Certum Quod Factum: How Formal Models Contribute to the Theoretical and Empirical Robustness of Organization Theory*

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October 23, 2019

Forthcoming in the *Journal of Management*

*The author thanks the organizers and participants of the 2018 NSF/University of Florida workshop on promoting robust and reliable research practice in the science of organizations and the 2014 AoM PDW on current research in organization design. The author also thanks Gwen Lee and Dan Levinthal for their encouragement as well as Don Bergh and three anonymous reviewers for their insightful comments.

Abstract

The aim of this commentary is to show how the use of formal models—both closed-form and computational—can improve theory development and theory testing in organization theory. I also provide practical suggestions (aimed at PhD students and researchers considering to develop a formal model) for dealing with challenges in developing and writing a formal modeling paper. By uncovering how formal models contribute to organization theory and presenting the constraints that formal modeling papers are subject to, this commentary can also help consumers of modeling papers to extract more value from this research method.

Keywords: formal models, closed-form models, computational models, research methods

This commentary first presents benefits—for theory development and theory testing—of using formal models. It then discusses challenges that a modeler needs to deal with when developing and writing a formal model. Doing so helps provide a fuller picture of the trade-offs that modelers face and, hence, provides a more realistic understanding of the opportunities and limitations of formal models as a research method in organization theory.

1 How formal models improve theory development

To understand the benefits of using formal models, it is helpful to start by defining them. A formal model is a precise description of the relationships among a set of variables, specified using mathematical relationships such as equations and if–then statements (Harrison, Lin, Carroll, & Carley, 2007, p. 1232). Formal models provide an abstraction of a phenomenon under study in a way that allows for thinking about the phenomenon using symbolic reasoning and computation (National Research Council, 2013, p. 62).

There are multiple reasons for using formal models to develop organization theory. First, organizational theories involve many actors and levels of analysis, which makes it hard to predict interactions and aggregation effects, identify boundary conditions, and engage in counterfactual thinking. Formal models are helpful in this regard, as they relieve the mind from having to derive such non-obvious implications; instead, they are mathematically or computationally derived from a model. For example, Csaszar & Eggers (2013) compare different ways of aggregating opinions of individuals who differ in their expertise about a topic (e.g., how the partners of a venture capital firm should decide about an investment: should they vote, average their predictions, or delegate the decision to the partner who knows the most about the deal?). Without a model, it would be extremely difficult, if not impossible, to elucidate the conditions under which the different ways of aggregating opinions are preferable (that paper shows, for instance, that averaging opinions is only useful when individuals have similar expertise and that the performance of voting is quite robust regardless of individuals' expertises). In other words, formal models are useful as a way to ensure that the implications of a set of assumptions are logically derived; this is particularly useful when many steps are necessary to derive these implications. In contrast, verbal theorizing is more likely to introduce logical errors and less likely to exhaustively explore the implications of a theory.

A second reason for using formal models is that organizations can be very difficult to observe and to experiment with. In this regard, models can help to study phenomena for which there is no ideal data. Underlying such use is the idea that models are an external representation—a tool—that to some extent can substitute for the underlying phenomenon being investigated. For example, as empirical standards increased during the 1980s and 1990s, empirical research on organizational structure stalled. Nevertheless, research on organizational structure was able to move forward during the 2000s by studying formal models of organizations (see, e.g., Rivkin & Siggelkow, 2003; Siggelkow & Rivkin, 2005). Then, as new empirical approaches were introduced in the 2010s, empirical investigation on the subject resumed (see, e.g., Csaszar, 2012; Gaba & Joseph, 2013; Raveendran, Puranam, & Warglien, 2016). In other words, formal models allow progress to be made on questions for which there are not yet ideal data, as long as one can create a model that is representative—at least of some aspects—of the real phenomenon. Such a model can be used to run thought experiments that can move the field forward.

