When you visualize does it materialize?
On the effects of (data) visualizations in research

Joachim Gassen
Sebastian Geschonke
Tobias Witter
Humboldt-Universität zu Berlin

This version: 2023-05-19

ABSTRACT

We study how researchers in economics visualize their quantitative findings and how this affects the impact of their work. Our analysis is based on observational and experimental data. Using articles from a set of leading (field) journals in economics, we first document that articles in generalist economics journals use relatively more figures than tables with both being used as complements for data visualization. In business and economics field journals, tables and figures are used as substitutes with tables being more common. Next, we show that across all our journals the use of visualizations (table or figures) is associated with higher impact as assessed by citations. This association seems to be predominantly driven by the use of figures in economics journals, while for business journals we find some suggestive evidence that the use of tables is more consistently associated with citation impact. Turning to the nature of data visualizations, we find that there is no clear difference in data-transparent visualizations (i.e., those that represent distributional properties, error intervals, or data points) across journal types. In generalist economics journals, however, these visuals seem to be a driving source for the association of figures with citations. To assess the causal link between visualization types and research impact, we conduct a large online experiment with scientifically trained participants. Randomizing different visualization types across participants, we fail to document an overall discriminating treatment effect for tables and figures consistent with the relative strengths of both visualization types and their ability to act as substitutes. However, we find that our participants assess studies using data-transparent figures as more internally valid and citable compared to studies featuring simple figures. This effect is predominantly driven by participants with a background in the natural sciences and speaks to the ability of researchers from this field to process highly informative data visualizations.

***JEL Codes*:** Y1, A14, A12

***Key Words*:** Data visualization, research impact, scientific visualizations, statistical graphs, graphical perception

Acknowledgements: We thank Ulf Brüggemann, Rico Chaskel, Nils Crasselt, Maximilian Müller, Thorsten Sellhorn, Felix Vetter (discussant), participants of the 2022 TRR 266 Annual Conference, the 2022 research workshop at Charles University in Prague, the 2022 doctoral seminar at Ruhr-University Bochum and the brown bag seminars at the Institute of Accounting and Auditing and the Institute of Economic History at Humboldt-Universität zu Berlin for their helpful comments and discussions. We acknowledge excellent research assistance by Yu Yu Aung, Cristian Nicolescu, Senadin Radas and Fikir Worku Edossa. All authors kindly acknowledge funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation): Project-ID 403041268 – TRR 266 Accounting for Transparency.

1 Introduction

"*A picture is worth a thousand words*" is a famous quote by Frederick Barnard emphasizing the power of a graph to communicate more effectively than long texts and hence, generate impact with an audience. Although graphs, or more broadly, visualizations are ubiquitous in academic research, evidence on their academic impact, and related mechanisms, is limited, field-specific and in parts conflicting (e.g., Lindsey, 1978; Hegarty and Walton, 2012; Tartanus *et al.*, 2013; Lee, West and Howe, 2017). To contribute to this literature, we study how researchers visualize quantitative findings in published research articles in economics and how visualizations affect the impact of academic work. We approach these questions with two methods. We first investigate the variation in data visualizations and associated citations of research articles in top-tier business and economics journals. For causal inference, we complement this descriptive observational study with a large-scale online experiment that tests how visualizations affect the perception of research.

When studying data visualizations (or, interchangeably, data visuals) we differentiate between tables and figures. We define a figure as a visual display of distributions or relations in (raw or transformed) data while tables are structured arrangements of numbers with textual description, which represent (raw or transformed) data (Hegarty 2011; Hegarty and Walton 2012). Different from tables, figures are layered visuals, i.e., they have different 'layers' that add upon each other and describe the elements which comprise a figure (Wickham 2010).

Prior work indicates that there is considerable variation in visualizations across scientific disciplines. Visualizations with figures tend to be more common in the natural sciences, while tables are more common in the social sciences and visuals are overall less common in the arts and humanities (Cleveland 1984; Goggin and Best 2013; Simonton 2006; 2004; Smith et al. 2000; 2002; Simonton 2015; Best, Smith, and Stubbs 2001; Kastellec and Leoni 2007; Kubina, Kostewicz, and Datchuk 2008). While a fair share of this variation might be attributable to the differences in data collection and usage across disciplines, a theory to explain this variation is the classification of scientific disciplines by their ‘hardness’ (‘hierarchy of sciences’).

'Hardness' defines how research results accumulate, i.e., to what extent current work builds on and extends earlier work. This notion also reflects the degree of consensus within a discipline (Cole 1983; Evans, Gomez, and McFarland 2016). In line with this argument, prior evidence suggests that figures offer a more transparent and efficient way to communicate complex phenomena in data compared to tables, which are better suited to summarize key findings and test results. Supposedly, harder sciences tend to rely on figures because of the relative importance of rigorous data analysis compared to the relative importance of contextualization and narrative discussions in 'softer' sciences (see Fanelli and Glänzel, 2013 on bibliometric differences between ‘hard’ and ‘soft’ sciences).

Building on this notion, we explore the variance of visualization use in economics by arguing that work in general economics journals (the so-called ‘Top 5’) puts relatively more emphasis on generalizability and abstraction while work in business and economics field journals is relatively more concerned with providing applied context and discussing the implications of the findings for the field. This yields three sets of expectations that motivate and guide our research design.

First, we expect figures to be relatively more prominent in general economics journals compared to field journals where we expect tables to be relatively more common. This prediction builds on the aforementioned finding that harder academic work visualizes with figures rather than tables (Cleveland 1984; Smith et al. 2000; 2002; Best, Smith, and Stubbs 2001). More applied fields, instead, tend to use fewer figures and more tables (Gelman, Pasarica, and Dodhia 2002; Kastellec and Leoni 2007; Gelman 2011).

Second, we expect visualizations, i.e., figures and tables, to be associated with increased impact of our journal articles. Studies from various research fields highlight the benefits of visuals in (scientific) texts on information acquisition and processing of readers (Van

Genuchten, Scheiter, and Schüler 2012; Isberner et al. 2013; Mayer et al. 1996; Wiley et al. 2017; Walsh, Sargent, and Grant 2021). Previous findings on how visuals, i.e., figures and tables, affect academic impact, however, seem somewhat mixed (Lindsey 1978; Lee, West, and Howe 2017; Hegarty and Walton 2012; Tartanus et al. 2013). In line with our first expectation outlined above, we expect the association between visuals and impact to be me more pronounced for figures in generalist economics journals while we expect tables to be relatively more responsible for the association in field journals.

Third, we expect data-transparent visuals to be more common and impactful in generalist economics journals. Oftentimes, scientific figures do not indicate uncertainty in measurements and estimations (Allen, Erhardt, and Calhoun 2012) and simple line graphs are the dominant figure type, even in top journals (Schwabish 2022; Friedman 2021). However, the argument advocating the use of figures builds on its ability to efficiently communicate complex phenomena in data. Thus, we expect that visualizations that communicate distributional properties, measurement uncertainties or single observations ('data-transparent visuals') to be more common and impactful in generalist economics journals.

Our observational evidence, based on 7,846 journal publications from eleven journals[1] spanning the time period 2010 to 2019 is largely consistent with our expectations. First, the use of figures and tables is paramount in economics journals and increases over time. In general, and after controlling for other documented determinants of citation impact, journals articles with visualizations are associated with higher citation counts, consistent with our second expectation. Interestingly, the article-level correlation of visualization types varies between top-

[1] We classify the eleven journals into our three groups as follows (journal name abbreviations in brackets): 'generalist economics journals' comprise the top 5 economics journals American Economic Review (AER), Econometrica (ECA), Review of Economic Studies (RESt), Journal of Political Economy (JPE), and Quarterly Journal of Economics (QJE); 'economics field journals' are the Journal of Development Economics (JDE), Journal of Labor Economics (JLE), and Journal of Monetary Economics (JME); 'business field journals' are the Journal of Accounting Research (JAR), Journal of Finance (JOF), and Management Science (MSci).

tier business and economics journals. Figure and table use correlates positively in generalist economics journals, suggesting that they serve as complements. In business and economics field journals however, this correlation is negative, consistent with a more substitutive use. This hints at a different use of visuals as extensions of scientific texts across our fields. Second, we document that the positive association of citations with visualizations can be mostly attributed to figures for general econ journals, consistent with our second prediction. We also provide suggestive evidence that tables are a driving source for this association for business journals. Third, we classify a subset of our figures into broad categories to see whether the nature of a figure (data-transparent or not) moderates its association with citation counts. While we document that plain line graphs are still the most common figure type for our three journal groups, we also find an increase over time for data-transparent figures. In addition, we find a modest moderating effect for data-transparent figures on the association of figures with citation counts for articles in generalist economic journals, supporting our third prediction.

Like prior work in the field, our observational evidence is subject to alternative explanations. To shed some light on causal mechanisms that might explain our observed associations, we conduct an online experiment with 823 academically trained participants. Our main experimental approach is a 5 × 1 between-subjects design which manipulates the display of identical research findings of a fictive scientific study. The baseline case shows the results as text only. In addition, we administer four visual treatments: We treat participants with either a table reporting the findings, or one of three figures with increasing data transparency (a box plot, a data-transparent box plot showing single observations or an estimation graph following Ho et al., 2019). Our main outcome variables are participants' (i) perceived internal validity of the fictive findings and (ii) indicated willingness to (hypothetically) cite the fictive study.

We report two main findings from this experimental setup. First, while visualizations in general seem to have a marginally positive effect on the perceived internal validity of a study, this effect is small in magnitude, depends on the visualization type and does not clearly differentiate between table and figure visualizations. We take this findings as being consistent with the general ability of both visualization types to communicate research findings efficiently. Second, we find that data-transparent figures, relative to their plain counterparts, have a positive impact on perceived internal validity and the hypothetical willingness of our participants to cite the respective study. Interestingly and consistent with the ‘hierarchy of science` theory mentioned above, this finding is predominantly driven by participants with a background in the natural sciences.

As a second experimental design element, after collecting our outcome variables, we survey treated participants on their assessment of the visuals along four dimensions (familiarity, informativeness, detail, information overload). For this, the participants that received the baseline treatment without visual are presented with all four visualizations, allowing us to observe within as well as between subject variation in responses across visuals. A path analysis of these post-experimental data reveals that subjects that are familiar with a certain visualization type generally find it easier to understand and use for data exploration. More importantly, it shows that after controlling for familiarity the assessed clarity and level of detail of a visual are explaining the assessment of internal validity and this in turn explains the hypothetical citability of the study. Taken together, these findings are consistent with clear and detailed figures helping to communicate the internal validity of a study, thereby increasing its impact.

Our findings contribute to our understanding how visualization shapes the impact of economic research (Schwabish 2022; Fourcade, Ollion, and Algan 2015; Kosnik 2018; Card and Della Vigna 2013; Hamermesh 2018; Christensen and Miguel 2018; Wei 2019) by showing that, first, prior classic findings on the heterogeneity of scientific fields (Cleveland and McGill 1984; Cleveland 1984; Cleveland and McGill 1986) to some extent translate into the area of economics: the more general the presented findings are, the more impactful seem figures to be. On the other hand, tables clearly also have their role, in particular in more applied areas of economics. These findings contribute to prior experimental (Henry 1993) as well as archival work (Marshall, Jay, and Freitas 2021). Turning to the type of figures, we contribute to the literature by providing causal evidence on the effects of data-transparent visuals (Weissgerber et al. 2015) on the perceived internal validity of research and by documenting that this effect is moderated by the familiarity of our participants with data-transparent figure types.

The remainder of the paper proceeds as follows. Section 2 briefly reviews the literature on the use and impact of visualizations in academic research to substantiate our predictions. Section 3 describes the research design of our observational study and its results. Section 4 describes the research design of our experiment and presents the experimental results. Section 5 concludes.

2 Prior literature and expectations

Starting with the seminal work by Cleveland (1984), researchers have been documenting the use of tables and figures in academic work and, doing so, have accessed its determinants. While on conceptual grounds, work predominantly placed in psychology, statistics, and information science has studied research-based guidelines on how to choose between visualization types (see Franconeri et al. (2021) for a recent overview), most of the work based on journal articles compares the use of visuals across scientific fields and/or time. It also uses bibliometric data to document associations that are related to visualization use.

For the field of economics, Schwabish (2022) documents an overall increasing use of visuals over time by classifying figure use in the American Economic Review. He also shows that line graphs, while declining in relative importance, remain the most prominent figure type in economics. Finally, he documents that the perceived quality of figures also increases over time. Other fields have reached similar conclusions (e.g., for Statistics, including a long time-series of data and introducing the ‘golden area of statistical graphics’: Friendly (2008); for Medicine: Chen et al. (2017); for Ecology: Friedman (2021)).

The guiding rationale for the variation of visual use across scientific fields is the concept of a ‘hierarchy of science’. It ranks sciences by their hardness, an idea going back to Auguste Comte. ‘Hardness’ captures how research results cumulate, i.e., how current extends earlier work and how fast a degree of consensus within a discipline is reached (Cole 1983; Evans, Gomez, and McFarland 2016). Building on this notion, natural sciences are classified as relatively ‘hard’, while social sciences are classified as relatively ‘soft’. Empirical evidence on the use of visualizations across research fields is consistent with this notion. Visuals, especially figures, tend to be more common in the natural sciences, while tables are more common in the social sciences and visuals are overall less common in the arts and humanities (Cleveland 1984; Smith et al. 2000; Best, Smith, and Stubbs 2001; Smith et al. 2002; Simonton 2004; Arsenault, Smith, and Beauchamp 2006; Simonton 2006; Kubina, Kostewicz, and Datchuk 2008; Goggin and Best 2013; Simonton 2015). Notably, this line of work finds that the use and size of figures are positively, and almost linearly, associated with hardness. Within scientific fields, harder subdisciplines use more, larger and more sophisticated figures. In turn, tables dominate in number and size in softer subdisciplines relative to figures (Smith et al. 2000; Kubina, Kostewicz, and Datchuk 2008).

Based on this literature, we develop our first set of predictions: We expect figures to be more common relative to tables when the focus lies on documenting the generalizability of findings. This focus should be more common in general economics journals. In turn, we expect tables to be more common in applied field journals where the contextualization of the evidence is relatively more important.

The literature studying the impact effect of journal visualizations generally builds on a broad literature that studies the effect of visualization on judgment and decision-making (see Eberhard (2023) for a recent overview). This literature provides various arguments for why and how visuals are capable to ease information acquisition and processing, but it also documents that the relative efficiency of the various visualization types is highly context-specific. Given this, it is not surprising that the literature has found somewhat inconclusive findings on how the use of visuals in journals associates with citation impact. This literature stream links to a broader discussion about the determinants of article citation impact (Stremersch, Verniers, and Verhoef 2007; Card and Della Vigna 2013; Hamermesh 2018; Jacques and Sebire 2010; Buter and van Raan 2011; Lindsey 1978; P. Hegarty and Walton 2012; Paiva, Lima, and Paiva 2012; van Wesel, Wyatt, and ten Haaf 2014). Within this stream of literature, only a handful of studies look at whether visuals affect academic research. While early literature finds that the use of figures positively correlates with the citations of a research article (e.g., Lindsey (1978) based on 205 psychology articles), more recent evidence investigating the link association visualizing and academic impact provides more nuanced findings.

Hegarty and Walton (2012, 1,133 psychology articles) find a strong negative correlation between the use of general figures and citations, a positive one for visuals based on structural models and no association for the use of tables. Tartanus et al. (2013, 3,132 articles from agricultural journals) provide evidence that journals with higher impact feature more figures. Similar results were found for other research fields (Marshall, Jay, and Freitas 2021). In a large sample study, Lee, West and Howe (2017, more than 650,000 research articles from biomedical and life sciences) find a robust positive correlation between visualizing with figures, specifically scientific diagrams, and citations of a research article, but no correlation of visualizing with tables and citations. Turning to economics fields, Stremersch, Verniers and Verhoef (2007) find no consistent associations of tables and figures with citation impact for a sample of 1,825 marketing articles. Finally, a qualitative meta study on the factors impacting citations of journal articles (Tahamtan, Safipour Afshar, and Ahamdzadeh 2016) reaches the conclusion that overall, figures seem to have a positive association with citations, but this conclusion seems to be derived from only three studies.

Based on the findings of this prior literature we predict that visualizations are associated with higher citation impact. While this prediction is in line with the work identifying positive communication effects of visualization and the majority of empirical evidence in the field, we are somewhat agnostic about the underlying causal mechanism. Most prominently, it might be that the article context drives both the use of visualizations and the impact of the respective academic study. In addition, even if visualizations cause impact, there needs to be a cost that limits the use of visualization. Besides the direct costs of creating visuals, an aspect that clearly has lost importance in recent years due to the wide-scale availability of charting and table packages for statistical software, journals may constrain (or encourage) visualizing, depending on their financial situation as well as editorial guidelines and preferences (Tartanus et al. 2013; Hartley et al. 2015).

There is only very limited and somewhat indirect evidence on the causal effect of visual use on citations. Several studies have used the introduction of visual abstracts by publishers as a setting to assess the citation impact of this visualization change. The at-least partly publisher-induced nature of this visualization decision makes it somewhat less endogenous and supports a slightly more causal interpretation of any observed effect. A recent study, also discussing findings from prior literature in the area of sports science (Bennett and Slattery 2023) cautiously concludes that there is no evidence of a citation impact of visual abstracts but evidence for an effect on Altmetric scores, which capture wider impact, also including social media. Related studies have used randomized control trials to show that visual abstracts have a positive effect on Twitter engagement (Ibrahim et al. 2017; Chapman et al. 2019). We will contribute to the question whether the visualization of research findings has a causal effect on academic impact by conducting our online experiment.

