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Dynamic Causal Effects in Econometrics with a Focus on the Nonparametric Method: A Review Paper

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Abstract

According to recent developments and research in causal inference applications, understanding applied modeling in causal effects is particularly important in econometrics. We also provide an outline of econometrics' use of causal Inference. While most economists recognize randomized controlled experiments as the preferred method for concluding, a considerable portion of empirical research in econometrics relies on observational data, which presents challenges such as confounding and potential loss of exogeneity. In this context, we examine two contemporary research types: randomized experiments and observational studies. When linear estimators are biased towards dynamic causal effects due to carryover facts or serial correlation in the imputation mechanism, applying a nonparametric framework is suggested. Because the nonparametric framework does not rely on functional assumptions about the underlying data-generating processes, such as linearity or limited. Our review of the dynamic causality study approach, the linear method, which includes LP and VAR, and nonlinear statistical modeling, which provides for BART and their use in econometrics, are all reviewed in this paper. Dynamic systems modeled using linear parametric models often encounter limitations impacting forecasting accuracy and policy implications. BART specifications can produce more precise tail forecasts than the VAR structure on the nonparametric framework. Finally, BART has the lowest RMSE in linear and nonlinear data generation processes, and the performance of BART essential variables in a macroeconomic data set is optimal compared to other regression estimators.

Highlights

- This study considers nonparametric methods for estimating impulse response functions (IRF) under linear and nonlinear assumptions, providing an overview of causal inference in econometrics.
- Although randomized controlled experiments are considered the gold standard, much empirical work in econometrics relies on observational data, which can introduce heterogeneity and external validity problems.
- Nonparametric frameworks, especially those utilizing Bayesian approaches like BART, show increased forecast accuracy and better handling of nonlinearities compared to traditional VAR models.

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1. Introduction

Finding causation is difficult since it requires concentrating on one variable while holding the others constant. In the real world, every variable shifts simultaneously. The study of causal Inference in the natural sciences considers variable elements. For example, in physics, we consider the force of friction when calculating the energy an object exerts on a surface. The Important question is whether it is possible to fix and consider social science variables while examining causal Inference. The relationship between data correlations and causal Inference can be modeled using statistical techniques like multivariate regressions. What will the causal effect be if the variable remains unchanged? For instance, did the level of education enhance income, or if not, would other things like having initial wealth and having good social connections cause revenue to increase? Can we now determine the direction of causality for both the individual with education and the one without the same education? The answer is negative. To compare an educated person with someone who shares the same traits as them would require finding that person, which is impossible because no two persons are alike. Can a group estimate be made for this? We create a group of factual and counterfactual by combining educated people with a group of uneducated people. We must determine if there are additional distinctions between the group of educated people and the group of illiterate people in addition to the difference in educational attainment. We must look into which demographics are educated and possess certain traits. For example, what was their parents' income level, education, and other factors that may have influenced their decision to pursue school? As a result, it is essential to look into the elements that influence continuing education and the process of choosing educated from uneducated individuals. There is a bias due to sample selection.

In general, randomized experiments and naturalistic observation are the two methods used in economics to determine causality. In randomized experiments, we consider numerous n samples and randomly select n of them rather than choosing n samples. Consider the scenario where 200 educated individuals are chosen rather than 100 and 100 of them are randomly assigned to a continuing education program. There will probably be similarities among these 100 individuals. Since we have established a situation where the causality variable does not change, those who have continued their education make up our experimental group, while those who have not been included in the control group. Due to with this randomization, the average consequences become equal, and by comparing these consequences, the causality can be ascertained. The outcomes are random in the basic sampling approach, while the treatment assignments are fixed. The assumption behind the Inference is that the population represented by the random sample is significantly greater than the entire population. In contrast, in the randomization-based approach, we assume that the potential outcomes of individuals (i.e., the outcomes that could occur under each treatment condition) are predetermined, and we consider the assignment of individuals to different treatments as a random process. In agriculture and medicine, randomization has a long history; nevertheless, its use in economics is relatively new. However, this profession has developed recently (Manning et al., 1987). For instance, Rothstein and Von Wachter's (2017) description of experiments with negative income taxes has seen a significant increase in random experiments in economics, particularly in development economics, as Robins (1985) noted. The efforts of Banerjee, Duflo, and Kremer, which led to the 2019 Nobel Prize in economics in the field of global poverty, have been an example of randomized experiments in the development of development economics (Banerjee et al., 2016).

The external validity of random experiments is a significant issue. The majority of random experiments exhibit high levels of internal validity. Randomized trials perform worse than alternative methods in improving external validity conditions.

Observational studies provide conditions for quasi-experiments. For instance, assuming all other conditions remain constant, will boosting wages raise unemployment? The rise and decrease effects are both supported by economic theory. We may look at this experiment by looking at two states that are close by and have a shared border. People are more likely to get along if they live close to a shared boundary. Naturally, a test and control group will exist in this situation. This study was carried out by Card and Krueger (2000) for the states of Pennsylvania and New Jersey. The findings indicate that increasing the minimum wage does not affect unemployment. Recent reviews have analyzed the outcomes of natural and randomized experiments to reach this conclusion.