A third reason for using formal models is that they increase theoretical precision. This happens because the interpretation of a formal model does not depend on a subjective system but rather, on following some formal transformation rules (e.g., the rules of logic, mathematics, and computation), which produce the same results regardless of who (or what) does the interpreting. So, for example, writing a theory as a computational model means that the theory is so clear that nothing has been left undefined—that every term and mechanism has a clear definition that even a completely "dumb" computer can understand.[1] Note that both closed-form and simulation models are formal models because their interpretation does not depend on a subjective system (for distinctions between these two types of formal models, see Smith & Conrey (2007) and Harrison (2007)).

An example of increased theoretical precision is the evolution of the term "value," which is central to the strategy literature. Until 1996, this concept was accompanied by much hand-waving. Although there was much said about "creating value," "destroying value," "adding value," and so on, there was no precise definition of "value." Brandenburger & Stuart's (1996) paper offered a formal way to think about value and related concepts. Similarly, Levinthal's (1997) paper allowed for a more precise way of thinking about "organizational adaptation," opening a path to myriad studies that examine how such adaptation is contingent on characteristics of the environment (e.g., its complexity and uncertainty) and the organization (e.g., its decision-making structure). Papers like these have increased the number of things researchers and practitioners can talk clearly about.[2]

The use of formal models improves theoretical precision so much that many equate developing a formal model with achieving a deep understanding. This view is, in fact, the origin of the word "mathematics," whose Greek root (μάθημα) means "that which is learnt" (Liddell & Scott, 1996, p. 1072). That is, ancient Greeks thought that stating a problem mathematically—developing a formal model—was the highest form of learning. Such a view of formal models is captured by one of Richard Feynman's favorite mottos: "what I cannot create, I do not understand" (which he kept written in a corner of his office blackboard until his death; see Figure 1). What he is saying is that because he himself built the model, every aspect of it is transparent to him. Feynman harks back to

[1] Or as Knuth (1974, p. 668) puts it "science is knowledge which we understand so well that we can teach it to a computer."

[2] For example, the ideas in Brandenburger and Stuart (1996) have allowed other researchers to predict the distribution of profits across complex supply chains and ecosystems. Similarly, the ideas in Levinthal (1997) have allowed predicting how the number of interactions in an industry affects outcomes such as firm heterogeneity, ease of adaptation, and competitive intensity. For recent surveys of the contributions stemming from these two seminal papers, see Gans & Ryall (2017) and Baumann, Schmidt, & Stieglitz, (2019), respectively.

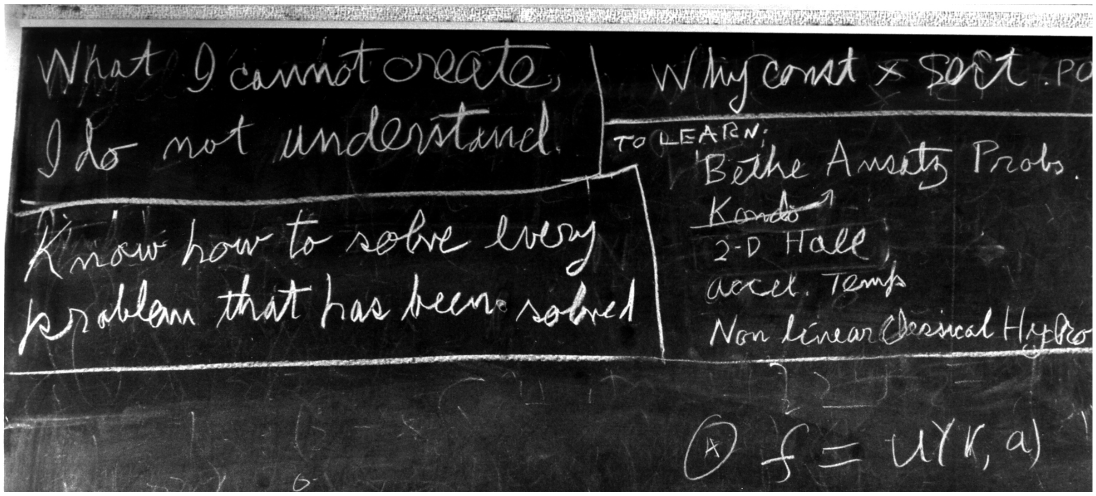

Figure 1: Richard Feynman's blackboard at the time of his death. (Used with permission from the Caltech Archives.)

the enlightenment philosopher Giambattista Vico (1668–1744), who said, "certum quod factum"; that is, "one is only certain of what one builds."[3] This is as good a statement as any to encapsulate why developing formal models is useful.

