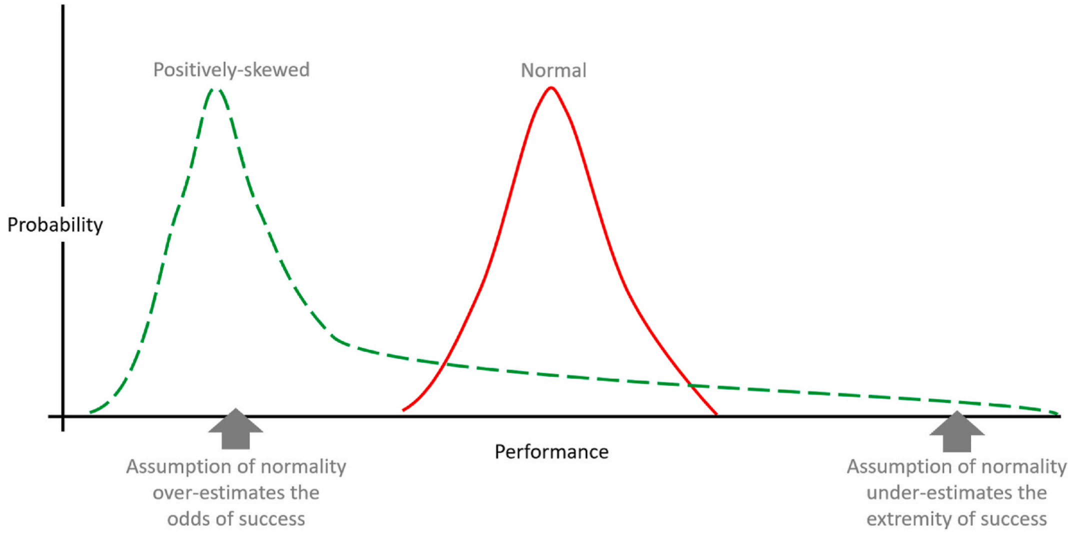

Fig. 2. Positively-skewed distribution versus normal distribution of entrepreneurial performance.

the use of *representativeness*, a heuristic wherein the *"subjective probability of an event, or a sample, is determined by the degree to which it: (i) is similar in essential characteristics to its parent population; and (ii) reflects the salient features of the process by which it is generated"* (Kahneman and Tversky, 1972, p. 430). Entrepreneurial judgments have been found to involve such heuristics and the resulting cognitive biases (Cossette, 2014). When viewed from a distributional perspective, an over-exposure to success stories and case studies of high performers is likely to manifest as an assumption of a negatively skewed distribution because students may conflate the extent of (extreme) success with the likelihood of (extreme) success. In other words, while entrepreneurial outcomes are characterized by heavy tails, the number of high performers is often a relatively small fraction of the overall pool of entrepreneurs (Booyavi and Crawford, 2023; Crawford et al., 2015). As illustrated in Fig. 3, an assumption of negative skew over-estimates the fraction of successful entrepreneurs while, paradoxically, resulting in an implicit truncation of the most influential outliers (Aguinis et al., 2013).

Both these distributional assumptions (i.e., normal and negatively skewed) are inaccurate, given consistent findings of positive skew in most entrepreneurial variables. As illustrated in Fig. 4, both assumptions underestimate the odds of failure or poor performance.

In sum, an accurate understanding of the distribution of performance is crucial for entrepreneurship students. Therefore, this study

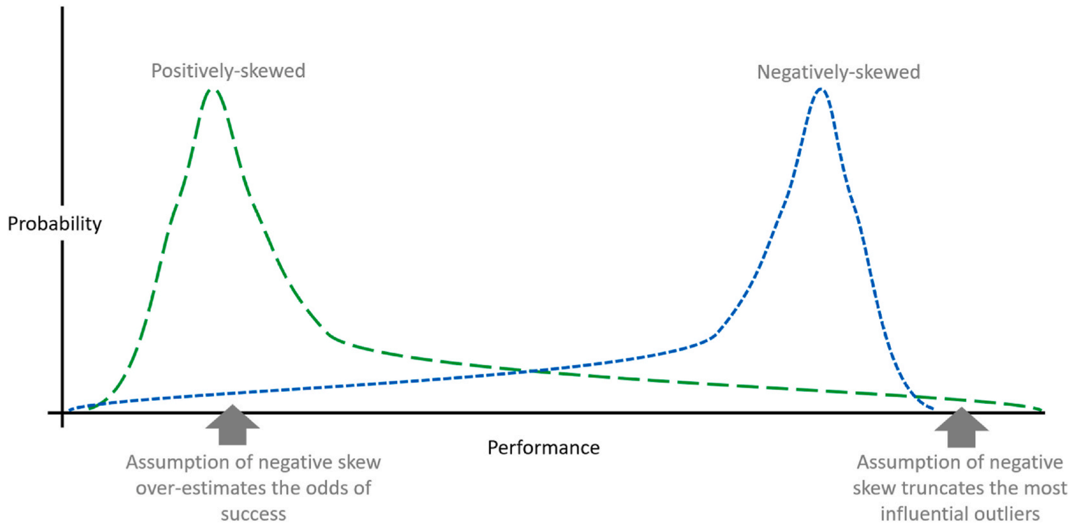

Fig. 3. Positively-skewed distribution versus negatively-skewed distribution of entrepreneurial performance.

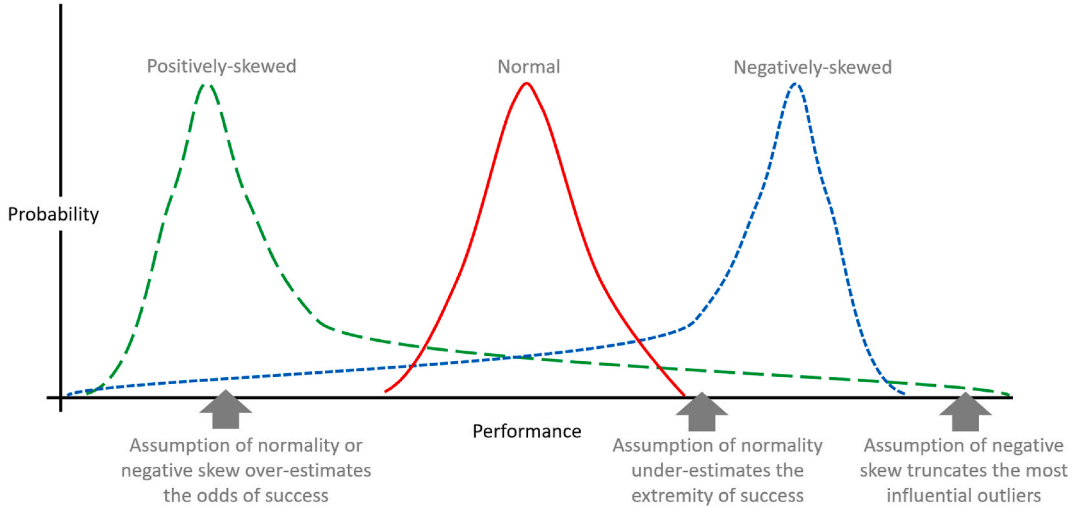

Fig. 4. Positively skewed, normal, and negatively skewed distributions of entrepreneurial performance.

examines whether students hold accurate assumptions of such performance distributions by drawing upon extant research into the elicitation of subjective probability distributions (Leemann et al., 2021; O'Hagan, 2019). Given that our sample does not constitute experts, we simplified the elicitation techniques to suit the empirical context.

