Investigating and Communicating the Uncertainty of Effects:

The Power of Graphs

Editorial

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Abstract

Entrepreneurial activities are inherently risky and related outcomes uncertain. Consequently, empirical studies to build entrepreneurship theory need to investigate not only the direction and average size of effects but also the uncertainty of these effects. Current research published in academic entrepreneurship journals tends to focus on dichotomous likelihood evaluations employing statistical significance tests. This editorial argues that graphs communicating the distribution of observed effects offer a far more useful way to communicate, evaluate and discuss uncertainty. Publishing such graphs will support theory building and offer more meaningful guidance to practitioners and policy makers.

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Academic entrepreneurship research focuses on the development of theories that explain and predict effects. Given the uncertainty inherently associated with entrepreneurial activities, meaningful propositions have to be probability statements.

The bulk of the currently published quantitative entrepreneurship studies employ statistical significance tests which translate the uncertainty associated with empirically observed effects into dichotomous "effect" or "no effect" conclusions. A p-value below .05 for observed effects is interpreted as a rejection of the "no-effect" hypothesis and support for the hypothesized effect. The simplicity of this clear dichotomous distinction is very appealing, but it has prevented scholars from discussing and sharing more fine-grained information about the uncertainty associated with proposed effects.[1]

The development of meaningful entrepreneurship theory, however, depends on explicitly modeling and discussing details about the uncertainty associated with hypothesized effects. Identifying the direction and average size of effects is important, but not sufficient. Hence, researchers and practitioners need to understand not only the direction and average strength of effects, but also the uncertainty associated with these effects. The current focus on

[1] For comprehensive discussions of the limitations of statistical significance tests see, for example: Gigerenzer (2004), Hubbard (2015), Nuzzo (2014) and Schwab et al. (2011). Recently, the sample size sensitivity of statistical significance tests and the need for explicit effect size evaluations have received notable attention, for example, in the guidelines to authors at major management journals (Bettis et al., 2016) and policy statements of the American Statistical Association (Wasserstein and Lazar, 2016).

dichotomous "effect or no effect" interpretations based on p-values constrains theory development, or, as Tukey (1991: 100) warned eloquently over 25 years ago:

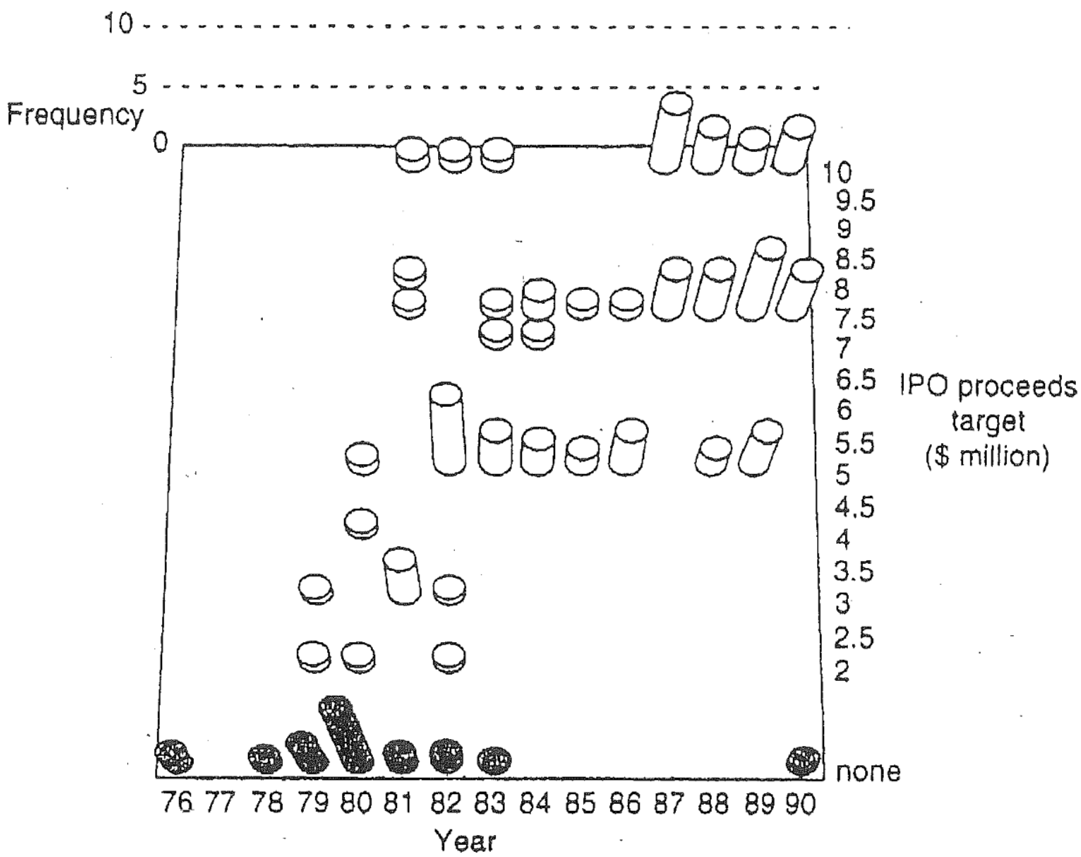
> "The worst, meaning the most dangerous, feature of accepting the null hypothesis is giving up of explicit uncertainty ... mathematics can sometimes be put in such black-and-white terms, but our knowledge or belief about the external world never can."