2 How formal models improve theory testing

Formal models not only help develop theory but also facilitate its testing. This is a direct consequence of formal models' increased theoretical precision: the fact that every part of a formal model is clearly defined simplifies the process of designing empirical tests. For instance, the formal model by Sah & Stiglitz (1986) defines two ways in which groups (a hierarchy and a polyarchy) make decisions and predicts the rate at which these groups make two types of errors (omissions and commissions). In such a model, all terms are defined (e.g., a hierarchy is a group in which all members need to agree before making

[3]It is not clear whether Vico ever used this exact wording. His original wording was "verum esse ipsum factum" (Vico 1710/1988, p. 46). However, the variations "verum ipsum factum" and "certum quod factum" have become more common citations, achieving adage status. A similar issue occurs with adages by Brandeis, da Vinci, and Einstein later mentioned, which are widely attributed to them, although quote investigators (see, e.g., www.quoteinvestigator.com) have not been able to prove that was the exact wording they used.

a decision; an omission error is not approving a good project) and all mechanisms are clear (i.e., the probability of each error occurring is derived from first principles). Such transparency of definitions and mechanisms provides useful guidance when designing empirical tests. For example, Csaszar (2012) directly measures all the constructs in Sah & Stiglitz (1986) in the context of mutual funds and corroborates their predictions. In contrast, verbal theories leave more room for alternative interpretations about how to test a theory.

A second way in which formal models contribute to theory testing is that formal models can point out new dimensions to consider. Because formal models are not constrained by available data, they allow the modeler to theorize about a broader range of ideas than a researcher who is moored to what is currently measurable. An example of this freedom of formal models is the introduction of the concepts of exploration and exploitation to organization theory. March (1991) developed a formal model to theorize about how exploration and exploitation (concepts borrowed from evolutionary theory; Holland, 1975) affect firm performance and depend on employee characteristics. Once March's formal model pointed out ways in which these concepts were relevant to organization theory, scores of empirical researchers devised ways to measure, test, and build on these concepts.

Finally, formal models can contribute to theory testing by providing new testable predictions. For example, models of imitation and competition on rugged landscapes (Rivkin, 2000; Lenox, Rockart, & Lewin, 2006) predicted that firm profits should follow an inverted U-shape, a prediction later corroborated in multiple contexts by Lenox, Rockart, & Lewin (2010) and Lee & Alnahedh (2016).

In sum, formal models can help empirical testing by simplifying the design of tests, pointing to new observable dimensions, and making testable predictions.

Among all the benefits—theoretical and empirical—of using formal models, perhaps the most valuable is that they can accelerate the speed at which organization theory advances. Platt (1964) proposed that the fields that advance more quickly are those that engage in fast cycles of theory development and theory testing (a process he calls "strong inference"). By providing clear definitions, measurable constructs, and transparent mechanisms, formal models contribute to creating and testing theories, thus propelling the virtuous cycle that Platt describes. For good examples on how several branches of science and technology experienced quantum leaps after it became possible to formally model them, see Strogatz (2019).

If models are so valuable, it is natural to ask whether they are always appropriate as a research method. A direct answer to this question stems from McGrath's (1981) classic "dilemmatics" article, which explains that there is no one perfect research method—each method has different advantages and disadvantages. Formal modeling is no exception. A model, for example, is very useful when trying to achieve generality, but a very poor way to precisely measure behavior and establish external validity.[4] Although this commentary advocates for formal models, one should not lose sight that advancing science requires combining and "triangulating" across multiple research methods (Burton & Obel, 2011).

