ARTICLE IN PRESS
JBR-08363; No of Pages 8
Journal of Business Research xxx (2015) xxx–xxx
Contents lists available at ScienceDirect
Journal of Business Research

Simple versus complex forecasting: The evidence

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ARTICLE INFO

Article history:
Received 1 October 2014
Received in revised form 1 January 2015
Accepted 1 March 2015
Available online xxxx

Keywords:
Analytics
Big data
Decision-making
Decomposition
Econometrics
Occam's razor

ABSTRACT

This article introduces this JBR Special Issue on simple versus complex methods in forecasting. Simplicity in forecasting requires that (1) method, (2) representation of cumulative knowledge, (3) relationships in models, and (4) relationships among models, forecasts, and decisions are *all* sufficiently uncomplicated as to be easily understood by decision-makers. Our review of studies comparing simple and complex methods – including those in this special issue – found 97 comparisons in 32 papers. None of the papers provide a balance of evidence that complexity improves forecast accuracy. Complexity *increases* forecast error by 27 percent on average in the 25 papers with quantitative comparisons. The finding is consistent with prior research to identify valid forecasting methods: all 22 previously identified evidence-based forecasting procedures are simple. Nevertheless, complexity remains popular among researchers, forecasters, and clients. Some evidence suggests that the popularity of complexity may be due to incentives: (1) researchers are rewarded for publishing in highly ranked journals, which favor complexity; (2) forecasters can use complex methods to provide forecasts that support decision-makers' plans; and (3) forecasters' clients may be reassured by incomprehensibility. Clients who prefer accuracy should accept forecasts *only* from simple evidence-based procedures. They can rate the simplicity of forecasters' procedures using the questionnaire at simple-forecasting.com.

1. Introduction

This article provides an introduction to this Special Issue on simplicity in forecasting. The call for papers was subtitled "Conditions and complexity in forecasting," and the objective was to publish "research to improve forecasting knowledge by comparing the usefulness of simple and complex alternatives under different conditions."

A trend toward complex forecasting has been underway for the past half-century or more. Econometricians who believe that complex statistical procedures yield greater forecast accuracy have led the trend (see, e.g., Armstrong, 1978). The trend is at odds with the common belief among scientists that scientists should strive for simplicity. The preference for simplicity in science can be traced back to Aristotle (Charlesworth, 1956), and is commonly identified with the 14th Century formulation, *Occam's razor*. Indeed "since that time, it has been accepted as a methodological rule in many sciences to try to develop simple models" (Jensen, 2001, p. 282). Zellner (2001) concludes social scientists too should strive for simplicity. He was joined in this conclusion by the 21 authors contributing to the book, *Simplicity, Inference and Modelling* (Zellner, Keuzenkamp, & McAleer, 2001).

This article first draws upon prior literature to develop an operational definition of simplicity in forecasting, then uses the definition to identify and analyze comparative studies that could be expected to provide evidence on the conditions under which complexity is useful. The review of studies includes new evidence presented in this Special Issue. Finally, this article examines evidence on why researchers, forecasters, and decision-makers are, despite the theoretical and empirical objections, attracted to complexity.

2. Defining simplicity in operational terms

Simplicity in forecasting seems easy to recognize, yet is difficult to define. The first definition in the *Oxford English Dictionary's* OED Online (2014) is, nevertheless, a useful starting point: "The state or quality of being simple in form, structure, etc.; absence of compositeness, complexity, or intricacy."

For the purpose of making practical distinctions between simple and complex forecasting, this article defines simple forecasting as processes that are understandable to forecast users. Specifically, the forecasting process must be understandable with respect to methods, representation of prior knowledge in models, relationships among the model elements, and relationships among models, forecasts, and decisions.

Complexity in forecasting is the opposite of simplicity. In contrast to some discussions of complexity in forecasting, by our definition

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http://dx.doi.org/10.1016/j.jbusres.2015.03.026
0148-2963/

complexity is *not* a function of the number of variables. Nor is complexity a function of the effort required to develop a model.

To conclude whether or not an instance of forecasting is simple, as defined here, ask forecast users if they understand – and, if so to explain – the forecasting method, how the specific model represents prior knowledge, how any parts the model has are related to each other, and how and why a forecast from the model would help them to make a better decision. A structured questionnaire to derive a measure of the simplicity of the forecasting procedures from forecast users' understanding – the Forecasting Simplicity Questionnaire – is available from simple-forecasting.com.

The test of simplicity provided by the questionnaire has face validity. Recounting his correspondence with Nobel Laureates and other leading economists, Zellner reports James Tobin telling him that he and his Council of Economic Advisors colleagues were skeptical of complex models of the economy because they "could not understand the workings and outputs of such models, and thus did not have much confidence in them" (Zellner, 2001, pp. 243-244).

Zellner (2001, p. 242) observes, "Some years ago, I came upon the phrase used in industry, 'Keep it simple stupid', that is, KISS, and thought about it in relation to scientific model-building. Since some simple models are stupid, I decided to reinterpret KISS to mean 'Keep it sophisticatedly simple.'" With that distinction in mind, this article is concerned primarily with comparisons of complex forecasting with simple forecasting procedures that have been validated by experimental comparisons.

