Experimental Reasoning in Social Science

Lorenzo Lagos
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The view that studies focused on experimental and quasi-experimental identification strategies give accurate estimates about things we don't care about, while studies using modeling and structural assumptions for identification give biased estimates about the things that actually matter is prevalent even within economics. Nowadays, a popular approach in economics is to have a setting with experimental variation for estimating a treatment effect but also impose a structural model to be able to talk about counterfactual scenarios. This is one way in which the million dollar data collection is not wasted on a five-dollar statistical analysis—a valid concern posed by Gelman. Moreover, I believe statisticians have much more to offer social sciences beyond "pimping up" the analysis. For example, the statisticians' approach of focusing on the data and letting them speak through descriptive analyses is often lacking among social scientists who are narrowly focused on sources of exogenous variation. The data itself provides the big picture through which one can later attempt to frame the relevant causal question.

I thought Gelman's list of attitudes toward causal inference from restrictive to permissive (p959) to be very accurate. A more controversial ordering would be in terms of credibility. In economics, there is a constant fight between the "structural" Heckman camp (less credible but more relevant) and the "reduced-form" Angrist camp (more credible but less relevant). However, the use of machine learning algorithms (on the most permissive side of Gelman's spectrum) has recently become popular for discerning relationships from big observational datasets in economics. Whether these relationships are causal is subject of much debate. To my understanding, the objective of these algorithms is prediction, not necessarily causality. Thus, a blind application of algorithms for causal inference may lead one to conclude that being Hispanic causes one to become a criminal, when in fact there is no causal relation here. Supposedly, a large enough dataset with all confounders would eliminate such spurious correlations. Nonetheless, without a model of human behavior to motivate a specification, simply running kitchen-sink regressions may lead to faulty conclusions with dangerous policy prescriptions.

I would also like to add something regarding the distinction made by Gelman between forward and backward causal inference. Forward inference studies the effects of causes (what are the effect of policy X), while backward inference studies the causes of effects (why did outcome Y occur). In my view, a well conducted forward inference study can enlighten backward inference questions. That is, if I can identify the *mechanisms* through which policy X leads to certain effects, I can then suggest causes for an outcome Y. For example, a paper that says being drafted to the Vietnam War reduces earnings is not very informative. If the mechanism through which the draft affects earnings is specified (e.g., latter entrance to the job market or lower educational attainment) one could then understand at least one reason why low earnings are prevalent among veterans (backward inference). Moreover, conditional on external validity, understanding mechanisms is necessary for policy prescriptions since the exact same policy event under study cannot be replicated elsewhere. In theory, as long as we get the mechanisms right, we should aim at manipulating those mechanisms in our favor.

Finally, I would like to briefly discuss Gelman's claim that there are no true zeros in the social sciences and that therefore identification based on conditional independence assumptions is not helpful. I would disagree to the extent that models are useful simplifications of a complex social world. Thus, although we will never get an exact zero, it is useful to make causal inference from models and settings where such assumptions are credible. Indeed, as Gelman posits, multiple causal models can coexists. It would be silly for social scientists to quibble over what the correct model is, especially when mutual causation abounds. Nonetheless, if there is a policy problem at hand, using a model that can provide an informed solution is (I would say) very helpful.