3 Developing a formal model

So far, we have discussed the benefits of using formal models. We now discuss how formal models are developed and written as papers.[5]

3.1 The process of building a model

Figure 2 outlines the typical process by which models are built. The process begins with listening. Modelers get the inspiration for their models from listening to many sources,

[4]See Figure 2 in McGrath (1981) for a nice summary of the trade-offs across research methods. See also Burton & Obel (2011) and Kozlowski et al. (2016) for ways in which modeling can complement other methods as well as Davis, Eisenhardt, & Bingham (2007) and Adner, Pólos, Ryall, & Sorenson (2009) and on the pros and cons of different modeling approaches.

[5]The ideas discussed here are guided by my experience reading, writing, reviewing, and editing modeling papers over the last decade. They are also informed by the conventional wisdom among modelers, much of which is encapsulated in pithy phrases that I quote below.

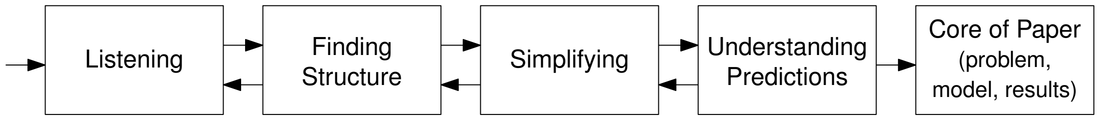

Figure 2: Typical process by which models are built.

ranging from their intuition to managers' problems to gaps in the literature. What the modeler listens *for* is an interesting problem—something that matters but is not well understood. In this step, the background of the modeler is important. The more theory and practice the modeler knows, the more the modeler can listen for.

Next, the modeler tries to find a structure for the problem. What are the core mechanisms behind it? Here, too, the modeler's background is important. The more tools he or she has—such as knowledge of different branches of mathematics, statistics, and computer science—the more phenomena the modeler will be able to model. As Feynman put it on that same blackboard, "know how to solve every problem that has been solved" (see Figure 1).

At this point, the modeler tries to capture the essence of the problem by simplifying the model as much as possible. This is likely to require circling back to the earlier steps, listening further and changing the structure of the problem. When successful, this simplification process leads to an elegant characterization of the problem. As Leonardo da Vinci said, "simplicity is the ultimate sophistication."

The next step is to analyze the model's predictions. This requires understanding how the model behaves over all its parameter space. Sometimes, why the model behaves as it does is hard to understand. When this happens, the modeler needs to inspect the model deeper (e.g., scrutinize each component separately) to fully understand what drives the model's behavior.

At the end of this model-building process, the modeler has (a) a clear problem, (b) a model, and (c) the model's results. This is the core of a modeling paper.

3.2 Is my model good enough?

Three main elements account for the quality of a model. The quality of a model depends on its simplicity, relevance, and surprise.

Simplicity. Models should avoid unnecessary complexity (or as often ascribed to Einstein: "everything should be made as simple as possible, but not simpler"). So, for example, if a model can make its point using $N = 2$ alternatives, it should not include more alternatives (of course, this does not apply if a larger N is part of the essence of the problem; for more discussion on these ideas see Burton & Obel (1995) and the special issue on model complexity introduced by Coen (2009)). Striving for parsimony is paramount because it leads to models that are more understandable (which is the main goal of modeling) and, arguably, it also leads to models that are more likely to be true (as postulated by research on the validity of Occam's Razor; MacKay, 2003, pp. 343–54; cf. Domingos, 1999).

As the number of built-in processes and parameters in a model increases, the model becomes less insightful. At the extreme, given enough complexity, a model can fit any arbitrary situation; that is, it can explain everything but predict nothing. John von Neumann expressed this idea colorfully: "with four parameters I can fit an elephant, and with five I can make him wiggle his trunk."

There are also practical advantages to parsimony. The simpler the model, the more likely it can be conveyed in a paper of publishable length. For instance, if a model has 10 parameters and each can take 10 levels, this implies 10^{10} combinations—a parameter space so large that is impossible to meaningfully cover in a paper. Another practical advantage is that a simpler model leaves fewer "open flanks" for reviewers to attack.