3. Methods

This paper used two exploratory studies to examine the research question. Both studies involved surveying undergraduate students enrolled in multiple sections of management and entrepreneurship courses at a large, research-intensive university in the Midwest US. Student samples are appropriate because they represent the population of interest and have been used in prior research to examine entrepreneurial cognition (e.g., Frederiks et al., 2019). A vignette featuring entrepreneurial performance on a digital platform was used as the context for eliciting distributions (see Appendix 1 for further details).

Including the reading of the vignette, participants had 25 minutes to complete the associated survey. Both studies were administered online using Qualtrics. Study 1 was administered to six sections of an undergraduate course. For the first section, students participated in-class, allowing the first author to hold a debrief session after participants completed the survey. In this debrief session, the first author asked participants if they had any difficulty following the questions in the survey – none did and, therefore, the same survey was used for the whole study.

3.1. Sample

375 students were invited to participate in Study 1, of whom 219 chose to participate (58.4% response rate). Of these, 12 were removed due to missing data, and 4 failed the attention checks, leaving a final sample of 203 cases. 106 students were invited to participate in Study 2, of whom 47 chose to participate (44.3% response rate). Of these, 4 were removed due to missing data and none failed the attention checks, leaving a final sample of 43 cases. There was no overlap between the participants in the two studies; they were conducted in different semesters of the academic year.

3.2. Measures - Judgment accuracy

Broadly, both studies sought to explore judgment accuracy – specifically, the assumptions students held related to distributions of entrepreneurial performance. In Study 1, participants' subjective probability distributions were elicited in two ways. First, they were asked to estimate points on a performance distribution. These questions are listed in Appendix 2. Second, they were asked to select one of six distribution shapes (exponential, Gumbel, lognormal, normal, power law, and Weibull). These shapes are illustrated in Appendix 3. For exploratory correlation analyses and T-tests, judgment accuracy was measured as a binary (1/0) variable, which was set to 1 if the participants selected (a) the correct range for at least three (i.e., 50%) of the six questions that involved selecting a point in the distribution and (b) any one of the three distributions with positive skew (i.e., exponential, lognormal, or power law).

In Study 2, we implemented two significant changes to provide an alternative perspective on judgment accuracy. First, participants were provided with the mean and median – instead of minimum and maximum – entrepreneurial performance. This modification complemented Study 1 by eliciting participants' assumptions of the 'best' and 'worst' performance (see Appendix 4 for further details). Second, we removed the question that asked participants to select one of six distribution shapes in case participants capitalized on chance while selecting a distribution shape. Instead, participants were directed to a website which required them to plot a distribution manually (Shinyapps, 2023). See Appendix 5 for a screenshot of the website. This website was a customized version of the Sheffield Elicitation Framework (SHELF, 2023), available as open-source code implemented in 'R' (Github, 2023).

This graphical method of eliciting probability distributions requires greater cognitive engagement by participants (Morris et al., 2014). Judgments were designated as 'accurate' if participants selected (a) the correct range for at least three (i.e., 50%) of the six questions listed in Appendix 4 and (b) plotted points (using the elicitation website) for which the best 'fit' was a positively skewed distribution with heavy tails, i.e., skewness >2 and kurtosis >7 (Byrne, 2010; West et al., 1995).

3.3. *Measures - Exploratory variables*

In Study 1, we explored several variables that may influence judgment accuracy in the entrepreneurship context. Besides collecting data on each participant's age, gender, undergraduate major, course type (in person or virtual), prior work experience, and family's business experience, we also administered scales to measure entrepreneurial self-efficacy (McGee et al., 2009), general knowledge overconfidence (Simon and Shrader, 2012), goal orientation (Vandewalle, 1997), prior entrepreneurial experience (Muehlfeld et al., 2017; Zhao et al., 2005), and willingness to take risks (Gomez-Mejia and Balkin, 1989). Notably, some course sections in the Study 1 sample were surveyed using first-person opportunity language while others were surveyed using third-person opportunity language (Shepherd et al., 2007).

3.4. *Consequential judgments*

For both studies, we sought to make the participants' judgments about performance outcomes relevant and consequential, following suggestions by Lonati et al. (2018). While participation was optional, students received extra credit for participating. None opted out for an alternative assignment that would require approximately the same time. Importantly, participants in each group were incentivized with monetary compensation in the form of Amazon gift codes valued between US$20 and US$40 (totaling US$720) tied to the judgment accuracy. Participants with the three most accurate judgments in each course section were awarded gift cards; *"such financial incentives motivate participants to be attentive and focused on the experiment and clarify the decision situation in which participants find themselves"* (Lonati et al., 2018, p. 22). Incentives are also likely to enhance overall response rates for non-working participants (Anseel et al., 2010).

4. Results

This exploratory study's objective was to examine the extent to which students carry accurate assumptions about the distribution of entrepreneurial performance. In both studies, we found evidence of largely inaccurate judgments, details of which we provide below.

4.1. *Study 1 results*

Of the 203 students in the final sample for Study 1, 85 (42%) selected a distribution with positive skew (i.e., exponential, lognormal, or power law) while 63 (31%) selected the normal distribution as the best characterization for entrepreneurial performance. However, only 32 (16%) selected at least three out of six correct points in the distribution, and only 27 (13%) selected both, thus qualifying as making an accurate judgment. Moreover, only 1 student selected all six correct points and a positively skewed shape. Overall, we found evidence consistent with the notion that students likely carry inaccurate assumptions about the distribution of entrepreneurial performance.

With respect to the exploratory variables measured in Study 1, analyses using T-tests indicated *no statistically significant difference* in the accuracy of judgments due to participants' age, prior work experience, (online/virtual), undergraduate major, whether participants' family members owned a business, whether participants were currently involved in a side hustle (i.e., a part-time job, business, or work that brings in extra money), or the delivery mode of the entrepreneurship course. Only *gender* influenced judgment accuracy; on average, male students made more accurate judgments than female students. Notably, judgment accuracy did not vary with the type (first-person or third-person) of opportunity featured in the vignette. We also conducted correlation analyses involving scale-based exploratory variables and found that the accuracy of judgments about the distribution of entrepreneurial performance was *not* associated in a statistically significant manner with prior entrepreneurial experience, entrepreneurial self-efficacy, general knowledge overconfidence, learning or performance goal orientation, or the willingness to take risks. Further details are available in Appendix 6.