Finally, turning to the different types of visualizations, past work referenced also above has documented that most figures used today are relatively simple in nature and often do not follow supposedly ‘best practice’ guidance (Chen et al. 2017; Schwabish 2014; 2022). As another example, Gordon and Finch (2015) rank almost 40% of 97 figures in top-rated applied science and statistics journals as ‘poor’. Relatedly, evidence from top-tier neuroscience journals finds that 80% of the figures do not indicate or fail to define the uncertainty of displayed estimates (Allen, Erhardt, and Calhoun 2012). This seems in contrast to the argument that figures should be used to clearly communicate complex phenomena in data. Consistent with this objective, recent voices demand the use of more data-transparent figures (e.g., Weissgerber et al. 2015; 2019) and introduce related visualization schemes into the literature (e.g., Allen et al. 2021; Ho et al. 2019).

Our third set of predictions picks up these arguments and posits that data-transparent figures should become increasingly common over time. In addition, we expect them to be more impactful compared to 'normal' figures. In line with our first set of predictions, we expect these trends to be more pronounced in generalist economics journals.

3 Observational evidence

3.1 Data collection

We collect data on the research articles published in eleven leading business and economics journals from 2010 to 2019. We focus on a time span of ten years to spot variation in visuals over time and end the sample period in 2019 to ensure, at least, two years of post-publication citation data. As *generalist economics journals*, we choose the 'top 5', American Economic Review (AER), Econometrica (ECA), Review of Economic Studies (REStt), Journal of Political Economy (JPE), and Quarterly Journal of Economics (QJE). Additionally, we include three leading *economics field journals*, the Journal of Development Economics (JDE), Journal of Labor Economics (JLE) and Journal of Monetary Economics (JME) and three leading *business field journals,* the Journal of Accounting Research (JAR), Journal of Finance (JOF) and Management Science (MSci).

Economics takes a low-to mid-range position in the hierarchy of sciences often ranging close to psychology or social sciences like sociology (Fanelli and Glänzel 2013; Arsenault, Smith, and Beauchamp 2006; Smith et al. 2000). The degree of mathematical formalization, development of paradigm and related characteristics of the discipline explain why it is at times ranked higher than related subdisciplines of social sciences (Simonton 2015; Cole 1983; Fourcade, Ollion, and Algan 2015). With increasing competition but also length of research articles (Card and DellaVigna 2013), it is an interesting field to study how researchers visualize in top publications. Studying business and economics together leaves us with a sufficiently homogeneous set of articles to tease out differences in how researchers visualize and its link to academic impact (van Wesel, Wyatt, and ten Haaf 2014).

While business and economics are oftentimes mentioned as one field of research, we categorize the eleven journals further into three journal types: Generalist economics journals, economics field journals and business field journals. These types help us to study differences between subdisciplines of a scientific discipline contributing to similar lines of work in other disciplines (Smith et al. 2002). Specifically, we compare generalist economics journals, i.e., journals which publish contributions of a wide topical range of economics and business studies, with field-specific journals. The latter group tends to publish contributions from their specific or closely related field, e.g., accounting studies in the Journal of Accounting Research. Field journals with their special focus are characterized by the degree of formalization, choice of methods and applied orientation. Hence, generalist economics journals tend to classify as harder on the hierarchy of sciences than business and economics field journals.

For the eleven journals, we algorithmically collect metadata and PDFs of research articles. We parse the PDFs of research articles to generate article-level data on the use of figures and tables. We then consult two leading bibliographic databases, *Scopus* and *Crossref*[2], to retrieve information on research articles' citations and to collect additional control variables. We use both databases to triangulate data quality and test results. Notably, citation count measures

[2] These databases are available at https://www.scopus.com and https://www.crossref.org.

of both databases correlate at 0.99. We decide use *Crossref* data to construct our main citation measure, $YCitations$, because of its higher coverage for our sample and fill missing values with data from *Scopus*. Lastly, we retrieve data on the forward citations of each article from *OpenCitations*[3]. All variables are defined in Appendix A. Table 1 provides descriptive statistics for our test variables (Panel A) and describes the sample (Panel B).

[insert Table 1 here]

Our sample comprises 7,846 research articles (Table 1, Panel A). The average research article has around 14,500 words, two authors and includes four figures and six tables. Compared to other disciplines, business and economics take a mid-range position in terms of visualizing with figures consistent with a mid-range position on the hierarchy of sciences: Articles in the biomedical and life sciences tend to use more figures (average of 7.4 figures per article, Lee, West, and Howe 2017), while psychology articles exhibit considerably fewer figures (average of 1.53, P. Hegarty and Walton 2012). 85% of the articles in our sample include at least one figure ($Has\ figures$) and 82% include at least one table ($Has\ tables$), which speaks to a balanced use of tables and figures over all journals. As expected, the number of citations is right-skewed. On average, a research article has 83 citations but the median is 44. For our tests, we divide the number of citations by the years a research article is in our sample, which results in 18 citations per year, on average. The sample comprises 3,053 research articles from generalist economics journals, 1,852 articles from economics field journals and 2,941 articles from business field journals. The number of articles increases over the sample period with around 39% more articles in 2019 (951 articles) relative to the beginning of the sample period 2010 (684 articles).

[3] This database is available at https://opencitations.net.

3.2 Findings

Based on our observational data. we assess our three expectations in three steps. We first report on the use of figures and tables across time and journal types. Next, we document the association of visualizations with citation impact. Finally, we categorize a subset of journal articles manually by figure type to assess whether the use of data-transparent figures varies across field and time and whether the use of data-transparent visual is associated with citation impact.

We begin our investigation by studying how researchers use visuals, i.e., figures and tables, across time and journal type. The average number of figures and tables increases with time (see Figure 1). While in 2010 research articles in our sample, on average, included around three to four figures and five tables, these numbers show an almost linear trend. In 2019, on average, a research article in our sample includes four to six figures and six to eight tables. Consequently, the use of visuals is paramount in business and economics journals and increases over time. This increase, however, varies with the type of journal (see Table 2).

[insert Figure 1 and Table 2 here]

As becomes apparent from Table 2, field journals visualize less with figures but more with tables (see Panel A). The average number of figures is 3.44 for field business and 4.06 for field economics journals, while the average number of tables is 6.05 and 6.62, respectively. Generalist economics journals, on average, use 4.59 figures and 5.03 tables. These differences are significant (Table 2, Panel B): Articles in field economics journals use around 1.5 tables more and 0.5 figures less than articles in generalist economics journals (both $p < 0.01$). For field business journals, this is one table more and one figures less per article (both $p < 0.01$), see also Figure 1. These results support the notion that journals catering to a more generalist audience are more likely to communicate their key findings by figures while context-sensitive field journals tend to favor tables.

We next turn to the article-level correlations of tables and figures. As Figure 2 captures, the article-level correlation of visualization types varies between generalist economics journals and field journals. It is positive and statistically significant for most of our sample-years for generalist economics articles, while it is negative for articles in field journals. We interpret these correlations in such a way that figures and tables tend to serve as complements in generalist economics journals, while they seem to serve as substitutes in business and economics field journals. This hints at a different use of visuals as extensions of scientific texts across journal types.

[insert Figure 2 here]

To assess the association of visualization with citation impact, we run the following regression model, pooled over all journals (Table 3, Panel A) and by journal type (Table 3, Panel B):

$$\log(YCitations) = \beta_1 \log(Figures) + \beta_2 \log(Tables) + Controls + \epsilon \tag{1}$$

The dependent variable ($YCitations$) is the number of citations of an article divided by the number of years the article is in our sample. The variable $Figures$ ($Tables$) is the count of figures (tables) of an article. The coefficients β_1 and β_2 are our coefficients of interest since they provide estimates for the association of visual use (figures and tables) with citations. $Controls$ include determinants of research articles' citations identified by prior work: The article length in words ($Words$) (van Wesel, Wyatt, and ten Haaf 2014; Lindsey 1978; Card and Della Vigna 2013; Hegarty and Walton 2012), the number of authors ($Authors$) (van Wesel, Wyatt, and ten Haaf 2014; Card and Della Vigna 2013), the number of references ($References$) (Lindsey 1978; van Wesel, Wyatt, and ten Haaf 2014; Hegarty and Walton 2012), the title length ($Words\ in\ title$) (Paiva, Lima, and Paiva 2012; van Wesel, Wyatt, and ten Haaf 2014). Additionally, we proxy with the lines with mathematical symbols and equations ($Equations$)

for analytical and econometric content since analytical and econometric articles tend to have fewer citations (Card and Della Vigna 2013). We run specifications with and without controls and for regressions with controls add with fixed effects at the journal, journal-year and journal-year-issue level to control for time-stable differences in citations across journals and time trends in citations[4]. We cluster standard errors at the journal-level to account for heterogeneity across journals.

We are interested in the sign and magnitude of the association between the use of visuals in an article and its citations, our measure of research impact. Related evidence on this association is limited, field-specific and in parts conflicting (e.g., Lindsey, 1978; Hegarty and Walton, 2012; Tartanus et al., 2013; Lee, West and Howe, 2017). Thus, we test the expectation that visuals are positively associated with the citation impact of articles. After controlling for other documented determinants of citation impact, articles with visualizations are associated with higher citation counts (Table 3, Panel A). The estimated signs of controls are in line with prior work on determinants of citations (Paiva, Lima, and Paiva 2012; van Wesel, Wyatt, and ten Haaf 2014; Hamermesh 2018). In particular, longer articles ($Words$) and articles with more authors ($Authors$) attract more citations, while articles with more analytical or econometric content ($Equations$) attract fewer citations.

[insert Table 3 here]

We use log-log specifications in Table 3 and coefficient estimates in our strictest specification with journal-issue-year fixed effects for $Tables$ and $Figures$ are 0.1 ($p < 0.05$) and 0.083 ($p < 0.01$), respectively (Panel A, column 5). This implies that, at the sample mean, one table more (an increase of 17.3%) is associated with a 1.6% increase of citations, while one

[4] As the number of citations predominantly is driven by the duration that the paper is available to the academic community and the magnitude of the potential readership, we use journal-issue-year fixed effects in our analysis.

figure more (an increase of 24.8%) is associated with a 1.9% increase in citations.[5] These results suggest a modest 'citation premium' for the use of visuals.

We test whether this association between our impact measure, $YCitations$, and $Tables$ and $Figures$ persist if we repeat our tests from Table 3, Panel A separately by journal type (Panel B). Our second expectation predicts that the citation impact of figures should be stronger as research findings become more general and cumulative while tables should be more impactful when research findings require more contextualization. Table 3, Panel B provides supporting associative evidence for this prediction as we document a strong association of figure use with citations for generalist economics articles (column 1, $Figures$: 0.22, $p < 0.01$). Results are weakly significant for economics field journals (column 4, $Figures$: 0.16, $p < 0.1$) but insignificant for business field journals (columns 7-9). The associations for economics journals persist after controlling for known determinants of citations as well as journal-issue-year fixed effects (columns 2-3, 5-6). It is considerably more significant for articles in generalist economics ($p < 0.01$) than economics field journals ($p < 0.05$), and suggests that, at the mean of generalist economics journal articles of 4.59 figures, one figure more is associated with 6.2% more citations.[6]

The use of tables associates stronger with citations for generalist and field econ journals (column 1, $Tables$: 0.305, $p < 0.01$; column 4, $Tables$: 0.271, $p < 0.05$) than for field business journals (column 7, $Tables$: 0.215, $p < 0.\ 1$). None of these associations persist after including controls and fixed effects (columns 2-3, 5-6, 7-9). Our results are suggestive for a modest 'citation premium' for articles that use figures as visuals for generalist economics journals. This

[5] For $Tables$: $1.173^{0.1} - 1 = 1.6\%$ more yearly citations and for $Figures$: $1.248^{0.083} - 1 = 1.9\%$ more yearly citations.

[6] For $Figures$ in articles of generalist economics journals: $\left(\frac{5.59}{4.59}\right)^{0.305} - 1 = 6.2\%$.

association seems somewhat statistically weaker for field economics but does not exist for field business journals.

We triangulate these results with yearly forward citations from the database *OpenCitations*. Other than our two other data sources for citations that only report the total number of citations and not their respective publication year, the data from OpenCitations allow us to assess how citation impact develops over time. The findings are reported in Figure 3. We use a median split on the number of visuals an article includes and plot yearly citations relative to the publication year of the respective article. The figure indicates that articles in generalist economics journals that visualize more with figures receive significantly more citations after publication (Figure 3, Panel A, third graph). Articles in field economics journals exhibit a similar but mild trend, while articles in field business journals do not seem to differ in their citation counts depending on the median split. We do not observe similar patterns for tables in economics journals. In field business journals, however, articles with more tables than the median tend to accumulate citations quicker (Figure 3, Panel B) which indicates that there is a citation premium only for tables, if any (see also Table 3, Panel B).

[insert Figure 3 here]

Overall, differences between journal types in researchers' use of visuals are associated with citations in a way that is consistent with our expectations: Visualization use is associated with more impact and this association seems more robust for figures for (general) economics journals while for business journals it seems to be predominantly linked to table use.

To provide observational evidence with regards to our last prediction, we study whether the data transparency of figures is associated with their usage across journal types and their citation impact. Recall that, if visuals are particularly useful to communicate complex phenomena in data in cumulative sciences, we would expect visuals to be richer and more informative in generalist economics journals and such figures also to have a stronger association with citation impact.

We manually classify all figures for a random sample of 220 articles (we classify each panel of multi-panel figures separately), stratified by journal and year, for their data transparency. We proceed in two steps: We classify the content type of the figure to identify figures which use empirical or simulated data. We then classify these figures for their figure type. Appendix B explains the classification scheme and procedure in detail, and provides some example classifications. We define a figure as data-transparent if it either displays data distributions univariately, distributional information for bar and line graphs, single data points (e.g., scatter plots) or extreme observations. This procedure provides us with a binary indicator whether a certain classified figure is data-transparent. We aggregate this figure panel-level data to the article level, yielding the variable $Transp$ indicating if a research article uses data-transparent figures and the variable $ShareTransp$ capturing the ratio of data-transparent figures to all figures of an article.

Our random sample of 220 articles contains 1,979 separate figures. Notably, across all journal types, the number of data-transparent figures as well as the number of research articles with data-transparent figures show a positive trend (see Figure 4). Table 4 provides descriptive statistics on the subset of 1,448 figures that are based on empirical or simulated data.[7] We classify these figures further to assess figure type and data transparency.

[insert Figure 4 and Table 4 here]

We note three findings from the data presented in Table 4. In line with prior work (Schwabish 2022), line and bar graphs are the dominant figure type in the data. For generalist economics journals, line graphs constitute a share of 64%, and bar graphs a share of 11%, adding up to a total of 75% of the classified figures. For field economics journals, line and bar

[7] From the 1,979 figures, we classify 109 as conceptual figures, 414 as theoretical figures, 222 as figures using simulated data, and 1,226 as figures using empirical data.

graphs have a share of 78%, in field business journals they comprise 88%. Only a relatively small share of the classified figures (39.85%) are data-transparent. As also is apparent from Figure 4, this share is roughly comparable across our journal types (39.37% for general economics, 38.68% for field economics and 43.48% for field business; differences are statistically insignificant, see Table 4). Figures that display data distributions univariately have a share of 5% (generalist economics), 7.5% (field business) and up to 13% (field economics). The share of bar graphs with displayed distributional information or estimation uncertainties ranges between 3.6 and 5.6%. Those of line graphs ranges from 19.4% to 28.9%. Interestingly, univariate, bar and line graphs tend to be more data-transparent in field journals. Generalist economics journals, however, use significantly more scatter plots (19.3%) relative to field economics (9.6%) and field business journals (10.7%). Hence, there is no clear evidence that researchers visualize more data transparent across all figure types in one of the journal types.

We use our manually classified data to study whether data transparency may explain the association between the use of figures and citations of research articles by estimating the following regressions:

$$YCitations = \beta_1 Transp + \epsilon \tag{2}$$

$$YCitations = \beta_1 ShareTransp + \beta_2 \log(Figures) + \beta_3 ShareTransp \times \log(Figures) \tag{3}$$

We run equations 2 and 3 for all journals and separately, for each journal type. For equation 2, β_1 is our coefficient of interest and we expect a positive sign if article-level data transparency explains citations. For equation 3, β_3 is our coefficient interest and we expect a positive sign if data-transparent figures can explain the correlation between the use of figures and citations of a research article. We do not include controls in equations 2 and 3 because of the small number of observations, but we do include journal fixed effects in equation 2 when running it for all journals. We cluster standard errors at the journal-level.

[insert Table 5 here]

For our small set of articles with hand-collected figure type data, the use (column 1, $Transp$: 0.353, $p < 0.05$) and share (column 2, $ShareTranp \times \log(Figures)$: 0.476, $p < 0.1$) of data-transparent figures, but not the bare use of figures ($\log(Figures)$), is associated with citations of a research article. When we split our sample by the three journal types, only the association for generalist economics journals remains marginally statistically significant (columns 3-4, $Transp$: 0.577, $p < 0.1$; $ShareTranp \times \log(Figures)$: 0.85, $p < 0.1$). Overall, our results using figure type data are consistent with data transparency, at least in part, explaining the association between the use of figures and citation impact for generalist econ journals.

While our observational evidence exhibits patterns largely consistent with what we expect based on theory and prior literature, it does not lend itself to causal interpretations. First and foremost, the characteristics of the articles under study will determine the feasibility of certain visualization types. To the extent that these characteristics, e.g., method or topic, have a direct effect on scientific impact, we are unable to attribute our associative findings to the causal path that links the use of (data-transparent) visuals with scientific impact. Please note that, while we control for variables that likely capture data usage, e.g., $Equations$, and hence, the likelihood of a research article to visualize data, these controls are clearly a less than perfect indicator to address this endogeneity concern.

