The fractured nature of real estate specialization, where most real estate professionals are focused on a narrow aspect of the business, such as lending, leasing, valuation, management, etc., makes it difficult for anyone to develop a detailed and holistic framework for the dynamic nature of how each function affects the others and to what extent. The fact is that professionals who focus on lending typically know very little about the development process. Architects typically know very little about property and asset management, though the management of a property is potentially affected by the design of that property. I know from my own experience that it often requires years of long days to develop an intuitive understanding of just one aspect of the business, much less how that one aspect fits into the larger real estate ecosystem.

Given the changes to the industry over the last decade or two (amount of data and increased exposure to larger economic/capital markets forces), I believe we must step back and rethink the fundamental framework of the real estate industry. Systems thinking is a great tool for understanding the parts of a process and Teixeira's model of estimating the value to the consumer of each individual step in the process is an excellent combination of methods for deciding where we should begin in attempting to address the complex monster that is the real estate industry.

The better we can identify areas that can be improved, the better able we will be to create value in the short term by identifying new business models and new areas for technology implementation. Real estate incumbents have not yet been displaced or heavily damaged by the technology wave. However, if a lesson can be learned from other industries, it is that incumbent business models are always a target and it probably will not be long until someone finds a way to disrupt your business. You can either wait for that to happen or you can be proactive in reinventing your business before someone reinvents your business for you.

The Theory that Would Not Die: How Bayes' Rule Cracked the Enigma Code, Hunted Down Russian Submarines, and Emerged Triumphant from Two Centuries of Controversy, by Sharon Bertsch McGrayne, 360 pages, September 25, 2019.

Reviewed by: Timothy Savage, New York University

My training as an econometrician, perhaps like many, lay in the canonical texts of Greene (multiple editions), Hamilton (1994), and Campbell et al. (1997). So ubiquitous are these texts that they need no specific reference, as my Bayesian prior places a high probability that at least one of these texts sits on the bookshelves on almost every reader of this review. So valuable are these texts that I invest in clean copies every few years to replace the worn stock. But these canonical texts have little to no discussion of Bayesian methods of estimation and inference. Hamilton, for example, has a small chapter that includes a treatment of Bayesian vector autoregression and some discussion of Markov chain Monte Carlo (MCMC) methods to simulate posterior distributions. The treatment does not include the standard MCMC methods used today, Gibbs sampling, or Metropolis-Hastings. Nor is there a discussion of the need for burn-in or the distinction between Bayesian credible intervals and classical confidence intervals. As Campbell et al. note in their introduction, Hamilton contains ‘‘elementary Bayesian inference.’’

With this backdrop, one might suppose that Bayesian methods have little role to play in the practice of empirical analysis, and particularly not real estate. As Sharon Bertsch McGrayne richly explores in *The Theory that Would Not Die*, however, the Bayesian approach to estimation and inference has survived every intellectual objection, both philosophical and utilitarian, for nearly two centuries. It has also been successfully used in applications when data are sparse, and researchers learn as data arrives over time. Moreover, McGrayne's approach to this important topic, its implementation as well as its intellectual objections, contains such rigor to justify its reading by professional economists. As I listened to the book, the humorous history made me chuckle enough times on crowded New York subways to draw attention from fellow passengers.

Wisely, before she presents the objections, McGrayne explores in detail the intellectual approach developed by the Reverend Thomas Bayes in the mid-18th century. At the time, the Age of Enlightenment and the scientific revolution had swept Europe, driven by a simple standard: the ideas worked when applied and worked much better than assuming divine intervention or the suspension thereof. As an example, consider Isaac Newton's demonstrable success at developing and applying mathematics to real-world observations for the purpose of prediction (or forecasting). Namely: our arrows kill more of the enemy if we actually have a workable model for how they will project. As McGrayne notes early in her book, ‘‘By updating our initial belief about something with objective new information, we get a new and improved belief.’’ In essence, this is a method of learning that can be deployed to make rational decisions in the face of uncertainty, an obviously appealing feature to economists and to an industry where data are sparse.

As McGrayne notes, given the age, Bayes' initial philosophical application was religious. Could one apply probability theory of the day to ‘‘prove’’ the existence of the god described in the Christian Bible? Bayes provided a description about how one might make such a conclusion through the process of updating beliefs based on the evidence one could observe. Given the delays in publication in that age, apparently only marginally worse than today, Bayes formulation would be published posthumously by his colleague, Richard Price. Hewing to the Bayesian notion of updating, Price's non-mathematical treatment needed improvement. It would require the genius of the French mathematician Pierre-Simon, marquis de Laplace, to properly formulate the Law of Inverse Probability. This reformulation allows for a decomposition of learning using data combined with an initial degree of belief, expressed probabilistically.