4.2. *Study 2 results*

Of the 43 students in the final sample for Study 2, 12 students (28%) selected at least three out of six correct points in the distribution, while 10 students (23%) plotted a positive skewed distribution with heavy tails, i.e., skew >2 and kurtosis >7, which were conservative thresholds compared to skew of 3.1 and kurtosis of 13.7 for the actual data. Moreover, only 7 participants (16%) qualified as making an accurate judgment about distribution points and distribution shape. When asked to estimate the maximum performance, only 10 participants (23%) opted for the top of the range with most participants failing to appreciate the extremity of success. Overall, we find evidence that, on average, only 1 in 4 students may be fully cognizant of the relatively high odds of sub-par outcomes and the extremity of success in entrepreneurship.

5. Discussion

Our central argument is that entrepreneurship education should embrace the non-normality that characterizes entrepreneurship. Doing so may alert students to the relatively low odds of above-average success while inspiring them to the extreme performance – exemplified by unicorns (Kuckertz et al., 2023) – made possible by technological and business innovations. Arguably, judgments involving entrepreneurial performance offer a suitable pedagogical context to help students internalize the heavy-tailed nature of entrepreneurship (Crawford et al., 2022).

5.1. Implications for theory

This paper seeks to enrich entrepreneurship education research, which often follows broader entrepreneurship research in oscillating between the extremes of (a) everyday entrepreneurs and small businesses and (b) hyper-growth unicorns (Aldrich and Ruef, 2018; Welter et al., 2017). To our knowledge, notions of heavy-tailed distributions, skew, kurtosis, and outliers have yet to be thoroughly incorporated into scholarly investigations or pedagogical interventions involving entrepreneurship students. Doing so first requires understanding the extent to which students carry accurate assumptions of how entrepreneurial performance is distributed. By providing empirical evidence that students may carry largely inaccurate assumptions, this paper establishes the need for inducing an 'outside view' – an approach wherein similar situations are used as analogies and reference points while making judgments (Lovallo et al., 2012).

Notably, the literature on heuristic decision-making largely relies on base rates, i.e., averages, to induce an outside view (Kahneman and Lovallo, 1993). However, we speculate that using only base rates may have adverse consequences due to the skewed nature of entrepreneurship. Instead, providing distributional information may help overcome the limitations of base rates in decision contexts characterized by heavy tails (Taleb et al., 2022). Because outliers pervade performance contexts (Aguinis & O'Boyle, 2014; Bradley and Aguinis, 2023), the unintended consequences of inducing base rate usage may have broader implications for decision-making research. This paper also seeks to leverage and enrich the emerging research on non-normality in important variables in entrepreneurship (Crawford et al., 2015). We extend these findings to entrepreneurship pedagogy by recommending that educators proactively incorporate distributions of input variables (e.g., capital raised) and output variables (e.g., revenues) into classroom exercises.

For scholars, we have three suggestions for future research. First, we suggest the use of data capturing methods such as those employed in Study 2, i.e., the use of graphical interfaces that allow participants to pick specific points or plot their beliefs, following recent research on elicitation of subjective probability distributions (Leemann et al., 2021; O'Hagan, 2019). Second, we call for studies that involve entrepreneurship students in collecting performance data and converting it into distributional forms to assess whether such active engagement can enhance judgment accuracy, as suggested by extant research (e.g., Gigerenzer et al., 1988). Third, we suggest that scholars conduct experiments wherein extant research on inducing an 'outside view' using base rates (e.g., Lovallo et al., 2012) is empirically tested in decision-making contexts such as entrepreneurship where base rate usage may fail to enhance judgment accuracy, calling for more nuanced interventions that involve distributions.

5.2. Implications for practice

This exploratory study identifies an important pedagogical opportunity centered on entrepreneurial performance involving real-world information. We suggest that entrepreneurship educators incorporate classroom exercises involving distributional information and judgments while embracing experiential learning (Hägg and Gabrielsson, 2020) and greater use of low-stakes testing (Dunlosky et al., 2013) that involves consequential decision-making exercises (Lonati et al., 2018). By doing so, educators can help students appreciate the substantial variance and high odds of failure or mediocre outcomes in entrepreneurship – in contrast to what the media often portrays – yet inspire them by drawing attention to performance outliers, i.e., star entrepreneurs. Arguably, the extremity of success is likely to increase in digital contexts, which increasingly pervade the economy (Nicholson, 2020). Moreover, students are more likely to engage in entrepreneurial endeavors in such contexts, particularly via side hustles enabled by the gig economy (van Gelderen et al., 2021).

Credit author statement

Kaushik Gala: Conceptualization, Data curation, Formal analysis, Software, Visualization, Writing – original draft preparation, Writing - Reviewing and Editing. Carlos D. Valladares: Data curation, Investigation, Methodology. Brandon A. Mueller: Funding acquisition, Supervision, Validation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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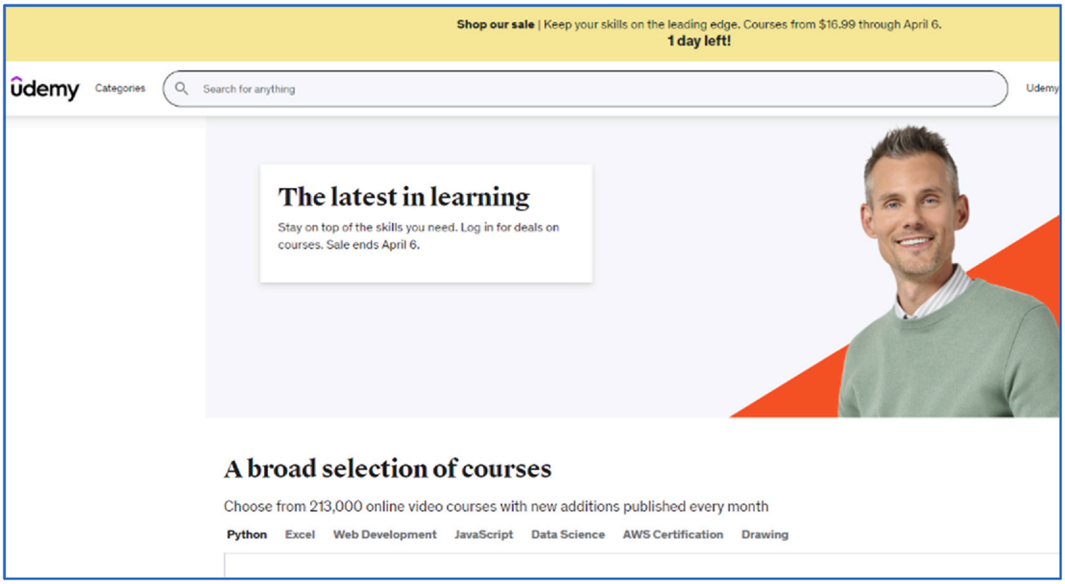
Appendix 1. (Study 1 and 2)

