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Contents

A Primer on Structural Estimation in Accounting Research

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ABSTRACT

This primer offers a hands-on accessible guide to writing and estimating structural models. We review commonly-used methodologies, including dynamic programming, maximum likelihood, generalized and simulated method of moments, conditional choice probabilities as well as tools to compute standard errors and common diagnostics and tests of economic hypotheses. Special attention is devoted to the bootstrap as a convenient toolbox to estimate complex economic interactions. The methods are illustrated with recent developments in earnings management, auditing, investment, accounting conservatism, and disclosure theory. Intuition and applications are emphasized over formalism.

[*] A github repository is maintained with all the estimation code used in this work at https://github.com/yingliang888/survey.

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Introduction

Structural estimation refers to a class of empirical models in which the economic assumptions describing decision problems are formally stated and used to mathematically derive the empirical model. The method has the potential to answer questions of causal inference that are difficult to resolve with traditional reduced-form modelling (Bertomeu *et al.*, 2015; Gow *et al.*, 2016). Continuing progress in developing theories more amenable to describe real data and a trend toward more efficient computing, but also the wide body of knowledge established from its use in other areas of the social sciences including economics, finance and marketing, provide opportunities to draw new empirical and theoretical insight from the method.

While this monograph will be primarily focused on developing practical tools, it is nevertheless useful to reflect on the fundamental premises that underlie what the method intends to achieve. As in the natural sciences, structural modelling postulates the existence of stable laws governing economic reality. These laws are expressed mathematically (i.e., a set of equations) as a function of both observable and unobservable factors. However, unlike, for instance, the law of universal gravitation, economic laws are highly complex, potentially involving a large number of unobservable variables. A full apprehension of the underlying law is impossible and even useless, for the same reason a full scale map would be useless (Borges, 1998). Hence, the structural approach formulates stylized (miniature) representations of the underlying laws which – despite their stylized nature – are expected to shed light on a specific, but hopefully important, aspect of economic reality. Assumptions are needed to isolate and characterize the causal impact of a single factor.

As Cartwright (2007) notes, the stylized nature of the theory, understood as a deviation from descriptive realism, is part of the research paradigm. Indeed, the high degree of idealization is essential to the ability of the model to reveal the real world.[1] To begin, the researcher formulates a theory model consisting of a set of assumptions. As Marschak (1974) puts it, a model is "(1) a set of relations describing human behavior and institutions, as well as technological laws, and generally involving non-observable random disturbances and non-observable random errors in measurement, and (2) the joint probability distribution of these random quantities." These assumptions are sufficient to generate a set of empirical predictions which, when the model is identified, are sensitive to the model's parameters. The model's predictions are thus contrasted with their empirical analogues, via statistical analysis, to produce parameter estimates.

For some questions, this approach offers several advantages relative to non-structural approaches. In his Memorial Lectures, Koopmans (1975) argues that "the decision not to use theory of man's economic behavior limits the value to economic science and to the maker of policies, of the results obtained [by empirical methods]." First, the model imposes restrictions on the data that satisfy sound economic principles, requiring the researcher to be explicit about what is assumed or ruled out. These assumptions discipline the analysis enforcing coherence throughout the study, which is hard to implement in the absence of formal theory, as

[1] The problem is the presence of "false assumptions" that provide internal validity but distort our deductions, something that, according to Cartright, pervades economic modelling. She argues that in economics we achieve empirical identification via assumptions that are not widely accepted, such as the principles of utility theory, but *ad hoc* and controversial. Structural models are also an opportunity to address this criticism by making explicit what the assumptions are, and, for suitable datasets, allow for departures guided by empirical evidence, i.e., violations of Bayesian updating, behavioral biases, or preferences other than standard expected utility.

this often leads to a situation where each hypothesis relies on a different set of potentially inconsistent assumptions.

Second, because the model aims to identify economic primitives that are exogenous to the mechanisms of the model, the researcher can answer “what if” questions and evaluate the consequences of such changes to the environment (also known as counter-factuals). The objective is to estimate primitives, defined as parameters that are invariant to changes in other parameters or policies within the scope of a research problem, and serves to guide policy makers interested in understanding the effect of policy changes (e.g., the effect of minimum salary on unemployment).