The now-familiar Bayes-Price-Laplace formula states that the posterior probability distribution over a parameter of interest is proportional to its prior probability distribution, the researcher's degree of belief, times the likelihood function describing the data. On paper, this is a logically-consistent approach to learning and hypothesis testing. But mathematically, closed-form solutions are limited, and only recent advances in computational power have made it tractable for general application.

Currently, the canonical ‘‘Stats 101’’ course introduces Bayes’ rule and Bayesian inference as an application of inverse probability for point estimation, often involving the probability that one has a disease conditional on a positive test result. Given the typical Stats 101 curriculum, the discussion of Bayes is isolated, and the topic is quickly dropped to return to the classical approach of estimation and inference using confidence intervals and the principle of ‘‘repeated samples.’’

McGrayne meticulously documents the scholarship that vehemently opposed the Bayesian approach, in particular that of Ronald Fisher and Jerzy Neyman. Their core opposition lay in the notion that Bayesian methods are subjective. In other words, the core objection to the Bayesian approach is not the law of inverse probability or the MCMC simulation of posteriors (which did not exist in Fisher’s or Neyman’s era). As noted, the prior belief must be expressed as a probability distribution over the support of a value or values that describe a system. The objection essentially boils down to the concept of a researcher expressing a prior belief.

The calm reaction to this objection involves some combination of the following. My beliefs are transparent. My beliefs can be vague (or diffuse). The data dominate my belief in the actual application. As a result, the range of hypotheses that I can examine is dramatically expanded. The Bayesian approach is iterative. A posterior from one analysis can seamlessly become the prior in a different analysis. Finally, in this age of computational enlightenment, it works in practice. To its benefit, computer science as a discipline has chosen to avoid this particularly bitter, and to me, pointless dispute. (And if we use a ‘‘proof of the pudding’’ standard, Ph.D. computer scientists have a larger range of job prospects than either economists or statisticians at the moment.)

One of the values of McGrayne’s book is to document the myriad ways in which Bayesian analysis was used successfully for generations, even if those applying it did not want to call it Bayesian. In the field of history, Bayes was deployed to resolve a dispute over the authorship of certain of the Federalist papers. It was an example of expressing a vague prior and continually updating it with new evidence. In a more profitable endeavor, it was deployed to develop actuarial tables for insurance companies when data were sparse. (For practitioners in real estate, this is an obvious problem.) The scientist Alan Turning deployed it to reduce the state space of combinatorics when he was deployed to break the German Enigma codes during World War II. Scholars have suggested this hastened the collapse of the Third Reich, together with the deaths of millions of Russians. McGrayne compellingly documents many other critical applications, including national polling used by CBS in the 1960s and 1970s. When I teach Bayesian analysis, I deploy it using the capital asset pricing model (CAPM), as the closure to an empirical arc that begins with CAPM, linear regression, and classical hypothesis testing. I show the greater number of hypotheses that can be explored, as well as the near-irrelevance of the prior.

As statisticians Bradley Efron and Trevor Hastie explore in *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science* (2016), one can separate the exploration of an hypothesis from the algorithm used to explore real-world data. As a result, hypothesis testing and algorithm training are conceptually different animals. An algorithm is an application. A hypothesis is a conjecture. One could train a deep learning algorithm to probabilistically predict whether a hand-written character is a zero (based on a training set). There is no explicit hypothesis being examined, other than perhaps the stability of correlation patterns. Hypothesis testing, in contrast, provides a coherent framework to examine conjectures about the world. But it can be done in the absence of either an algorithm or data. In real estate research, we apparently now call this ''thought leadership,'' which seems to be focused on turning the phrase ''anything could happen'' into PowerPoint decks. An example of this is the time I heard a prominent real estate researcher say that he/she could see ''the handle on the U.S. 10-year'' at either 1% or 3% a year from the prediction, a conjecture invalidated by reality.

The physicist Richard Feynman once said that, ''I can live with doubt and uncertainty... I have approximate answers and possible beliefs and different degrees of certainty about different things, and I'm not absolutely sure of anything...'' Arguably, this is not a statement that sees probability as the outcome of history of coin flips. Economics and finance researchers study constrained decision-making under uncertainty. Real estate development and investing, given its vast array of risk, is a case study for living with doubt and uncertainty. For every real estate success, there may be a large corpus of failure, where probability as the outcome of a history provides little guidance. As a result, a Bayesian approach, either philosophical or practical, might be a tonic. Alas, not so. Or at least not yet.