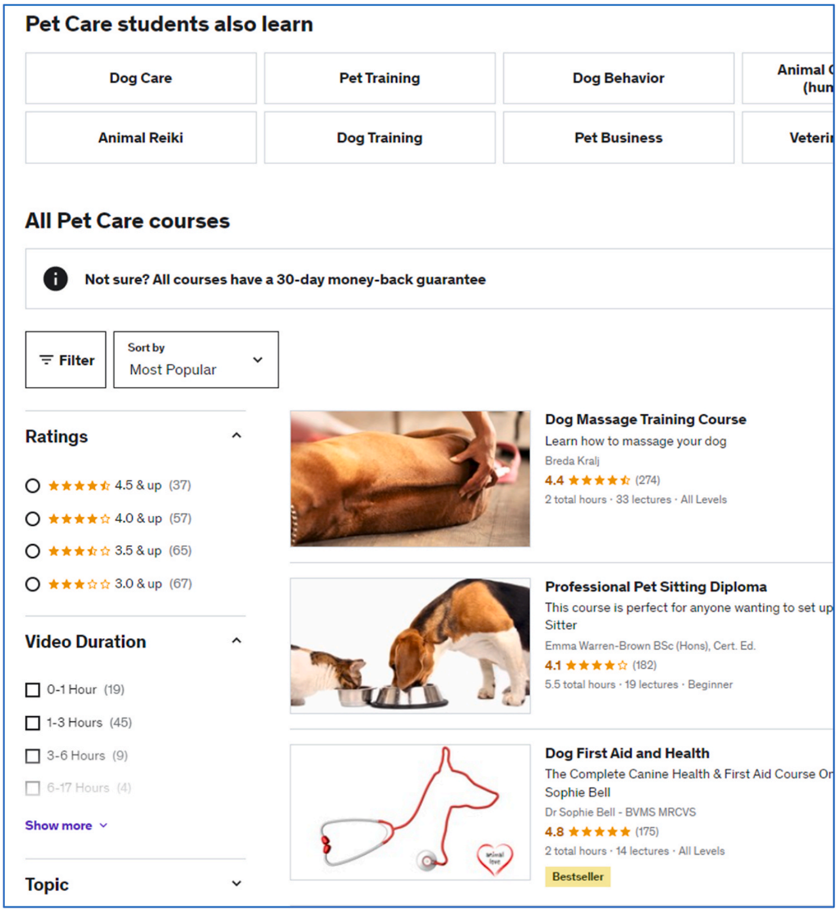
Vignette

This vignette was not hypothetical; the data that constitutes it reflects actual categories, courses, and instructor performance on a global, online learning platform (Udemy, 2023a). We selected Udemy because our study participants (and target population) are undergraduate students who are likely to be familiar with (a) digital platforms in general, (b) online learning platforms in particular, and (c) consuming – and perhaps creating – digital content focused on education. Moreover, of the 130 categories used by Udemy to organize courses, we select the 'Pet Care and Training' category because it is likely the most familiar to our target population, both as consumers of pet-related content and as future providers (instructors) of pet-related courses (Udemy, 2023b).

Udemy (https://udemy.com) is a digital platform where instructors sell recorded video courses. Currently, there are over 60,000 instructors on Udemy; together, they have over 60 million students enrolled in their courses. This online platform features over two hundred thousand courses across one hundred and thirty categories ranging from data science and design to meditation and music.



One Udemy category is Pet Care & Training. Courses in this category cover topics such as communicating with cats, ensuring good nutrition for pets, and training a puppy. In this category, there are a total of 100 instructors.



Appendix 2. (Study 1)

Eliciting Distribution Points to Measure Judgment Accuracy

First Person Opportunity

As mentioned above, for Udemy's Pet Care & Training category, there are 100 instructors. The minimum number of students for an instructor is 2 and the maximum number of students for an instructor is 114,000. Across all 100 instructors, there are a total of 470,000 students.

Imagine ranking instructors by their performance, i.e., the number of students (rank 1 = best performer; rank 100 = worst performer). Also, imagine that – several years ago – you chose to become a Udemy instructor and offer courses in this category, i.e., Pet Care & Training. Thus, you are one of these 100 instructors.

Survey question related to first person opportunity.

1	Imagine you currently have the same number of students as the average across all 100 instructors. What's your best guess about how many students you have?
2	*Imagine you currently hold a rank of **20** among all instructors (i.e., nearly 80% instructors have fewer students than you). What's your best guess about how many students you have?*
3	*Imagine you currently hold a rank of **80** among all instructors (i.e., only 20% instructors have fewer students than you). What's your best guess about how many students you have?*
4	*Imagine you currently hold a rank of **50** among all instructors (i.e., half the instructors have fewer and half have more students than you). What's your best guess about how many students you have?*
5	*Imagine you currently hold a rank of **33** among all instructors (i.e., nearly two-thirds of all instructors have fewer students than you). What's your best guess about how many students you have?*
6	*Imagine you currently hold a rank of **66** among all instructors (i.e., only one-thirds of all instructors have fewer students than you). What's your best guess about how many students you have?*

Third Person Opportunity

As mentioned above, for Udemy's Pet Care & Training category, there are 100 instructors. The minimum number of students for an instructor is 2 and the maximum number of students for an instructor is 114,000. Across all 100 instructors, there are a total of 470,000 students.

Imagine ranking instructors by their performance, i.e., the number of students (rank 1 = best performer; rank 100 = worst performer).

Survey question related to third person opportunity.

1	Instructor A has an average number of students. What's your best guess about how many students A has?
2	*Instructor B has a rank of* ***20*** *among all instructors (i.e., nearly 80% instructors have fewer students than B). What's your best guess about how many students B has?*
3	*Instructor C has a rank of* ***80*** *among all instructors (i.e., only 20% instructors have fewer students than C). What's your best guess about how many students C has?*
4	*Instructor D has a rank of* ***50*** *among all instructors (i.e., half the instructors have fewer and half have more students than D). What's your best guess about how many students D has?*
5	*Instructor E has a rank of* ***33*** *among all instructors (i.e., nearly two-thirds of all instructors have fewer students than E). What's your best guess about how many students E has?*
6	*Instructor F has a rank of* ***66*** *among all instructors (i.e., only one-thirds of all instructors have fewer students than F). What's your best guess about how many students F has?*

For all six questions and both types of opportunity (first-person and third-person), participants selected one of the following eleven choices:

1. Between 2 and 10,000
2. Between 10,000 and 20,000
3. Between 20,000 and 30,000
4. Between 30,000 and 40,000
5. Between 40,000 and 50,000
6. Between 50,000 and 60,000
7. Between 60,000 and 70,000
8. Between 70,000 and 80,000
9. Between 80,000 and 90,000
10. Between 90,000 and 100,000
11. Between 100,000 and 114,000

The correct range for each of the six questions was determined using the actual data collected by the first author for instructor performance on Udemy.com in the relevant category.