Reporting summary measures of dispersion is not enough

The generally reported summary statistics of dispersion (e.g., the standard deviation) provide valuable information for the evaluation of uncertainty of observed effects, but more often than not, a more detailed investigation and reporting are necessary. In the case of dichotomous outcome variables, empirical information on how frequently which effect occurred and the size of the respective effects might be sufficient to obtain a sense of the uncertainty of the related hypotheses. When encountering non-dichotomous outcomes, however, the distribution of effects turns out to be a much more complex and difficult-to-evaluate issue. For continuous variables, for example, the observed variation around an average effect can be narrow or broad, unimodal or multimodal, skewed or fat-tailed. The distribution of effects will always deviate from the typically assumed normal or Poisson distributions, and potentially may deviate substantially.

In their longitudinal study of Silicon Valley entrepreneurs, for example, Suchman, Steward and Westfall (2001) investigated how the emergence of cognitive institutional frames affected entrepreneurial behavior. They examined the conversion triggers in the investment contracts entrepreneurs signed with venture capitalists. Conversion triggers specify the level of total proceeds from an initial public offering (IPO) that will lead to an automatic conversion of all preferred stock into common stock. Suchman et al. (2001) observed what they labeled "typification without homogenization." By the mid-1980s, all financing contracts contained conversion triggers and the triggers' average IPO dollar value had increased over time, as had the triggers' range and standard deviations. These summary statistics, however, did not reveal an important underlying change over time, a change that is made immediately obvious by looking at Figure 1. This graph shows that after 1983, the conversion-trigger decision was narrowed to a ritualized choice between three values: small ($5 million), medium ($7.5 million), or large ($10 million).

Figure 1
Mandatory Conversion Triggers by Financing Date



Note: Figure adopted from Suchman, Steward and Westfall (2001: 10)[2]

This Silicon Valley study illustrates how detailed distributional information can provide crucial information for the interpretation of empirical data. Any investigation focused only on the overall frequency of conversion trigger use or on the average conversion-trigger value and its standard deviation would have missed this important deeper effect-distribution pattern. Here, the identification of a multimodal pattern is crucial for understanding and theorizing about the emergence of institutional frames. This includes deeper theorizing about how a frame affects the likelihood of specific outcomes. Such deeper investigations of outcome distributions are especially relevant for entrepreneurs who frequently deal with high-risk decisions and diverse ranges of possible outcomes. In general, detailed outcome distributions enable entrepreneurs and policy makers to obtain a deeper understanding of the associated up-side and down-side risks.

Summary statistics of dispersion

Published entrepreneurship studies tend to provide information about outcome distributions in the form of summary statistics, such as standard deviations, ranges, percentiles, coefficients of variation, skewness, or kurtosis. Each statistic provides helpful partial information. To obtain a more comprehensive sense for the overall distribution, however, readers must mentally combine the information from various statistics. What are the possible shapes of distributions with a mean of 20, a standard deviation of 12, a range from 2 to 45, a

[2] This 3-D graph is difficult to read. Its design, in my opinion, could benefit from the use of color, shifts in perspective, and potentially animation.