Relevance. Relevance has to do with the number of conversations that are affected by the model. This means that the paper contributes to academic and/or practitioner conversations (or creates new ones). Hence, relevance captures the extent to which the model changes (ideally for the better) how researchers and managers think and act.

Mathematician Richard Hamming (1986) suggests this heuristic for picking research topics: "Ask yourself three questions: 1. What are the most important problems in my field? 2. Am I working on one of them? 3. Why not?" This approach is particularly germane to the field of organizations, where there are so many important unsolved problems.

Surprise. There is little value in a model that only predicts what we already know. The model may be correct, but it does not advance the field. Bertrand Russell (1918, p. 53), speaking of his field of inquiry, said, "the point of philosophy is to start with something so simple as not to seem worth stating, and to end with something so paradoxical that no one will believe it." Russell's quote applies to modeling because, like philosophy, modeling relies on deductive reasoning; that is, on deriving logical implications from initial assumptions. And, almost by definition, the only interesting implications are those that are surprising (see Davis (1971) for an engaging elaboration of the ways in which a paper can be interesting).

3.3 Should a model be closed-form or simulation?

This is not a decision the modeler needs to make in advance. In fact, it is not a decision the modeler should make at all (at least in an ideal world where the modeler is proficient with both methods). If a modeler tries to model a particular phenomenon and proceed through the steps mentioned in the context of Figure 2, then at some point the question will answer itself. Some problems will turn out to have a closed-form and others will not. Related to this issue, Albert Einstein said "God does not care about our mathematical difficulties. He integrates empirically." In other words, the responsibility of the modeler is to recognize the nature of the problem being modeled. That nature will dictate whether the model can be stated as a closed-form or not.

Figure 3: Continuum of model complexity. Model complexity should depend on how much knowledge one has about the model's constituent parts.

3.4 How complex should a model be?

The answer to this question varies from field to field. But to a large extent, the answer to this question depends on how much one knows about the phenomenon motivating the model. The more one knows about it, the more justified one is to build a complex model of it. (Which is not to say that complexity is *required.*) Flight simulators, for example, use thousands of parameters—to account for the shape of the wings, the terrain below, the weather, and so on—but such complexity is justified because so much is known about the physics of flight.[6]

In the field of organizations, we do not have nearly such detailed knowledge, so we need to keep our models much simpler (see Figure 3). It is, thus, critical to resist the temptation to add bells and whistles. In fact, adding parameters and mechanisms is costly. The more of them in a model, the smaller the portion of the model's behavior that can be described in the paper, leaving readers with many doubts and little understanding.

In practice, when it comes to formal models in organization theory, von Neumann's suggestion that five parameters are too many is about right most of the time.[7]

The ultimate cost of model complexity is captured by "Bonini's Paradox": as a model

[6]I thank Nicolaj Siggelkow for initially contrasting flight simulators vis-à-vis models of organizations.

[7]Although in the context of statistical models there is growing acknowledgment of the benefits of simplicity (usually couched in terms of not overfitting the data; see, e.g., Burnham & Anderson (2002) and Hastie, Tibshirani, & Friedman (2009)), what accounts for a "simple" statistical model is typically orders of magnitude more complex than what accounts for a simple formal model (think about all the interactions, controls, individuals fixed-effects, and nuisance parameters that are customarily estimated in a standard econometric analysis). This is because most parameters in statistical models serve to de-noise the data (improving the accuracy of the main effects), something which is irrelevant in the context of formal models. In sum, formal models face a more stringent trade-off than statistical models vis-à-vis adding parameters.

becomes more realistic, it becomes as hard to understand as the real-world phenomenon it represents (Starbuck, 1976, p. 1101). This is also why one should avoid analyzing a formal model by running regressions; doing so usually implies that the model is so complex that one could not directly observe the mechanisms producing the results. Regressions are common tools to develop variance theories but not process theories (Mohr, 1982, chap. 2).

4 Writing a formal modeling paper

4.1 The audiences for a modeling paper

The previous section described some of the main challenges in coming up with a model, now I discuss the main challenges modelers face when writing a modeling paper and during the review process.