As a second point, prior work on the cognitive effects of data visuals highlights that visuals are used to communicate new and complex insights (Henry 1993; Gelman and Unwin 2013). To the extent that such insights are more likely to get cited, the use of visuals and the citation count could be unrelated consequences of the demanding research of a certain research article. We tackle both points by conducting an experiment, which compares text, tables and (data-transparent) figures as alternatives to display scientific findings to see how they may affect the reception of research.

4 Experimental evidence

4.1 Data collection

We administer our experiment as an online survey experiment via the platform Prolific on June 8-10, 2022.[8] We require participants to speak English fluently and to hold, at least, a master's degree as proxy for academic training. Participants read the summary of a fictive randomized lab experiment. The baseline group reads the findings of this fictive study as text. Treated participants see the same text supplemented with one of four treatment visuals, either a table or one of three figures with increasing data transparency, summarizing the findings of the fictive study. Appendix C describes the experimental design in detail.[9]

We first implement a 5 × 1 between-subjects design and let participants assess the internal validity of the fictive study with three items (variable $IntVal$) and ask whether participants would (hypothetically) be willing to cite the fictive study ($Citable$). In a post-experimental survey, we let treated participants assess their treatment visual. Baseline participants assess all four treatment visuals in randomized order. We ask participants to assess four distinct aspects of the visuals. These include clarity ($Clarity$), complexity ($Complexity$), familiarity ($Familiarity$) and flexibility ($Flexibility$) (see Appendix C, Table C.1). After collecting outcome variables, we gather data for control variables. All variables are defined in Appendix A.

---

[8] We chose Prolific because it allows us to recruit a considerably large group of academically-trained participants in a short period of time and with decent data quality (Peer et al. 2022).

[9] The pre-registered experimental design and related materials are available from our pre-registration at the Open Science Framework, DOI: 10.17605/OSF.IO/CRH92, see https://osf.io/crh92. This experiment received an ethical approval without reservation by the acting ethics committee of the School of Business and Economics of Humboldt-Universität zu Berlin on 4 April 2022 (Ethics Approval No. 2022-03).

We aimed at collecting 1,000 responses, and 200 responses per group, since our pre-registered power analyses indicated a required minimum of 700 participants to detect an effect of 0.5 Likert points with a two-sided test at a 5% significance-level and a power level of 80%. We limit the sample to complete responses and those responses passing attention checks and thus use N = 777 responses for tests. Table 6 provides an overview of the sample and descriptive statistics.

[insert Table 6 here]

The N = 777 responses are distributed relatively evenly across the five groups ranging from 147 responses of participants treated with the estimation figure to 168 responses for the plain figure (Table 6, Panel A). The datapoint figure receives the highest assessments both for perceived internal validity ($IntVal$) and willingness to cite ($Citable$). Panel B provides a breakdown of statistics by treatment group. Participants evaluate the table as being more familiar and flexible, but more complex relative to the figures. Unsurprisingly, participants evaluate the estimation figure as being less familiar, less clear but more complex and more flexibles consistent with the idea that this type of figure is rather new (Ho et al. 2019). Panel C shows descriptive statistics for our control variables. 13% of participants hold a PhD or doctorate, 34% state that they are active researchers and 24% have their major in natural sciences. Participants, on average, assess their preferences for visual learning and statistical competencies with 5 Likert points (7-point scale).

4.2 Findings

We treat participants of our experiment with visuals that extend text and depict fictive scientific findings. While all participants receive the same information content, the treatments (table or one of three figures) visualize this content. We increase data transparency over the figure treatments: A plain figure only shows the test results, a datapoint figure adds the underlying data distribution and the estimation figure provides data and the distribution of the resulting test statistic. We report two main findings from this experimental setup.

Our participants generally perceive findings presented by visualizations to be marginally more internally valid and citable, but these differences across groups are not statistically significant at conventional levels (see Table 6, Figure 5 and 6). This overall effect is small in magnitude and does not clearly differentiate between table and figure visualizations[10]. We evaluate this finding as being consistent with the general ability of both visualization types to communicate research findings efficiently.

[insert Figure 5, Figure 6 here]

We formally test for treatment effects with the following regression model:

$$Response = \beta_1 DataTransp + Controls + \epsilon \tag{4}$$

The dependent variable $Response$ is one of our two outcomes, perceived internal validity ($IntVal$, average of three items assessed on a 7-point Likert scale) or citability ($Citable$, one item assessed on a 7-point Likert scale). The variable $DataTransp$ is a binary indicator that equals one if participants were treated with a data-transparent figure; tested against the plain figure group ($DataTransp$). Appendix C shows the treatment visuals and explains how we operationalize the increasing data transparency across figures.

We test equation 4 with and without control variables and with controls interacted with main independent variable $DataTransp$. We include five control variables: Three binary indicators equaling one if participants hold a PhD, doctorate or similar ($HoldsPhD$), indicate they are active researchers ($ActiveRes$) and state their research fields is in natural sciences

[10] Regression results are available in the Internet Appendix. The registered experimental design is available at the Open Science Framework, DOI: 10.17605/OSF.IO/CRH92, see https://osf.io/crh92.

($NatSciences$). We further include variables for the self-assessed visual learning preferences ($VisLearn$) and statistical competencies ($StatComp$).

We find that data-transparent figures, relative to their plain counterparts have a positive impact on perceived internal validity and the hypothetical willingness of our participants to cite the respective study (see Table 7, columns 1-2, 4-5). We report a statistically significant effect of around 0.2 Likert steps for both outcomes, implying that participants perceive findings that are supported with data-transparent figures to have a higher internal validity and to be more citable compared to results that are supported by a 'plain' box plot figure that only visualizes distributional moments.

[insert Table 7 here]

We support this last conclusion from the multiple regression analysis with a sub-sample analysis where we divide our participants by their scientific fields and contrast the effects of data-transparent figures relative to the baseline case of no visualization. While the average effect is relatively small in magnitude, a clear differentiation of the treatment effect across fields emerges (Figure 7; also, interactions $DataTransp \times NatSciences$, Table 7, columns 3, 6). Participants with a background in the natural sciences assess results supported by data-transparent figures to be about 0.5 Likert steps more internally valid and citable than results that are not supported by a visual. Participants from the field of arts and humanities, social sciences and technology and engineering do not seem to differentiate between the two presentation formats. This is consistent with the ‘hierarchy of science’ (see Section 2).

[insert Figure 7 here]

4.3 Post-experimental survey on visual treatments

Our post-experimental survey asks participants to evaluate the four treatment visuals to further explore the mechanisms that may drive treatment effects of the visuals on perceived internal validity and citability of the fictive results. Precisely, we ask for participants’ to assess their familiarity with the different visuals and to evaluate them in terms of clarity, complexity and flexibility (see Appendix C, Table C.1). For this, the participants that received the baseline treatment without visual are presented with all four visualizations, allowing us to observe within as well as between subject variation in responses across visuals. We use their answers to estimate a structural equation model that tests the paths from treatment with data-transparent figures to the assessed attributes of the visuals and the outcomes of our study (see Figure 8).

Figure 8 documents that the statistically significant main effect of the treatment is completely explained by our four visual attributes. Participants assess data-transparent figures to be clearer (0.38, $p < 0.05$) and to provide more detail (1.08, $p < 0.05$). On the other hand, they also perceive them to provide them with more information than they need (0.64, $p < 0.05$). While familiarity affects clarity (0.49, $p < 0.05$) and the perceived level of detail (0.29, $p < 0.05$) positively, the aspects that ultimately seem to drive the perception of internal validity positively are the perceived clarity (0.16, $p < 0.05$) and the level of detail (0.14, $p < 0.05$) of the visual. Finally, perceived internal validity seems to be the sole determinant of citability (0.74, $p < 0.05$).

[insert Figure 8 here]

In sum, participants that are familiar with a certain visualization type generally find it easier to understand and use to explore data. More importantly, after controlling for familiarity, the assessed clarity and level of detail of a visual are explaining the assessment of internal validity and this in turn explains the hypothetical citability of the study. These findings are consistent with clear and detailed figures helping to communicate the internal validity of a study, thereby increasing its impact.

5 Conclusion

Our study investigates how visuals, i.e., figures and tables, affect the impact of academic research. Using observational and experimental data, we document the following results: Visuals are paramount in business and economics research and their use increase with time. Articles in generalist economics journals use more figures and less tables than articles in business and economics field journals. Also, in generalist economics journals, the use of figures is robustly associated with the impact of research articles – this is not the case for field journals. We document that data-transparent figures (i.e., those that display distributional properties, error intervals, or single observations) can explain this association.

Our experiment provides evidence for a positive treatment effect of data transparency on participants' perceived internal validity of and willingness to cite a fictive study. The perceived clarity and level of detail of data-transparent figures explain this treatment effect. This effect is predominantly driven by participants from the natural sciences, which speaks to the ability of researchers from this field to process richer data visualizations. We contribute to the literature that investigates determinants of the impact of economic research (Schwabish 2022; Fourcade, Ollion, and Algan 2015; Kosnik 2018; Card and Della Vigna 2013; Hamermesh 2018; Christensen and Miguel 2018; Wei 2019) by showing that, first, prior classic findings on the heterogeneity of scientific fields in terms of data visualization (Cleveland and McGill 1984; Cleveland 1984; Cleveland and McGill 1986) translate into economics. We also extend studies on the impact of (data) visualization (Lindsey 1978; Hegarty and Walton 2012; Goggin and Best 2013; Tartanus et al. 2013; Lee, West, and Howe 2017) with field-specific evidence.

While we hope that our results are informative, we also leave plenty of room for future research. First, our observational data are of associative nature and our evidence on figure types is based on a very small sample of articles. As we do not understand well what determines the decision of an author (team) to use certain visuals when writing and publishing an article, it seems not feasible to draw causal conclusions from observational field data. In that regard, it would also be interesting to explore the role of the review process for visualization decisions.

To some extent, our experimental study is designed to address some of these shortcomings. However, its results are also not fully conclusive. While it features sufficient power so that its (null) results for the overall effect of visuals and its variance across visualization types should be informative, one can debate whether they might be an artefact of the specific participant pool or the experimental design. Our cross-sectional findings across various research fields speak to this. Thus, we would applaud work that uses similar designs with field-specific and maybe more experienced participant pools to assess whether for these, the effects of data visualizations on research impact become larger and more pronounced. Finally, our notion of data-transparent figures is inherently vague, and our experimental implementation only captures a limited aspect of this broad conceptual notion. We encourage future research that explores in more depth what makes visualizations impactful in various scientific fields.

References

Allen, Elena A., Erik B. Erhardt, and Vince D. Calhoun. 2012. "Data Visualization in the Neurosciences: Overcoming the Curse of Dimensionality." *Neuron* 74 (4): 603–8.

Allen, Micah, Davide Poggiali, Kirstie Whitaker, Tom Rhys Marshall, Jordy van Langen, and Rogier A. Kievit. 2021. "Raincloud Plots: A Multi-Platform Tool for Robust Data Visualization." *Wellcome Open Research* 4 (January): 63.

Arsenault, Darin J., Laurence D. Smith, and Edith A. Beauchamp. 2006. "Visual Inscriptions in the Scientific Hierarchy: Mapping the 'Treasures of Science.'" *Science Communication* 27 (3): 376–428.

Ball, Ray, Xi Li, and Lakshmanan Shivakumar. 2015. "Contractibility and Transparency of Financial Statement Information Prepared Under IFRS: Evidence from Debt Contracts Around IFRS Adoption." *Journal of Accounting Research* 53 (5): 915–63.

Bennett, Hunter, and Flynn Slattery. 2023. "Graphical Abstracts Are Associated with Greater Altmetric Attention Scores, but Not Citations, in Sport Science." *Scientometrics*, April.

Best, Lisa A., Laurence D. Smith, and D. Alan Stubbs. 2001. "Graph Use in Psychology and Other Sciences." *Behavioural Processes* 54 (1–3): 155–65.

Bouchaud, Jean-Philippe, Philipp Krüger, Augustin Landier, and David Thesmar. 2019. "Sticky Expectations and the Profitability Anomaly." *The Journal of Finance* 74 (2): 639–74.

Buter, R. K., and A. F.J. van Raan. 2011. "Non-Alphanumeric Characters in Titles of Scientific Publications: An Analysis of Their Occurrence and Correlation with Citation Impact." *Journal of Informetrics* 5 (4): 608–17.

Card, David, and Stefano Della Vigna. 2013. "Nine Facts about Top Journals in Economics." *Journal of Economic Literature* 51 (1): 144–61.

Chambers, John M., William S. Cleveland, Beat Kleiner, and Paul A. Tukey. 1983. *Graphical Methods for Data Analysis*. *Graphical Methods for Data Analysis*.

Chapman, S J, R C Grossman, M E B FitzPatrick, and R R W Brady. 2019. "Randomized Controlled Trial of Plain English and Visual Abstracts for Disseminating Surgical Research via Social Media." *British Journal of Surgery* 106 (12): 1611–16.

Chen, Jennifer C., Richelle J. Cooper, Michael E. McMullen, and David L. Schriger. 2017. "Graph Quality in Top Medical Journals." *Annals of Emergency Medicine* 69 (4): 453-461.e5.

Christensen, Garret, and Edward Miguel. 2018. "Transparency, Reproducibility, and the Credibility of Economics Research." *Journal of Economic Literature* 56 (3): 920–80.

Clark, Christopher, and Santosh Divvala. 2016. "PDFFigures 2.0: Mining Figures from Research Papers." *Proceedings of the ACM/IEEE Joint Conference on Digital Libraries* 2016-Septe: 143–52.

Cleveland, William S. 1984. "Graphs in Scientific Publications." *American Statistician* 38 (4): 261–69.

Cleveland, William S., and Robert McGill. 1984. "Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods." *Journal of the American Statistical Association* 79 (387): 531–54.

———. 1986. "An Experiment in Graphical Perception." *International Journal of Man-Machine Studies* 25 (5): 491–500.

Cole, Stephen. 1983. “The Hierarchy of the Sciences?” *American Journal of Sociology* 89 (1): 111–39.

Eberhard, Karin. 2023. *The Effects of Visualization on Judgment and Decision-Making: A Systematic Literature Review*. *Management Review Quarterly*. Vol. 73. Springer International Publishing.

Echenique, Federico, and Kota Saito. 2015. “Savage in the Market.” *Econometrica* 83 (4): 1467–95.

Evans, Eliza D., Charles J. Gomez, and Daniel A. McFarland. 2016. “Measuring Paradigmaticness of Disciplines Using Text.” *Sociological Science* 3: 757–78.

Fanelli, Daniele, and Wolfgang Glänzel. 2013. “Bibliometric Evidence for a Hierarchy of the Sciences.” *PLoS ONE* 8 (6).

Fourcade, Marion, Etienne Ollion, and Yann Algan. 2015. “The Superiority of Economists.” *Voprosy Ekonomiki* 2015 (7): 45–72.

Franconeri, Steven L., Lace M. Padilla, Priti Shah, Jeffrey M. Zacks, and Jessica Hullman. 2021. “The Science of Visual Data Communication: What Works.” *Psychological Science in the Public Interest* 22 (3): 110–61.

Friedman, Alon. 2021. “Data and Visual Displays in the Journal of Ecology 1996–2016.” *Information Visualization* 20 (1): 35–46.

Friendly, Michael. 2008. “The Golden Age of Statistical Graphics.” *Statistical Science* 23 (4): 502–35.

Gelman, Andrew. 2011. “Why Tables Are Really Much Better than Graphs.” *Journal of Computational and Graphical Statistics* 20 (1): 3–7.

Gelman, Andrew, Cristian Pasarica, and Rahul Dodhia. 2002. “Let’s Practice What We Preach: Turning Tables into Graphs.” *The American Statistician* 56 (2): 121–30.

Gelman, Andrew, and Antony Unwin. 2013. “Infovis and Statistical Graphics: Different Goals, Different Looks.” *Journal of Computational and Graphical Statistics* 22 (1): 2–28.

Genuchten, Erlijn Van, Katharina Scheiter, and Anne Schüler. 2012. “Examining Learning from Text and Pictures for Different Task Types: Does the Multimedia Effect Differ for Conceptual, Causal, and Procedural Tasks?” *Computers in Human Behavior* 28 (6): 2209–18.

Gicheva, Dora. 2013. “Working Long Hours and Early Career Outcomes in the High-End Labor Market.” *Journal of Labor Economics* 31 (4): 785–824.

Goggin, Claire, and Lisa A. Best. 2013. “The Use of Scientific Inscriptions in Criminology and Criminal Justice Journals: An Analysis of Publication Trends between 1985 and 2009.” *Journal of Criminal Justice Education* 24 (4): 517–35.

Gordon, Ian, and Sue Finch. 2015. “Statistician Heal Thyself: Have We Lost the Plot?” *Journal of Computational and Graphical Statistics* 24 (4): 1210–29.

Hamermesh, Daniel S. 2018. “Citations in Economics.” *Journal of Economic Literature* 56 (1): 115–56.

Hartley, James, Guillaume Cabanac, Marcin Kozak, and Gilles Hubert. 2015. “Research on Tables and Graphs in Academic Articles: Pitfalls and Promises.” *Journal of the American Society for Information Science and Technology* 66 (2): 428–31.

Hegarty, Mary. 2011. “The Cognitive Science of Visual-Spatial Displays: Implications for

Design." *Topics in Cognitive Science* 3 (3): 446–74.

Hegarty, Peter, and Zoe Walton. 2012. "The Consequences of Predicting Scientific Impact in Psychology Using Journal Impact Factors." *Perspectives on Psychological Science* 7 (1): 72–78.

Henry, Gary T. 1993. "Using Graphical Displays for Evaluation Data." *Evaluation Review* 17 (1): 60–78.

Ho, Joses, Tayfun Tumkaya, Sameer Aryal, Hyungwon Choi, and Adam Claridge-Chang. 2019. "Moving beyond P Values: Everyday Data Analysis with Estimation Plots." *Nature Methods* 16 (7): 565–66.