Appendix 3. (Study 1)

Using Distribution Shape to Measure Judgment Accuracy

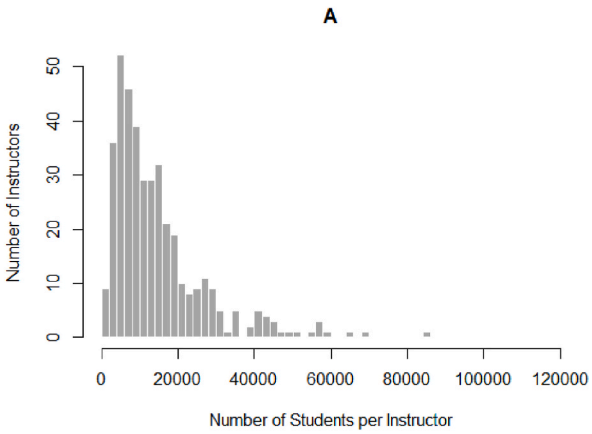
Distribution shapes were created in 'R' using the *DescTools, poweRlaw,* and *stats* packages. Each shape was characterized by approximately the same minimum (2) and maximum (114,000) values for the number of students per instructor and had the same number of instructors (100). Participants selected one of six distributions: lognormal (A), normal (B), Gumbel (C), exponential (D), Weibull (E), or power law (F).

Survey Question (First Person Opportunity)

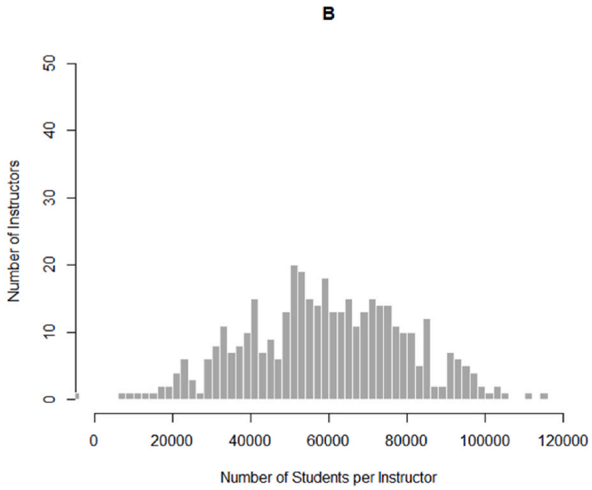
For this question, imagine plotting a graph where the X axis is the number of students per instructor and the Y axis is the number of instructors, including you and the other 99. For Udemy's Pet Care & Training category, the X axis goes from 0 to 120,000 (because the maximum number of students for an instructor is 114,000).

Survey Question (Third Person Opportunity)

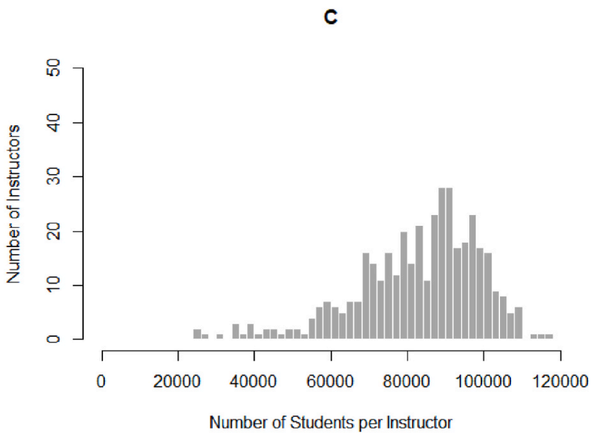
For this question, imagine plotting a graph where the X axis is the number of students per instructor and the Y axis is the number of instructors. For Udemy's Pet Care & Training category, the X axis goes from 0 to 120,000 (because the maximum number of students for an instructor is 114,000).



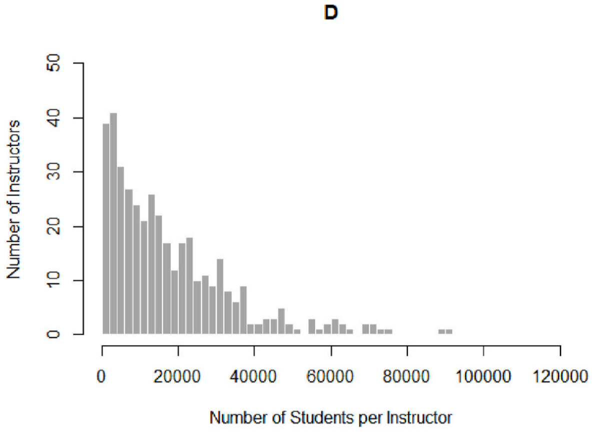
Lognormal distribution.



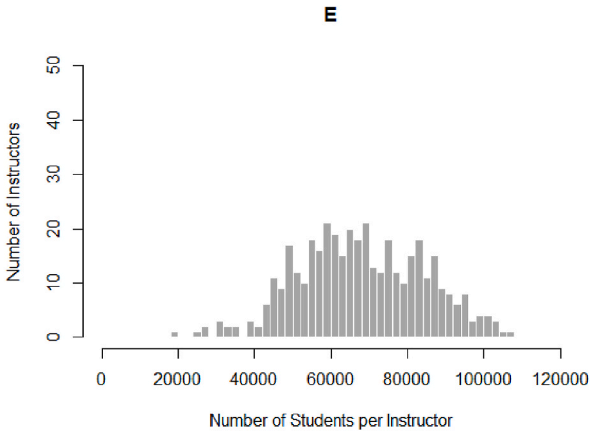
Normal distribution.



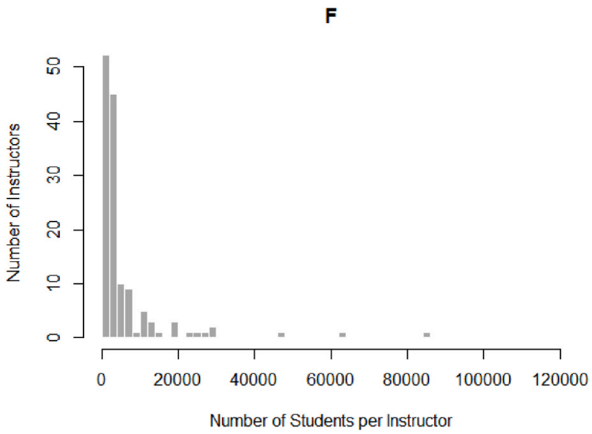
Gumbel distribution.



