## 1 Introduction

Structural models have traditionally been used to perform welfare analysis of policy changes affecting the choice environment of firms and individuals. Because this environment is explicitly modeled along with preferences, beliefs of decision-makers, and constraints, such models can be used to predict the impact of a counterfactual change of the choice environment holding preferences and beliefs constant. Estimation of structural models discussed in this Element begins by first specifying an economic model where a decision-maker is assumed to derive value (omitting subscripts for the time being) $V(c, \mathbf{x}, \boldsymbol{\theta})$ for all alternatives $c$ in their choice set (whether discrete or continuous). Values typically reflect utility, expected utility, etc…, and depend on variables defining the choice environment $\mathbf{x}$ of that decision-maker, as well as on a vector of structural parameters $\boldsymbol{\theta}$. Structural parameters characterize preferences and beliefs when relevant. A statistical model is derived in a second step from $V(c, \mathbf{x}, \boldsymbol{\theta})$ by introducing randomness in some way (see e.g. Section 3.1). Statistical models provide a mapping between the distribution of choices (or moments of this distribution) and the structural parameters $\boldsymbol{\theta}$.[1]

An attractive feature of structural models is that there is no way to hide what is driving the predictions that are generated – preferences, beliefs, constraints, and the choice environment are normally all clearly laid out. The acceptance of structural modeling as a useful empirical approach for inferences on mechanisms driving behavior varies across fields of economics. Keane (2010) paints a somewhat pessimistic view of the future of structural modeling, arguing a decline in adoption can be explained by several key factors. In particular, the first reason he highlights relates to the amount of labor involved in writing a good paper, possibly discouraging young doctoral students and junior professors seeking tenured positions. The second reason concerns the notion that structural modeling requires imposing strong assumptions (behavioral and statistical) relative to simpler reduced-form approaches. Rust (2010) responds to Keane (2010) by arguing that his pessimism is not entirely warranted. While acknowledging that structural work has declined in some areas (public and labor economics in particular), he highlights fields in economics where structural modeling is either commonly accepted (such as industrial organization)

[1] Other "structural" models in econometrics focus instead on estimating the causal impact of possibly endogenous explanatory variables on a given outcome variable using reduced-form techniques. In these models, researchers do not specify an economic model in a first step. Rather, they directly specify a statistical model to jointly model the outcome variable and the explanatory variables of interest. These "structural" models are labeled so in many econometric textbooks, often when discussing approaches using instrumental variables (see e.g. Greene, 2003).

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or growing and well accepted (judging from publications in top journals), including behavioral economics.

Behavioral economics provides a rich set of explicit models of nonclassical preferences and belief formation which can be estimated using a structural model. At the same time, experimental approaches allow researchers to exogenously vary components of the decision-making environment. The synergy between behavioral and experimental economics provides a natural setting for the estimation of structural models. Importantly, this synergy offers possibilities to reduce the importance of the factors identified by Keane (2010) and which are believed to limit adoption of the approach. In this Element several examples will be provided to highlight the following messages:

1. *Experimental data can be used estimate structural models under weaker assumptions, thereby increasing their credibility.*

Examples will be provided to highlight how computational requirements and thus labor involved in estimating a structural model can be reduced when exploiting experimental data. Intuitively, experiments provide exogenous variation of key variables and thus does not emerge from the behavior of subjects themselves. Such exogenous variation can be exploited to reduce behavioral and distributional assumptions. Absent such data, researchers need to model the possibly endogenous change in key model variables, requiring additional assumptions at various levels. Paarsch and Shearer (1999), for example, estimate a principal agent model using nonexperimental firm-level data. There, incentives are assumed to be endogenously set by the firm on the basis of working conditions and worker outside options. Estimation of the model taking into account this endogeneity involves nonlinear estimation methods. Shearer (2004) estimates the same preference structure for workers using data from a field experiment where incentives are varied exogenously. The model is estimated using simple linear regression methods without assumptions about how the firm sets the level of incentives.

