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Interventionism and the "Time" in the Causal Analysis in Historical Social Studies

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Abstract

When analyzing social science issues within the framework of interventionism, the problem of time effects inevitably arises. This paper focuses on the clarification of interventionism and the delineation of causal objects in the historical social studies, making time the central theme of the study. It indicates that a strictly defined intervention must necessarily and sufficiently control for time variable in order to control all potential confounding variables varying over time, leading to potential outcomes and causally possible worlds. Lastly, the paper critically analyzes the differences between treat time as a variable and object-in-time as history, the object itself, as well as the implications of these differences in interpretation. From this perspective, causal inference in historical social studies is further understood as the study of causally possible histories, emphasizing the rigor of interventions and the difference between internal and external validity. And therefore this kind of studies have their special meaning different from pure science, pure descriptive history and just made-up fictions.

Keywords: Interventionism; Time effect; Potential Outcome Framework; DID; History

Catalogue

Interventionism and the "Time" in the Causal Analysis in Historical Social Studies

I. Introduction

The interventionist causal interpretation provides us with clear and concise guidance for understanding causality and judging causal relationships (Woodward 2003). The practice closely aligned with the interventionist perspective is best exemplified by J. Pearl's causal inference method (Pearl 2009). Meanwhile, econometrics, since the credibility revolution of the 1970s, has been continuously pursuing rigorous identification and exploration of causality, developing its own methods of causal inference. Econometrics has established itself as a causal science within the social sciences and demands rigor in causal identification. Donald Rubin's potential outcomes framework, proposed in 1974 (Rubin 1974) (Rubin 2005), has become the mainstream framework for causal analysis in econometrics to this day. It is evident that the causality elucidated by philosophical interventionism and the causality pursued by econometrics are fundamentally consistent. Therefore, it is enlightening to understand the methodological approach of econometrics within the framework of interventionism.

However, as pointed out in previous literature, interventionism may encounter difficulties in understanding and evaluating the Difference-in-Differences (DID) method in econometrics (Wu 2021). Specifically, we cannot defend the validity of the DID method within the framework of interventionism, and the core issue lies in controlling for time related variables varying over time.

This paper also takes this entry point and makes the analysis of time in the causal analysis in historical social studies the central focus. I will argue later that in the field of social sciences, a rigorous intervention should fully consider time effects and strictly control necessarily and sufficiently for time variable. This strict control is well reflected in the potential outcomes framework, thus, in this sense, the potential outcomes framework and the interventionist framework are equivalent.

In the following sections, I will first provide a brief overview of the basic ideas of interventionism and two causal inference methods that directly reflect interventionist thinking: structural equation modeling and instrumental variables (Virtue 1929). In the third section, I will discuss the historical character of social research and the heterogeneous time as history, as well as the challenges that time effects pose to causal analysis. I will clarify this through a description of the potential outcomes framework. In the fourth section, I will outline how potential outcomes can be inferred through randomized experiment and quasi-experimental methods (Angrist et al. 2008).

The remaining four sections will focus on how different understandings of time shape our understanding of causal analysis. In the fifth section, I will further explore the problem of bad controls (Cinelli et al. 2022) and discuss the position of time as a covariate in causal analysis. In the sixth section, I will explore the interesting implications when time itself is not only a covariate but also treated as an independent variable, even though whether time can be considered an independent variable remains debatable (Woodward, 2016). Additionally, in the seventh section, I will provide a framework that does not treat time as a variable and further conceptualize the objects of specific causal research as history itself. I will view causal inference as the study of the structure of causally possible histories. Finally, in the eighth section, I will differentiate the unique significance of causal analysis in different disciplinary perspectives by distinguishing between internal validity and external validity, also basing on the entire analysis and framework presented earlier. I will conclude that causal analysis in historical social research enables us to narrate the causality of history in a more profound and rigorous manner, distinct from natural science research, descriptive history, or purely made-up fictional narratives.