Exponential distribution.



Weibull distribution.



Power law distribution.

Appendix 4. (Study 2)

Eliciting Distribution Points to Measure Judgment Accuracy

Third Person Opportunity

As mentioned above, for Udemy's Pet Care & Training category, there are 100 instructors. The average (mean) number of students for an instructor is 2850 and the median number of students for an instructor is 245. Imagine ranking instructors by their performance, i.e., the number of students (rank 1 = best performer; rank 100 = worst performer).

Survey question related to third person opportunity.

1	Instructor A has the minimum number of students. What's your best guess about how many students A has?
2	*Instructor B has the **maximum** number of students. What's your best guess about how many students B has?*
3	*Instructor C has a rank of **20** among all instructors (i.e., nearly 80% instructors have fewer students than C). What's your best guess about how many students C has?*
4	*Instructor D has a rank of **80** among all instructors (i.e., only 20% instructors have fewer students than D). What's your best guess about how many students D has?*
5	*Instructor E has a rank of **33** among all instructors (i.e., nearly two-thirds of all instructors have fewer students than E). What's your best guess about how many students E has?*
6	*Instructor F has a rank of **66** among all instructors (i.e., only one-thirds of all instructors have fewer students than F). What's your best guess about how many students F has?*

For all six questions, participants selected one of the following eleven choices:

1. Less than 10,000
2. Between 10,000 and 20,000
3. Between 20,000 and 30,000
4. Between 30,000 and 40,000
5. Between 40,000 and 50,000
6. Between 50,000 and 60,000
7. Between 60,000 and 70,000
8. Between 70,000 and 80,000
9. Between 80,000 and 90,000
10. Between 90,000 and 100,000
11. More than 100,000

The correct range for each of the six questions was determined using the actual data collected by the first author for instructor performance on Udemy.com in the relevant category.

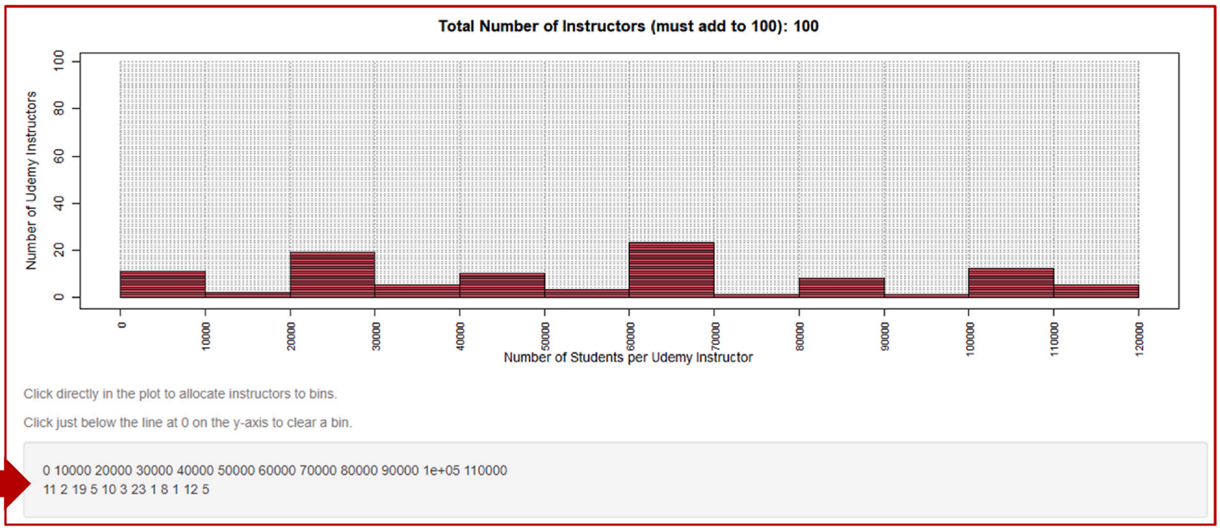
Appendix 5. (Study 2)

Using Graphical Interfaces to Elicit Distribution

As mentioned above, for Udemy's Pet Care & Training category, there are 100 instructors. The minimum number of students for an instructor is 2 and the maximum number of students for an instructor is 114,000. Go to this website (https://entrepreneurship.shinyapps.io/elicitation/) and note the graphical area. The X axis is the number of students per instructor and the Y axis is the number of instructors. For Udemy's Pet Care & Training category, the X axis goes from 0 to 120,000 (because the maximum number of students for an instructor is 114,000).

Note.

1. Click directly in the plot to allocate instructors to bins (make your best guess!).
2. Click just below the line at 0 on the y-axis to clear a bin.
3. The total number of instructors (updated automatically) across the bins must add to 100.



Once you are done allocating instructors and they add up to 100 as shown in the example above, copy the entire text in the box (indicated by the arrow) and paste it into the corresponding text box in the survey page.

Appendix 6. (Study 1)

Analyses for Exploratory Variables

Table A6.1 below summarizes T-test analyses of exploratory variables. This involved the comparison of judgment accuracy (as defined in Section 3.2) across two groups with the null hypothesis of no difference between the two groups. Only gender influenced judgment accuracy; on average, male students made more accurate judgments than female students.

Table A6.1
T-test Analyses for Comparison of Judgment Accuracy Between Groups

Exploratory Variable	Group 1	Group 2	T-test p-value
Age	≤20 years (n = 98)	>20 years (n = 105)	0.225
Gender	Male (n = 97)	Female (n = 106)	0.006**
Course Type	In person (n = 128)	Virtual (n = 75)	0.383
Family Business	Yes (n = 72)	No (n = 131)	0.553
Business Major	Yes (n = 143)	No (n = 60)	0.341
Side Hustle	Yes (n = 107)	No (n = 96)	0.464
Opportunity Type	First-person (n = 74)	Third-person (n = 129)	0.376
Full-time Work Experience	≤1 year (n = 109)	>1 year (n = 94)	0.836

Note: *$p < 0.05$; **$p < 0.01$.

Table A6.2 below summarizes correlation analyses of scale-based exploratory variables. We did not find a statistically significant correlation between judgment accuracy and *any* of these exploratory variables.