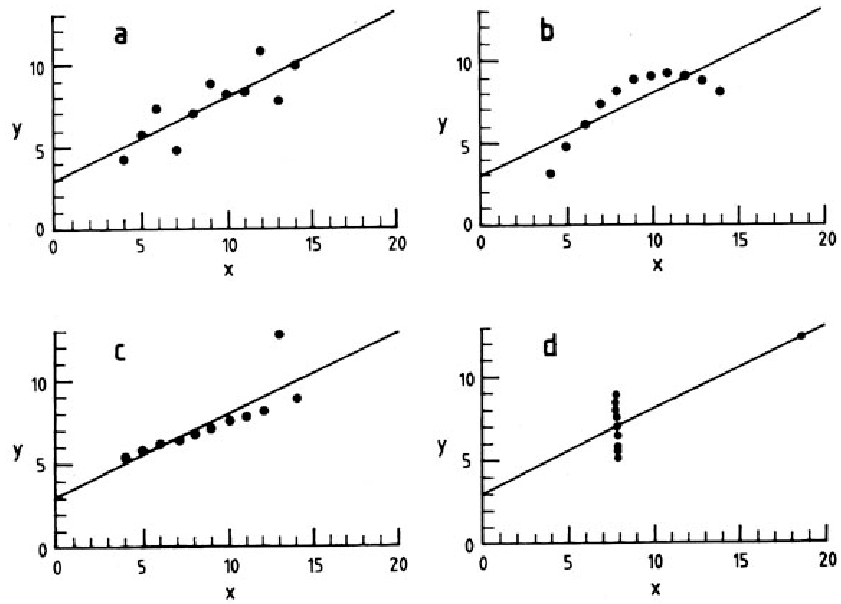
kurtosis score of 2 and a skewness score of .75? This combined interpretation requires readers with well-developed statistical intuitions.

The obvious alternative to readers mentally visualizing distributions is authors providing such visualizations in the form of graphs. Humans have the capability to intuitively and quickly comprehend provided graphical visualization (Kosslyn, 2006). Such graphs have the potential to communicate fine-grained and rich information about outcome distributions (Cumming & Finch, 2005; Gelman & Stern, 2006; Wilkinson & Task Force on Statistical Inference of the American Psychological Association, 1999).

Dangers of superficial dispersion investigations

Summary statistics aggregate information and focus on a specific distributional characteristic. The following classic quartet of four data sets illustrates the substantial risks associated with such aggregations (Anscombe, 1973). The four data sets depicted in Figure 2 have identical means and variances for the independent variable (x) and the dependent variable (y), as well as identical correlations between x and y, identical best-fitting regression lines, and identical standard deviations.

Figure 2
Anscombe's Quartet



Note: Downloaded October 31, 2017 from
https://ned.ipac.caltech.edu/level5/Wall2/Figures/figure3.jpeg

Simple scatter plots of the underlying observations, however, immediately reveal fundamentally different effect distributions. Current research reporting practices focused on communicating summary statistics --- often only means, correlation coefficients, and standard deviations -- combined with a dichotomous effect/no-effect evaluation based on statistical significance are ignoring a wealth of potentially valuable outcome-distribution information contained in the collected data, information that is crucial for a deeper understanding of the uncertainties associated with observed outcomes and for developing theories that capture and model these uncertainties.

Advances in graph-creation technology and expertise

Method scholars have long advocated graphs as a tool for interpreting and communicating detailed information about distributions (Tukey, 1977; Wilkinson & Task Force on Statistical Inference of the American Psychological Association, 1999). Today's statistical software packages facilitate graph creation. Common spreadsheet programs, such as MS Excel, have continuously upgraded their graph-creation capabilities. Commercial statistics programs, such as Stata, SPSS, SAS, or MatLab, and open-source programs, such as R, now include commands to conveniently create a variety of different graphs. In addition, software packages are available that specialize in the creation of graphs (for a list see: https://en.wikipedia.org/wiki/List_of_information_graphics_software).[3] These graph-creation capabilities are supplemented by an improved understanding of how individuals absorb and interpret graphs. Related research has developed increasingly specific and effective guidelines for graph construction (Kosslyn, 2006; Tufte, 2006). It is beyond the scope of this editorial to introduce these various graph development guidelines or to evaluate the large number of available software solutions. The availability of more sophisticated graph software and guidelines, however, clearly indicates opportunities that today's entrepreneurship researchers should consider and exploit.