As we know, causal effects are at the heart of many of the most significant macroeconomic concerns. Issues with causality show how macroeconomic indicators are affected by changes in Economic conditions or policy. Dynamic interactions between treatments and observed results brought on the challenging separation of causes from effects. Given these challenges, parametric models are frequently used in the existing literature on the use of dynamic causal effects in macroeconomics. SVAR Sims (1980a) and LP Jordà (2005) are appropriate. Most current studies on SVAR and LP estimates involve parametric models, but some data is nonparametric in the social and economic sciences.

This paper is structured as follows: Section 2 concisely reviews the literature on causal effects and emphasizes the significance of causal Inference and the causal approach within econometrics. The discussion of causal model validation continues in Section 3, and the topic of random and observational studies in a nonparametric setting is covered in Section 4. The linear studies of VAR and LP models in the causal nonparametric structure are reviewed in Section 4, and the nonlinear studies of these models, including Bayesian Nonparametric Causal Inference, are evaluated in Section 6. Finally, Section 7 closes the paper with concluding remarks.

2. Causal Inference

Recent methods for causal models that are both popular and useful include counterfactuals. These models utilize principles and ideas from economists during the early 20th century. However, not all statisticians concur that Inference based on counterfactuals, which are not observable in theory and practice, is valid. Several statisticians proposed the notion of multiple versions of responses. However, the details were only sometimes explicitly elucidated, and ultimately, the differences between these versions were causal effects that aligned with the same counterfactual concept. (Liu, 2009).

The distinction between Fisher (1926) and Neyman and Iwaszkiewicz (1935) was in the Inference drawn. Fisher thought that Inference should be made at the level of the individual unit. Suppose each unit can receive a genuine therapy or a placebo control. Fisher (1926) states that for no causal effect, the difference between the response to treatment and the response to control for each unit should be zero. According to Neyman and Iwaszkiewicz (1935), the null hypothesis of no treatment effect posits that the average difference in impact across the entire population equals zero. The non-counterfactual and counterfactual perspectives are the primary conflicting theories for causal Inference in statistics. One, in particular, is founded on the counterfactual provided by (Rubin, 1974, 1978, 1990, 2004) and (Holland, 1986).

We follow the counterfactual problem and consider u a unit or person. Units may be considered coming from a population of U. In the following, we examine two causes or treatments: treatment (W = 1) and control (W = 0). These treatments are administered to the units.

Before administering any treatment, two possible responses exist from unit u, Y1(u) and Y0(u). Y1(u) corresponds to the unit u's reaction when treatment 1 is applied, while Y0(u) represents the response when treatment 0 is administered. When unit u receives treatment 1, the answer Y0(u) becomes a counterfactual as treatment 0 was not implemented, rendering it unobservable. Similarly, if unit u undergoes treatment 0, the response Y0(u) is observed, and Y1(u) becomes the counterfactual. Thus, each potential outcome becomes the response, while the opposite likely product is the counterfactual. In specific analyses aiming to evaluate causality, researchers are interested in quantifying the disparity between the reactions under treatment 1 and treatment 0. This disparity reflects the causal effects observed within distinct groups of units (Liu, 2009).

2.1 The Fundamental Problem of Causal Inference

Due to the challenges of observing both Y1(u) and Y0(u) for the same unit, it becomes impractical to determine the difference in impact between Treatment 1 and Treatment 0 on unit u. The primary issue with causal Inference is discussed in this article (FPCI). The problem is the counterfactual that could never be theoretically observed. Upon observation, one of the two potential outcomes manifests as the actual observed outcome, while the other outcome remains unobserved. As a result, it is impossible to immediately perceive the effect or the difference Y1(u) − Y0(u). However, it may be reasonable that FPCI is not given. Consider a situation where time is stable, but the causation is erratic and transient. Temporal stability indicates that even a slight modification in the treatment schedule does not impact the final result. Causal transience refers to the fact that earlier exposure of the unit to another treatment has no bearing on the outcome of the first treatment. If both of these assumptions hold, it becomes possible to administer one treatment to a unit before proceeding to the other treatment, treating them as if they were both applied simultaneously. Consequently, the effect is equivalent to the difference between the two observed outcomes. Another frequently used assumption to avoid the Fundamental Problem of Causal Inference (FPCI) is the unit homogeneity assumption, which assumes that the units are homogeneous with respect to the treatments and outcomes. If this assumption is valid, it is possible to treat two different types of units differently, considering the observed outcome of one unit as the hypothetical outcome of the other unit (Liu, 2009).

Inferring causes from treatments requires careful consideration of the assignment mechanism of the reasons. Covariates and observed responses may be significant in developing ignorable assignment mechanisms, but counterfactuals are not. The term "ignorable" implies that the assignment mechanisms are fully comprehended, as the unobserved counterfactuals have no impact and can thus be disregarded. On the other hand, nonignorable assignment mechanisms rely on the existence of counterfactuals. Therefore, one cannot fully understand how the tools operate because counterfactuals cannot be ignored. The wholly randomized treatment assignment mechanism is considered an "ignorable" and unbiased approach. In this mechanism, all assignments have an equal constant probability not influenced by covariates, counterfactuals, or other units. This approach represents the simplest form of random selection. Similar to entirely unexpected-sized treatment assignments, regular designs permit factors to affect the probability of treatment assignment, introducing variation between different units (Rubin, 2004).

2.2 Causal approach in econometrics

The introduction of structural models by Jan Tinbergen in the 1930s, followed by the research conducted at the Cowles Commission, significantly expanded the application of the causal approach in econometrics (Hoover, 2006). These advancements contributed to a broader understanding of causal relationships in economic analysis, emphasizing the importance of considering the causal effects of variables and interventions. The work of Tinbergen, Koopmans, and Klein played a pivotal role in shaping the field of econometrics and furthering the study of causality in economics.