2.1. Simple methods

Simple forecasting methods are relatively few compared to complex methods, which are limited in number only by the imaginations of statisticians. The titles and abstracts of forecasting papers in academic journals attest to the proliferation of complex methods. Not only managers, but also practitioners and many researchers are likely to struggle to comprehend typical forecasting papers.

Incomprehension of forecasting methods, even by the people who pay for them, seems common. For example, as part of a three-person consulting team, the second author of this article interviewed several analysts in a large firm to assess their understanding of a complex model provided at high cost by an outside vendor. The model was designed to forecast the effects of advertising expenditures on the company's market share. The vendor provided courses to explain the method to their clients. Even so, none of the analysts could explain how the model worked (Armstrong & Shapiro, 1974).

2.2. Simple representation of prior knowledge in models

A scientific, or evidence-based, approach to forecasting requires an effort to represent cumulative knowledge (Armstrong, Green & Graefe, in this issue). Before the 1970s, econometricians often based their forecasting models on a priori analyses. They used domain experts' knowledge and what evidence they could glean from prior research to guide their selection of variables, to determine directions and the nature of the relationships, and to estimate the magnitudes of the relationships. While the process is a logical scientific procedure and is simple to explain, much time and effort by experts is often required in order to carry it out.

In contrast to the high cost of a thorough a priori analysis, applying complex statistical methods to large databases is inexpensive. McCloskey and Ziliak (1996) and Ziliak and McCloskey (2004) show that many researchers follow the low-cost approach. Their analyses of *American Economic Review* papers found that 75 percent of the papers in the 1980s that used regression analysis went beyond statistical significance to consider other information when selecting variables for regression models. The figure dropped to 32 percent in the 1990s.

Regression analysis identifies statistical patterns in a particular set of data. If the data are non-experimental, no matter how "big" they are, there is little reason to expect the process to identify causal relationships (Armstrong, 2012; Armstrong et al., in this issue). In practice, a big data set is likely to include variables that are not independent of one another, variables that vary little or not at all, and irrelevant variables, while excluding variables that are important. The need for theory, domain knowledge, experimental data, and careful thinking for specifying and estimating causal models has not changed.

Bayes' method provides another way to incorporate prior knowledge in forecasting models. The method has the disadvantage of being too complex for most people to understand. We have been unable to find evidence that Bayesian approaches yield ex ante forecasts that are more accurate than forecasts from simple evidence-based methods. The first M-Competition (Makridakis et al., 1982) includes tests of Bayesian forecasting for 1 to 18 period ahead forecasts for 997 time series. Forecasts from simple methods, including naïve forecasts on deseasoanlized data, were more accurate than Bayesian forecasts on the basis of mean absolute percentage error (MAPE). Forecasts from the benchmark deseasonalized single exponential smoothing method reduced error by 12.4 percent (from Makridakis et al., 1982, Table 2a). Bayesian forecasts were not included in subsequent M competitions. Graefe, Küchenhoff, Stierle, and Riedl (forthcoming) found that simply averaging forecasts from different methods yields forecasts that reduced error by an average of 5 percent across five studies compared to those from Bayesian approaches to combining economic and political forecasts. Goodwin (in this issue) demonstrates that for many forecasting problems that involve choosing between two alternatives, two simple methods would each lead to the same decision as Bayes' method.

The simplest representations of prior knowledge in forecasting models are no-change models. Forecasts from appropriately formulated no-change models are hard to beat in many forecasting situations, either because prior knowledge is insufficient to improve on no-change or because prior knowledge leads to the conclusion that the situation is stable.

2.3. Simple relationships among the model elements

Decomposition provides a path to simplicity for many forecasting problems. Decomposition in forecasting consists of breaking down or separating a complex problem into simpler elements before forecasting each element. The forecasts of the elements are then combined.

Some researchers suggest that decomposition increases complexity relative to forecasting the aggregate directly – such as the works cited by Brighton & Gigerenzer, in this issue – but that is not the case with the definition proposed in this article.

Decomposition is a key strategy for simplifying problems in management science, and in other scientific fields. Decomposition can be used with any forecasting method. The method is most useful when different elements of the forecasting problem are forecast by different methods, when there is valid and reliable information about each element, the elements are subject to different causal forces, and when they are easier to predict than the whole.

A study on forecasting traffic accidents by García-Ferrer, de Juan, and Poncela (2006) provides evidence on the benefits of disaggregation when these conditions are met. Their approach of disaggregation by estimating separate models for urban and other roads produced forecasts that were more accurate for between 76 and 85 percent of the 63 comparisons, depending on the criterion used.

If there are few data on each element, however, decomposition may not improve forecast accuracy. Huddleston, Porter & Brown (in this issue) examine the trade-off in their tests of different approaches to forecasting highly variable district-level burglary rates.

The relationships among the elements of the decomposed problem should be simple. Decomposition based on additive relationships, an approach that is often referred to as segmentation, is

Please cite this article as: Green, K.C., & Armstrong, J.S., Simple versus complex forecasting: The evidence, *Journal of Business Research* (2015), http://dx.doi.org/10.1016/j.jbusres.2015.03.026