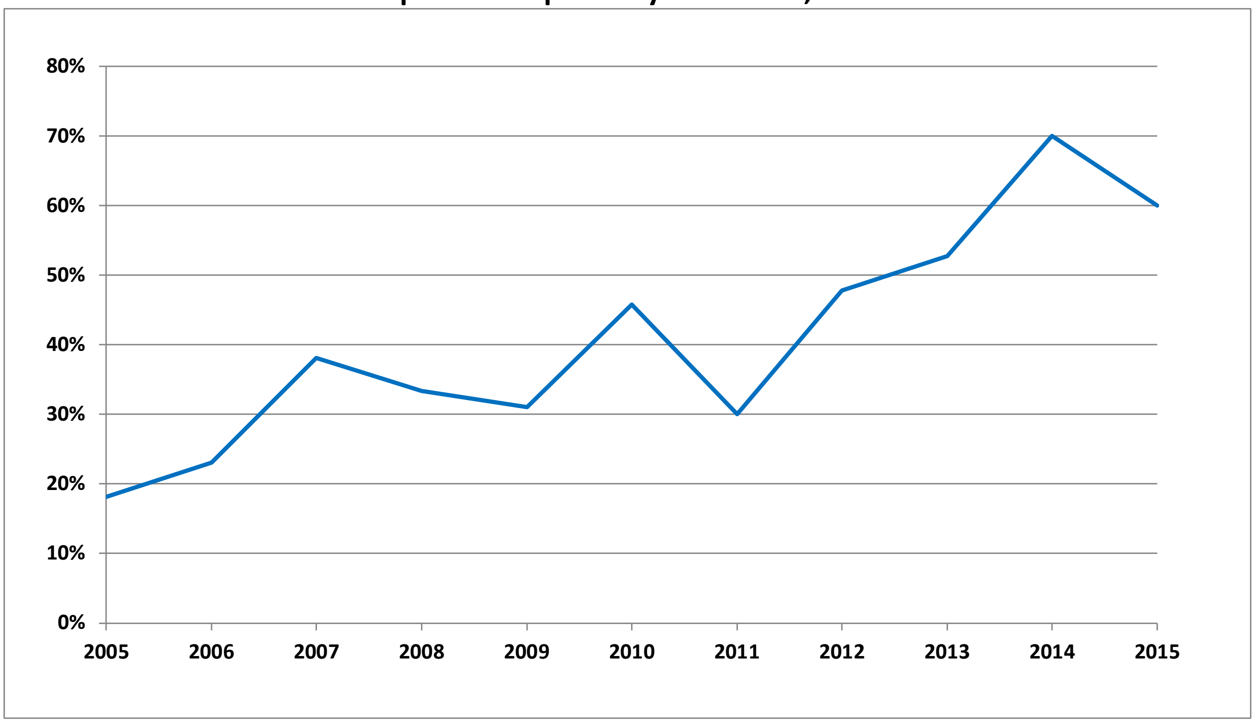
How entrepreneurship researchers use graphs

A quick survey of all the quantitative studies published in *Entrepreneurship Theory and Practice* (ETP) between 2005 and 2015 shows that the primary mode of communicating

[3] An anonymous reviewer provided helpful information on the variety of available software packages.

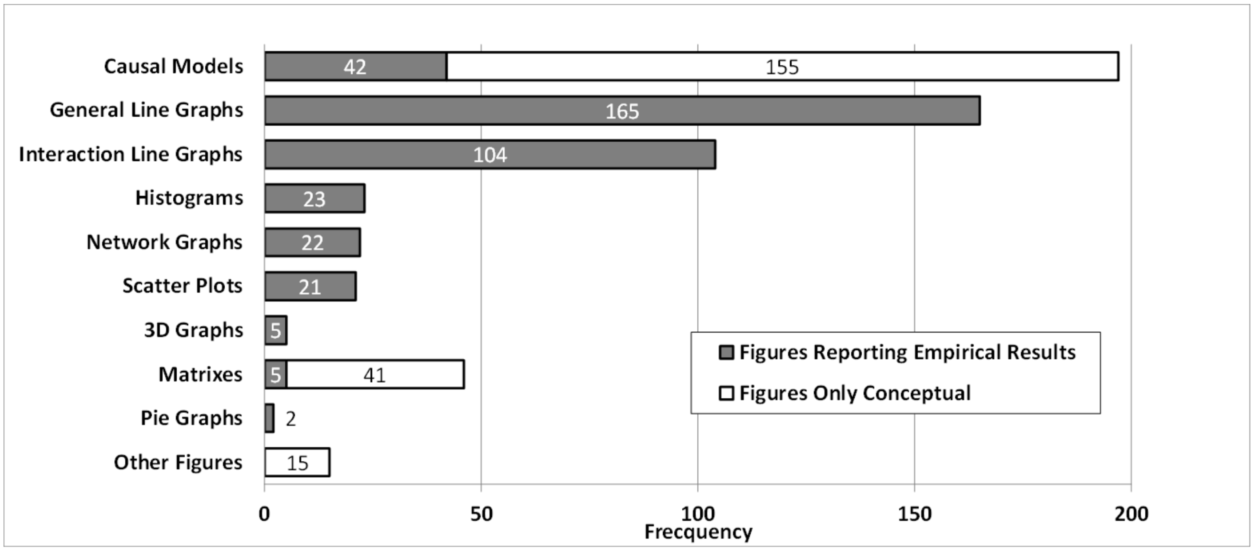
detailed empirical data are tables. The proportion of papers that supplement tables with graphs, however, has increased over time (see Figure 3).