II. Interventionism, Structural Equations and Instrumental Variables

Let's start by considering the understanding of causal relationships and the requirements for causal inference in interventionism. According to interventionism, the causal relationship between variable *X* and variable *Y* is understood as follows: under specific conditions, the intervention on *X* can bring about changes in *Y*. The conditions that an intervention or manipulation *I* must satisfy for *X* can be divided into two aspects (Woodward 2003). Firstly, *I* must have determinative power over *X*, meaning that the values of *I* can set the values of *X*, and the intervention of *I* on *X* cuts off all other variables that determine *X*'s causal effects. Therefore, the value of *X* depends solely on *I*. Secondly, *I* must possess exogeneity with respect to the entire causal network, meaning that *I* only influences *Y* through its effect on *X*, independent of any variables outside the *X*-to-*Y* pathway that affect *Y*. This interventionist perspective is actually consistent with the fundamental goal pursued by econometrics since the advent of multiple regression, which is to interpret the causal effect of *X* on *Y* as the amount of change in *Y* when controlling for all other variables. The ultimate aim is to eliminate confounding causal paths and examine the directed relationship between *X* and *Y* in a clear and precise manner. The practice of causal inference typically representing the idea of interventionism are J. Pearl's work in data science and the instrument variable in traditional econometrics.

J. Pearl extended the ideas of interventionism into a mathematical model using his structural equation model or directed acyclic graph (which are equivalent). He introduced a unique operator called the "do operator" (Pearl 2009). Complex causal structures between variables can be represented as directed acyclic graphs, ultimately composed of three fundamental causal structures (V-structures): chains, forks, and colliders. In order to identify the causal structure among variables, Pearl precisely requires the intervention proposed by Woodward. This "intervention" is mathematically represented as "do", indicating the application of an intervention that sets a variable to a specific value, denoted as do(*X*=*C*). By introducing this operator, we can distinguish between "causal relationships" and "correlations" using big data to identify the causal structure of variables.

Besides the method proposed by Pearl, the instrumental variable (*IV*) method in the field of econometrics, which originated in Philip G. Wright's work "The Tariff on Animal and Vegetable Oils" in 1928 (Virtue 1929), is another statistical analysis approach that embodies the interventionist thinking. An instrumental variable *IV* is considered to infer the causal impact of *X* on *Y* if and only if it satisfies the conditions of relevance and exogeneity. The former requires that *IV* has an influence on *X*, while the latter requires that *IV* is independent of all other factors that could potentially affect *Y*, except for *X* (Stock 2015). It can be seen that the values of the instrumental variable represent a weakened version of intervention (*I*) (or, conversely, *I* represents the strongest instrumental variable, where the correlation coefficient between *I* and *X* is one). Apart from not requiring *IV* to uniquely determine *X*, all other requirements are almost the same. The underlying idea is that since the *IV* is exogenous to the system, its impact on *Y* can only occur through the pathway of *X*. Therefore, if we can simultaneously determine the causal effects of *IV* on *Y* and *IV* on *X*, we can obtain their ratio. The significance of this ratio lies in quantifying the causal impact of changes in *X*, set by exogenous intervention, on *Y*. In other words, it represents the causal effect of *X* on *Y* through an exogenous intervention.

However, there is another set of causal inference techniques in the econometrics based on the power of panel data which contains each same individual's data in different time points. They are regarded as natural experimental and quasi-experimental methods, with Difference-in-Differences (DID) being a prominent representative. However, there may be difficulties in defending the validity of these methods directly using interventionism framework, and the core issue lies in that the analysis are over-time (Wu 2021). And the specialized study of time effects is reflected in another causal analytical framework, the Potential Outcome framework.

III. Time effect and Potential Outcome Framework

Disciplines such as economics and sociology, like natural sciences, seek to understand causality. However, the difference lies in the fact that social sciences—whether it be economics, sociology, political science, or history—often deal with historical phenomena as their subjects of study, which lack the strong homogeneity found in the objects of natural sciences. While we can attribute the force of gravity as the cause of an apple falling to the ground at any time and in any situation, we cannot make the same claim about financial speculation being the cause of an economic crisis. The key point here is that the subjects of social science analysis are always situated within a contextualized time and space that lacks the homogeneity of natural sciences. A social science research subject exists within a heterogeneous historical context and specific location. The economic crisis in 19th-century Europe and the financial crisis in 21st-century America are not comparable. It is precisely because of this that causal analysis in social science often faces more challenges.[1]