A modeling paper has two very different audiences: a technical audience and a general audience. Both must be kept in mind while writing the paper. If a modeling paper only addresses the technical audience, it will have a small audience; if it only addresses the general audience, its findings will not be credible. In both cases, it will be unlikely to pass the review process. The main challenge of writing a modeling paper is to simultaneously satisfy these two audiences.

Some distinctive concerns of the technical audience are the following:

- *Reproducibility.* Is it possible for a technical reader to reproduce the paper's results?
- *Precision.* Are all the definitions, processes, derivations, and analyses clear? Technical readers abhor hand-waving.
- *Modeling insight.* The technical audience will "give extra credit" to papers that provide new tools that others can use to study different phenomena.

The general audience has different concerns:

- *Relevance.* Is the paper about something that real-world organizations care about? Does it affect their performance and other relevant outcomes?

- *Behavioral plausibility.* Are the assumptions of the model realistic?

- *Extending theory.* Does the model build on the state-of-the-art understanding of the problem or phenomenon, so that it moves the state of the art forward?

- *Readability.* Can the general reader understand the paper easily? Oftentimes this is not the case, as modelers are prone to suffer from the "curse of knowledge," which hampers their ability to predict how the general audience will interpret their work.

How can the writer of a modeling paper serve these two audiences? A practical way of doing so is to serve the general audience first. This implies putting the phenomenon and the theory front and center as well as making the motivation clear: why is this phenomenon worth the attention of the general audience? The paper must be readable without understanding all the equations, as most of the general audience will not understand them. As Richard Hamming (Hamming, 1962, p. v) explained, "the purpose of computing is insight, not numbers." The resulting insight from a model should be easy to grasp, even if some details of the model are not.

Still, a modeling paper needs to satisfy the technical audience, who demands reproducibility and precision. Thus, most modeling papers will include equations and technical material. However, to avoid bogging down the general reader, it is usually a good idea to include most of these in appendices.

Here are some of the valuable contributions a modeling paper can make to both of its audiences:

- *Shed light on a significant problem.* For example, a model can help solve a current debate by pointing out the circumstances in which apparently conflicting theories apply. Models can also offer a more general way of thinking; for example, by showing how different phenomena are, in fact, different expressions of one mechanism.

- *Present unanticipated predictions.* Models can point out unexpected implications of current theories. As mentioned before, the modeler puts forth well-established assumptions and then lets the formal model speak for itself. After defining the model, modelers essentially tie their hands. When implications derived in this way turn out to be unexpected, the model has produced novel testable propositions (relating, e.g., to interactions, aggregation effects, boundary conditions, and the role of random variation; see Denrell, Fang, & Liu 2015 for details on this last item).

- *Show how to think more formally about an important but previously vague concept.* As mentioned above in the context of the concepts of value (Brandenburger & Stuart, 1996) and organizational adaptation (Levinthal, 1997), much can be gained by increasing theoretical precision. There are many other important concepts in strategy and organizations awaiting models that will grant them such clarity.

4.2 How to motivate a modeling paper

Motivating a modeling paper is paramount. Why should the reader make the significant cognitive effort to decipher a modeling paper if it does not promise any relevant contribution?

A modeling paper needs both "macro" and "micro" motivations. At the macro level, the paper needs to make evident what is the theoretical gap it proposes to fill and/or the empirical puzzle it proposes to solve. At the micro level, the paper needs to always motivate each new construct it proposes and each analysis it conducts. Providing examples, whether real-world or stylized, serves as a good motivation when introducing concepts. A natural way of motivating the results is to present results in ways that are meaningful to the readers. In this context, the equivalent of the advice for fiction writers "show, don't tell" becomes "elaborate, don't just mention." For example, when discussing a figure, do not just say "Y increases with X," but elaborate it: express it in plain English, explain the mechanisms that produce this behavior, and illustrate what it means for theory and practice.

4.3 How to structure a modeling paper

Most papers are well-served by the typical five-part structure: (1) Introduction, (2) Theoretical motivation, (3) Model, (4) Results, (5) Discussion.