Figure 3
Proportion of Quantitative Studies with Figures Reporting Results in Entrepreneurship Theory & Practice, 2005-2015



Yet about 35% of these graphs are conceptual and only outline causal models, theoretical frameworks and constructs (Figure 4). As the discussions in the next section will delineate in more detail, researchers so far rarely use graphs that capture empirical results to communicate the distribution of observed effects.

Figure 4
Frequency of Figures in Quantitative Studies
in Entrepreneurship Theory & Practice, 2005-2015



How to use graphs to communicate uncertainty of observed effects

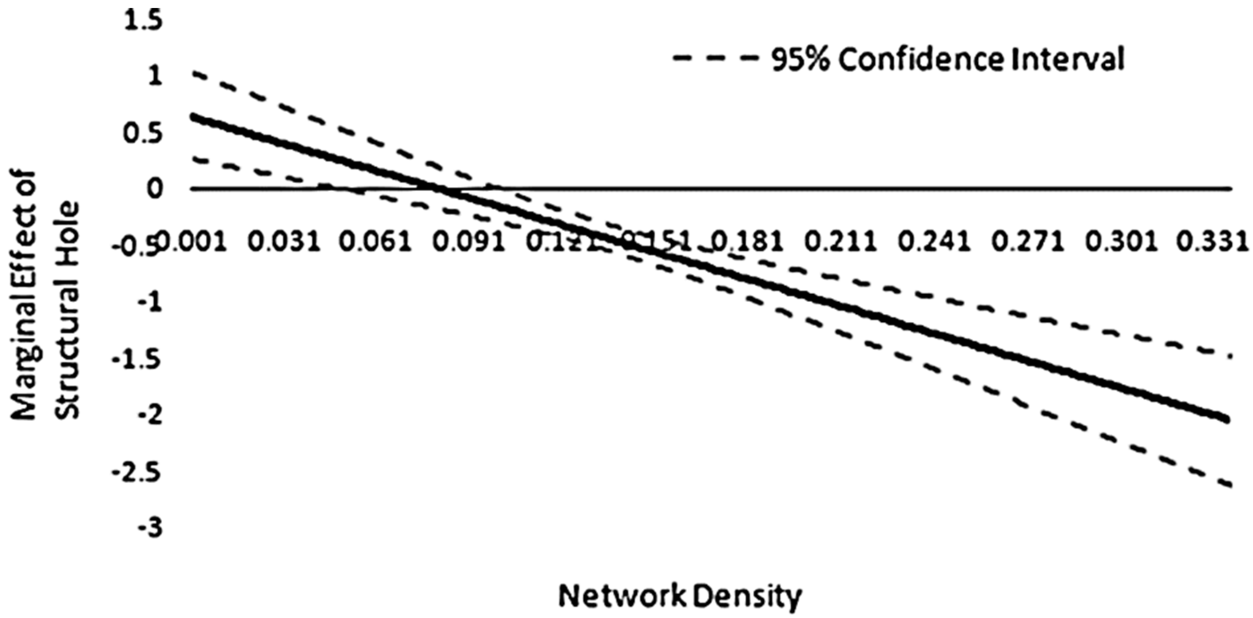
Graphs are a very flexible tool for communicating distributional information. A variety of alternative types of graphs are available to communicate the dispersion of observed outcomes, including various line and bar graphs, box-plot graphs, and scatter plots.

Box-plot graphs, for example, represent a well-known type of bar graph specifically developed to communicate variability information (Tukey, 1977). Box plots show quartiles of the observed distribution anchored on the average effect size. Box-and-whisker plots in addition communicate variability outside of the upper and lower quartiles. Researchers are highly familiar with box-plot graphs, as standard statistics courses and textbooks cover them. In addition, software advancement has made it easier to generate box-plot graphs, including sophisticated box-plot graphs that incorporate scatter-plots, heat maps and other features (for examples, see: http://www.r-graph-gallery.com/portfolio/boxplot/). Nevertheless, box-plot graphs are rarely used by entrepreneurship researchers. Among the 389 figures that communicated empirical results in quantitative papers published in ETP during the 2005 to 2015 period, I found no box-plots.