Third, there is no other approach that can offer a complete empirical description of an economic model: as a scientific exercise, this approach is an effort to quantitatively uncover (an aspect of) laws organizing the data. Since all theoretical implications are spelled out, this approach often allows us to reject theories that are not consistent with the data, even if on the surface they might seem so. Thus, the structural approach satisfies the riskiness criterion that Popper (2014) highlights as the defining feature of a genuine science: a structural model typically offers many experiments that can (and often) lead to the rejection of the underlying theory. This is important: one of the benefits of the structural approach is that, as a researcher, one is never left empty-handed: rejecting a meaningful theory is itself an important discovery that requires creativity and often leads to new and more realistic theories.

The problem of using data to quantify the predictions of economic models is, of course, not new. Stepping outside of social sciences, almost all models in the hard sciences are structural. Models of epidemiology, for example, are based on assumptions about the spread of infectious diseases; in physics, models of particles satisfy primitives about the standard model. Likewise, in macroeconomics, authors have used structural models to pin down the effect of monetary and fiscal policy long before it was realistic or computationally feasible to use statistical methods (Kydland and Prescott, 1982). Rather than just a tool, structural models are a philosophical viewpoint using theory to organize data starting from assumptions about laws of nature.

Having noted these broader objectives, the monograph aims to provide an introductory primer to researchers interested in incorporating structural models into their analysis. The essay is designed for researchers with little or no prior knowledge of structural models, and with the objective to make technical barriers to entry into this literature no greater than in other theoretical or empirical exercises. The emphasis is on adequate use of the methods in applied work. Readers interested in these issues will find many textbook references in text with various developments, formal analyses and proofs. While most examples are drawn from accounting research, many of the methods can be (and have been) applied more generally to other related areas such as finance, marketing, and economics.

A theme developed throughout is that substance is more important than form. By substance, one means bringing into the model economic mechanisms or questions that were, prior, not fully resolved by theory or reduced-form empirical work. Tools can help answer a richer question but are always means to an end. It is rare to find a "better" tool that does not have its own limitation. A larger model, i.e., which includes more economic trade-offs, can be more obscure, require more technical assumptions, be less computationally stable or hard to replicate, and require more data. An asymptotically more accurate estimator may be more sensitive to misspecification and unnecessarily complicated when simpler approaches are sufficiently precise for the question of interest. In summary, a better model is not a more general model, but one that gives a persuasive robust answer to the question after taking account of technical and empirical challenges. To this effect, the objective is to develop a set of methods that can be applied over a variety of contexts, so that one may choose the more transparent tool for the question.

Whited (2021) offers the following common objectives for a structural model, ranked from more challenging to easier in typical applications. The first objective is to estimate the parameters of interest to understand an empirical setting. The second objective is to falsify a theory in order to help find a better theory. The third objective is to run counterfactual "what if" exercises if a particular course of actions were undertaken. To these important functions, we add a fourth broader objective that subsumes all three: to provide scientists with a plausible and internally-consistent representation of economic reality that unifies theory and data.

The first objective is probably the most difficult. Most structural models in social sciences do not aim to offer a descriptively accurate representations of an empirical setting. They are simplifications to reduce a complex set of interactions to important first-order considerations. The interpretation of identified parameters is usually not as primitive laws of nature but in terms of their implications about decision-making. Nevertheless, for classic models of broad general interest, certain fundamental parameters may be economically meaningful even in a simplified model. For example, the bankruptcy cost and cost of external finance in Hennessy and Whited (2007) are parameters fundamental in Modigliani-Miller theorems, learning about managerial ability is fundamental in theories of endogenous turnover (Taylor, 2010), the frictions to unravelling in Bertomeu *et al.* (2020) are foundational in disclosure theory, and the cost of shirking estimated in Gayle and Miller (2005) underlie all agency theory.

The second objective usually takes the form of assessing the fit of a model or comparing a model against another. It is a scientific process to identify areas of disagreement between model and data in order to guide model choice and potential improvements. In asset pricing, the equity premium puzzle of Mehra and Prescott (1985) led to considerable innovation in model building incorporating richer preferences and types of risks. But assessing theory using a structural model is subject to caution because test statistics used for model diagnostics are joint tests of economic assumptions and many ancillary technical assumptions, such as functional forms and unobserved heterogeneity.