Keep in mind that modeling papers do not have the "Hypotheses" section typical of empirical papers. This is because a modeling paper does not generate empirical data and, hence, cannot test a theory, just propose one (testing hypotheses with a model would be akin to testing hypotheses with a verbal theory; Knudsen, Levinthal, & Puranam, 2019). The model may have implications suggesting some new hypotheses or propositions, but these properly belong in the "Discussion" section.

4.4 Writing clearly

Clarity is crucial in modeling papers, even more so than for empirical papers. This is so because reading a modeling paper is usually harder than reading an empirical one. Modeling papers force the reader to attend to two languages: the natural language in which the theory is explained and the formal language in which the model is described.[8]

The key to reducing that cognitive load to a manageable level is to write very clearly. Time spent writing and rewriting a modeling paper will be time well spent. As Louis Brandeis said, "there is no great writing, only great rewriting." This is certainly true of

[8]Although not all general readers will be able to understand the math, most will at least try to make sense of it, which increases their cognitive load. In addition, trying to understand the argument without the supporting math may be more difficult than it otherwise would be. The technical reader, of course, will get a more nuanced understanding of the paper by going through the math, but that still increases the cognitive load. So a modeling paper is more work for everybody.

modeling papers. In my experience as reviewer and editor, some 60% of modeling papers submitted to journals provoked some variety of the reviewer response: "I don't understand what you are doing." The thinking may have been valid, but the writing was murky.

Clear writing can be effectively complemented with graphic material (e.g., diagrams, plots, and tables) that presents the content in an easy-to-understand format. Much thought should be put on how to best design these materials, which benefit both the general and technical audiences. Because there is plenty of good advice on how to write well (see, e.g., Strunk & White, 1999; Williams & Bizup, 2014; McCloskey, 2000) and how to create effective visuals (see, e.g., Tufte, 1983; Cleveland, 1993; Frankel & DePace, 2012), I will not say more about these topics here.

4.5 Keeping the model reproducible

As mentioned above, reproducibility matters. Reproducibility is not just a concern for the technical audience but an important tenet of science (recently highlighted by strong calls for increased transparency and reproducibility; see, e.g., Christensen & Miguel (2018) and references therein). Because modeling papers do not depend on data and usually present simple models, these papers should be the easiest to reproduce. Regrettably, this is not always the case. Two ways in which modelers can increase the reproducibility of their work follow.

- *Providing enough detail.* The paper should provide enough detail so that a technical reader can reproduce the findings. To ensure this, it is a good idea to ask a colleague to try to reproduce the results with only the paper as a guide.

- *Keeping the files and code neat.* If the model involves code, the code should be clear and fully commented. A modeler should always write and comment code so that *someone else* can understand it, keeping in mind that the someone else might well be the modeler some years down the road. Finally, modelers should never neglect to make backups.

5 Conclusion

Creating a modeling paper is challenging. A model needs: (i) to make a clear contribution, (ii) to be expressed clearly, (iii) to have a clear and strong motivation, (iv) to be simple, and (v) to be reproducible. Note that the common element in all these requirements is *clarity*. That is the purpose of a model in the first place—to clarify some area of research. If a model meets all these challenges, it will have expanded the realm of things that can be discussed and reasoned about. That is a very fine contribution indeed.

Building a model is hard work.[9] It requires exploring many theories and tools. It is an iterative process: the modeler needs to be willing to keep changing the model until getting to the core of the problem. The mathematician and physicist David Wolpert put it very aptly: "To purchase insight you must pay beforehand, in confusion."

But building models is very rewarding. It is a creative act—modelers create tools that will go on to live outside themselves. It also involves continually learning about problems and tools. At its highest level of expression, modeling embodies transcendental research values—the pursuit of "truth, beauty, and justice" that Lave & March (1975, ch. 3) revered. Finally, creating formal models can strengthen the organizations literature theoretical and empirical foundations; and this is important, because, as the mathematician Leonard Savage (1954, p. 1) put it, "no science can be more secure than its foundations."

[9]In their classic introduction to models in the social sciences, Lave and March (1975, p. 2) playfully lament that "God has chosen to give the easy problems to the physicists."

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