2. *Experimental methods can easily be used to validate structural models.*

In some instances the use of experimental data provides the means to conduct a convincing test of the underlying model structure even without implementing hold-out treatments. Bajari and Hortacsu (2005) validate structural models of bidding behavior in auctions using data from the lab. These models allow to recover the distribution of private valuations of bidders in the auctions analyzed. Distributions of private values are never observed in nonexperimental bidding data. However, these distributions are known to experimenters who use them to assign private values to subjects. Distributions of private values predicted by structural models fitted using experimental data can thus be compared to the experimental distributions used to assign private values to subjects in the experiments. In other instances running new experimental treatments to test implications of an estimated structural model (in the lab and perhaps in the field) is often feasible and almost surely desirable. The benefits of validating a model using data from new experimental treatments in lab or the field provide additional evidence supporting the predictions of a model. Duflo, Hanna, and Ryan (2012), for example, validate a structural model estimated using non-experimental data by comparing the predicted impact of introducing incentives to increase workplace performance with the experimental impact of introducing such incentives in the field.

3. *Many popular models in behavioral economics can be estimated without any programming skills using existing software.*

The scope of this Element is to provide an introductory overview of approaches to estimate and validate structural models using experimental data from either the lab or the field.[2] Examples include estimation of outcome-based preferences (constant elasticity of substitution utility, Fehr and Schmidt [1999], Bolton and Ockenfels [2000]) and belief-dependent preferences (guilt aversion and reciprocity). the paper also discusses estimation of risk and ambiguity preferences. The choice of preferences shape the choice-specific value function $V(c, \mathbf{x}, \boldsymbol{\theta})$ that is specified in the economic model. Special attention will be devoted to measurement of probabilistic beliefs and expectations which are central to models with uncertainty, and how to incorporate these in structural models through the specification of $V(c, \mathbf{x}, \boldsymbol{\theta})$. The Element will also discuss different approaches to capture randomness in behavior, leading to the specification of a statistical model. We will consider adding errors to $V(c, \mathbf{x}, \boldsymbol{\theta})$ (or to a function of $V(c, \mathbf{x}, \boldsymbol{\theta})$). We will also discuss approaches allowing structural parameters $\boldsymbol{\theta}$ to vary with both observable and unobservable characteristics of the decision-maker. Stata codes are provided through the online appendix, a subset of which will be presented and discussed in the main text via text boxes highlighted for this purpose. With the exceptions of models where value functions are not a linear combination of parameters (e.g. risk preferences), most models presented in this Element can be estimated without any programming skills, using basic built-in commands, with minor tweaks. Naturally, other

[2] DellaVigna (2018) discusses related issues regarding structural modeling in behavioral economics. He notably covers structural models of present bias which are not covered in the current paper.

or more general structural models can be estimated but doing so will require additional programming. These models (apart from those involving risk and ambiguity) mostly fall outside of the scope of this Element which aims to encourage adoption of the approach by reducing entry barriers as much as possible.

Despite the benefits experimental methods provide to facilitate structural modeling, not all research questions benefit from estimation of a structural model. Put differently, the research question should in general dictate the empirical approach that is followed.[3] With the same data, some research questions may require nonstructural methods while other questions can only be answered by specifying and estimating a structural model. Bellemare and Shearer (2009), for example, analyze the effect of a windfall gain (a gift) of $80 on planter daily productivity in a tree-planting firm based in British Colombia (Canada). Their research question is simple: did the gift increase worker performance and firms profits? A nonstructural approach is sufficient to answer this question. The authors use linear panel data methods to measure heterogeneity of worker response to the gain and compute value to the firm of the heterogenous responses. They find that workers reciprocate by significantly raising their average productivity, but the value of the productivity increase is not sufficient to compensate the value of the gift by the firm. This is a common finding in field experiments on gift-giving: when a significant response is observed, it does not provide sufficient value to the firm to justify gift-giving (see discussion in Bellemare and Shearer [2009]). Bellemare and Shearer (2011) use the *same* data to answer a different yet related question: what type of gifts and under which labor market conditions is gift-giving expected to be profitable in this firm? A structural approach is required to address this question for two reasons. First, extensive experimentation may be too costly and problematic. This is probably more important in the field where the target population (e.g. workers) may start being aware of the experiment and adjust their behavior for reasons unrelated to the treatment manipulation. Second, in some settings, structural model can vary elements not controllable using experiments such as the outside options of workers who take part in an experiment. The model of Bellemare and Shearer (2011) was used to perform counterfactual predictions of the effects of various monetary gifts under both tight or slack labor market conditions, conditions that cannot be varied experimentally. They find that gift-giving can be profitable under slack market conditions and when gifts are

[3] See Nevo and Whinston (2010), who make a similar argument in the specific area of industrial organization.

presented to workers in the form of piece-rate increases rather than lump-sum windfall gains.