Therefore, in social science, it seems impossible to achieve rigorous interventions in the reality of a research subject. This is because even seemingly exogenous interventions for individuals, such as sudden policy implementations or natural disasters, always occur within a historical time, that is, within a specific social context. Thus, our causal analysis is always possible to be influenced by other confounding factors that change over time. Let's take a classic example from institutional economics to illustrate this. Economists want to know if land ownership reform has improved grain production. For the research units, such as households or villages, they did not experience land ownership reform in period t_1 but underwent the reform in period t_2. However, it is challenging to attribute the difference in grain production between t_2 and t_1 solely to the causal effect of land ownership reform, even if we consider the implementation of the policy as an exogenous event for the households. There are many variables varying over time that may confound our causal

[1] I will discuss the significance of this historicity later.

identification, such as advances in agricultural technology and improvements in village infrastructure. Assuming that the level of agricultural technology, denoted as A, changes from A_1 in t_1 to A_2 in t_2, we cannot determine whether the difference in grain production between the two periods is due to land reform or the advancement in technology. Fundamentally, since we do not control the values of these variables that change over time, an apparently exogenous intervention, always entangled with time, cannot be considered a valid intervention because it is not well-controlled.

So, what kind of policy shock can be considered a valid intervention? In theory, it requires us to control all other variables that could potentially cause confounding. Because policy shocks are inevitably associated with variables that change over time, meaning they determine the values of these variables, as a result, the intervention no longer influences our outcome variable solely through a clean path. Furthermore, since we do not know specifically which variables that change over time may interfere with our causal identification, or in other words, we cannot exhaustively enumerate these potential confounding variables, which are likely to be uncountable, the only possible and fundamental method is to control time itself, i.e., control the variable T that indicates the time point itself when the individual is at. Only by doing so can we completely eliminate all potential interference and make the intervention strictly compliant with requirements. However, this requires one thing: to intervene and not intervene for the research subject at the same time. Using the previous example, this would require implementing land reform for a certain household or village at a specific point in time while simultaneously not implementing the reform, in order to compare the difference in grain production between the two scenarios. Therefore, this requirement introduces a counterfactual scenario. This analysis clearly embodies the framework of potential outcomes (PO) proposed by Neyman and developed by Rubin (Rubin 1974) (Rubin 2005).

The framework of potential outcomes distinguishes between intention and reality, explicitly highlighting the counterfactual meaning of causality. Ultimately, our assessment of causality focuses on the difference in the outcome variable for individuals who received the treatment compared to the potential outcome if they had not received the treatment. That is:

$$CausalEffect = \mathrm{E}[\mathrm{Y_{it}}(1) - \mathrm{Y_{it}}(0) \mid \mathrm{D_i} = 1, \mathrm{T_t} = 2]$$

D = 1 indicates the portion of individuals in the treatment group, while *T = 2* represents the time point indicating it is after the treatment or shock. And we also have actual outcomes of being exposed to the treatment *(Y(1))* and potential outcomes not being exposed to the treatment *(Y(0))*. When assessing the causal effect of the treatment *D* on *Y*, we already imply an intervention, meaning that the exogenous treatment *D* itself is an intervention, and the variation in the values of *D* constitutes an intervention on *D* itself. However, the difficulty lies in the fact that *Y(0)* represents a counterfactual situation that does not exist in reality. Therefore, we need to utilize other methods to infer this information, and the inference of this information constitutes the main theme of causal inference and econometric empirical strategies.

IV. The Inference of Potential Outcomes in the Counterfactual Situations

For far too long, the ideal randomized controlled experiment has served as the gold standard for inferring counterfactual. Its core idea involves randomly assigning study subjects to experimental and control groups, applying a specific treatment (*D = 1*) to the experimental group, and then comparing the differences in outcome variables *Y* between the experimental and control groups to determine the causal effect of the treatment on the outcomes.

$$CausalEffect = E(Y \mid D = 1, T = 2) - E(Y \mid D = 0, T = 2)$$

As can be seen, this approach aligns with the interventionist perspective. The causal effect indicated by the equation is precisely achieved through the external intervention of the experiment, where the variation in *D* from 0 to 1 corresponds to the changes in *Y*. Simultaneously, the fundamental assumption of the ideal randomized controlled experiment relies on the use of randomization to ensure comparability between the potential outcomes of the control and treatment groups, therefore the control group constitutes the inference for the potential counterfactual of treatment group at same time point. Since we compare the differences between the control and treatment groups at the same time, the time effect is also controlled.