Ibrahim, Andrew M., Keith D. Lillemoe, Mary E. Klingensmith, and Justin B. Dimick. 2017. "Visual Abstracts to Disseminate Research on Social Media." *Annals of Surgery* 266 (6): e46–48.

Isberner, Maj Britt, Tobias Richter, Johanna Maier, Katja Knuth-Herzig, Holger Horz, and Wolfgang Schnotz. 2013. "Comprehending Conflicting Science-Related Texts: Graphs as Plausibility Cues." *Instructional Science* 41 (5): 849–72.

Jacques, Thomas S, and Neil J Sebire. 2010. "The Impact of Article Titles on Citation Hits: An Analysis of General and Specialist Medical Journals." *JRSM Short Reports* 1 (2): 1–5.

Kastellec, Jonathan P., and Eduardo L. Leoni. 2007. "Using Graphs Instead of Tables in Political Science." *Perspectives on Politics* 5 (4): 755–71.

Kosnik, Lea Rachel. 2018. "A Survey of Jel Codes: What Do They Mean and Are They Used Consistently?" *Journal of Economic Surveys* 32 (1): 249–72.

Kubina, Richard M, Douglas E Kostewicz, and Shawn M Datchuk. 2008. "An Initial Survey of Fractional Graph and Table Area in Behavioral Journals." *The Behavior Analyst* 31 (1): 61–66.

Lee, Po-Shen, Jevin D. West, and Bill Howe. 2017. "Viziometrics: Analyzing Visual Information in the Scientific Literature." *IEEE Transactions on Big Data* 4 (1): 117–29.

Lindsey, Duncan. 1978. *The Scientific Publication System in Social Science*.

Marshall, Guy Clarke, Caroline Jay, and André Freitas. 2021. "Number and Quality of Diagrams in Scholarly Publications Is Associated with Number of Citations." *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* 12909 LNAI: 512–19.

Mayer, Richard E., William Bove, Alexandra Bryman, Rebecca Mars, and Lene Tapangco. 1996. "When Less Is More: Meaningful Learning from Visual and Verbal Summaries of Science Textbook Lessons." *Journal of Educational Psychology* 88 (1): 64–73.

Paiva, Carlos Eduardo, João Paulo da Silveira Nogueira Lima, and Bianca Sakamoto Ribeiro Paiva. 2012. "Articles with Short Titles Describing the Results Are Cited More Often." *Clinics* 67 (5): 509–13.

Peer, Eyal, David Rothschild, Andrew Gordon, and Ekaterina Damer. 2022. "Data Quality of Platforms and Panels for Online Behavioral Research." *Behavior Research Methods* 54 (5): 2618–20.

Scheuer, Florian, and Iván Werning. 2017. "The Taxation of Superstars." *The Quarterly Journal of Economics* 132 (1): 211–70.

Schwabish, Jonathan. 2014. "An Economist's Guide to Visualizing Data." *Journal of Economic Perspectives* 28 (1): 209–34.

———. 2022. "Categorizing and Ranking Graphs in Economics Research: The American Economic Review over the Last Century." *Journal of Benefit-Cost Analysis* 13 (1): 20–33.

Simonton, Dean Keith. 2004. "Psychology's Status as a Scientific Discipline: Its Empirical Placement Within an Implicit Hierarchy of the Sciences." *Review of General Psychology* 8 (1): 59–67.

———. 2006. "Scientific Status of Disciplines, Individuals, and Ideas: Empirical Analyses of the Potential Impact of Theory." *Review of General Psychology* 10 (2): 98–112.

———. 2015. "Psychology as a Science within Comte's Hypothesized Hierarchy: Empirical Investigations and Conceptual Implications." *Review of General Psychology* 19 (3): 334–44.

Smith, Laurence D., Lisa A. Best, D. Alan Stubbs, Andrea Bastiani Archibald, and Roxann Roberson-Nay. 2002. "Constructing Knowledge: The Role of Graphs and Tables in Hard and Soft Psychology." *American Psychologist* 57 (10): 749–61.

Smith, Laurence D, Lisa A Best, D Alan Stubbs, John Johnston, and Andrea Bastiani Archibald. 2000. "Scientific Graphs and the Hierarchy of the Sciences: A Latourian Survey of Inscription Practices." *Social Studies of Science* 30 (1): 73–94.

Stremersch, Stefan, Isabel Verniers, and Peter C. Verhoef. 2007. "The Quest for Citations: Drivers of Article Impact." *Journal of Marketing* 71 (3): 171–93.

Tahamtan, Iman, Askar Safipour Afshar, and Khadijeh Ahamdzadeh. 2016. "Factors Affecting Number of Citations: A Comprehensive Review of the Literature." *Scientometrics* 107 (3): 1195–1225.

Tartanus, Malgorzata, Agnieszka Wnuk, Marcin Kozak, and James Hartley. 2013. "Graphs and Prestige in Agricultural Journals." *Journal of the American Society for Information Science and Technology* 64 (9): 1946–50.

Tufte, Edward R. 2001. *The Visual Display of Quantitative Information*.

Walsh, Erin I, Ginny M Sargent, and Will J Grant. 2021. "Not Just a Pretty Picture: Scientific Fact Visualisation Styles, Preferences, Confidence and Recall." *Information Visualization* 20 (2–3): 138–50.

Wei, Guangyue. 2019. "A Bibliometric Analysis of the Top Five Economics Journals During 2012–2016." *Journal of Economic Surveys* 33 (1): 25–59.

Weissgerber, Tracey L., Natasa M. Milic, Stacey J. Winham, and Vesna D. Garovic. 2015. "Beyond Bar and Line Graphs: Time for a New Data Presentation Paradigm." *PLOS Biology* 13 (4): e1002128.

Weissgerber, Tracey L., Stacey J. Winham, Ethan P. Heinzen, Jelena S. Milin-Lazovic, Oscar Garcia-Valencia, Zoran Bukumiric, Marko D. Savic, Vesna D. Garovic, and Natasa M. Milic. 2019. "Reveal, Don't Conceal." *Circulation* 140 (18): 1506–18.

Wesel, Maarten van, Sally Wyatt, and Jeroen ten Haaf. 2014. "What a Difference a Colon Makes: How Superficial Factors Influence Subsequent Citation." *Scientometrics* 98 (3): 1601–15.

Wickham, Hadley. 2010. "A Layered Grammar of Graphics." *Journal of Computational and Graphical Statistics* 19 (1): 3–28.

Wiley, Jennifer, David Sarmento, Thomas D. Griffin, and Scott R. Hinze. 2017. "Biology Textbook Graphics and Their Impact on Expectations of Understanding." *Discourse Processes* 54 (5–6): 463–78.

Wilke, Claus O. 2019. *Fundamentals of Data Visualization: A Primer on Making Informative and Compelling Figures*.

Wu, Jiahua, Mengze Shi, and Ming Hu. 2015. "Threshold Effects in Online Group Buying." *Management Science* 61 (9): 2025–40.

Appendix A: Variable Definitions

Variable name	**Variable definition**
Panel A: Observational study	
Dependent Variables	
Citations	Citation count of a research article obtained from Crossref. We fill missing values with data from Scopus.
YCitations	*Citations* divided by the number of years the article is in our sample.
OCitations	Citations of an article for a given year obtained from the database OpenCitations.
Independent and additional variables	
Has figures	Binary variable equal to one if a research article has a figure, zero otherwise.
Has tables	Binary variable equal to one if a research article has a table, zero otherwise.
Figures	Number of figures of a research article; multipanel figures are counted as one figure.
Tables	Number of tables of a research article; multipanel tables are counted as one table.
Transp	Binary variable equal to one if a research article visualizes data-transparently. This is the case if it includes a figure that (i) shows data distributions univariately, (2) indicates uncertainties (second moment) in bar or line graphs, or (3) plots data as single observations (e.g., scatter plots).
ShareTransp	The ratio of the count of data-transparent figures to the overall count of figures in a research article. For the definition of data transparency, see variable *Transp*.
Journal type	Generalist economics journals, business field journals, economics field journals (see research design)
Words	Number of words of a research article
Authors	Number of authors of a research article
References	Number of references (backward citations) of a research article
Words in title	Numbers of words of the title of a research article.
Equations	Number of lines with mathematical expressions of a research article; we take the natural logarithm of this variable for distributional purposes if we use it in statistical tests.
Panel B: Experimental study (see Appendix C for detail on experimental materials and implementation)	
Dependent variables	
IntVal	Arithmetic mean of three items by which participants assess the internal validity of the fictive study. All three items are measured on a 7-point Likert scale.
Citable	Participants' stated willingness to cite the fictive study measured on a 7-point Likert scale..
Familiar	Participants stated familiarity with a treatment visual measured on a 7-point Likert scale.
Clear	Participants assessment of the clarity of a treatment visual measured on a 7-point Likert scale.
Complex	Participants assessment of the complexity of a treatment visual measured on a 7-point Likert scale.
Flexible	Participants assessment of the familiarity of a treatment visual measured on a 7-point Likert scale.
Independent and additional variables	
DataTransp	Binary variable equal to one if participants were treated with a data-transparent visual (datapoint figure or estimation figure) and zero for treatment with plain figure.
HoldsPhD	Binary variable equal to one if participants indicate they hold a Ph.D., doctorate or similar; zero otherwise.
ActiveRes	Binary variable equal to one if participants indicate they are active researchers; zero otherwise.
NatSciences	Binary variable equal to one if participants state their primary research field is in natural sciences; zero otherwise.
VisLearn	Participants stated preference for visual learning measured on a 7-point Likert scale.
StatComp	Participants stated statistical competence measured on a 7-point Likert scale.

Appendix B: Classification of data transparency of scientific figures

B.1 Classification scheme and procedure

For the classification, we proceed in two steps. We first classify the content type of the visual by selecting one of the content type categories. Then, we classify the figure type by selecting one or multiple figure type categories that apply. The second step includes categories for visuals displaying distributional information of data. The following table shows the content type and figure type categories with explanations for each category.

Categories	Explanations
Step 1: Content type categories	
1. Conceptual visualization	Figures visualizing concepts by texts, boxes, arrows etc. (e.g., timelines or flowcharts). These are not classified further and multi panel figures are not broken up.
2. Theoretical visualization	Figures visualizing predicted associations of theoretical constructs. These figures are common in theory papers but can also show up in empirical papers. They are often displayed as graphs of functions (line graphs). These are not classified further and multi panel figures are not broken up.
3. Simulated data	Figures displaying simulated data are coded as data visualizations when they display the (random) variance of simulations and not when simulations are used to assess the functional form predicted by theory. In this case, they would be classified as 'theory'.
4. Empirical data	Figures displaying empirical data.
Step 2: Figure type categories	
1. Line graph	A visual of dots, bars, or lines that displays values of a y variable over values of an in-principle continuous x variable. Often the plotted values are medians or means of a bin of y values. The figure type (line, bars, points, lollipop etc.) does not matter for classification. Please note that observation counts by time dimension are classified as bar graphs (see below).
2. Line graph (distributional info)	A line graph with distributional information (e.g., confidence intervals or percentiles).
3. Bar graph	A visual of bars, dots, or (inappropriately) lines that displays values of a y variable over values of a discrete x variable. Often the plotted values are counts, medians or means of a discrete value of y. Counts by time dimension are classified as bar graphs. Figure type (line, bars, points, lollipop etc.) do not matter for classification.
4. Bar graph (distributional info)	A bar graph with distributional information (e.g., confidence intervals or percentiles).
5. Histogram	
a) Histogram (discrete)	Describes the distribution of a variable over its discrete values.
b) Histogram (continuous)	Describes the distribution of a variable for bins of continuous values. Often displayed as a bar graph, but for continuous histograms also other displays (e.g., density function plots) are feasible.
6. Scatter plot	Plots observations of a sample for two variables in two dimensions. A scatter with regression line counts as both a scatter and a line graph. The plotted data points can be derivative in nature (e.g., residual plots). Also, the plotted points can be aggregate statistics for cross-sectional groups or bins of the x variable.
7. Extreme value scatter	A figure plotting not all relevant observations but only influential observations (such as the extreme values in a classical boxplot).
8. Comparison	A figure that compares values of a variable with a benchmark. For example, a figure comparing parameter estimates with their expected value.
9. Choropleth	A figure mapping a variable across its spatial dimension.
10. Screenshot	A visual capturing computer screen content, for example to visualize an experimental design. The screen shot can also be annotated.
11. Image	A visual image of something that classifies as data. For example, a photograph of an experimental setting.
12. Other (residual)	A catch-all category for figures that are not classified as 'conceptual' or 'theory', meaning that they present data but that cannot be classified into any of the above categories.

Although we are well-aware of the various options to extract and classify figures with software packages (e.g., Clark and Divvala 2016), we deliberately decided to manually classify scientific figures to better understand how data transparent researchers visualize for three reasons. First, we aim at classifying the content type to specifically classify empirical data visualizations. We decided to include simulated data visualizations, too, since they are close to empirical data visualizations and also here, a transparent visual allows the reader a better grip on the underlying data. We do not classify conceptual and theoretical figures further. Automated procedures cannot grasp these differences, but they are important for our study. Second, evaluating data transparency requires us to understand the figure type. Oftentimes, researchers visualize using figure types inappropriate to the displayed data, e.g., line graphs instead of bar graphs if observations represented by x-axis binds are independent of each other. Third, our classification includes a specific look at the way data is displayed and hence, we abstract from the aesthetics of a figure. Classifying figures with statistical software packages would hardly allow this kind of abstraction.

B.2 Examples of content type and figure type classifications

We provide examples for content type and figure type classifications below. Since we classify only figures using simulated and empirical for their figure type, we provide one example each for conceptual and theoretical figures and two examples each for figures using simulated and empirical data. The summary statistics from our manual classification are available in Table 4.

Figure IV of Scheuer and Werning (2017) is classified as conceptual figure. We do not classify the figure type.

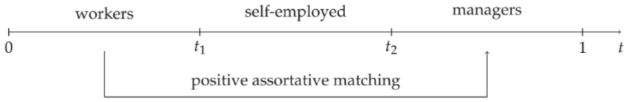


FIGURE IV
Equilibrium Sorting and Matching

Figure 1 of Echenique and Saito (2015) is classified as theoretical figure. We do not classify the figure type.

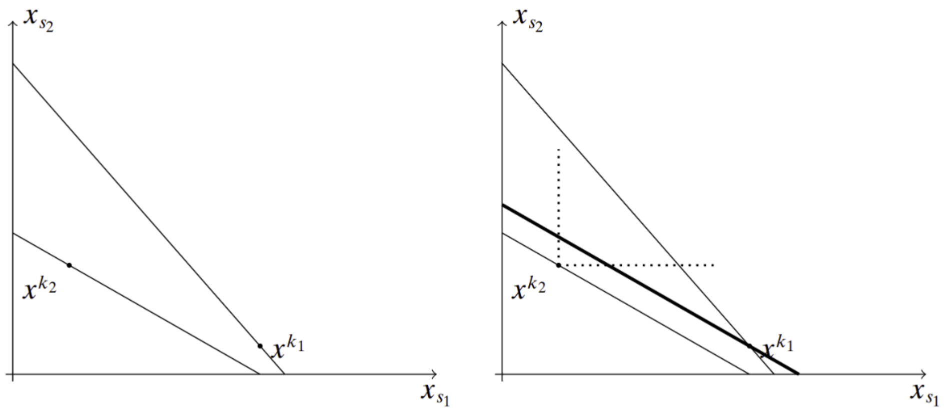


FIGURE 1.—A violation of requirement (5).

Figure 3 of Bouchaud et al. (2019) is classified as figure based on simulated data. We classify the figure type. Both panels are classified separately as ‘histogram continuous’.

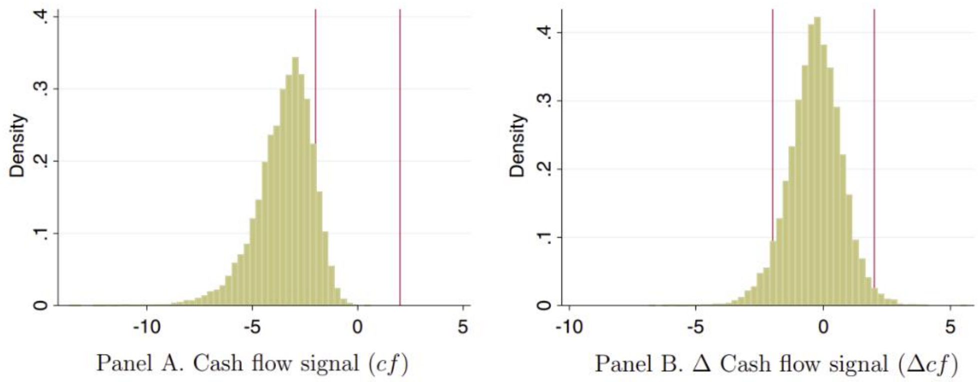


Figure 3. *t*-statistics of double-sorts under the null of rational expectations: Results from simulations. These histograms present the distribution of t-statistics from double-sorts by profitability and stickiness for 10,000 simulations under the null hypothesis that expectations are *not* sticky. Each simulation works as follows. For 2,000 firms over 12 years, we simulate our baseline model assuming $\lambda = 0$.

Figure 1 of Gicheva (2013) is classified as figure based on simulated data. We classify the figure type. Both panels are classified separately. The first panel is classified as ‘scatter plot’, the second panel as ‘line graph’. With our definition of data transparency, the first panel is data-transparent since it plots single observations, the second panel is not data-transparent since it does not provide information on the second moment of the predicted change in log wage.