Table A6.2
Correlation of Judgment Accuracy with Scale-Based Exploratory Variables

Exploratory Variable	Mean	SD	Ent Exp	ESE	GKO	LGO	PGO	WTR
Entrepreneurship Experience (EntExp)	1.97	0.82	*(0.82)*					
Entrepreneurial Self-efficacy (ESE)	3.26	0.63	0.39**	*(0.90)*				
General Knowledge Overconfidence (GKO)	0.25	0.17	0.05	−0.05	-			
Learning Goal Orientation (LGO)	3.91	0.56	0.20**	0.29*	−0.07	*(0.78)*		
Performance Goal Orientation (PGO)	3.20	0.53	0.01	0.02	0.16*	−0.12	*(0.69)*	
Willingness to Take Risk (WTR)	2.70	0.75	−0.19**	−0.23**	0.18*	−0.32**	0.41**	*(0.71)*
Accurate Judgment (0/1)	0.13	0.34	−0.07	0.00	−0.07	0.05	−0.05	−0.01

Note: *$p < 0.05$; **$p < 0.01$. Numbers in brackets are scale reliabilities. N = 203.
Note: A reviewer noted that the maximum values in figures A, D, and F of Appendix 3 are in the range of 85,000 to 90,000 – this may have nudged participants of Study 1 towards inadvertently selecting figures B, C, or E. Therefore, we conducted a robustness test for Study 1 wherein judgment accuracy is measured without including responses to the question involving six shapes; the findings corresponding to Tables A6.1 and A6.2 remain the same.

Appendix 7. (Study 1 and Study 2)

Attention Checks

We used several attention checks in Study 1 and Study 2. Following recommended guidelines to use multiple attention checks and multiple types of attention checks (e.g., Abbey and Meloy, 2017), we interspersed such checks throughout the survey. Participants were marked as failing the attention check if they incorrectly responded to all of the following questions.

Question: Are you enrolled in the virtual/online section of the course?

Answer choices: Yes/No.

Rationale: Because we knew what section (in-person or virtual) the participants were enrolled in, this question served as an attention check.

Question: I am currently a high school student.

Answer choices: Strongly disagree/Somewhat disagree/Neither/Somewhat agree/Agree.

Rationale: Because all participants are college students and, therefore, this statement is not true, this item served as an attention check. Attentive participants should have selected “Strongly disagree” as the answer.

Question: Select the category under which the online courses were listed.

Answer choices: Travel/Pet Care/Life Hacks/Music/Dorm Life.

Rationale: Because the Udemy vignette had an image and text that clearly specified the category, attentive participants should have selected “Pet Care” as the answer.