According to (Wold, 1954), the controlled experiment is the best instrument, although most econometrics deals with non-experimental observations. Although most economists concur with Wold that the randomized controlled trial is the gold standard for Inference, it should be noted that the external validity of controlled trials can be called into question. (Athey & Imbens, 2017) and we will look at this topic in Section 3.

Since a significant portion of empirical work in econometrics uses observational data, it is crucial to consider factors like the potential for confounding and the loss of exogeneity. The Nieman-Rubin causal model, which compares a treatment's effect to its counterfactual effect, is now frequently used by economists when discussing non-empirical data. This approach has been criticized by Heckman (2008). He thinks the prospective result model is a black box device that makes the opposite assumption without simulating the factors that determine the outcome and without considering a theory that could account for the product. Of course, it should be remembered that the randomized controlled experiment is also subject to the same critique. The issue of time is another factor that emphasizes the significance of causality in econometrics. The relevance of an experiment is independent of time; hence, the natural sciences are, by their very nature, outside of historical time. For example, in physics science, at any time we throw an object, assuming the stability of other factors, the acceleration of the object's movement is the same. Still, in economics science, this is not the case: past events give economists the information they need to generalize from and make decisions about the future (Mouchart et al., 2020).

Heckman and Pinto (2022) In econometrics, there is a clear distinction between defining causal parameters and the task of identifying them. The Neyman-Rubin approach, which has its roots in experimental statistics, and the do-calculus, developed in computer science, are two alternative approaches that share the goal of addressing similar problems as the econometric approach. However, it is essential to note that these alternative models have limitations, which may not be as transparent and flexible as the econometric approaches. According to Heckman and Pinto (2022), the econometric approach separates the responsibilities of defining and identifying causal parameters. The Neyman-Rubin approach, which has its roots in experiment statistics, is the first approximating strategy. The second is the do-calculus approach, which has its roots in computer science. In both the latter models, they try to solve some of the same issues solved by the econometric method. Each has different and vital limitations, which are more precise and adaptable than econometric approaches.

The do-calculus incorporates a distinct set of criteria for identifying causal parameters that deviate from probability theory and rely on a narrow range of assumptions regarding behavioral equations. These rules primarily rely on conditional independence and recursive directed cyclic networks. The Nieman-Rubin approach avoids the benefits of structural equations and many practical strategies for their identification due to its rigid criteria, which forbid using many conventional identification and estimation approaches. It locates the cause and frames all policy issues under the "treatment control" paradigm. Sometimes, it conflates definition problems with issues of identification. The non-dependence of causal effects on structural equations with explicit links to theory and explicit analyses of unobservable makes it challenging to interpret the estimates obtained from the Neyman-Rubin approach or its economic research uses the broad toolkit of contemporary econometrics.

3. Causal Effects and Validity

3.1 Aspects of the Causal Effects Validity

Cook et al. (2002) review various factors of validity of causal effects studies. Internal and external validity are the most crucial arguments for validating causal relationships. Internal validity is defined as a "causal relationship in which the variables are changed," as evidenced by the observed covariance between a treatment and an outcome. The term internal validity refers to a study's capability to estimate causal effects within its study population. It is worth noting that internal validity mainly applies to observational research, as properly conducted randomized experiments inherently possess internal validity. This is only sometimes the case in experimental circumstances where the unit of interference is an issue.

The question of external validity is the second validity concern. When people, places, treatments, and results change, how generalizable the causal relationships remain is known as external validity. The extension of causal conclusions from one population and environment to another, where these alternative contexts may include different populations, different outcomes, or different contexts, is what external validity is concerned with.

Cook et al. (2002) claim that causal studies are of little value without internal validity when discussing the significance of internal fact. The critical point is that it is impossible to ensure the external validity of randomized and observational studies.

One of the main reasons for this phenomenon in experiments involving human subjects is that the individual usually requires informed consent, which means they often have to give their support. Willing to participate in the investigation. The estimated population that knowingly consents cannot always be generalized to the estimated population that is unaware since the participants may differ depending on whether they know the experiment is being conducted. In this regard, non-experimental methods offer no advantage over randomized studies with the same population and sample size. Essentially, heterogeneity in treatment effects accounts for most of the external validity problems. (Athey & Imbens, 2017).

3.2 Selection from super populations: finite population versus random sample

In the empirical analysis, it is common to consider the sample under study as a random sample randomly selected from a large, almost infinite, super population. Since information about the entire population comes from perfect knowledge of the estimates, uncertainty is considered to arise from this sample. However, in other cases, this view needs to be revised. We observe some population units that received one level of treatment, but we do not observe what would happen to these units if they received a different level of treatment, causing some. The estimated portion needs to be reported. The sample selection process has been the subject of numerous discussions, many of which have been covered in Abadie et al. (2014).

3.3 Potential Outcome Framework

Three key characteristics define the Rubin causal model (RCM) or prospective outcome framework. The first is that it connects causes to possible results. For instance, there are two possible outcomes if the patient receives treatment in both drug- and non-drug-assisted modes. The causal effect is the comparison between these two possible outcomes. The fundamental problem of causal Inference we mentioned in the previous section is the critical problem (see Holland (1986)). Most likely, we will only notice one of these potential consequences: the result of the treatment or its opposite, that is, no treatment. Because there can be no causation without manipulation, according to Rubin (1974), there must be a way for us to manipulate the causal conditions such that these prospective results of the treatment are observable.