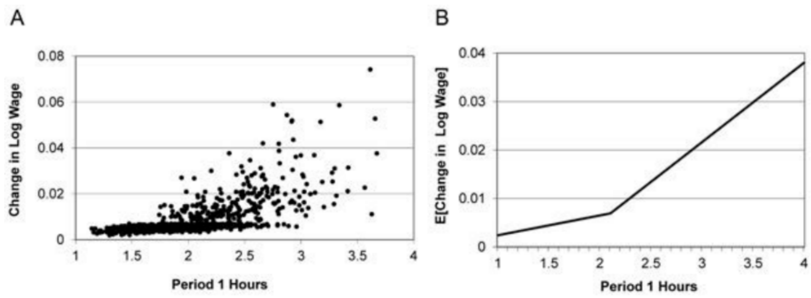
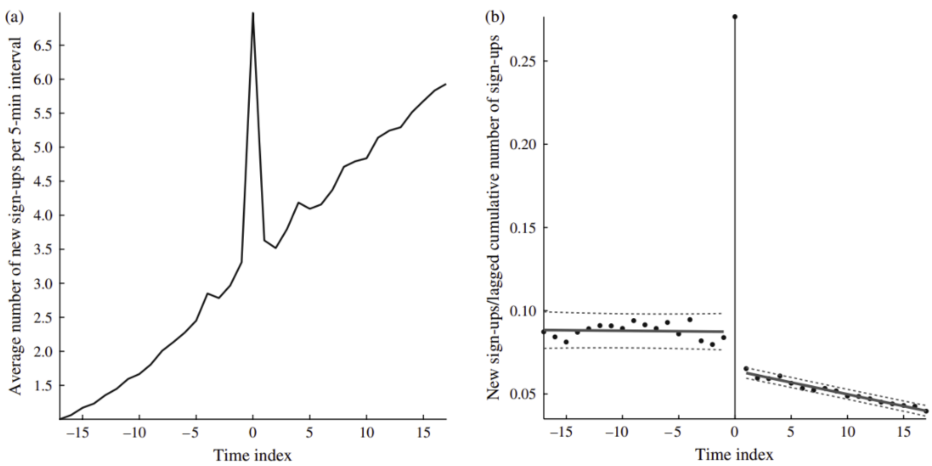


FIG. 1.—Hours and wage growth from simulations. *A*, Model simulation results, $N = 1{,}000$. *B*, Simulation results: predicted change in log wage, $N = 100{,}000$. Simulated data based on the model in Section II. The choice of the disutility parameter b and inherent ability θ is such that $300b$ and 200θ have χ^2 distributions with 50 degrees of freedom. Other parameter values: $\eta_1 = 0.1$; $c_1 = 0.075$; $c_2 = 0.52$; $d_1 = 0.616$; $d_2 = 0.545$.

Figure 1 of Wu, Shi, and Hu (2015) is classified as figure based on empirical data. We classify the figure type. Both panels are classified separately. The first panel is classified as ‘line graph’, the second panel as ‘line graph (distributional info)’. With our definition of data transparency, the first panel is not data-transparent since it does not provide information on the second moment of the average number of new sign-ups during each five-minute time interval, the second panel is data-transparent since it plots confidence intervals for the fitted values from first-order polynomial regressions.

Figure 1 **Sign-Up Pattern During the One-and-a-Half-Hour Time Window Before and After the Threshold Was Reached**



Notes. The *x* axis indicates the time index. The *y* axis in panel (a) denotes the average number of new sign-ups during each five-minute time interval. The *y* axis in panel (b) denotes the ratio between the number of new sign-ups during a time interval and the cumulative number of sign-ups up to the end of the previous time interval. Solid lines are fitted values from first-order polynomial regressions on either side of the time interval when the threshold was reached, and dotted lines are 95% confidence intervals.

Figure 2 of Ball, Li, and Shivakumar (2015) is classified as figure based on empirical data. We classify the figure type. Both panels are classified separately. Both of them are classified as ‘line graph’. With our definition of data transparency, both panels are not data-transparent since they do not provide information on the second moment of the average accounting covenant frequency and intensity.

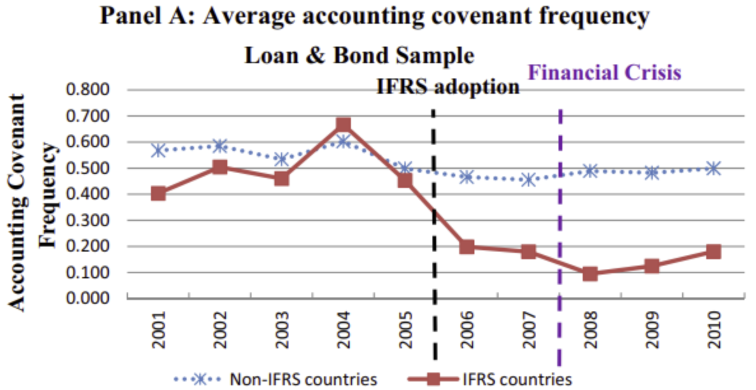
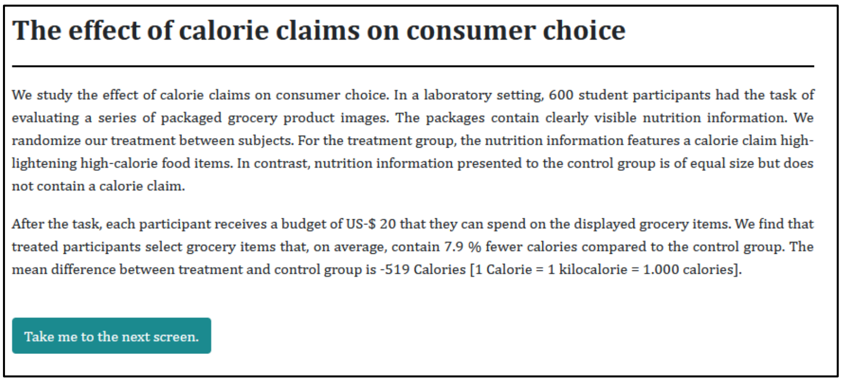


FIG. 2.—Accounting covenant use over time. In panel A (B), the red solid line labeled "IFRS countries" plots the mean value of *D_ACov* (*Num_ACov*) for debt (loans and bonds) issued by firms domiciled in IFRS adopting countries. The blue dotted line labeled "Non-IFRS countries" plots the mean value of *D_ACov* (*Num_ACov*) for debt issued by firms domiciled in countries that did not mandate IFRS adoption during the sample period. *D_ACov* is a dummy variable indicating that the debt contract contains at least one accounting-based covenant. *Num_ACov* is the total number of accounting covenants contained in a debt contract. The vertical line "IFRS adoption" indicates the date when IFRS was mandated in the treatment sample (December 2005). The line "Financial Crisis" indicates the date when the recent financial crisis started (July 2007).

Appendix C: Experimental design

C.1 Experimental case

Our experiment is based on a fictive experimental study, for which we use simulated data, and designed as an online experiment using oTree[11]. The experimental design comprises ten screens. After a landing page explaining the topic of the study, the privacy policy and conditions to participate, participants read an introductory statement on the upcoming screens. They are informed that they will read the summary of a fictive experiment, which assesses the effects of calorie claims on consumer choice and that we will ask questions on the fictive experiment and its findings. These screens follow: (i) a short abstract of the fictive experimental study (Figure C.1), (ii) a brief description of the research design showing a table with descriptive statistics on covariate balance (Figure C.2), (iii) the main findings of the fictive experiment (treatment screen, Figure C.3) and (iv) a conclusion on the fictive experiment (Figure C.4). The treatment screen shows the summary of the fictive experiment as either text only (baseline), table, or one of three visuals.


The effect of calorie claims on consumer choice

We study the effect of calorie claims on consumer choice. In a laboratory setting, 600 student participants had the task of evaluating a series of packaged grocery product images. The packages contain clearly visible nutrition information. We randomize our treatment between subjects. For the treatment group, the nutrition information features a calorie claim high-lightening high-calorie food items. In contrast, nutrition information presented to the control group is of equal size but does not contain a calorie claim.

After the task, each participant receives a budget of US-$ 20 that they can spend on the displayed grocery items. We find that treated participants select grocery items that, on average, contain 7.9 % fewer calories compared to the control group. The mean difference between treatment and control group is -519 Calories [1 Calorie = 1 kilocalorie = 1.000 calories].

Take me to the next screen.

Figure C.1: Experimental screen 'A short abstract of the fictive experimental study'

[11] Chen, D.L., Schonger, M., Wickens, C., 2016. oTree - An open-source platform for laboratory, online and field experiments. Journal of Behavioral and Experimental Finance, Vol. 9: 88-97.

Descriptive statistics and covariate balance

600 student participants, all from the same university, participated in our experiment. They were randomly assigned to the treatment group (300 participants) or the control group (300 participants). The table below reports demographic statistics for our participants, allowing the assessment of the covariate balance across the two groups. It displays the mean and standard deviation of demographic statistics separately for the treatment group and the control group. The t-statistics reported in the last column reflect that the variables' means for the treatment group and the control group are not significantly different from each other (at conventional levels of 5 % significance with 1.96 as the critical value not to exceed).

For a mobile device you might want to use the landscape mode for a better display of the table.

Covariate Balance Table

	Treatment Group		**Control Group**		**Group Differences**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Δ Means**	**t-statistic**
Age	22.05	1.09	22.01	1.01	0.04	0.43
Male	0.42	0.49	0.44	0.50	-0.02	-0.49
Household Members	1.88	1.10	1.75	0.98	0.14	1.60
STEM Student	0.22	0.42	0.19	0.40	0.03	0.90
Study Year	2.94	0.81	2.95	0.78	-0.01	-0.15

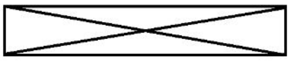
Notes: The variables are defined as follows. **Age** *is the participants' age in years.* **Male** *is a binary variable that is equal to one when a participant identifies as male and zero otherwise.* **Household Members** *is the number of persons that live in the household of the participant.* **STEM Student** *is a binary variable that is equal to one when the participant is enrolled in the areas of Science, Technology, Engineering or Mathematics and zero otherwise.* **Study Year** *is the participant's year of study.* **Δ Means** *is the difference between the means of the treatment and control group for a given variable.*

Take me to the next screen.

Figure C.2: Experimental screen 'Descriptive statistics and covariate balance'

Findings

To assess the effect of calorie claims on consumer choice, we use the total Calories of the grocery items that participants choose based on their budget of US-$ 20 as our dependent variable. We compare this outcome across the treatment and the control group.



For the control group, the chosen grocery items result in a mean total of 6,535 Calories (Minimum: 2,770 Calories, 25th quantile: 5,566 Calories, Median: 6,421 Calories, 75th quantile: 7,646 Calories, Maximum: 10,688 Calories), while for the treatment group, we observe a mean total of 6,016 Calories (Minimum: 2,035 Calories, 25th quantile: 5,050 Calories, Median: 5,946 Calories, 75th quantile: 6,990 Calories, Maximum: 10,720 Calories). The mean difference between treatment and control group is -519 Calories, i.e., treated participants choose grocery items containing 7.9 % fewer calories relative to the control group. This difference is significant at conventional levels (t-statistic: -4.04).

Take me to the next screen.

Figure C.3: Treatment screen with crossed out rectangle as placeholder for visual

Conclusion

Our student participants that are presented with images of product packages featuring nutrition information with additional calorie claims select grocery items that, on average, contain -519 (-7.9 %) fewer Calories compared to the control group that received images of product packages featuring nutrition information only. Given our experimental setup and the balance in the demographic characteristics between the treatment and the control group, we interpret our findings as indicating that students react to calorie claims by significantly lowering their calorie demand. We leave it to future research to explore whether these results extend to other populations.

Take me to the questions.

Figure C.4: Experimental screen 'Conclusion'

C.2 Experimental treatments

We use four visuals to visualize the findings of the fictive experiment on the treatment screen in addition to the text, a table and one of three graphs. The text summarizing the findings on the treatment screen is the same across all treatments. Hence, all participants had the same information but this information visualized differently across treatments. The table treatment displays descriptive statistics for the outcome variable (Calories) the mean, minimum, 25th and 75th percentile and median. Additionally, it displays the difference in means of the treatment and control group of the fictive experimental study with t-statistic (see Figure C.).

	Control	Treatment
Mean	6,535	6,016
Minimum	2,770	2,035
Q25	5,566	5,050
Median	6,421	5,946
Q75	7,646	6,990
Maximum	10,688	10,720
Difference in Means (Treatment - Control)	-519 (t-stat: -4.04)	

Figure C.5: Table (visual treatment)

The box plots are the figure treatments (see Figure C.). They visualize the same statistics the table treatment shows as numerical format. The whiskers indicate minimum and maximum, the boxes indicate the 25th and 75th with a median line and the diamond indicates the mean. We increase the data transparency of the 'simple' box plot (Figure C., Panel A) by adding data points for the single observations of the fictive treated and control group (Figure C., Panel B). This allows our participants to assess the underlying data distribution.

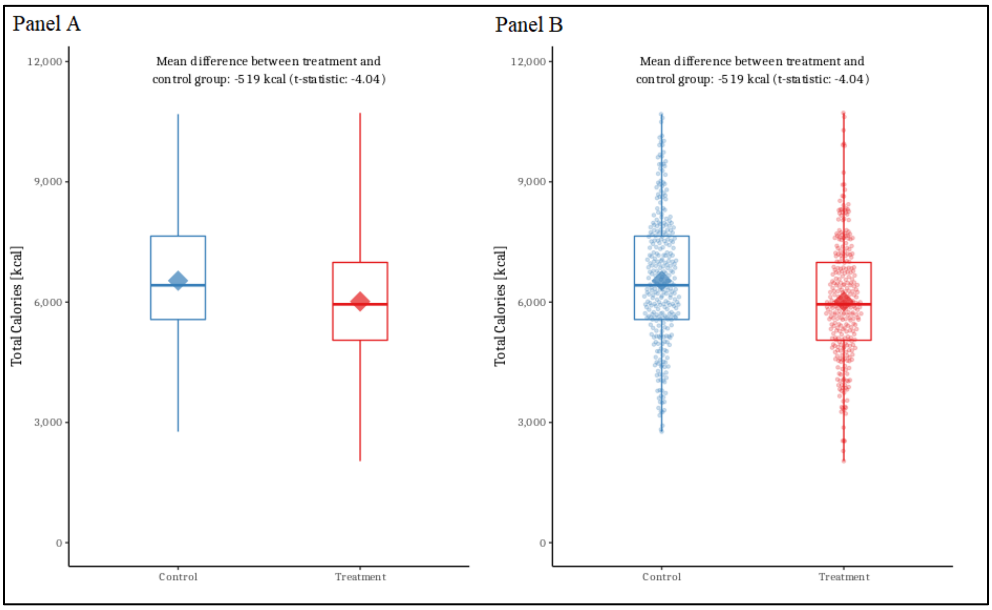


Figure C.6: Box plot and data-transparent box plot (visual treatment)

As a fourth visual treatment, we include an estimation graph (Ho et al. 2019). We use the same design elements of the data-transparent box plot (Figure C., Panel B), but add a visualized t-test showing the mean difference with t-Student distribution on a second y-axis (Figure C.). The estimation graph is more data transparent relative to the data-transparent box plot since it allows participants not only to assess the underlying data distribution, but also to evaluate the test statistic distribution. This provides full control to participants for assessing the fictive experiment's findings.

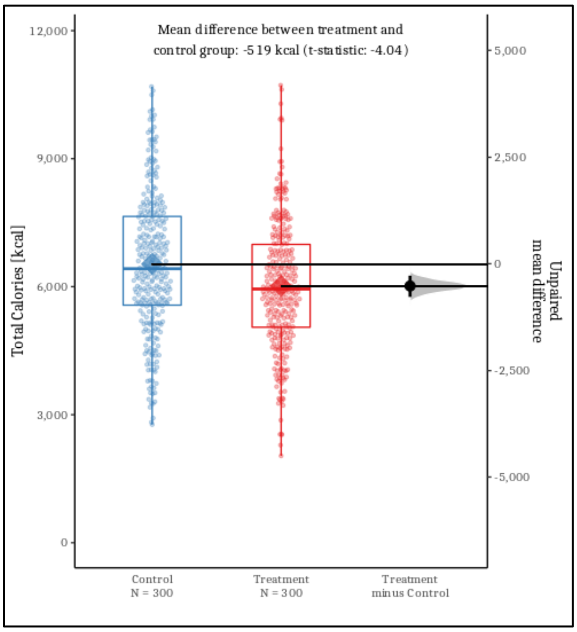


Figure C.7: Estimation graph (visual treatment)

C.3 Experimental question items

After participants had the chance to read the fictive case and findings, they view four screens to (i) evaluate the fictive study, (ii) show attention and recall, (iii) assess the treatment visuals and (iv) provide us with additional and demographic information.

The first outcome screen asks participants to assess four statements on the fictive study on a 7-point Likert scale[12] in a 5x1 between-subjects design. Three of these statements ask participants about their assessment of the internal validity of the fictive study in randomized order (Table C.1, No 1-3) and the fourth question asks them about their judgment on the citability of the fictive study (Table C.1, No 4). Participants can provide comments on a separate text field on the screen. On the next screen, we ask participants three questions on their recall of important elements of the fictive experimental case and include one attention check.

[12] Whenever we refer to our 7-point Likert scale, we use the following answer options in the experiment: 'strongly disagree', 'disagree', 'somewhat disagree', 'neither nor', 'somewhat agree', 'agree', 'strongly agree'; always optional to choose 'no answer'.