References

Abbey, J.D., Meloy, M.G., 2017. Attention by design: using attention checks to detect inattentive respondents and improve data quality. J. Oper. Manag. 53, 63–70.
Aguinis, H., Gottfredson, R.K., Joo, H., 2013. Best-practice recommendations for defining, identifying, and handling outliers. Organ. Res. Methods 16 (2), 270–301.
Aguinis, H., O'Boyle Jr., E., 2014. Star performers in twenty-first century organizations. Person. Psychol. 67 (2), 313–350.
Aldrich, H.E., Ruef, M., 2018. Unicorns, gazelles, and other distractions on the way to understanding real entrepreneurship in the United States. Acad. Manag. Perspect. 32 (4), 458–472.
Anseel, F., Lievens, F., Schollaert, E., Choragwicka, B., 2010. Response rates in organizational science, 1995–2008: a meta-analytic review and guidelines for survey researchers. J. Bus. Psychol. 25, 335–349.
Azoulay, P., Jones, B.F., Kim, J.D., Miranda, J., 2020. Age and high-growth entrepreneurship. Am. Econ. Rev.: Insights 2 (1), 65–82.
Baron, R.A., 1998. Cognitive mechanisms in entrepreneurship: why and when enterpreneurs think differently than other people. J. Bus. Ventur. 13 (4), 275–294.
Berger, E.S., Von Briel, F., Davidsson, P., Kuckertz, A., 2021. Digital or not–The future of entrepreneurship and innovation: introduction to the special issue. J. Bus. Res. 125, 436–442.
Berkhout, P., Hartog, J., Van Praag, M., 2016. Entrepreneurship and financial incentives of return, risk, and skew. Entrep. Theory Pract. 40 (2), 249–268.
Booyavi, Z., Crawford, G.C., 2023. Different, but same: a power law perspective on how rock star female entrepreneurs reconceptualize "gender equality". J. Bus. Ventur. Insights 19, e00374.
Bradley, K.J., Aguinis, H., 2023. Team performance: nature and antecedents of nonnormal distributions. Organ. Sci. 34 (3), 1266–1286.
Byrne, B. M. (2010). Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. Routledge.
Cassar, G., 2010. Are individuals entering self-employment overly optimistic? An empirical test of plans and projections on nascent entrepreneur expectations. Strat. Manag. J. 31 (8), 822–840.
Cossette, P., 2014. Heuristics and cognitive biases in entrepreneurs: a review of the research. J. Small Bus. Enterpren. 27 (5), 471–496.
Crawford, G.C., Aguinis, H., Lichtenstein, B., Davidsson, P., McKelvey, B., 2015. Power law distributions in entrepreneurship: implications for theory and research. J. Bus. Ventur. 30 (5), 696–713.
Crawford, G.C., McKelvey, B., Lichtenstein, B.B., 2014. The empirical reality of entrepreneurship: how power law distributed outcomes call for new theory and method. J. Bus. Ventur. Insights 1, 3–7.
Crawford, G.C., Skorodziyevskiy, V., Frid, C.J., Nelson, T.E., Booyavi, Z., Hechavarria, D.M., et al., 2022. Advancing entrepreneurship theory through replication: a case study on contemporary methodological challenges, future best practices, and an entreaty for communality. Entrep. Theory Pract. 46 (3), 779–799.
Dean, M.A., Shook, C.L., Payne, G.T., 2007. The past, present, and future of entrepreneurship research: data analytic trends and training. Entrep. Theory Pract. 31 (4), 601–618.
Delmar, F., Wallin, J., Nofal, A.M., 2022. Modeling new-firm growth and survival with panel data using event magnitude regression. J. Bus. Ventur. 37 (5), 106245.
Dunlosky, J., Rawson, K.A., Marsh, E.J., Nathan, M.J., Willingham, D.T., 2013. Improving students' learning with effective learning techniques: promising directions from cognitive and educational psychology. Psychol. Sci. Publ. Interest 14 (1), 4–58.
Frederiks, A.J., Englis, B.G., Ehrenhard, M.L., Groen, A.J., 2019. Entrepreneurial cognition and the quality of new venture ideas: an experimental approach to comparing future-oriented cognitive processes. J. Bus. Ventur. 34 (2), 327–347.
Fried, H.O., Tauer, L.W., 2015. An entrepreneur performance index. J. Prod. Anal. 44, 69–77.
Gigerenzer, G., Hell, W., Blank, H., 1988. Presentation and content: the use of base rates as a continuous variable. J. Exp. Psychol. Hum. Percept. Perform. 14 (3), 513.
Github (2023). GitHub - OakleyJ/SHELF: Tools to Support the Sheffield Elicitation Framework (SHELF). https://github.com/OakleyJ/SHELF.
Gomez-Mejia, L.R., Balkin, D.B., 1989. Effectiveness of individual and aggregate compensation strategies. Ind. Relat.: A J. Econ. Soc. 28 (3), 431–445.
Hägg, G., Gabrielsson, J., 2020. A systematic literature review of the evolution of pedagogy in entrepreneurial education research. Int. J. Entrepreneurial Behav. Res. 26 (5), 829–861.
Hall, R.E., Woodward, S.E., 2010. The burden of the nondiversifiable risk of entrepreneurship. Am. Econ. Rev. 100 (3), 1163–1194.
Hogarth, R.M., Karelaia, N., 2012. Entrepreneurial success and failure: confidence and fallible judgment. Organ. Sci. 23 (6), 1733–1747.
Kahneman, D., Lovallo, D., 1993. Timid choices and bold forecasts: a cognitive perspective on risk taking. Manag. Sci. 39 (1), 17–31.
Kahneman, D., Tversky, A., 1972. Subjective probability: a judgment of representativeness. Cognit. Psychol. 3 (3), 430–454.
Kardes, F.R., 1996. In defense of experimental consumer psychology. J. Consum. Psychol. 5 (3), 279–296.
Kauffman Foundation (2019). Entrepreneurship Education Comes of Age on Campus. https://www.kauffman.org/entrepreneurship/reports/entrepreneurship-education-comes-of-age-on-campus/.
Khurana, I., Tamvada, J.P., Audretsch, D.B., 2023. The weaker sex? A tale of means and tails. J. Bus. Ventur. Insights 20, e00407.
Kuckertz, A., 2021. Why we think we teach entrepreneurship-and why we should really teach it. J. Enterpren. Educ. 24 (3), 1–7.
Kuckertz, A., Berger, E.S., Prochotta, A., 2020. Misperception of entrepreneurship and its consequences for the perception of entrepreneurial failure–the German case. Int. J. Entrepreneurial Behav. Res. 26 (8), 1865–1885.
Kuckertz, A., Scheu, M., Davidson, P., 2023. Chasing mythical creatures - a (not-so-sympathetic) critique of entrepreneurship's obsession with unicorn startups. J. Bus. Ventur. Insights 19, e00365.
Kuratko, D.F., 2005. The emergence of entrepreneurship education: development, trends, and challenges. Entrep. Theory Pract. 29 (5), 577–597.
Landström, H., Gabrielsson, J., Politis, D., Sørheim, R., Djupdal, K., 2022. The social structure of entrepreneurial education as a scientific field. Acad. Manag. Learn. Educ. 21 (1), 61–81.
Leemann, L., Stoetzer, L.F., Traunmüller, R., 2021. Eliciting beliefs as distributions in online surveys. Polit. Anal. 29 (4), 541–553.
Lonati, S., Quiroga, B.F., Zehnder, C., Antonakis, J., 2018. On doing relevant and rigorous experiments: review and recommendations. J. Oper. Manag. 64, 19–40.
Lovallo, D., Clarke, C., Camerer, C., 2012. Robust analogizing and the outside view: two empirical tests of case-based decision making. Strat. Manag. J. 33 (5), 496–512.
Lucas, J.W., 2003. Theory-testing, generalization, and the problem of external validity. Socio. Theor. 21 (3), 236–253.
McGee, J.E., Peterson, M., Mueller, S.L., Sequeira, J.M., 2009. Entrepreneurial self–efficacy: refining the measure. Enterpren. Theor. Pract. 33 (4), 965–988.
Morgan, J., & Sisak, D. (2013). Entrepreneurship and Loss-Aversion in a Winner-Take-All Society. University of California-Berkeley Working Paper.
Morris, D.E., Oakley, J.E., Crowe, J.A., 2014. A web-based tool for eliciting probability distributions from experts. Environ. Model. Software 52, 1–4.
Muehlfeld, K., Urbig, D., Weitzel, U., 2017. Entrepreneurs' exploratory perseverance in learning settings. Entrep. Theory Pract. 41 (4), 533–565.
Nabi, G., Liñán, F., Fayolle, A., Krueger, N., Walmsley, A., 2017. The impact of entrepreneurship education in higher education: a systematic review and research agenda. Acad. Manag. Learn. Educ. 16 (2), 277–299.
Nicholson, J. R. (2020). New Digital Economy Estimates. Bureau of Economic Analysis.
O'Hagan, A., 2019. Expert knowledge elicitation: subjective but scientific. Am. Statistician 73 (Suppl. 1), 69–81.
Sears, D.O., 1986. College sophomores in the laboratory: influences of a narrow data base on social psychology's view of human nature. J. Pers. Soc. Psychol. 51 (3), 515.
Shane, S., 2009. Why encouraging more people to become entrepreneurs is bad public policy. Small Bus. Econ. 33, 141–149.
Shinyapps (2023). Entrepreneurial Performance. https://entrepreneurship.shinyapps.io/elicitation/.
SHELF (2023). Sheffield elicitation Framework. https://shelf.sites.sheffield.ac.uk/.
Shepherd, D.A., McMullen, J.S., Jennings, P.D., 2007. The formation of opportunity beliefs: overcoming ignorance and reducing doubt. Strateg. Entrep. J. 1 (1-2), 75–95.
Simon, M., Shrader, R.C., 2012. Entrepreneurial actions and optimistic overconfidence: the role of motivated reasoning in new product introductions. J. Bus. Ventur. 27 (3), 291–309.
Taleb, N.N., Bar-Yam, Y., Cirillo, P., 2022. On single point forecasts for fat-tailed variables. Int. J. Forecast. 38 (2), 413–422.

Udemy (2023a), Online Courses – Learn Anything, on Your Schedule | Udemy. https://udemy.com.
Udemy (2023b), Pet Care and Training Courses for the Dedicated Pet Owner | Udemy. https://www.udemy.com/courses/lifestyle/pet-care-and-training/.
van Gelderen, M., Wiklund, J., McMullen, J.S., 2021. Entrepreneurship in the future: a Delphi study of ETP and JBV editorial board members. Entrep. Theory Pract. 45 (5), 1239–1275.
VandeWalle, D., 1997. Development and validation of a work domain goal orientation instrument. Educ. Psychol. Meas. 57 (6), 995–1015.
Welter, F., Baker, T., Audretsch, D.B., Gartner, W.B., 2017. Everyday entrepreneurship—a call for entrepreneurship research to embrace entrepreneurial diversity. Entrep. Theory Pract. 41 (3), 311–321.
West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: problems and remedies. In R. H. Hoyle (Ed.), Structural Equation Modeling: Concepts, Issues, and Applications (pp. 56–75). Sage Publications, Inc.
Zhao, H., Seibert, S.E., Hills, G.E., 2005. The mediating role of self-efficacy in the development of entrepreneurial intentions. J. Appl. Psychol. 90 (6), 1265.