Following the framework of the ideal randomized controlled experiment, econometricians have devised some quasi-experimental methods using observational data, including difference-in-differences, regression discontinuity, and propensity score matching et al. Here, we just primarily focus on the DID method. The idea behind DID is that even if conducting a randomized experiment in reality is challenging, if a policy (treatment) is implemented for some individuals at a specific point in time while not for others, we can classify all individuals into treatment and control groups based on whether they receive the policy treatment. But the problem here is that the assignment of individuals to the treatment group is not random. Therefore, if we directly compare the differences between the groups after the policy implementation, we cannot distinguish the policy effect from systematic differences between the two groups. However, we can perform the following operation: subtract the pre-policy differences between the groups from the post-policy differences. That is:

$$CausalEffect = (Y_{t2}^{T} - Y_{t2}^{C}) - (Y_{t1}^{T} - Y_{t1}^{C})$$

Where *T* indicates the treatment group and *C* the control group. The assumption for conducting a DID analysis is that the treatment and control groups share a common trend. This means that in the absence of the policy intervention, the differences between the two groups should remain unchanged over time. If the parallel trends assumption holds, then we have

$$\begin{aligned}&\mathrm{E}[\mathrm{Y}_{\mathrm{it}}(0) \mid \mathrm{D}_{\mathrm{i}} = 1, \mathrm{T}_{\mathrm{t}} = 2] = \mathrm{E}[\mathrm{Y}_{\mathrm{it}}(0) \mid \mathrm{D}_{\mathrm{i}} = 0, \mathrm{T}_{\mathrm{t}} = 2] + \\ &\{\mathrm{E}[\mathrm{Y}_{\mathrm{it}}(0) \mid \mathrm{D}_{\mathrm{i}} = 1, \mathrm{T}_{\mathrm{t}} = 1] - \mathrm{E}[\mathrm{Y}_{\mathrm{it}}(0) \mid \mathrm{D}_{\mathrm{i}} = 0, \mathrm{T}_{\mathrm{t}} = 1]\}\end{aligned}$$

In fact, the equation above precisely represents the synonymous formulation of the parallel trends assumption. Take the same example of the land ownership reform, the causal effect of land reform should be defined as the grain product between the real product of the households accepting the policy and the potential grain product of the same households if there is no policy conducted. And the latter is not observable but if we assume the parallel trend holds, then we can think that if the policy did not exist, the difference between the product of households who actually would be affected by it and those who would never be affected should remain constant regardless of time. So we can infer that the potential product of our treatment group after the time of policy is exactly the actual product of the control group after plus the difference between two groups before.

To conduct a DID analysis, econometrists include time fixed effects in the regression model to control for time trends and potential confounding factors.

$$Y_{it} = \alpha_i + \lambda_t + \beta(D_i \times T_t) + \varepsilon_{it}$$

This regression equation controls for individual fixed effects (α) and time fixed effects (λ). The individual fixed effects capture the initial differences between the groups, while the time effects capture the changes over time that would have occurred in the absence of the policy intervention. By conditioning on these two variables, we are comparing the effects of being exposed to the policy within the same individual and at the same time.

So, what insights does this framework provide, and how is it related to interventionism? Firstly, the causal effect expressed by this PO framework, whether achievable or not, actually meets the requirements of interventionism. By conditioning on the exposure variable D, which is independent of individual characteristics, and the time effects T, we simultaneously control for all other potential confounding factors that may interfere with causal identification. However, the notion of "potential outcomes" reveals the fact that achieving this form of intervention is impossible in the real. In other words, any causal analysis is just a inference for the counterfactual, therefore if we claim that our pursuit is causality in a rigor definition in term of interventionism, then our ontological assumption is that counterfactual possible worlds are meaningful. We just consider that the potential outcomes can not be observed but if we are inferring it, we have already regard it as something meaningful and existing. Any scholars in the field of social study will never claim that they are study something fictitious, after all, they won't accept that their serious studies of the PO in the possible world with rigor statistics methods and data which may cost millions of dollars to collect are just the same stuff as just the fictions or made-up stories. In other words, the ontological presupposition of causal analysis especially in social studies inevitably requires modal realism. I will talk more about this in the section VIII.