The current Element focuses on behavioral models that have been estimated using data from laboratory and field experiments. Low and Meghir (2017) provide a complementary and less technical overview of the benefits of combining structural econometric modeling and randomized control experiments. They also emphasize and document synergies that emerge through the combination of methods, including enriching structural models as well as using data from randomized experiments for model validation. One interesting example discussed in Low and Meghir (2017) concerns the analysis of the effects of the PROGRESA experiment, a conditional cash transfer program intended to boost school attendance in rural areas of Mexico. Communities were selected before being randomized to either treatment (immediate program implementation) and control conditions (delayed program implementation). Nonstructural data analysis concluded that PROGRESA successfully increased school attendance of children (see Paul Schultz, 2004). Todd and Wolpin (2006) instead estimate a structural dynamic model of educational attainment using data from control communities alone. They subsequently conduct a counterfactual prediction by reducing the wage in the model by an amount compatible with the cash transfer of the program. The hold-out sample of treated communities was used to validate the predictive power of the model. These applications as well as those discussed in the current Element demonstrate that experimental data, regardless of its nature, can enhance structural modeling and add value to collection of experimental data.

*Notation:* The notation $V_c$ will sometimes be used interchangeably with $V(c, \mathbf{x}_i, \boldsymbol{\theta})$ to represent the choice-specific value function. This is done to simplify reading and presentation. Subject specific subscripts $i$ will also be added (e.g. $V_{ic}$) to express variation of the function across subjects. In some cases, $V_{ic}(\boldsymbol{\theta}_i)$ will also be used to emphasize models where structural parameters are allowed to vary (or not) across subjects.

The remainder of the Element is structured as follows. Section 2 presents an example to illustrate the benefits of estimating structural models using experimental data. Section 3 discusses estimating structural models using first-order conditions of an optimization problem. Section 4 discusses estimation of structural models using a discrete choice framework. Section 5 presents models in the presence of risk and uncertainty. This section will also discuss measurement of beliefs and expectations as well as simple approaches to handle potential endogeneity of these variables. Section 6 discusses model validation using experimental data. Section 7 concludes.

## 2 A Motivating Example

In this section we present an example to demonstrate possible synergies between structural modelling and experimental methods. Consider the following model of worker behavior in response to changes in compensation (see Shearer, 2004). Here, the economic model is based on a value function capturing utility of worker $i$ at period $t$. This function is modeled by

$$V_{it} = r_{it}y_{it} - C_i(e_{it}), \tag{1}$$

where $r_{it}$ is the piece-rate paid to the worker per unit of daily output $y_{it}$, and $C_i(e_{it})$ is an increasing convex function capturing cost of effort $e_{it}$. Here, worker compensation does not include a fixed wage, although adding such a wage to the analysis has no consequences as issues related to worker participation are not considered in the example. Assume that worker output is determined by the multiplicative production function

$$y_{it} = e_{it}s_{it}, \tag{2}$$

where $s_{it}$ denotes random factors (e.g. weather conditions) determining worker output which are unrelated to the effort exerted. A useful parametrization of the cost of effort function $C_i(e_{it})$ is

$$C_i(e_{it}) = \kappa_i \frac{\gamma e_{it}^{(\gamma+1)/\gamma}}{(\gamma + 1)},$$

where $\kappa_i$ is a worker specific productivity parameter and $\gamma$ captures elasticity of output with respect to the piece-rate. Solving for the optimal effort $e_{it}^*$ of the worker given a piece-rate $r_{it}$, and replacing optimal effort in the multiplicative production function (2) yields the following expression for optimal worker output

$$y_{it}^* = \frac{(r_{it}s_{it})^{\gamma_i}}{\kappa_i^{\gamma_i}}. \tag{3}$$

Taking natural logs on both sides yields

$$\ln(y_{it}^*) = \gamma_i \ln(r_{it}) - \gamma \ln(\kappa_i) + \gamma \ln(s_{it}). \tag{4}$$

This model can be written as a classical linear panel data regression model with unobserved individual heterogeneity.[4]

[4] The model is written as

$$\ln(y_{it}^*) = \alpha_0 + \gamma \ln(r_{it}) + \alpha_i + \epsilon_{it},$$

where $\alpha_0 = \mathbf{E}\left((\gamma + 1)\log(s_{it})\right) - \gamma\log(\kappa_1)$, $\alpha_i = -\gamma\log(\kappa_i) + \gamma\log(\kappa_1)$, and $\epsilon_{it} = (\gamma + 1)\log(s_{it}) - \mathbf{E}\left((\gamma + 1)\log(s_{it})\right)$.