Table C.1: Experimental question items

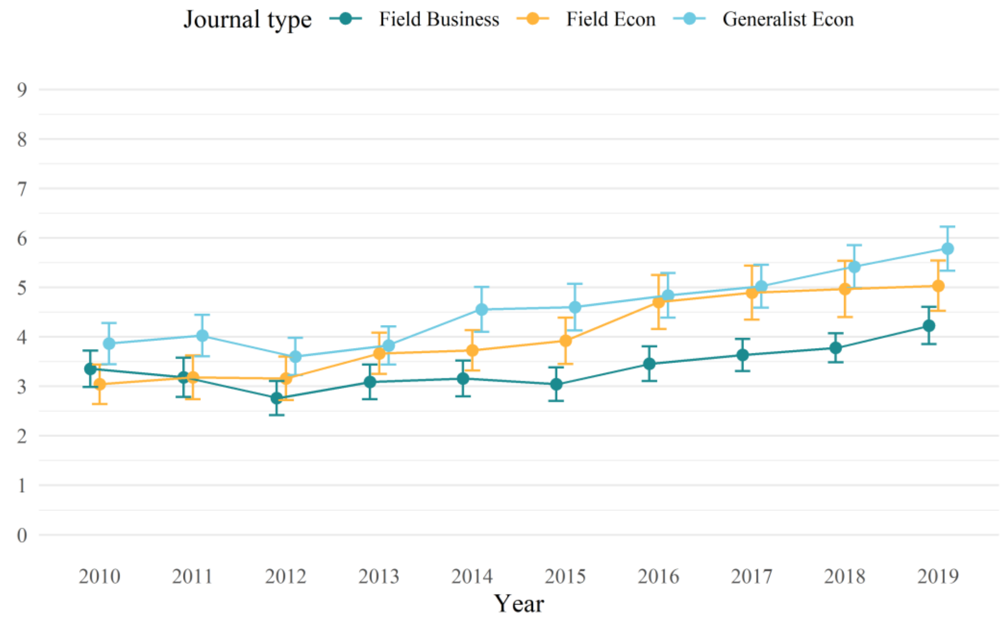
Item No	Statement
All statements were evaluated with a 7-point Likert scale and preceded by "Please imagine our fictive experiment on calorie claims to be a real piece of scientific work and tell us to which extent you agree with the following statements."	
Internal validity/citability	
1	I am confident that the effect size has been reliably estimated.
2	The data analysis of the experiment is methodologically sound.
3	The data supports the conclusion that the calorie claims caused the student participants to choose fewer high-calorie grocery items.
4	If I were working as a researcher in the field of the fictive study and the study were to add new insights to the literature, I would cite it.
Evaluation of visuals [data collection screen 3]	
5	[concept: clarity/understandability] The [figure/table] makes the findings understandable. Item derived from discussions of clarity/understandability (e.g., Tufte 2001).
6	[concept: complexity] The [figure/table] provides me with more information than needed. Item derived from discussions of complexity/information overload (e.g., Chambers et al. 1983; Wilke 2019).
7	[concept: interpretability/familiarity] The layout of the [figure/table] is familiar to me. Item derived from discussions of interpretability/familiarity (e.g., Chambers et al. 1983).
8	[concept: flexibility] The [figure/table] allows me to explore the data in detail. Item derived from discussions of flexibility of a visual for exploration (e.g., Chambers et al. 1983).

After completing the first attention check, participants answer four questions on the visuals (Table C.1, No 5-8). Specifically, we ask for clarity, complexity, flexibility, interpretability of the visuals (see Section 2 for a discussion). We survey treated participants with the four questions on their assessment of the visual they see on the treatment screen in a randomized order. Since we have four treatment groups that receive findings supported with a visual (i.e., table or figure), we are able to receive participants' assessment of the visuals as a 4x1 between-subjects design. Baseline participants do not see this screen. For baseline participants, we implement a 1x4 within-subjects design instead. They see a screen that shows all four visuals in a randomized order each with the four questions on the assessment of visual, also in a randomized order. We decided to implement both designs to triangulate participants' assessment of the visuals, which mitigates concerns that the design of our fictive experimental case affects participants' assessment of our four treatment visuals in unintended ways.

We end the data collection with a screen asking for participants' attitude towards visuals, their familiarity with statistical inference and demographic questions. On this screen, we generate the control variables for our regressions. We ask if participants hold a doctorate, PhD degree or similar ($HoldsPhD$), if they are active researchers ($ActiveRes$) and if their main research fields is in the natural sciences ($NatSciences$). We further ask for the self-assessment of participants on their visual learning preferences ($VisLearn$) and statistical competencies ($StatComp$). This last data collection screen includes a second attention check. We require participants to pass at least one of the two attention checks to be included in our experimental sample. The experiment finishes with a screen on which participants may provide comments and a farewell screen.

Panel A: Number of figures per article by journal type

N = 7,846



Panel B: Number of tables per article by journal type

N = 7,846

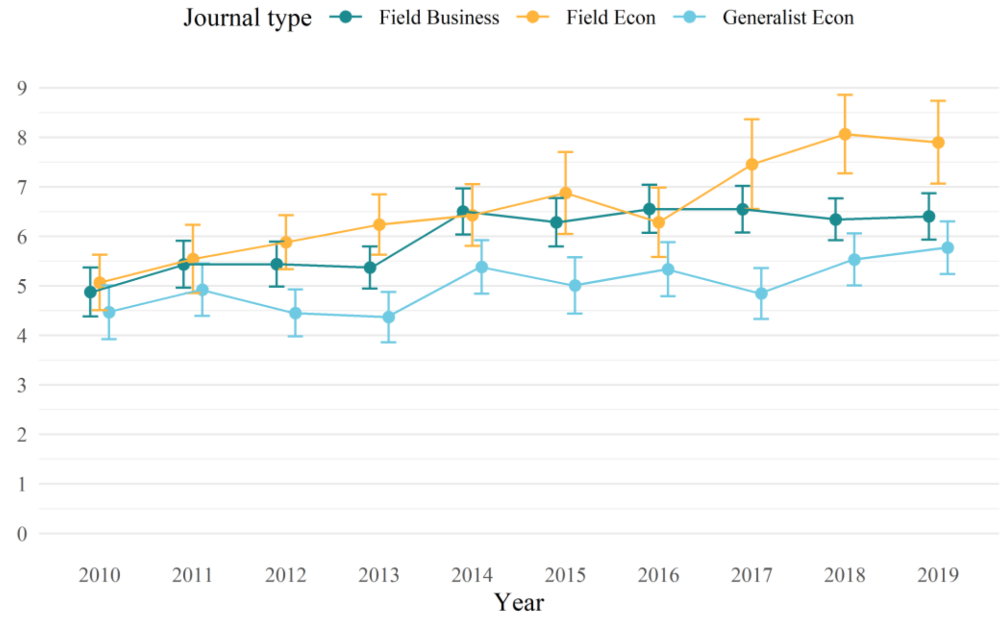


Figure 1: Number of visuals by journal type

This figure shows the average number of figures (Panel A; variable Figures) and tables (Panel B; variable Tables) per research article by journal type. Journal types are defined as follows: Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (REStud); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). All variables are defined in Appendix A.

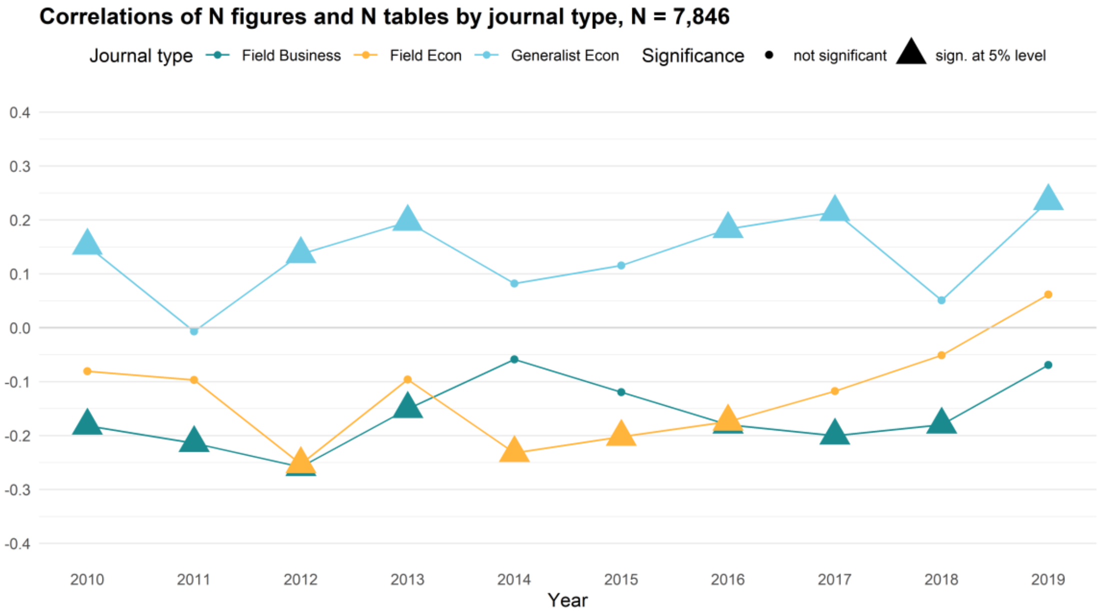


Figure 2: Correlations of number of figures and tables by journal type

This figure plots Pearson correlations of the number of figures and tables per article by journal type (Field Business, Field Econ, Generalist Econ) over the sample period from 2010 to 2019. Plotted bold triangles indicate whether the correlation is significant at the 95%-confidence interval. The horizontal grey line indicates zero. The figure provides information on whether research articles use figures and tables as substitutes (negative correlation) or complements (positive correlation).

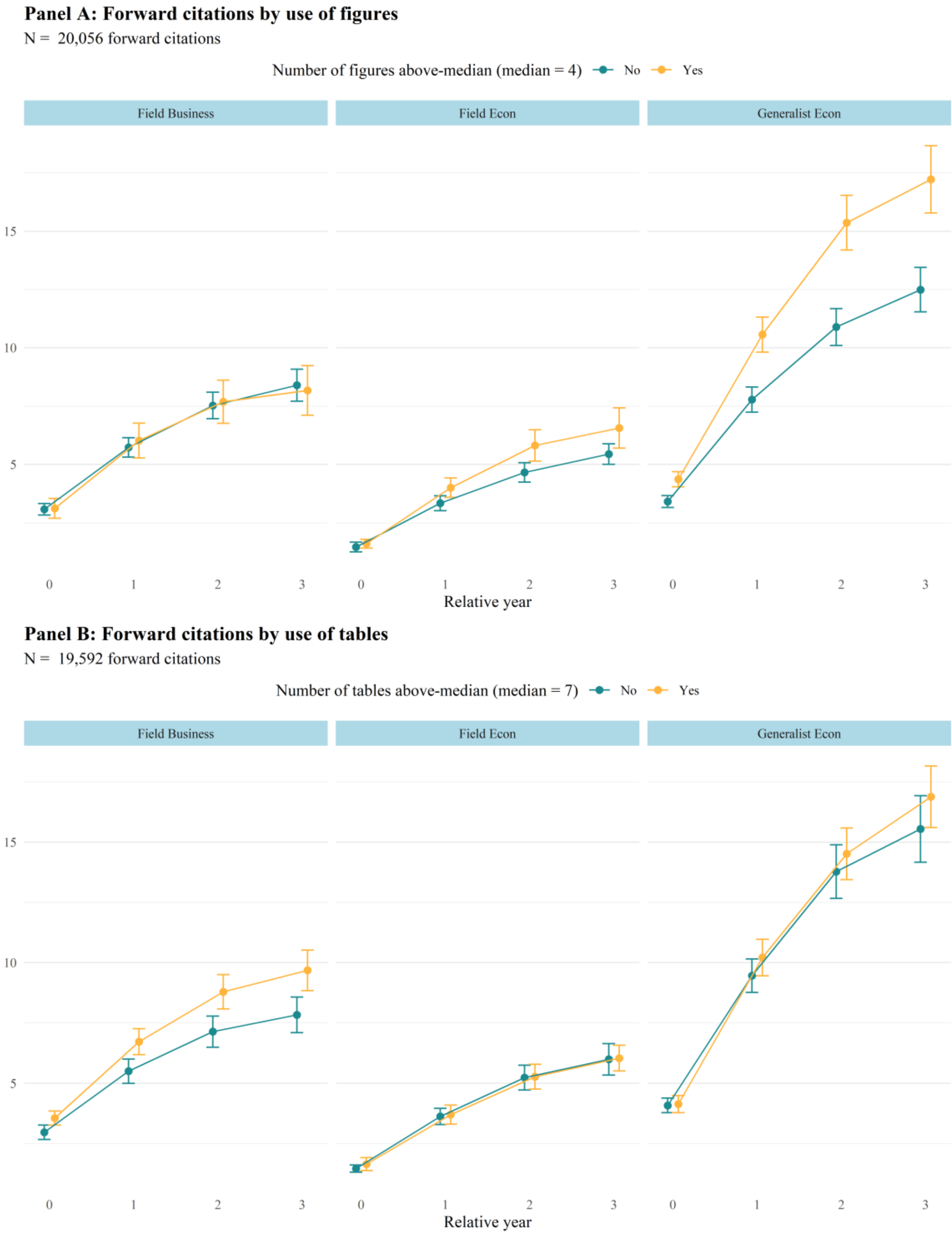


Figure 3: Forward citations by use of visuals and journal type

This figure shows the average number of forward citations per article (FWCitations) by journal type relative to the year of the publication of the article (t = 0) for the use of figures (Panel A) and tables (Panel B). Journal types are defined as follows: Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (REStud); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). All variables are defined in Appendix A.

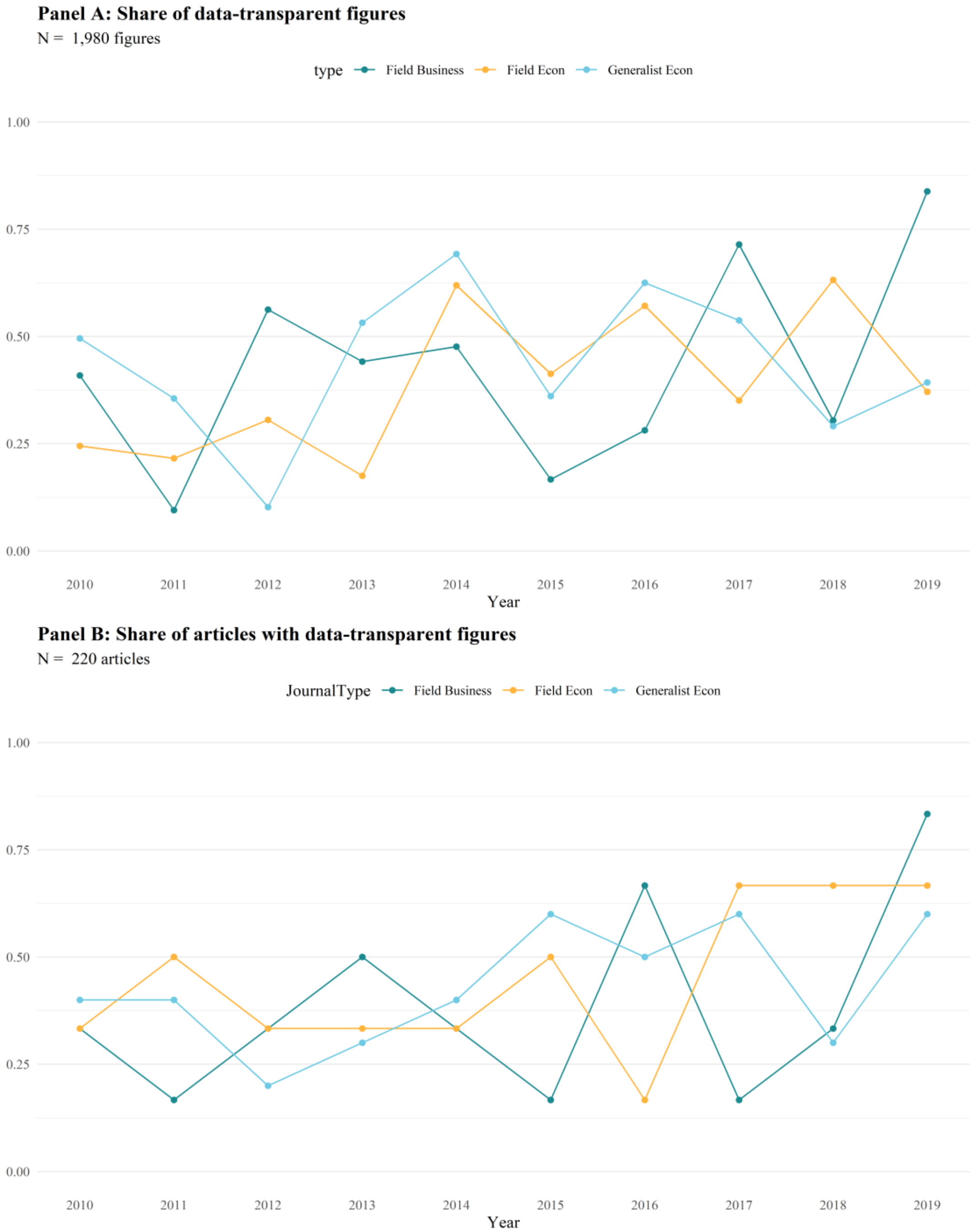


Figure 4: Data transparency over time

This figure plots yearly the share of figures (Panel A) and share of articles (Panel B) which we classify as data transparent in our manual classification of figures from a subset of 220 research articles drawn from our main sample stratified by journal and year (two articles each). We classify a figure as being data transparent if it visualizes data distributions univariately if it indicates the second moment of statistics for line or bar graphs and if it is a scatter plot or plots extreme observations with their data points. Journal types are defined as follows: Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (REStud); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). All variables are defined in Appendix A.