The requirement of multiple units is the second characteristic of the framework of prospective consequences. We need to see the results for many units since we can only see one of the possible results for each unit. Having several units does not automatically fix the issue because more unique therapies are now available. Each unit has two degrees of therapy; there are twice as many units as treatments in the entire vector. Between the two of them, any comparison is a legitimate causal effect.

The central position of the allocation process is the third crucial aspect of RCM. Out of two treatment modalities, why was only one treatment unit received? In causal research, random trials have a unique place in this. The allocation mechanism in a randomized experiment of a known function of the observed characteristics of the units under study. When parts of the allocation method are unknown and may depend on the units' unobserved characteristics (including expected outcomes), they are called observational studies rather than randomized trials.

We can only see one of the possible outcomes; hence, it is impossible to make reasonable and accurate deductions about the causal effect, such as the difference $Y0(u) - Y1(u)$, without causing further assumptions or knowing more details. The issue is that, in theory, the outcomes could vary depending on how each unit is treated. In many instances, it is plausible to believe that the unit's prospective results wholly rely on the care that unit u receives. This significant limitation on the outcomes is also unachievable in many contexts. For example, training some unemployed people may improve their chances of finding employment and expose certain students to educational interventions that can change the outcomes of their classmates.

The most important limitation is that, for randomized trials, we prohibit reliance on possible outcomes and assume that the functional form of the assignment mechanism is known. It can be challenging to analyze observational studies if the assignment process depends on the possible outcomes in potentially complex ways; such analyses often rely on debatable presumptions (Athey & Imbens, 2017).

4. Nonparametric model

Two techniques are described by Bojinov et al. (2021) for concluding dynamic causal effects. The weak null hypothesis that no average emotional causal effect is first tested by performing conservative, nonparametric Inference using the bounded distribution. The second provides an exact stochastic test of the absolute null hypothesis that there is never a dynamic causal effect on any unit at any time. Then, the finite population probability bounds of many typical linear estimation techniques commonly used on panel data, including the unitary fixed effects estimator and the fixed effects estimator two-dimensional definition, are drawn to demonstrate the broader applicability of this framework. Their results highlight the importance of our proposed nonparametric estimator by showing how these linear estimators are biased towards dynamic causal effects whenever There is no transition effect or serial correlation in the assignment mechanism.

According to Plagborg-Møller and Wolf (2021), their approach requires the nonparametric assumption of weak stationarity in the data and unrestricted lag structures in the two specifications. This means linear LPs and VAR methods are equally "robust to nonlinearities" in the population setting. This finding is important because although it applies specifically to linear estimation methods, their argument is nonparametric, meaning it does not rely on assumptions about linearity or dimensionality finiteness of the underlying data generation processes to ensure its validity.

Three new alternative BART-based nonparametric VARs were developed by Clark et al. (2021), and they offer characteristics that make them potentially useful for macroeconomic forecasting, especially in times of uncertainty. As a result of the models' nonparametric components, they can account for nonlinearities or multimodalities like those that Adrian et al. (2019), another recent analysis of sequence risks for productivity development, highlighted. The exact distribution exhibits significant nonlinearity if we observe a considerable difference between the two expected densities (since the approximation errors become relatively large). These findings are not shocking, given that the recession experienced an unprecedented drop in GDP growth and increased unemployment significantly higher than the historical average. Nonparametric methods in this circumstance readily adjust to these ex- treme observations. Therefore, they recommend nonparametric techniques, which are better, particularly for more extensive VAR.

4.1 Randomized Experiments

Randomized trials have long been considered the most reliable method for concluding causation. "Experiments yield more trustworthy evidence on causation than

observational research," Freedman (2006) states plainly. However, some scientists still need to be more convinced about the relative benefits of randomized trials. Deaton (2010), for instance, makes the following claim: “I argue that evidence from randomized experiments has no special priority. Randomized experiments cannot automatically trump other evidence; they do not occupy any special place in some hierarchy of evidence”. The distinctive aspect of a randomized experiment is that researchers have control over the assignment mechanism, enabling them to eliminate selection bias when comparing treated and control units. However, it is essential to note that randomized experiments cannot answer all questions about causation. There are many different reasons why randomized experiments may not be suitable for answering specific questions.

Let us first consider a situation in which we are interested in the causal effect of a particular intervention on a unit: what would happen to a specific company without a merger, as opposed to what would happen after a merger? No randomized experiment will ever be able to tell us the causal answer in that situation or many other macroeconomic topics. However, it is possible to conduct investigations or find data from pseudo-experiments, even in macroeconomics, once the interest lies in repeated intervention. Angrist and Kuersteiner (2011) employ the possible outcome framework to explore causal studies in a macroeconomic time series environment, expanding on the work of Romer and Romer (2004). Second, experimenting could not be moral. It is frequently impractical to deny specific educational services to people in educational contexts so that their benefits can be assessed. In these situations, it could be necessary to conduct some observational study, perhaps randomizing the incentives for program participation.