Line and bar graphs offer several other straightforward ways to communicate distributional information. They can, for example, communicate the entire frequency distribution of observed effects. Alternatively, both line and bar graphs communicate uncertainty information by displaying confidence intervals around observed average effects, enabling readers to evaluate the size and variability of effects simultaneously. If researchers are concerned that data might not satisfy the normality assumptions of confidence interval calculations, they can instead use bootstrapping to generate distributions and confidence intervals for any statistic by sampling repeatedly with replacement from the observed data.

Studies of interaction effects, for example, frequently report line graphs showing average effects across relevant moderator values. Tan, Zhang and Wang (2015) used these simple moderated effect graphs to also communicate the associated confidence intervals. as well. Figure 5 shows that the marginal effect of structural holes is negative for moderate to large levels of network density, which is consistent with the summary statistics the authors provide in the text and tables in support of the corresponding hypothesis. The provided graph, however, conveys important additional information; it shows that the hypothesized effect is in the opposite direction for low levels of network density. The graph also shows the degree to which the confidence intervals of the observed effects are larger for the more rarely observed small and large levels of network density.

Figure 5
The Marginal Effect of a Firm's Structural Hole on Its Innovation Performance



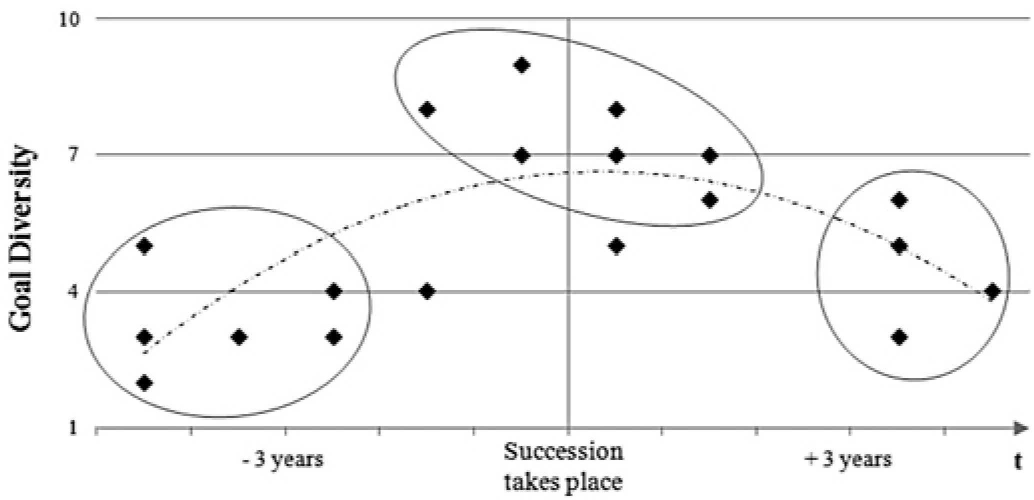
Note: Figure adopted from Tan, Zhang, & Wang (2015: 1201).

Between 2005 and 2015, ETP authors reported 104 line graphs of observed moderated effects. Except for a few notable exceptions (e.g., Patel & Conklin, 2012; Tan et al., 2015), however, these published graphs did not report confidence intervals or other variability information. None reported bootstrapped variability information.

Scatter plots represent another well-established way to communicate detailed information about the distribution of observed effects. Scatter plots are covered extensively and endorsed in statistics courses and textbooks. Still, a search of ETP publications for illustrative examples indicated that researchers so far rarely include scatter plots in their publications (Figure 4). A notable exception is a study by Kotlar and De Massif (2013) which investigated how succession events affect goal diversity in family firms. The scatter plot in

Figure 6 shows how goal diversity peaks during a four-year time window around succession events.