V. Bad Control Problem and Time as a Covariable

As we have discussed earlier, it is precisely because of the presence of time effects that we need to introduce potential outcomes as counterfactual scenarios in comparison to the actual situations. Therefore, a feasible intervention that satisfies the requirements does not exist in reality because it is impossible to simultaneously intervene and not intervene on the same object at the same moment. And we have emphasized that in order to eliminate interference from all potential variables (which may be infinite in number and cannot explicit observed) that change over time, the proper and only proper method is to control time itself, specifically by adequately and necessarily controlling the variable that indicates time, such as $T=1, 2, 3...$, representing the object being in the first period, second period, third period, and so on. This indicates that, in any case, causal analysis in social science factly treats time as a variable, at least as a crucial covariate that must be taken into account.

However, before we talk more, we may ask that: is time a good control and in which position does it lie in the causal structure. Before further exploration, it is necessary to clarify the concepts of good control and bad control, as the issue of bad control has become something that econometric research explicitly acknowledges and seeks to avoid. It suggests that we should not indiscriminately control as many variables as possible in causal identification because, in certain cases, controlling certain variables can actually lead to the failure of causal identification (Angrist et al. 2008).

Generally speaking, good control aims to eliminate bias caused by omitted variables in causal identification. A typical illustration of good control is depicted in the following graph, showing the relationship between the control variable Z and the variables of interest, X and Y:

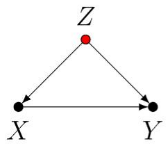

Figure 1. An Example of Good Control

That is, the fork structure starting from Z creates a correlation between the possibly originally unrelated X and Y variables, as Z is both correlated with X and a determinant of Y.

However, in the following scenario, controlling for variable Z would be a bad control, as shown in the figure:

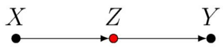

Figure 2. An Example of Bad Control

In this case, Z appears in the causal pathway from X to Y, meaning that X affects Y through its influence on Z. Z plays the role of a mediating mechanism in the causal transmission from X to Y. If we control for Z in this scenario, we essentially disrupt the causal effect of X on Y through Z, resulting in a failure to identify the causal chain from X to Y.

In fact, the problem of bad control exists not only in the chain structure illustrated in the figure but also in many similar structures. Some scholars extensively summarize and analyze the criteria for identifying good and bad controls in their work. They use directed acyclic graphs to illustrate the causal chain structures in each specific case (Cinelli et al. 2022). In general, bad control has the characteristic of controlling a variable that lies in the middle of the causal pathway from X to Y or at an extension of the causal pathway, where X influences Y through Z or X influences Y while Y also affects Z. In both of these cases, controlling for Z would lead to predetermined values of Y. Therefore, in such situations, any variation in Y caused by the intervention on X would be contaminated by the control. After all, we would have aimed to examine the effect of exogenously manipulating X on Y through the entire system of variables. However, controlling for a bad control variable itself represents another form of intervention. If this control lies on the causal chain from X to Y, the causal effect shown by the original intervention becomes confounded with the intervention represented by the control.

Furthermore, the problem lies in the impossibility of achieving a realistic fully good intervention, as we mentioned earlier, due to the lack of control over time effects. However, whether controlling for time effects is a good control is itself a question. If the time variable itself is a bad control, then ignoring the time variable would be a reasonable approach. Therefore, we are essentially asking: Where does the time variable reside in the causal chain of the intervention, and does it belong to any node in the causal chain from X to Y?

My answer is no. The value of the time variable T is not influenced by the value of variable X. It does not belong to any node in the causal chain from X to Y. If it did, we could change the value of T by altering X, but manipulating time itself is impossible. So, when we say that an exogenous intervention I changes the value of X while being naturally associated with time, how is the time variable T causally linked to our causal intervention experiment?

One possible explanation is that the value of the intervention I simultaneously determines the values of both T and X. Therefore, I does not affect Y solely through its influence on X; instead, apart from impacting X, I affects Y through the pathway of T. This violates the requirement of a good intervention, as shown in the following figure:

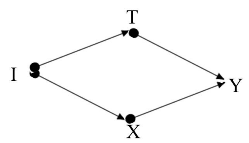

Figure 3. An Explanation of Position of Time

It is evident that controlling for T is a good control as it severs the causal pathway from I through T to Y, allowing I to only affect Y through its impact on X.