The third objective is to offer a quantitative assessment of the economic consequences of a policy decision *that has not yet been made* and, hence, for which data does not exist. A regulator may wish to assess the effect of a change in regulation which, with reduced-form analysis only, would require to conduct randomized trials. Taking aside the potential costs and fairness of such experimentation, for many firm-level questions in accounting, randomized trials are infeasible because all firms are inter-connected and an experiment on one set of firms would affect other firms held as controls. Structural models do not provide the same level of certainty as an *ideal* randomized trial, but they are the only tool available to conduct such policy "what if" policy experiments when experimentation are unavailable. Indeed, random assignments can be less effective at providing useful counter-factuals than a structural model when the random assignment destroys choices made empirically (for example, signalling or information acquisition) and no longer represent the same environment (Hennessy and Chemla, 2022).

The process of writing a structural model is unusual compared to other methods because it involves a back and forth dialogue between theory and data. This process can be daunting and, without organization, may involve restarting a project multiple times and wasting valuable insights because of unclear diagnostics on the parts of the model that work versus those that fail. Hence, some researchers may find it useful to organize a workflow to decompose the analysis into smaller steps and features decision points that require revision to parts of the model or the method used to resolve it.

Step 1: Know the available data. Unlike traditional theory, not all questions will be answerable with a structural model because identification, a problem that we discuss in more detail later on, is a function of the information contained in the data. The structural model will draw connections between observable and unobservable empirical elements so, ideally, the objective is to identify which data elements should be in the model, what the research question is about and, critically, whether the data will be likely sufficient to answer this question.

To know the data, a useful preliminary step is to approach the question as one to be answered in reduced-form. At this preliminary stage, the researcher is using qualitative models but placing structure only on observables and noise terms, not on the original decision problem. To what extent can the question be resolved from features of the data? Are there stylized facts suggesting that the theory is plausible? What theories are thoroughly incompatible with these stylized facts? The objective of this critical first step is to limit the question to structural models suitable to the empirical sample: these problems are usually at the intersection of stylized facts suggesting that the theory is adequate but with open questions unanswered by the reduced-form analysis.

Step 2: Write a preliminary theoretical model, usually (but not always) by simplifying a theoretical bookshelf model from the relevant theoretical literature. This model need not have all the generality of a theoretical model because, unlike formal theory which aims to be used conceptually across applications, its analysis will be facilitated by institutional details in a sample. However, the model should capture the important empirical observables and contain a plausible first-order effect.

This step is often the most misunderstood in structural models. Like any scientific exercise, the modeler aims to offer an improvement over our current understanding but is not considering a realistic or complete description of all forces. Therefore, the model is not an attempt at realism; in fact, orthogonal error terms in the statistical model will serve to capture factors that were omitted from the analysis. The preliminary model serves to organize these thoughts into a set of coherent forces and provides the researcher with a conceptual understanding of how the model organizes the data. As an example of this approach, Bertomeu *et al.* (2020) estimate the static disclosure model in Dye (1985) and Jung and Kwon (1988) before overlaying a full multi-period model with endogenous learning about disclosure frictions.

Step 3: Solve the model either numerically or analytically, and check the main quantitative properties of this model against related features of the data. Usually, the requirement for a model to be amenable for structural is that its variables should not be too stylized and that quantities correspond to those observed. For example, a model with high-level implications about the social value of information and with discrete outcomes may not be well-suited to continuous data in a narrow institutional setting. To know if a model is amenable for structural analysis, a good question to ask is: how many ad-hoc additional assumptions or data interpretations are required to identify the theoretical constructs?

When using full-solution methods, the model should be solvable in reasonable time, robustly over many parameters without manual adjustments. The time required to solve the model may also guide the appropriate estimation method: a model that is quick to solve can always be estimated by minimizing a distance between simulated model features and data features. In a typical estimation, the model will be evaluated over many parameter values, so a robust solving algorithm is often required.

Step 4: Revise the model to capture first-order effects that may not be theoretically interesting, in that they may not bring new intuition, but whose interactions with the research problem may substantively affect the estimation. Naturally, the problem here is not to model all possible realistic forces (hence, the important word "substantively") but to think about components with essential interactions.