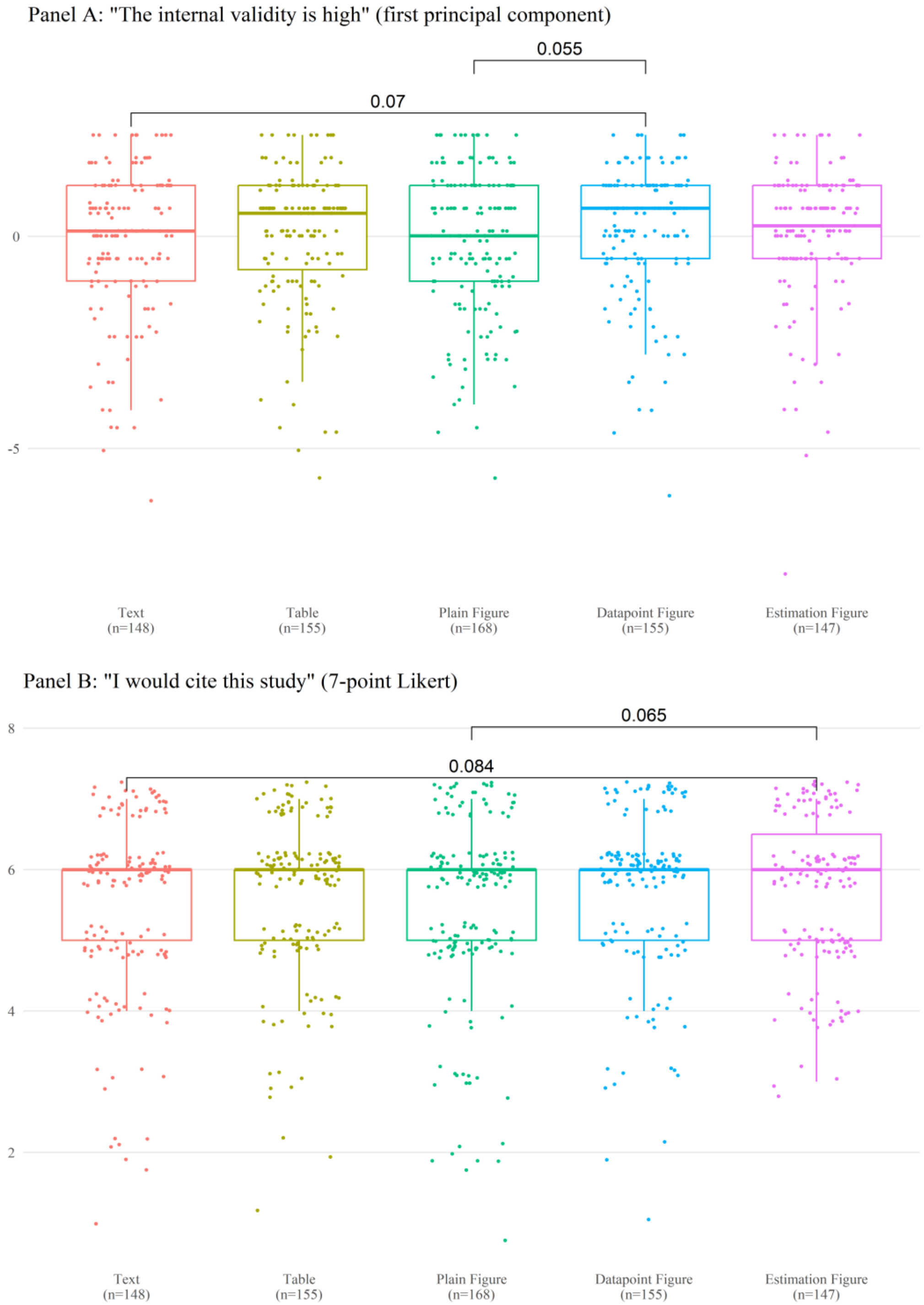
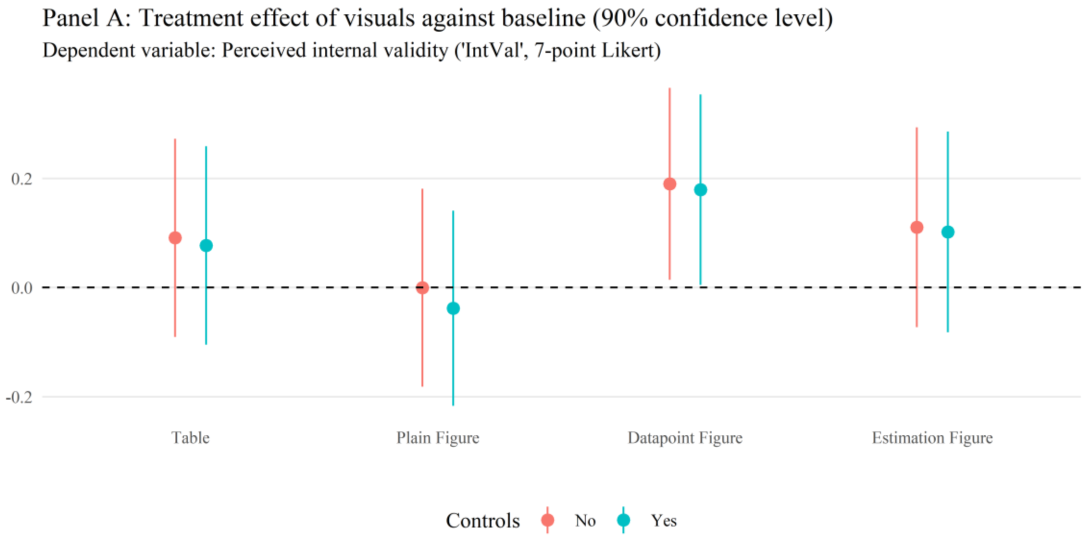


Figure 5: Treatment effect plots

This figure plots the treatment effects of our experiment for the two outcome variables perceived internal validity (IntVal, Panel A) and citability (Citable, Panel B). If the treatment effect is significant group differences are indicated by rectangular brackets showing the p-value of the two-sided t-test. We grouped participants into five groups: baseline participants who saw the findings of a fictive experimental study as text only (Text), those who saw it as a table (Table), as a plain box plot (Plain Figure), as a box plot showing the underlying data distribution (Datapoint Figure) or as a box plot showing the data distribution and in addition the distribution of the underlying test statistic (Estimation Figure). All variables are defined in Appendix A.



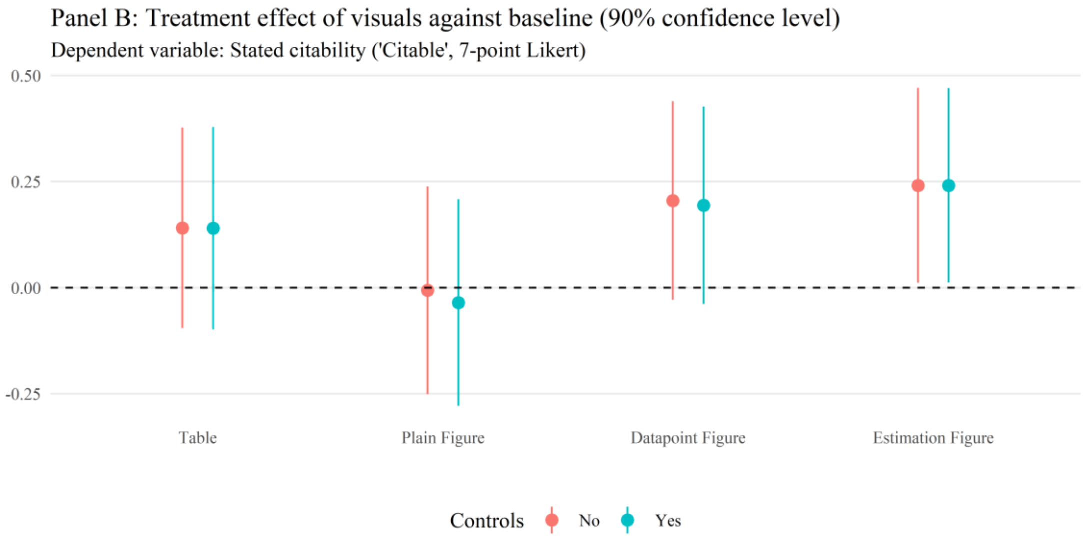


Figure 6: Treatment effects of visuals against baseline

This figure plots the treatment effects of our experiment for the two outcome variables perceived internal validity (IntVal, Panel A) and citability (Citable, Panel B). We test each visual (Table, Plain Figure, Datapoint Figure and Estimation Figure) separately against our baseline case (Text). Vertical bars indicate confidence intervals (90% confidence level). The horizontal dashed line indicates zero. We show estimates with and without control variables as indicated in the legend. We grouped participants of the experiment into five groups: baseline participants who saw the findings of a fictive experimental study as text only (Text), those who saw it as a table (Table), as a plain box plot (Plain Figure), as a box plot showing the underlying data distribution (Datapoint Figure) or as a box plot showing the data distribution and in addition the distribution of the underlying test statistic (Estimation Figure). All variables are defined in Appendix A.

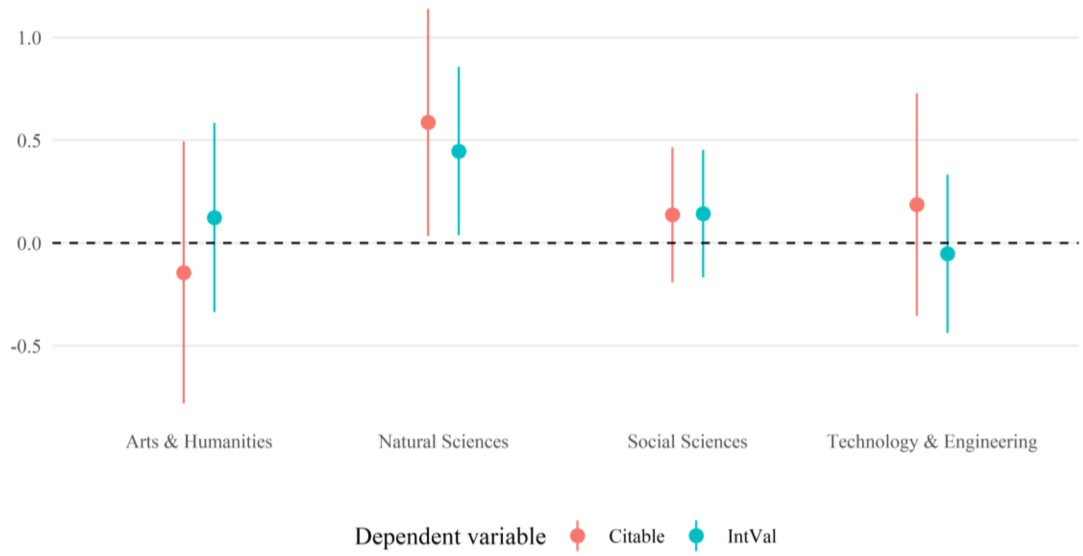


Figure 7: Treatment effect of data-transparent figures by participant research field

This figure plots the treatment effect of data-transparent figures (Datapoint Figure, Estimation Figure) relative to the baseline case (Text) by research field. The two outcome variables are perceived internal validity (IntVal) and citability (Citable). We grouped participants by their stated primary research field (Arts & Humanities, Natural Sciences, Social Sciences and Technology & Engineering). Vertical bars indicate confidence intervals (95% confidence level). The horizontal dashed line indicates zero. In the experiment, we grouped participants into five groups: baseline participants who saw the findings of a fictive experimental study as text only (Text), those who saw it as a table (Table), as a plain box plot (Plain Figure), as a box plot showing the underlying data distribution (Datapoint Figure) or as a box plot showing the data distribution and in addition the distribution of the underlying test statistic (Estimation Figure). All variables are defined in Appendix A.

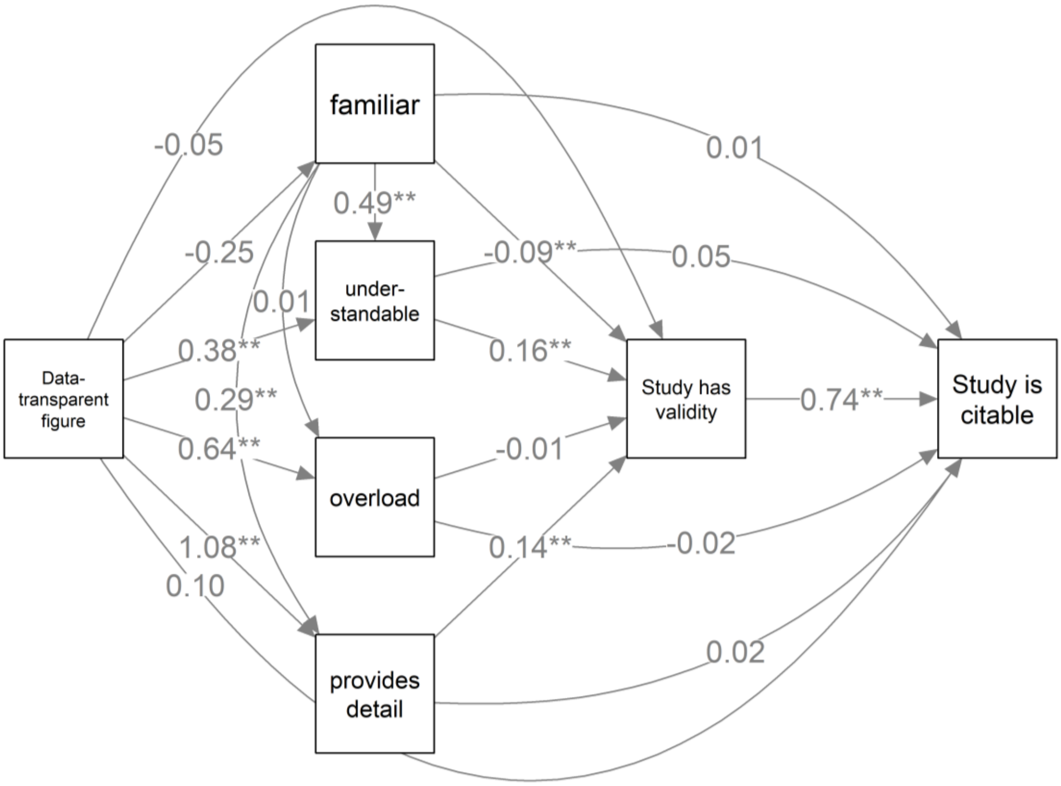


Figure 8: Path analysis for experiment

This figure plots the results of a path analysis for our experiment comparing treatment with a data-transparent figure against plain figure treatment. The first layer is an indicator variable equal to one if participants were treated with a data-transparent figure, zero it were a plain figure ("Data-transparent figure"). The second layer comprises dimensions for which participants had to evaluate treatment visuals (Familiarity: "familiar", Clarity: "understand-able", Complexity: "overload", or Flexibility: "provides detail"; all items were assessed on a 7-point Likert scale). The third layer represents participants' perceived internal validity ratings ("Study has validity"; 7-point Likert scale). The last layer is participants stated willingness on whether they would cite the fictive experimental study ("Study is citable"; 7-point Likert scale) All variables are defined in Appendix A.

Table 1: Descriptive Statistics for Observational Data

Panel A: Article-level descriptive statistics								
	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
Citations	7,846	83.23	129.37	0	20	44	96	3,567
YCitations	7,846	18.25	26.35	0	5	10	22	892
Has figures	7,846	0.85	0.36	0	1	1	1	1
Figures	7,846	4.03	3.53	0	1	3	6	36
Has tables	7,846	0.82	0.38	0	1	1	1	1
Tables	7,846	5.79	4.64	0	2	6	9	38
Words	7,846	14,489.85	4,188.88	2,036	11,710	14,279	16,996	46,076
Authors	7,846	2.38	0.98	1	2	2	3	11
References	7,846	40.82	22.32	0	28	40	53	445
Words in Title	7,846	9.16	3.72	1	6	9	12	27
Equations	7,846	67.55	78.13	0	13	40	95	792

Panel B: Sample across journal and years												
Journal type	Journal	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Sum
	AER	95	119	126	101	137	112	113	114	103	120	1,140
	ECA	58	46	72	59	54	57	49	57	56	52	560
Generalist Econ	JPE	30	30	30	29	30	32	39	44	66	68	398
	QJE	44	45	41	39	40	40	40	40	40	40	409
	RES	49	50	52	52	52	47	51	51	66	76	546
	JDE	73	80	105	108	118	70	81	71	118	89	913
Field Econ	JLE	26	23	24	31	25	37	47	37	36	48	334
	JME	71	42	54	57	72	77	67	50	57	58	605
	JAR	29	34	33	34	36	27	32	32	34	31	322
Field Business	JOF	68	59	59	67	70	69	70	61	64	70	657
	MSC	141	135	139	166	166	172	194	238	312	299	1,962
Sum:		684	663	735	743	800	740	783	795	952	951	7,846

This table reports article-level descriptive statistics for our sample of research articles (Panel A) and the number of observations research articles) across journals and time (Panel B). Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (RESt); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). All variables are defined in the Appendix A.