However, in this explanation, it seems that the value of the time variable is "determined" by the intervention. If we do not like this explanation since we may think the time cannot be determined, on the other hand, a symmetric explanation is that since interventions always occur within a specific time frame, the value of the time variable itself determines whether the intervention takes place. Thus, the causal diagram can also be represented as follows:

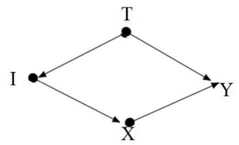

Figure 4. An Explanation of Position of Time

In this case, the value of *T* directly influences *Y*, and at the same time, *T* affects *Y* through its impact on *X*, which is determined by the value of *I*. In this scenario, controlling for *T* is also a good control as it severs the influence of *T* on both *I* and *Y*, ensuring the exogeneity of *I*. Otherwise, *I* would no longer be an exogenous intervention.

Through these two scenarios, we have demonstrated that controlling for *T* is a necessary good control, rather than a bad control. Furthermore, we can see that controlling for *T* requires that our intervention *I* no longer determines time, nor is it determined by time itself. This independence implies that the value of our intervention can be flexible at a given time.

VI. Time As a Variable of Interest

Based on the analysis above, we have come to understand that the time variable is a crucial good control variable for causal identification based on interventionism, and therefore must be taken into consideration. Now, let's shift our focus to the time variable itself and uncover its speciality and distinctiveness in relation to other variables. The idea here is, we want to know what would be given to us if time is considered as the variable of interest. Of course, according to certain criteria for variable selection, treating time as the dependent variable in causal structural analysis may not be appropriate (Woodward 2016). However, these criteria for variable selection are more based on a scientific causal perspective rather than a historical causal analysis perspective. Nevertheless, I will demonstrate that treating time as an independent variable can be explained within the framework of interventionist analysis, providing us with an interesting perspective on the differences between causal analysis in natural sciences and history and social sciences. And further more, in the next section, I will propose an alternative understanding that does not treat time as a variable.

Consider the following question: for a subject under study, if no external interventions are applied, are there any endogenous variables that determine the value of the time variable itself? Clearly, the answer is negative. The moment at which an object exists is not determined by its other attributes. On the contrary, the value of the time variable is solely determined by the time itself in which the object exists. This fact indicates that there is no causal chain pointing towards the time variable. However, precisely because of this, the changes in the time variable corresponding to the passage of time constitute a form of effective intervention. In other words, the changes in the time variable itself are exogenous and solely determine themselves while influencing other variables along their own path. This can be represented in the following figure:

$$T \bullet\!\!\longrightarrow T \bullet\!\!\longrightarrow Y$$

Figure 5. An Explanation of Time as Variable of Interest

If we consider time as a independent variable and adhere to interventionism in our causal explanations, then we should also elucidate the causal effects of the time variable on other variables, interpreting the evolution or variation of other variables over time as the causal effects of the time variable on them. To achieve this, we need to consider whether additional control of other variables is necessary when providing such explanations. However, the aforementioned discussion on good and bad controls has already indicated that in this case, any additional control is superfluous and may even be detrimental. This is because there are no causal arrows pointing towards the time variable, denoted as *T*. Therefore, any other variables are part of the causal chain originating from *T*, and we do not need to control them.

Thus, at this point, we can fully explain the evolutionary process of other variables in terms of the causal effects of the time variable on all other variables. This explanation does not require invoking hypothetical worlds as demanded by the counterfactual framework, as the objects with different time values constitute a concrete comparative context. Consequently, we arrive at a counterintuitive conclusion: The changes in any other real variable of an object cannot be explained as the causal effects of one variable, other than the time variable, on another variable since to identify such causal relationships, we must hold the time variable constant, necessitating the use of counterfactual hypothetical worlds. But conversely, all other real variable changes over time can be explained in the sense of a well-defined intervention as the causal effects of the time variable.