Is the problem irreducibly dynamic or can the first-order effects be seen in a static model, possibly using different data subsets? Are there observable firm characteristics endogenous to the forces of the model? Is there unobserved heterogeneity that should be written down in the model? A bigger model is a not a better model, because incorporating more elements also involves making additional assumptions and may require more data. Hence, this step should focus on the elements that are feasible and essential to use the model in an empirical setting.

Step 5: Ensure that the revised model can be solved, or has useable restrictions. There exist two approaches to estimating structural models that we will discuss in greater detail in text: (5a) solve the model completely (full solution methods) and derive either the data likelihood or moments according to the model – in the latter case, if the model restrictions are not in closed-form, these model moments can be obtained by simulating data from the model; (5b) write theoretical restrictions from the model, which usually are constraints on the decision problems individuals solve and implications from optimality conditions.

The full solution method is the conceptually simpler approach given that, if the model can be solved numerically, an estimation procedure can be obtained by computing (numerically) economic features of interest in the model, and find parameters that best match these model predictions to data. Full solution methods combined with selecting adequate features can also achieve more precise estimates, because they use all the optimality implications of the model. They are also theoretically more transparent in principle because the researcher can assess the behavior of the model by simulation; for example, Zakolyukina (2018) estimates a dynamic model of earnings management and, before the estimation, plots manipulation choices predicted by the model as a function of the stock price before manipulation. This preliminary analysis prior to estimation can open the black box of a complex theoretical model. On the other hand, full solution method can be computationally-intensive and, as a result, the implementation of these methods is usually for parsimonious models with few parameters. Recent developments in computing have nevertheless dramatically expanded the scope of problems solvable with full solution methods.

A different approach is to use theoretical restrictions from the model, which may be a subset of the theoretical restrictions. Many endogenous objects in the model, which could be (in principle) solved as a function of model parameters, are observable empirically as individuals or firms making optimal choices. So, rather than solving the model, one can substitute in empirical estimates of endogenous objects and then identify parameters of interest from theoretical restrictions on these objects. The consumption Euler moment condition in asset pricing (Hansen and Singleton, 1982; Rust, 1994), which link current and future consumption, is a classic example of this method. Conditional choice probabilities are another example in which the value function can be written in terms of observables. Gerakos and Syverson (2015) and Cheynel and Zhou (2020a) are recent applications that estimate client preferences for auditors from observed auditor replacements. These methods are usually computationally more accessible and thus can allow for more richness in models.

Step 6: Fit the model, that is, program code that finds parameter values that ensure that the theoretical restrictions from steps (5a) and (5b) are best met by the data. In the context of a full solution method, the usual approach is to simulate data from the model with various parameter values until the dimensions of interest least distinguish data and model; put differently, knowing how to solve a model numerically is in principle sufficient to be able to fit the model. To be checked is whether the fit economically explains the data: is the model consistent with the motivating facts? Note that a parsimonious model may not always pass a statistical test assessing whether the model is a complete explanation of the data, but should nevertheless generate magnitudes consistent with the data on the main constructs of interest.

There are many diagnostics informative about the performance of a model but one should note that rewriting a model until it passes a test implies that the asymptotic test statistics are no longer valid. Textbook asymptotic distributions of test statistics do not hold if the researcher systematically searches for a model to pass a test, and therefore the statistical meaning of a test statistic p-value is lost. Put differently, the researcher should enter a diagnostics step with a plausible model, and, given that all models will feature some degree of hypothesis testing, the diagnostic should be read in terms of a performance score rather than a binary pass-or-fail.

Step 7: And, of course, answer the research question. This can be a measurement of a hidden quantity of interest and, often, a counter-factual analysis: how would quantities relevant to firms and individuals change in response to different parameters or a new policy changing the specification of the game? This usually involves changing one part of the model while keeping all the remaining parameter estimates as given, and solving the model numerically with this change. A counter-factual can be a policy that changes the rules of the game, a change in a parameter, or an application of the estimates to a setting with less data.