Table 2: Use of Visuals by Journal Type

Panel A: Statistics of visuals across journal types

		Tables		Figures	
Journal type	N	% (n > 0)	Average n	% (n > 0)	Average n
Generalist Econ	3,053	73.11	5.03 (4.72)	85.42	4.59 (3.89)
Field Econ	1,852	89.20	6.62 (5.04)	87.15	4.06 (3.4)
Field Business	2,941	86.81	6.05 (4.15)	82.59	3.44 (3.11)

Panel B: t-test for mean differences

	Tables		Figures	
Journal type	Generalist Econ	Field Econ	Generalist Econ	Field Econ
Generalist Econ	-	-	-	-
Field Econ	1.585***	-	-0.530***	-
Field Business	1.023***	-0.562***	-1.146***	-0.615***

This table reports in Panel A for each journal type the number of articles, the percentage of articles with the respective visual (% n > 0), and the average number of visuals per article (Average n; standard deviation in brackets). Panel B reports pair-wise for each journal type pair (row minus column), the mean differences with significance level obtained from t-tests. Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (RESt); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 3: Visualization and Citation Impact

Panel A: All journals pooled					
	Dependent variable = log(*YCitations*)				
	(1)	(2)	(3)	(4)	(5)
log(*Figures*)	0.163***	0.097***	0.101***	0.082***	0.083***
	(0.047)	(0.030)	(0.017)	(0.014)	(0.014)
log(*Tables*)	0.223***	0.074	0.098**	0.093**	0.100**
	(0.041)	(0.042)	(0.034)	(0.032)	(0.032)
log(*Words*)		1.032***	0.604***	0.552**	0.503**
		(0.177)	(0.158)	(0.183)	(0.191)
log(*Authors*)		0.418***	0.390***	0.352***	0.352***
		(0.107)	(0.062)	(0.057)	(0.062)
log(*References*)		-0.030	0.164***	0.181**	0.238***
		(0.039)	(0.049)	(0.060)	(0.041)
log(*Words in title*)		-0.194**	-0.083**	-0.081**	-0.086**
		(0.063)	(0.027)	(0.031)	(0.029)
log(*Equations*)		-0.084**	-0.112***	-0.111***	-0.100**
		(0.032)	(0.022)	(0.031)	(0.032)
Num.Obs.	7,846	7,846	7,846	7,846	7,846
R2 Adj.	0.064	0.180	0.307	0.339	0.355
Fixed effects: Journal	No	No	Yes	No	No
Fixed effects: Journal x Year	No	No	No	Yes	No
Fixed effects: Journal x Year x Issue	No	No	No	No	Yes

Panel B: By journal type									
	Generalist Econ			Field Econ			Field Business		
	Dependent variable = log(*YCitations*)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log(*Figures*)	0.220***	0.135***	0.098***	0.160*	0.145**	0.104**	0.028	0.017	0.011
	(0.011)	(0.017)	(0.012)	(0.042)	(0.033)	(0.017)	(0.021)	(0.009)	(0.021)
log(*Tables*)	0.305***	0.094	0.096	0.271**	0.156	0.159	0.216*	0.093	0.043
	(0.038)	(0.061)	(0.065)	(0.049)	(0.083)	(0.059)	(0.062)	(0.077)	(0.024)
log(*Words*)		0.820**	0.775**		0.188	0.257		0.553*	0.192**
		(0.237)	(0.266)		(0.106)	(0.112)		(0.178)	(0.032)
log(*Authors*)		0.410***	0.319***		0.582**	0.537**		0.206	0.251*
		(0.056)	(0.054)		(0.110)	(0.082)		(0.083)	(0.079)
log(*References*)		0.004	0.200**		0.277***	0.256***		0.375***	0.372***
		(0.024)	(0.062)		(0.015)	(0.019)		(0.015)	(0.019)
log(*Words in title*)		-0.062	-0.079*		-0.129**	-0.111		-0.262	-0.101
		(0.039)	(0.035)		(0.028)	(0.039)		(0.152)	(0.058)
log(*Equations*)		-0.168*	-0.147**		-0.108*	-0.141***		-0.046	-0.044
		(0.063)	(0.044)		(0.030)	(0.011)		(0.017)	(0.020)
Num.Obs.	3,053	3,053	3,053	1,852	1,852	1,852	2,941	2,941	2,941
R2 Adj.	0.168	0.267	0.386	0.078	0.162	0.230	0.037	0.125	0.248
Fixed effects: Journal x Year x Issue	No	No	Yes	No	No	Yes	No	No	Yes

This table shows the results for our OLS tests of the association between the use of visuals in research articles and the citations of the articles pooled over all journals (Panel A) and by journal type (Panel B). The outcome variable is the natural logarithm of the number of citations of a research article divided by the years the research article is in our sample (YCitations). We specify the regression models in Panel A as follows: Columns (1) shows the association without controls, column (2) with controls and columns (3), (4) and (5) use fixed effects for journal, journal times year and journal times year times journal issue, respectively. We specify the regression models in Panel B as follows: Columns (1), (2) and (3) shows results for generalist econ journals, column (4), (5) and (6) for field econ journals, and (7), (8) and (9) field business journals. In the specifications we control for determinants of research articles' citations identified by prior studies as indicated: The length of a research article as log word count (Words), the log number of authors (Authors), the log number of references (References), the title length in words (Words in title), and the log number of lines with mathematical equations (Equations). We use interacted fixed effects as indicated in the table and cluster standard errors at the journal level since expect heterogeneity in citations across journals. All variables are defined in Appendix A. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Data Transparency of Visuals by Journal Type

	All	Generalist Econ	Field Econ	Field Business
Classified figures	1,448	696	499	253
Percent of line graphs	68.09	64.37***	68.14	78.26***
- of which line graphs not data-transparent	78.18	79.02	80.56	71.15***
- of which data-transparent line graphs	21.82	20.98	19.44	28.85***
Percent of bar graphs	10.08	10.63	9.42	9.88
- of which bar graphs not data-transparent	95.10	94.40	96.39*	94.47
- of which data-transparent bar graphs	4.90	5.60	3.61*	5.53
Percent of univariate graphs	8.29	5.17***	13.03***	7.51
Percent of scatter plots	14.43	19.25***	9.62***	10.67**
Percent of other figures	8.70	12.21***	6.81*	2.77***
Percent of data-transparent figures	39.85	39.37	38.68	43.48

This table reports the results of our manual classification of data transparency of figures for a by-journal-year stratified random sample of 220 research articles. The table reports for each journal type the number of manually classified figures (we classify each panel of multi-panel figures separately). We classify visuals that use simulated or empirical data into line graphs (classified as data transparent when they show distributional information), bar graphs (classified as data transparent if they show distributional information), univariate (e.g., histogram, densities, always classified as data transparent), and scatter plots (also including plotting of extreme observations, always classified as data transparent). The categories do not add up to 100% since multiple classifications for visualizations types are possible, e.g., line graphs with scatter plots, or bar graphs displaying extreme value scatter plots. Data visuals not falling into these categories are classified as other and are not classified as data transparent. Appendix B describes the classification scheme in more detail. Journal types are defined as follows: Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (RESt); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). Significance stars indicate the result of a two-sided t-test for mean difference of the journal type of a column against the other two type groups. Insignificant, if there are no stars at a value (except for the number of figure). Significance levels are defined as follows: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Data Transparent Visualizations and Citation Impact

	All journals		Generalist Econ		Field Econ		Field Business	
	Dependent variable = log(*YCitations*)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Transp	0.353**		0.577*		0.105		0.220	
	(0.125)		(0.257)		(0.166)		(0.123)	
ShareTransp		-0.333		-0.840		0.090		-0.085
		(0.326)		(0.940)		(0.474)		(0.617)
log(*Figures*)		0.160		0.113		0.089		0.231
		(0.100)		(0.153)		(0.156)		(0.322)
ShareTransp × log(*Figures*)		0.476*		0.850*		0.227		0.194
		(0.228)		(0.390)		(0.340)		(0.648)
Num.Obs.	220	220	100	100	60	60	60	60
R2 Adj.	0.271	0.299	0.080	0.095	-0.014	0.0006	-0.002	-0.002
Controls	No	No	No	No	No	No	No	No
Fixed effects: Journal	Yes	Yes	No	No	No	No	No	No

This table shows the results for our OLS tests of the association between data-transparent visualization and citations of research articles. We test this association using the data from our manual classification of a by journal-year stratified random sample of N = 220 research articles (two research articles per journal-year; eleven articles without figures or tables are dropped). The outcome variable is natural logarithm of the number of citations of a research article divided by the years the article is in our sample (YCitations). We specify the regression models as follows: Columns (1) and (2) test with a binary variable and an interaction of a binary indicator for data transparency and the number of figures whether the incidence and share of data-transparent visuals in a research article is associated with its citations. We control for journal fixed effects to control for journal differences. Columns (3) and (4) then repeat the test of columns (1) and (2) generalist econ journals without journal fixed effects. Columns (5) and (6) do this for field econ journals and columns (7) and (8) for field business journals. We cluster standard errors at the journal level since we expect heterogeneity in citations across journals. Generalist Econ: American Economic Review (AER), Econometrica (ECA), Journal of Political Economy (JPE), Quarterly Journal of Economics (QJE), Review of Economic Studies (RESt); Field Econ: Journal of Development Economics (JDE), Journal of Labor Economics (JLE), Journal of Monetary Economics (JME); Field Business: Journal of Accounting Research (JAR), Journal of Finance (JOF), Management Science (MSci). All variables are defined in Appendix A. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Descriptive Statistics for Experimental Data

Panel A: Experimental outcome variables by treatment

	IntVal				Citable			
Treatment	N	Mean	Median	SD	N	Mean	Median	SD
Text	148	5.55	5.67	0.99	148	5.45	6.00	1.32
Table	155	5.65	6.00	0.92	155	5.59	6.00	1.17
Plain Figure	168	5.55	5.67	0.96	168	5.45	6.00	1.31
Datapoint Figure	155	5.74	6.00	0.86	155	5.66	6.00	1.15
Estimation Figure	147	5.66	5.67	0.91	147	5.69	6.00	1.06

Panel B: Participants' assessments of visuals by treatment

		Familiar			Clear			Complex			Flexible		
Treatment	N	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Table	155	5.45	6.00	1.38	5.14	6.00	1.48	4.26	4.00	1.75	5.08	5.00	1.45
Plain Figure	168	4.97	5.00	1.74	5.01	5.00	1.58	3.05	3.00	1.46	3.98	4.00	1.58
Datapoint Figure	155	5.01	6.00	1.72	5.62	6.00	1.21	3.48	3.00	1.47	4.94	5.00	1.46
Estimation Figure	147	4.41	5.00	1.85	4.89	5.00	1.61	3.90	4.00	1.60	5.03	5.00	1.44

Panel C: Control variables

	N	Mean	Std. dev.	Min.	25 %	Median	75 %	Max.
HoldsPhD	777	0.13	0.34	0	0	0	0	1
ActiveRes	777	0.34	0.47	0	0	0	1	1
NatSciences	777	0.24	0.42	0	0	0	0	1
VisLearn	777	5.14	1.53	1	4	5	6	7
StatComp	777	4.94	1.52	1	4	5	6	7

This table shows the descriptive statistics for the variables of our experiment. Panel A shows descriptive statistics for our outcome variable, perceived internal validity (IntVal) and citability (Citable). Panel B shows descriptive statistics for our dimensions by which participants evaluate our treatment visuals by treatment group. These dimensions include familiarity (Familiar), clarity (Clear), complexity (Complex) and flexibility (Flexible). We treat participants with one of four visuals, a table (Table), a simple box plot (Simple), a box plot visualizing the data distribution (Rich), and a box plot visualizing the data distribution and the distribution of the test statistic (Estimation). Panel C provides descriptive statistics for our control variables. All variables are defined in Appendix A.

Table 7: Regression test of data-transparent against plain figures

Hypothesis: A data-transparent visualization increases perceived internal validity relative to a plain figure.						
	IntVal	IntVal	IntVal	Citable	Citable	Citable
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.554***	5.294***	5.034***	5.446***	4.825***	4.507***
	0.070	0.190	0.305	0.091	0.247	0.398
DataTransp	0.152*	0.164*	0.522	0.229**	0.236**	0.705
	0.088	0.087	0.380	0.114	0.113	0.496
HoldsPhD		-0.357***	-0.510**		-0.0009	-0.171
		0.135	0.242		0.175	0.316
ActiveRes		-0.099	-0.168		0.049	0.017
		0.094	0.159		0.122	0.207
NatSciences		-0.117	-0.426**		-0.259*	-0.511**
		0.105	0.176		0.137	0.229
VisLearn		0.022	0.037		0.030	0.087
		0.028	0.047		0.037	0.061
StatComp		0.049*	0.108**		0.103***	0.125*
		0.029	0.051		0.038	0.067
DataTransp × HoldsPhD			0.189			0.201
			0.292			0.381
DataTransp × ActiveRes			0.115			0.064
			0.197			0.257
DataTransp × NatSciences			0.460**			0.366
			0.220			0.287
DataTransp × VisLearn			-0.018			-0.085
			0.059			0.077
DataTransp × StatComp			-0.087			-0.032
			0.063			0.082
Num.Obs.	470	470	470	470	470	470
R2 Adj.	0.004	0.025	0.029	0.006	0.021	0.018
Std.Errors	IID	IID	IID	IID	IID	IID

This table shows the results for our tests of hypothesis H1c, whether data-transparent visuals (DataTransp) increase the perceived internal validity (IntVal) and citability (Citable). We specify the regression models as follows: Columns (1) to (3) test show the test for perceived internal validity (IntVal) with regression specifications without and with control variables as well as with control variables interacted with the main variable of interest (DataTransp). Columns (4) to (6) repeat the tests of the first three columns using our citability measure (Citable). Control variables include a binary indicator equal to one of a participant holds a PhD or doctorate (HoldsPhD), a binary indicator equal to one if the participants states that he or she is an active researcher (ActiveRes), a binary indicator if the participant's research field is natural sciences (NatSciences) as well as two score variables for the participants self-assessment visual learning preferences and statistical competencies (VisLearn, StatComp). All variables are defined in Appendix A. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Internet Appendix

Table IA.1: Regression results of visuals against baseline case

Hypothesis: A visual increases perceived internal validity relative to the baseline case.						
	IntVal	IntVal	IntVal	Citable	Citable	Citable
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.554***	5.423***	5.656***	5.453***	5.008***	5.102***
	0.077	0.160	0.328	0.099	0.208	0.423
Visual	0.096	0.071	-0.235	0.141	0.130	-0.016
	0.085	0.085	0.368	0.111	0.110	0.475
HoldsPhD		-0.283***	-0.092		0.034	0.170
		0.104	0.212		0.135	0.275
ActiveRes		-0.048	-0.112		0.113	0.136
		0.075	0.174		0.098	0.228
NatSciences		-0.185**	-0.471**		-0.268**	-0.727***
		0.083	0.192		0.107	0.250
VisLearn		-0.0002	-0.075		0.013	-0.025
		0.022	0.048		0.029	0.063
StatComp		0.050**	0.091*		0.083***	0.119*
		0.024	0.053		0.031	0.068
Visual × HoldsPhD			-0.254			-0.184
			0.243			0.316
Visual × ActiveRes			0.071			-0.030
			0.193			0.252
Visual × NatSciences			0.357*			0.570**
			0.213			0.277
Visual × VisLearn			0.095*			0.050
			0.054			0.071
Visual × StatComp			-0.050			-0.042
			0.059			0.076
Num.Obs.	773	773	773	773	773	773
R2 Adj.	0.0003	0.018	0.021	0.0008	0.014	0.014
Std.Errors	IID	IID	IID	IID	IID	IID

Table IA.2: Regression results of figures against table

Hypothesis: Relative to a table, a figure increases perceived internal validity.

	IntVal	IntVal	IntVal	Citable	Citable	Citable
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.645***	5.413***	5.529***	5.594***	5.082***	5.474***
	0.074	0.176	0.365	0.095	0.228	0.472
Figure	0.006	0.010	-0.131	0.00007	0.006	-0.498
	0.085	0.084	0.408	0.110	0.109	0.528
HoldsPhD		-0.346***	-0.368		-0.014	-0.146
		0.118	0.244		0.153	0.316
ActiveRes		-0.041	0.164		0.106	0.347
		0.082	0.169		0.107	0.218
NatSciences		-0.114	-0.099		-0.158	0.104
		0.090	0.175		0.117	0.226
VisLearn		0.021	0.013		0.025	0.005
		0.024	0.049		0.032	0.063
StatComp		0.041	0.013		0.077**	-0.006
		0.026	0.056		0.034	0.073
Figure × HoldsPhD			0.027			0.167
			0.280			0.361
Figure × ActiveRes			-0.270			-0.307
			0.193			0.250
Figure × NatSciences			-0.018			-0.363
			0.205			0.265
Figure × VisLearn			0.011			0.026
			0.057			0.073
Figure × StatComp			0.035			0.108
			0.064			0.082
Num.Obs.	625	625	625	625	625	625
R2 Adj.	-0.002	0.016	0.011	-0.002	0.006	0.005
Std.Errors	IID	IID	IID	IID	IID	IID

Table IA.3: Regression results of estimation figure against datapoint figure

Hypothesis: Adding estimation graph features increases perceived internal validity.						
	IntVal	IntVal	IntVal	Citable	Citable	Citable
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	5.744***	5.606***	5.822***	5.658***	5.185***	5.162***
	0.071	0.233	0.312	0.089	0.290	0.387
EstFigure	-0.080	-0.075	-0.502	0.036	0.040	0.094
	0.102	0.103	0.449	0.127	0.128	0.558
HoldsPhD		-0.326**	-0.526**		0.032	-0.172
		0.161	0.217		0.200	0.270
ActiveRes		-0.046	-0.112		0.078	-0.139
		0.115	0.162		0.143	0.202
NatSciences		0.032	-0.078		-0.145	-0.267
		0.130	0.181		0.162	0.225
VisLearn		0.017	-0.007		0.003	-0.029
		0.035	0.049		0.043	0.061
StatComp		0.020	0.017		0.093**	0.157**
		0.035	0.051		0.044	0.063
EstFigure × HoldsPhD			0.394			0.346
			0.329			0.408
EstFigure × ActiveRes			0.104			0.442
			0.235			0.291
EstFigure × NatSciences			0.243			0.279
			0.261			0.324
EstFigure × VisLearn			0.051			0.064
			0.070			0.087
EstFigure × StatComp			0.004			-0.130
			0.071			0.088
Num.Obs.	302	302	302	302	302	302
R2 Adj.	-0.001	0.0003	-0.0007	-0.003	0.0006	0.005
Std.Errors	IID	IID	IID	IID	IID	IID