Figure 6
Goal Diversity in Studies Firms by Stage of Intra-Family Succession



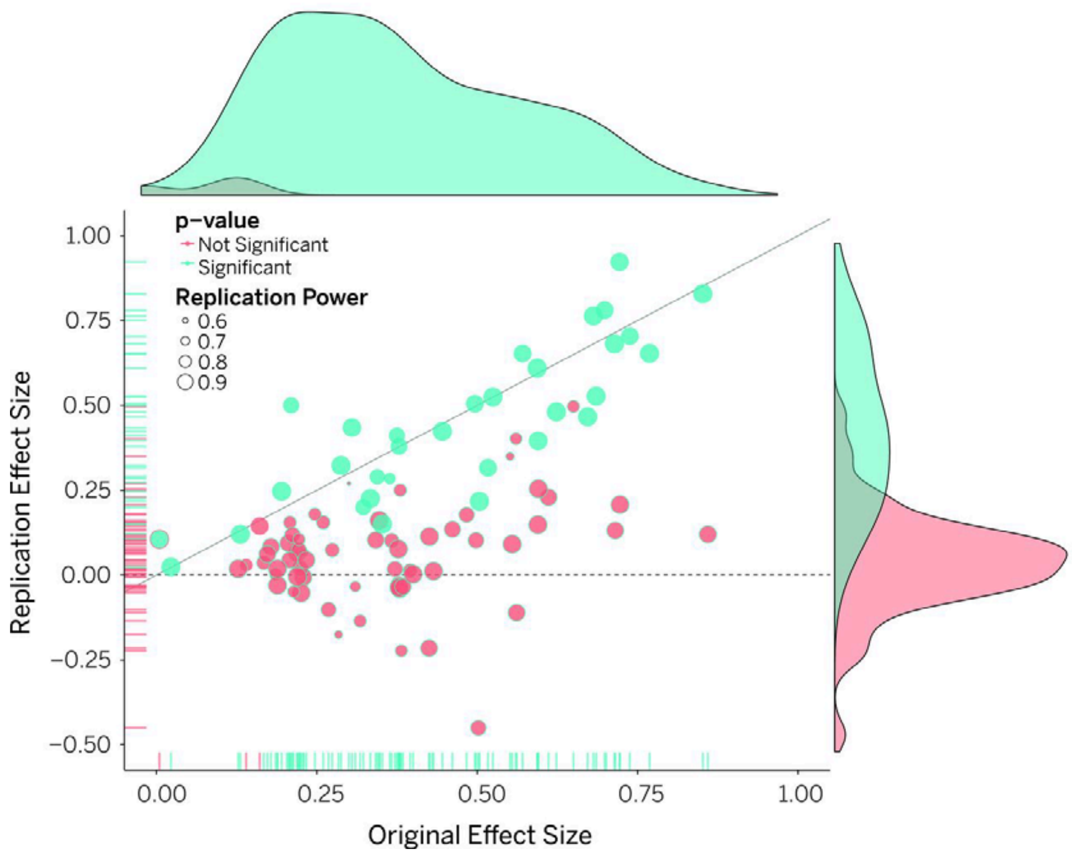
Note: Figure adopted from Kotlar and De Massif (2013: 1275)

This scatter plot also contrasts observed effects with effects predicted by a hypothesized model. The dotted line In Figure 6 represents predicted effects. This graph allow the evaluation of both prediction accuracy and the amount of unexplained variation.

If moderated effects are hypothesized, combinations of two-dimensional and three-dimensional scatter plots are often useful. The most recent APA Handbook for Research Methods in Psychology, for example, contains an entire chapter that outlines various approaches to graphing and interpreting moderated effects -- including illustrative examples, and links to the corresponding software for developing these graphs (Aiken, West, Luhmann, Baraldi, & Coxe, 2012).

Combining different graph types. Line graphs, bar graphs and scatter plots all can communicate, in different ways, valuable dispersion information. At times, it may make sense to combine these different graphs to create even more powerful visuals. One of the most widely recognized recent methods studies in psychology provides an illustration (Collaboration, 2015, see Figure 7). This study compared the effect sizes of replication studies (Y-axis) and original studies (X-axis). The average effect size (r) in the 100 replication studies (M = 0.197, SD= 0.257) was about half in magnitude of the effect sizes reported in original studies (M = 0.403, SD = 0.188). While 97% of the original studies reported statistically significant effects, only 36% of the effects in replication studies were statistically significant. Figure 7 illustrates nicely how a customized visual can communicate effectively a wealth of fine-grained information about distributions by combining a scatter plot with several line graphs. The authors also effectively used color and the size of dots.

Figure 7
Sophisticated Scatter Plot Example



Note: Figure adopted from Open Science Collaboration (2015: 943).

In my opinion, adding key descriptive statistics to this figure would have made this visual even more powerful by reducing the need for readers to skip back and forth between text, tables and figures (Sweller, Chandler, Tierney, & Cooper, 1990; Tufte, 2006). Entrepreneurship scholars, so far, rarely use similar powerful visuals that combine several graphs to communicate their quantitative empirical findings.

What will the future bring?

Academic publishing is rapidly transitioning to the online distribution of content. Online journals are creating new opportunities for the use of visuals and graphs. Online journals, for example, eliminate the substantial additional expenses associated with multi-colored graphs in hard-copy publications. The use of color can help readers to better absorb graphs (Kosslyn, 2006). In this paper, Figures 1 would have also benefited from use of color.