Equally important, the economic model and its structure now transition to a statistical model which can be estimated using appropriate data. This transition follows because the economic model embeds a stochastic term $s_{it}$ capturing randomness in productivity for a given worker, conditional on a given piece-rate $r_{it}$.

The following observations highlight some of the synergies between structural modeling and experimental data.

**Observation 1 (Weaker behavioral assumptions):** *Paarsch and Shearer (1999) estimate $\gamma$ (restricted to the same value for all workers) using payroll data from a tree-planting firm based in British Columbia (Canada). They face a significant endogeneity problem – the firm sets higher piece-rates $r_{it}$ on planting blocks which are relatively harder to plant (lower values of $s_{it}$). This practice ensures workers accept to work under difficult planting conditions. However, this practice also introduces a negative correlation between planting conditions ($s_{it}$) and observed piece-rates $r_{it}$. Paarsch and Shearer (2000) solve this problem by making additional assumptions about how the firm sets $r_{it}$, namely assuming the piece-rate is set such that the least productive worker in the firm is indifferent between working or the minimal wage (the outside option). Shearer (2004) illustrates how experimental data can be used to estimate $\gamma$ without assumptions about how the firm sets piece-rates. He randomly assigned piece-rates to workers on different treatment blocks. The randomization ensures that $r_{it}$ varies across workers for a given $s_{it}$.*

The previous observation underlines the weaker behavioral assumptions that are imposed to estimate the model using experimental data. The following observation focuses on the weaker distributional assumptions that are imposed when estimating the model using experimental data.

**Observation 2 (Weaker distributional assumptions):** *Paarsch and Shearer (1999) estimate their model using Maximum Likelihood which requires additional distributional assumptions about $s_{it}$. Experimental data can be used to estimate $\gamma$ using simple linear regression methods with minimal distributional assumptions (conditional moment restrictions).*

Both observations lead to the specification of a simple linear regression model. The latter can be estimated in Stata using the following command (see code `pamodel.do` in the online appendix).

Principal agent model: Stata example (`pamodel.do`)

```
generate logr = log(r)
regress logy logr if gift == 0, cluster(id)
```

`r` and `logy` are respectively the independent and dependent variables, and `id` is a variable identifying the different workers/subjects. Here, clustered standard errors are computed given randomization of piece-rates to workers ensures that $r_{it}$ varies across workers for a given $s_{it}$ as discussed above. The data file `pamodel.dta` associated with the Stata code above contains simulated data of worker response both when monetary gifts are provided, and when they are not. We discuss below an extension of the basic model to capture reciprocal preferences associated with gift-giving. The command line above can be executed using only observations for which no gift was given (hence the variable `gift` is set to 0 to select these observations).

**Observation 3 (Random effects vs Fixed effects):** *Experimental data allow researchers to use more efficient estimators. Random assignment of experimental subjects to treatment (assignment of workers to piece-rates in the example above) supports maintaining the assumption that unobserved heterogeneity is independent of treatment. As is well known, fixed-effects estimation is relatively inefficient relative to random-effects estimation under these assumptions. Fixed-effects estimation is justified when researchers believe there could exist a relation between unobserved heterogeneity and treatment assignment. This is possibly more likely in the field where researchers may not have perfect control of the assignment of subjects to treatment (as per the case where assignment is delegated to a third party such as a firm). Shearer (2004), for example, estimates equation* (4) *using fixed-effects out of an excess of caution. In the latter case, the firm made the final assignment of workers to piece-rates and fixed-effects estimation would capture any bias due to nonrandom assignment of workers to treatment resulting from imperfect treatment assignment.*

A final observation presented below requires an extension of the simple model above. Gift-giving has the potential to be used as an effort-inducing device (e.g. Akerlof, 1982). Numerous laboratory and field experiments have found empirical support for the gift-exchange hypothesis (Fehr, Kirchsteiger, and Riedl, 1993; Gneezy and List, 2006; Bellemare and Shearer, 2009; Kube, Maréchal, and Puppe, 2012). Surprise wage cuts trigger a stronger (negative)