To illustrate all of these steps in a single application, consider the model by Beyer *et al.* (2019), which aims to estimate the noise in reported earnings caused by earnings management. The data used is prices and earnings, over a panel of firms (step 1). There are two bookshelf models that speak to a relation between noisy earnings management and price responses (step 2) in Fischer and Verrecchia (2000) and Dye and Sridhar (2004). These models yield an equation in which the earnings response is a function of the fundamental uncertainty and the earnings management driven uncertainty (step 3). However, mapping this model to data is problematic because the model assumes that agents report the value of the firm, while (in practice) firms report periodic earnings. Answering the question requires to be explicit about value as a dynamic sequence of reported earnings.

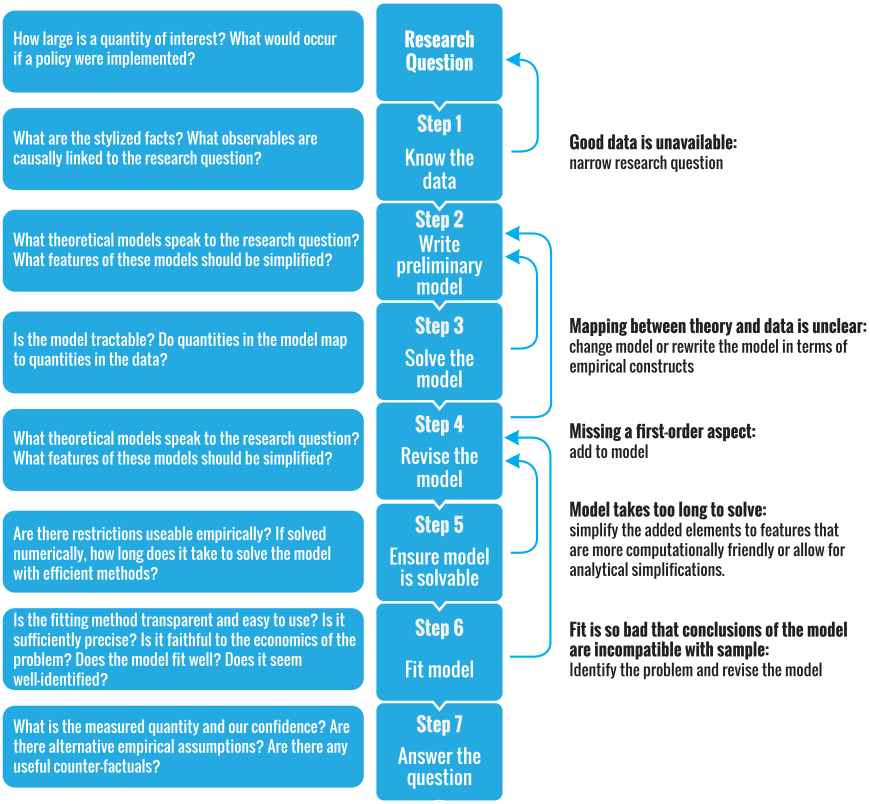

Figure I1: Structural models: A workflow.

Beyer *et al.* (2019) rewrite the model as a repeated sequence of manipulation choices, adapting the static model (step 4). Fortunately, as is common in linear updating models, the same guess-and-verify methods to solve a single-period model can be applied to a dynamic model and therefore, the model implies a relation between prices as well as current earnings and lagged earnings and prices (step 5). This relation can then be estimated to recover the economic primitives (step 6). The last step is to measure the amount of uncertainty due to earnings noise or, equivalently, how much pricing error would be removed in a counter-factual where enforcement against manipulation is perfect, and yields that the noise due to earnings management is about half of the fundamental uncertainty (step 7).

This primer is divided into eight sections, which are inter-connected but can be also read in isolation. Section 1 presents two simple guided examples of structural estimation exercises, in which the logic of the main tools can be absorbed with minimal formalism. Section 2 presents a step-by-step approach to structural estimation, generalizing the methods applied in the two examples. Section 3 discusses more details of the econometric methods for readers interested in applying statistical concepts and widely-used mathematical formulas for estimators and their standard-errors. Section 4 discusses special topics required in estimation approaches using dynamic models, including dynamic programming. Sections 5–7 discuss contemporary advances in the context of principal-agent theory, disclosure theory, and earnings management, respectively. Section 8 concludes.

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