The typical population estimands for time series experiments are only possible by making significant, frequently irrational assumptions about the prob-item's characteristics. Bojinov and Shephard (2019) identified a broad class of estimates and proposed a method for estimating them without making assumptions about the potential outcomes. Instead, they require treatments to be probabilistic rather than predictive. They designate method B as the method handling (Wt = 0) and method A as the method controlling (Wt = 1). When applying it to all ten markets, they get a highly significant result, indicating that method A's slippage is likely more minor than way B's. The results show that method A outperforms method B. Using only the randomization, they derive two nonparametric inferential techniques. One of these methods provides a precise randomization test for the absence of causation in a time series. Then, they extrapolate our findings to the case with numerous units. They can define unit-level causal estimands because the core of their time series experiments is probable outcome paths. They specify a large category of causal effects and demonstrate how to estimate the number of significant cases using a weak, non-anticipating treatment assignment assumption.

The seminal panel study by Robins (1986) sparked a massive body of work on dynamic causal effects (Abbring & Heckman, 2007; Blackwell and Glynn, 2018; Boruvka et al., 2018; Dahabreh et al., 2020; Heckman et al., 2016; Heckman

& Navarro, 2007; Lechner, 2011; Murphy et al., 2001). Most recently, Bojinov et al. (2021) used a panel test to examine dynamic causal effects and develop a model of alternative outcomes. This paper presents a structured framework for integrating uncertainty into group experimentation, particularly on accounting for innovation. The authors assumed that random assignment was the only source of randomness and that potential outcomes remained constant. They proposed a nonparametric estimator, demonstrating its neutrality in capturing dynamic causal effects with p-lag relative to random distribution. Additionally, they established that the obtained estimators with linear unit fixed effects were unbiased for assessing causal effects within dynamic causal effects and treatment assignment mechanisms.

Researchers then developed instrumental techniques to conclude these dynamic causal effects. They introduced an asymptotically conservative test based on weak Neyman-type null hypotheses and a randomization-based test of Fisher-type null hypotheses. They also test the finite population probability bounds of the linear unitary fixed-effects estimator and the two-way fixed-effects estimator, showing that these estimators exhibit robustness asymptotic bias for contemporaneous causal effects when there are causal dynamics and persistence in the treatment allocation mechanism. To illustrate their findings, they reanalyzed an experiment by Andreoni and Samuelson (2006) and conducted a comprehensive simulation study. The chosen investigation was particularly suited for applying the techniques developed in this study for two reasons. Firstly, it showcased a conventional panel structure, where each participant engaged in a prisoner’s dilemma game multiple times with various randomly assigned payout structures. Second, because games are sequential, past assignments may influence what players do in the future. This dynamic causal effect could confound commonly used techniques for measuring causal effects in panel experiments. We looked at examples of random experiments with time series and panel data. Now, let’s discuss how to derive causality from observational studies.

4.2 Observational Studies

Most of the time, a series of randomized experiments designed with probable outcomes for nonparametrically measuring dynamic causal effects were undertaken in economics. However, observational time series data comprise most of those utilized in economics. Randomized experiments often have excellent internal validity, and their analysis is quite simple (Athey & Imbens, 2017). However, as described in Glennerster and Takavarasha's (2013) study, trials are frequently constrained in the size and depth of the data gathered and represent attentiveness, causing issues with external validity. However, observational studies often need more internal validity, and using such data sets to determine causal effects is challenging.

In their research, Bojinov and Shephard (2019) introduced a time series of potential outcomes as a nonparametric approach to measuring dynamic causal effects in randomized time series experiments conducted in financial markets.

However, it should be noted that most time series data in economics is observational. To address this limitation, Rambachan and Shephard (2019) have developed the necessary tools to apply a time series framework of potential outcomes to observational data, thereby establishing a nonparametric observational framework for measuring dynamic causal effects.

While Angrist and Kuersteiner (2011) also investigate time series using potential outcomes, their work differs significantly from Bojinov and Shephard (2019). Angrist and Kuer-Weiner (2011) focus on possible results based on a single prior treatment, omitting discussion of treatment pathways. Furthermore, the main contributions of Bojinov and Shephard (2019), such as the special cases of instruments, shocks, linear potential outcomes, and the formulation of the causal response function, still need to be covered. Accessed in Angrist and Kuersteiner (2011) and Angrist et al. (2018).

To quantify the dynamic causal effects of nonparametrically conducted randomized time series experiments on financial markets, Bojinov and Shephard (2019) created a time series

of prospective outcomes. However, observational time series data comprise most of those utilized in economics. The tools needed to apply a time series framework of potential consequences to observational data were developed by Rambachan and Shephard (2019), creating a nonparametric observational framework for calculating the impacts of dynamic cause and effect. Angrist and Kuersteiner (2011), who also study time series using possible outcomes, are the authors of the closest piece of literature to the potential outcome time series paradigm. Unlike Bojinov and Shephard (2019), this work makes a significant difference by avoiding discussing treatment pathways and characterizing possible outcomes based on a single treatment approach. Most before. More importantly, Angrist and Kuersteiner (2011) and Angrist et al. (2018) do not consider the main contribution of this study, which is the development of the causal response function and the specific cases of instruments, shocks, and linear potential outcomes.