Animated and interactive graphs represent another novel opportunity associated with online publications. Animated graphs show sequences of related graphs to highlight differences between them. They can, for example, show how scatter plots (http://www.r-graph-gallery.com/271-ggplot2-animated-gif-chart-with-gganimate/) or heat maps (http://www.r-graph-gallery.com/78-levelplot-from-a-square-matrix) change over time. They can show different perspectives of 3-D graphs (http://www.r-graph-gallery.com/3-r-animated-cube/; http://www.r-graph-gallery.com/167-animated-3d-plot-imagemagick/).

Interactive graphs go even further by empowering readers, reviewers and editors to explore how changes in scales, perspectives, moderator values and other parameters affect corresponding graphs. In the case of interactive 3-D graphs, for example, readers can rotate and dissect plotted planes. Such interactive features not only allow for deeper evaluation of internal validity of reported findings but also enable readers to better engage in exploratory and abductive investigations based on published research reports (Powell, 2001; Schwab & Starbuck, 2017; Wigboldus & Dotsch, 2016). Established software provides increasingly user-friendly ways to create interactive graphs (e.g., R; http://www.r-graph-gallery.com/portfolio/interactive-r-graphics/).

Currently, creating animated and interactive graphs still requires substantial effort and compatibility with a journal's publication platform. The standardization of platforms and further software improvements promise to reduce the related effort in the future. Interactive features, however, pose some additional challenges. They require that authors provide the journal with the source data necessary to generate these graphs. Such data sharing can create challenges in cases of proprietary data or requirements to protect respondents. Researchers may also be concerned about losing control over who can access and use their empirical data. In the past, related challenges have stifled more general data-sharing efforts by psychology and economics journals (Banks et al., 2016; Chang & Li, 2015). Deindividualizing data and adjusting anonymity assurances to respondents represent one set of strategies to address these challenges. LeBreton, Parrigon and Tay recently introduced an interesting framework addressing data sharing issues specifically with regards to publishing graphs. They enable researchers to create a set of restrictions that prevent the reconstruction of the data from graphs. They have started to develop a corresponding software platform allowing interactive visualizations for different analyses regularly performed in psychology and management research (see www.graphicaldescriptives.org). These initiatives attempt to better reconcile demands for anonymity with demands for transparency. Related solutions promise to facilitate more beneficial data sharing and use of interactive graphs in the near future.

Bayesian analyses represent a well-established alternative approach to using empirical data to identify support for hypothesized effects and to develop theories (Hahn, 2014; Jebb & Woo, 2014; Kruschke, Aguinis, & Joo, 2012). Currently, quantitative empirical investigations in management use Fisherian statistical significance tests almost exclusively. These tests employ a threshold-based, dichotomous approach to uncertainty evaluations. In contrast, Bayesian statistics explicitly estimates and reports the distribution of hypothesized effects from the empirical data. Employing Bayes' theorem, this approach estimates what is called a "posterior" distribution, which captures the frequency distribution of hypothesized effects in a line or bar graph format. These posterior distributions enable fine-grained probability statements about hypothesized effects. It is beyond the scope of this editorial to discuss the potential benefits of Bayesian investigations or to inform readers on how to implement Bayesian studies. In the wake of a rapidly increasing number of published Bayesian studies in the management literature (Zyphur, Oswald, & Rupp, 2015), however, it is noteworthy that it is an established practice for Bayesian studies to graphically communicate posterior distributions in published research reports. Statistics packages such as Stata, SAS or R include commands and procedures to create these graphs. Consequently, researchers interested in deeper investigations of effect uncertainty should consider Bayesian approaches as a promising alternative.

Conclusions

Dichotomous evaluations of the variability of observed effects dominate current quantitative studies of entrepreneurship. The reporting of graphs that communicate more detailed and richer information about the observed distribution of effects and outcomes promises deeper and more appropriate evaluations of the uncertainty associated with effects. Such graphs will support related theory development that better accounts for the uncertainty inherently associated with entrepreneurial activities and that moves beyond current discussions of whether or not effects exist. More fine-grained communication of effect distributions will also facilitate subsequent meta-analyses (Rauch, Wiklund, Lumpkin, & Frese, 2009; Schmidt &

Hunter, 2014) and future Bayesian investigations (Hahn, 2014; Zyphur & Oswald, 2015). Graphs represent powerful instruments for the communication of such detailed and rich distributional information. For these reasons, researchers should actively embrace and explore opportunities to communicate effect distributions better via graphs.

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