The framework of nonparametric potential outcome time series for experiments was adapted by Rambachan and Shephard (2019) to capture dynamic causal effects in observational time series data formally. They introduced three critical elements of the potential outcome time series: tool, shock, and linear. In addition, they introduced a fourth concept, the finite-sample-weighted causal effect, as well as its superpopulation counterpart, called the causal reaction function, to enhance our understanding of dynamic cause and effect effects. These four concepts give the impulse response function, an essential tool economists use to measure emotional, causal effects and nonparametric causal meaning. They demonstrated how the LP-IV estimator determines a weighted average of dynamic causal effects, where the weights are based on the temporal variability in the relationship between the instrument and treatments. They show that a strictly parameterized model, such as a structural moving average, is not necessary to provide a causal explanation of these factors.

In their study, Athey et al. (2020) propose statistical techniques to systematically combine experimental and observational data to take advantage of the strengths of both types of data. They focus on a general scenario in which information about individual processing tasks and secondary outcomes is available in experimental and observational data. However, observational data only contain information about the primary outcome of interest, usually long-term outcomes. Additionally, they examined a situation where the experimental sample provided data on the secondary effect, whereas the observational study provided data on both the primary and secondary outcomes. Uncovering objective information about secondary outcomes from trial data provides a new premise for understanding biases in observational studies' comparisons between primary and secondary products. To illustrate their findings, they merged data from the Project STAR trial with observational data from the New York school system. The results show that although the calibration process based on experimental data produces more reliable results, significant biases still exist in observational studies.

Most research on causal Inference considers deterministic interventions that set the processing of each unit to some fixed value. However, these treatments can lead to indeterminacy, ineffectiveness, and only minimal practical application in violation of positivity. Further, because the curse of dimensionality is so sensitive to matching effects in long-term investigations, unrealistic parametric models are frequently used. By using incremental interventions that alter propensity score values rather than imposing fixed values on treatments, Kennedy (2019) proposes a new approach to these problems. There are several significant benefits to incremental actions. They start by altogether avoiding positive assumptions. Second, they permit a straightforward characterization of longitudinal effects regardless of the number of time points while requiring no parametric assumptions.

5. Nonparametric techniques to estimate the IRF: VAR and LP

Both linear local projections (LPs) and vector autoregressions (VARs) produce similar population impulse responses. It is possible to obtain any VAR impulse response function, even potentially non-recursive, through an LP by incorporating appropriate control variables. Similarly, any LP impulse response function can be generated through a properly ordered recursive VAR. This finding applies to the various commonly used implementations of local projections mentioned in the literature, including those presented by Jordà (2005) and Ramey (2016).

Since Sims (1980a), vector autoregressive models (VARs) have increased in the empirical economic literature. Impulse response functions (IRFs) are unquestionably the most often utilized tools in VAR models. Macroeconomists mainly rely on IRFs for causal Inference, multiplier estimation, and analyzing the dynamics of the primary macroeconomic aggregates in stochastic models. Researchers have extensively studied the statistical characteristics of VAR impulse response functions due to their use. One of the main advantages is that from the first step, VAR models generate optimal and robust misspecification IRF (Stock & Watson, 1999). Of course, the disadvantages are now also understood. These mainly concern the reliance on Wold's decomposition theorem (Brugnolini, 2018).

Vector autoregressive models are used in impulse response analysis to describe how variables in the model change in response to a shock in one or more variables. With the help of this feature, it is possible to track the propagation of a single shock within a chaotic system of equations. In other words, one of the features of an IRF that makes it valuable for assessing economic policy is its ability to follow the transmission of a single shock inside a system of equations. The model-free or local projection (LP) estimator (Jordà (2005) uses nonparametric approaches to estimate impulse response functions. Additionally, the estimator is not restricted by the invertibility presumption, allowing the computation to proceed even without a Vector Moving Average representation. In addition to this significant advantage, the author also shows how the estimator considers nonlinear factors such as state dependence and sign. Furthermore, it shows how local projection can outperform an imprecise VAR model in computing impulse response functions. This result has attracted much criticism, and Kilian and Kim (2011) have started a discussion about the validity of this single estimator by demonstrating how poorly it performs in terms of range compared to IRF VAR.

Brugnolini (2018) Performance evaluation of the local projection (LP) method and the vector autoregressive (VAR) model impulse response function estimator. They recreate the two authors' Monte Carlo simulation, showing the justifications for their conclusions about VAR IRFs. The results demonstrate that when the model is poorly described, the VAR impulse response produces a vector of points far from the facts and has a narrow confidence range. The local projection estimator, in contrast, gives points with wide confidence bands closer to the actual values. Simulations also show that choosing the offset length once and for all projections improves the performance of the LP IRFs. Although some of the disparities between the SVAR and LP estimations are substantial, the differences are not statistically significant due to their estimated errors. The differences between the estimates from local projections (LP) and structural vector autoregressions (SVAR) do not support the claim that the SVAR model needs to be more precise due to the lack of invertibility. The table presented in the study demonstrates no statistically significant evidence to reject the null hypothesis of invertibility despite substantial economic disparities between the two estimates of impulse responses (Stock & Watson, 2018).

The local projections (LP) method is often supported based on its resilience to potential misspecifications in vector autoregression (VAR) models, such as lag length, nonlinear, and state dependence. However, Stock and Watson (2018) dismiss these arguments by assuming a structured moving average representation with linear and constant coefficients. They establish conditions for instrument validity within an LP instrumental variables (LP-IV) framework and demonstrate that, under these conditions, LP-IV can estimate dynamic causal effects without assuming reversibility. This means they do not require the assumption that structural shocks can be accurately extracted from the data's observed current and lag values. They consider the steps that can be taken to perform IV estimation in SVAR (SVARIV method). This approach, which does not require the exogeneity of the lead delay, is asymptotically more efficient than LP-IV under asymptotically strong device conditions. But for this strategy to be effective, invertibility is necessary. The assumption of invertibility is powerful despite being frequently stated. Suppose there is a scenario where a forecaster utilizing a vector autoregression (VAR) model would not observe any advantage in incorporating information on the actual macroeconomic shocks, even if these shocks seemed to emerge unexpectedly. To determine if the structural VAR (SVAR) model is invertible, one can employ a test similar to the one proposed by Hausman (1976). There is also a more efficient estimator called SVAR-IV, which requires reversibility to ensure consistency, and a less efficient estimator called LPIV, which does not require reversibility reverse. In cases where an instrument satisfies the condition of no lead-lag exogeneity but fails to meet the necessity of contemporaneous exogeneity due to its correlation with prior shocks, a viable approach is to introduce additional regressors, namely lagged macro variables, to account for the influence of those lagged shocks.

Plagborg-Møller and Wolf (2021) proved that LP and VAR models estimated Impulse responses, and this nonparametric result requires unconstrained lag structures. They produced diverse results that diverged from research showing LP models' superiority over VAR. First, they concluded that LP and VAR are not fundamentally distinct methods; instead, they are part of a spectrum of ways to reduce range through standard estimates, although they differ in variance bias. Second, LPs could be used to perform VAR-based structural estimation and vice versa. In practice, local linear projections (LP) and vector autoregression (VAR) give similar estimates of the population impulse response. Specifically, any LP impulse response function can be obtained via a streamlined recursive VAR and any (potentially non-recursive) VAR impulse response function can be generated by LP with appropriate control variables. The main requirements for these estimates are the nonparametric assumptions that the lag structure in both specifications is unconstrained and that the data exhibit weak stationarity. Third, recursive methods could be used to estimate the structural properties of a single instrument VAR, even in modes that are not invertible. As strong as nonlinear LPs, liner VARs are also effective. The equivalence of VAR and LP estimands is significant since it has numerous effects on structural estimation in applied macro econometrics.

6. Bayesian Nonparametric Causal Inference

Several recent approaches that have been suggested require fitting two models and assuming that the treatment assignment mechanism is ignorable. One model is used for the response surface, while the other is employed for the assignment mechanism. In contrast, Hill (2011) proposes an alternative approach that focuses primarily on modeling the response surface in a highly flexible manner using a Bayesian nonparametric modeling technique called Bayesian Additive Regression Trees (BART). In simulated scenarios with nonlinear relationships, BART provides more precise estimates of average treatment effects than methods such as propensity score matching, propensity-weighted estimators, and regression adjustment. Furthermore, the treatment effect estimates derived from BART demonstrate significantly greater accuracy than estimates produced by equally available alternatives such as linear regression, propensity-weighted estimators, and propensity score matching with regression adjustment in the considered nonlinear settings.

Some recently proposed approaches require fitting two models and assuming that the treatment allocation mechanism is ignored. One model is used for the response surface, while the other is for the assignment mechanism. In contrast, Hill (2011) offers a different approach that mainly focuses on modeling the response surface in a very flexible way-

in a nonparametric Bayesian modeling technique called Bayesian Additive Regression Trees (BART). In simulation scenarios with nonlinear relationships, BART provides more accurate estimates of the average treatment effect than methods such as propensity score matching, propensity weighting estimators, and regression adjustment. Furthermore, treatment effect estimates obtained from BART show significantly higher precision than estimates produced by alternative methods such as linear regression, propensity-weighted estimation, and Propensity score matching with regression adjustment in a nonlinear setting.

A novel method for estimating random experiments was put to the test by Clark et al. (2021). Their approach shows that a more reliable yet more straightforward modeling strategy is now available to accurately predict the causal effects in this situation, based on recent developments in Nonparametric Bayesian with incredibly flexible functional forms. This approach is based on accurately modeling the response surface using a nonparametric (or equivalent, highly parametric) modeling strategy called BART. (Chipman et al., 1998).

The BART method is simple and only requires the researcher to enter results, treatment assignments, and confounding variables. Knowledge of the parametric relationship between these variables is optional. However, BART can detect interactions and nonlinearities on the response surface, which, among other advantages, facilitates the detection of different treatment effects. Additionally, BART naturally generates consistent posterior intervals, unlike techniques such as propensity score matching and subclassified, for which there is disagreement regarding the best methods for estimating intervals (Hill & Reiter, 2006; Imbens, 2004), although Abadie and Imbens (2006) recently proposed an estimator that could be a viable option in some instances.

Finally, in the nonlinear setting considered here, point estimates of intervention effects calculated using BART appear significantly more accurate than estimates from commercially accessible competitors., such as linear regression, functional weight estimator trends, and regression-fitted propensity scores (e.g., as measured) equal to the mean squared error). In simulations, BART performs approximately the same as linear regression, the "proper" model for this situation, even when the response surface is linear to additive treatment effects. As a result, BART is a simple method that is potentially reliable and accurate for estimating causal effects. New multivariate models that assume nonlinear correlations between macroeconomic variables, their lags, and perhaps error lags have been introduced using BART. In the following sections, they have created MCMC estimate algorithms for both the homoskedastic and heteroskedastic BART specifications. Their findings imply that using nonparametric models typically increases forecast precision. Remarkably, when attention is focused on the posterior prediction tails, flexible models outperform traditional VAR models with SV. The key conclusions are as follows: there is a minor asymmetry in downside risk in out-of-sample predicted density plots when using BART to handle nonlinear problems; The BART specification can provide more accurate tail forecasts than the BVAR-SV.

Researchers have utilized the Bayesian Additive Regression Trees (BART) technique in various macroeconomic and financial studies. For instance, Zhang and Härdle (2010) tended BART into the classification context by incorporating financial statement information to distinguish between solvent and insolvent firms, which they called the Bayesian Additive Classification Tree (BACT) technique—in the area of credit scoring, de Brito and Artes (2018) compared the performance of BART and random forest models with logistic regression. They found that BART and random forest performed better than logistic regression in balanced and unbalanced samples.

Additionally, in an evaluation of real-time forecasting performance for a set of US macroeconomic and financial indicators, Clark et al. (2021) compared different BART models to a Bayesian Vector Autoregressive Stochastic Volatility (BVAR-SV) model, which served as a benchmark. The results demonstrated that the BART specifications can provide more accurate tail forecasts, especially for the unemployment rate, than the BVAR-SV model.

Overall, the applications of the BART technique have showcased its effectiveness in various domains, including classification, credit scoring, and macroeconomic forecasting.

Mumtaz and Piffer (2022) introduce a flexible local projection (Jordà, 2005) that generalizes the model to a nonparametric one using Bayesian Additive Regression Trees (BART). They apply BART-LP to fiscal and financial shocks in the United States and show that financial shocks have a nonlinear economic impact. The (Sims, 1980b) vector autoregression model assumes that lagged dependent variables linearly affect contemporaneous values. Huber and Rossini (2022) relax this assumption by combining the literature on BART and VAR models. The BAVART model can handle arbitrary nonlinear relationships between endogenous and exogenous variables. They apply the model to the term structure of interest rates in the United States and show that the BAVART model produces accurate point and density forecasts.

On a related note, Huber and Rossini (2022) aim to relax the assumption in vector autoregression (VAR) models that the lagged dependent variables have a linear impact on contemporary values. They achieve this by combining the concepts from the BART model literature with VARs, resulting in their proposed method called BAVART. The BAVART model can effectively capture arbitrary nonlinear relationships between endogenous and exogenous variables. To illustrate the effectiveness of the BAVART model, the authors apply it to the US interest rate term structure and demonstrate its ability to generate an accurate point and density forecasts.

7. Discussion and Conclusions

In the field of randomized experiments and observational studies, nonparametric studies of causal effects are considered in this study. We also discuss nonparametric methods for estimating IRF under linear and nonlinear assumptions.

Our review studies support the literature on causal Inference and the Fundamental Problem of Causal Inference (FPCI). The assumptions commonly used to avoid FPCI are the assumptions of stability over time and uniform homogeneity. We also provide an overview of the use of causal Inference in econometrics. Most economists agree that randomized controlled experiments are the gold standard for inferences, but in reality, a significant portion of empirical work in econometrics relies on observational data, which, along with other factors, have the potential to cause confusion or loss of homogeneity, must be taken into account. Many cliometricians currently use the Neyman-Rubin causal model, where the effect of a treatment is compared to the impact of its counterfactual, whether dealing with non-experimental data or prospective outcomes.

Although it can be challenging to demonstrate the external validity of randomized trials, they appeal to economists because of their high internal facts. However, non-experimental methods differ from randomized experiments with the same population and sample size. Essentially, heterogeneity in treatment effects is the leading cause of external validity problems.

When linear estimators are biased towards dynamic causal effects due to carryover facts or serial correlation in the imputation mechanism, applying a nonparametric framework is suggested. Because the nonparametric framework does not rely on functional assumptions about the underlying data-generating processes, such as linearity or limited

dimensionality, displacement structures are not constrained when the data are weakly stationary. For macroeconomic forecasting, nonparametric frameworks are helpful, especially during uncertain periods. The models' nonparametric components allow them to capture nonlinearities or multimodalities. We also looked at other papers that used observational data and randomized experiments in nonparametric structures.

We examine nonparametric linearity estimation methods for impulse response functions (IRF). The impulse response functions are estimated using nonparametric local projection (LP) methods at the estimation stage. Additionally, the estimator is not restricted by the invertibility presumption, allowing the computation to proceed even without a Vector Moving Average representation. Furthermore, several studies demonstrate that local projection can outperform a poorly defined VAR model for estimating impulse response functions. However, this result has attracted criticism and sparked discussion about the validity of this single estimator, showing how poorly it covers the data compared to IRF VAR and demonstrating that this nonparametric result only requires an unbounded lag structure. The results of these comments differ from the research results, showing the superiority of the LP model over VAR. Testing for nonlinearity, The point estimates of treatment effects calculated using BART have significantly higher precision in the nonlinear parameters considered here than estimates from available competitors, using nonparametric techniques to estimate impulse response functions (IRFs) via a Bayesian approach. According to the data, utilizing nonparametric models generally increases forecast accuracy. The primary conclusions are that it is less critical to account for heteroskedasticity when using BART to handle nonlinearities; there is little risk of asymmetry in out-of-sample predicted density plots, and BART specifications can provide more accurate tail forecasts than BVAR-SV.

Finally, because it provides more accurate estimates in the same data category, we advise future researchers to apply the BART technique to the nonparametric framework.

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