In fact, econometric analysis of multicollinearity has already revealed this point, demonstrating that any variable of an object can be expressed linearly as a combination of individual dummy variables and time dummy variables. That is:

$$Y_{it}^{l} = \phi_t(D_i T_t)$$

The left side of the equation represents the value of variable Y^l for individual i at time t, while on the right side, D_i and T_t represent the observation point of individual i at time t. If individual i is the object of our causal analysis, and the individual variable D_i is fixed, then the time variable T completely determines the values of all other variables. Due to the exogeneity of T, Φ can be directly interpreted as a causal effect. And the DAG of the understanding is shown as the following figure:

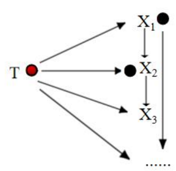

Figure 6. An Explanation of Time as Variable Pointing at Other Variables

T points at any other variables X_1, X_2, ..., and any X_i may also points at other X_j, so if we want to study the casual relationship of X_i to X_j, it is clear we should conduct intervention on X_i that is free of T.

Is it meaningful to study the relationship between T and other variables or in other words the coefficient Φ? For natural sciences and social sciences setting natural science as the role model, this coefficient may seem meaningless. However, the causal expression of time T on other variables constitutes the primary research subject for descriptive historical studies or descriptive statistics. The series of values for the coefficient Φ itself forms a description of a particular history of something. Let's continue with the example of land reform: for descriptive research, it does not need to rely on potential outcomes and counterfactual worlds; its task is solely focused on describing history. Therefore, the series of values for the coefficient Φ becomes a chronicle of local agricultural development. Accurately describing this chronicle, which involves precise observations or inferences of the coefficient Φ (e.g., archaeology), remains significant within its domain.

VII. Time Not as a Variable and Object of Causality as Time Trend Itself

The analysis above indicates that once we fully consider the time variable and adopt an interventionist interpretation, the time variable itself acquires a causal significance among all variables. However, this analysis leads our understanding of causality in an unfamiliar direction. Under this understanding, when we say that the change in variable X causes a change in variable Y, this change does not occur in time (but rather just manifests as a discrepancy between potential and actual situations). In the other side, any change occurring in time can and can only be explained as a causal effect of the time variable. This analysis contradicts our intuitive understanding of causality, which suggests that causality should involve some form of relationship between events that occur successively in time.

We have demonstrated that considering time as a variable necessitates the introduction of the counterfactual framework and causal possible worlds when interpreting general causality. Simultaneously, due to the unique nature of the time variable, we arrive at conclusions that align with interventionism but defy intuition. In order to realign with our intuitive understanding of causality while retaining the causal interpretation of interventionism, we cannot view time as just another variable of an object due to its speciality. Therefore, an alternative approach to interpretation is to shift the object of causal explanation, incorporating time into the objects of causal research, that is, make the history itself the object of study.

We can acknowledge that the time variable does indeed represent all other variables. However, we can treat this representation itself as the object of study. In other words, we can consider the functions or entities representing the changes of individual variables over time or the evolution of variables within time as the objects of causal research, that is, wee see the entity-in-time as a whole. Consequently, the causal effect of one variable on another transforms into the impact of the time trend of one variable on the time trend of another variable. Thus, we consider the following matrix as the object of study:

$$E_{w=1}=\begin{bmatrix} X_{1t_1} & \ldots\ldots & \ldots\ldots & X_{1t_t} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ X_{nt_1} & \ldots\ldots & \ldots\ldots & X_{nt_t} \end{bmatrix}=\begin{bmatrix} f_1(t_1) & f_1(t_2) & \ldots\ldots & f_1(t_t) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ f_n(t_1) & \ldots\ldots & \ldots\ldots & f_n(t_t) \end{bmatrix}=\begin{bmatrix} \phi_{11}\mathbf{1}(T=1) & \ldots\ldots & \ldots\ldots & \phi_{1t}\mathbf{1}(T=t) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \phi_{n1}\mathbf{1}(T=1) & \ldots\ldots & \ldots\ldots & \phi_{nt}\mathbf{1}(T=t) \end{bmatrix}$$

The rows of the matrix display the values of variable X_i in each period from 1 to t, representing the sequence of coefficients Φ_{ij} of the time variable $1(T=j)$, where j ranges from 1 to t. Thus, it depicts the evolutionary history of X_i. Simultaneously, the matrix composed of n row vectors represents the entire history of the object regarding the temporal trends of the n variables of interest. Describing a matrix $E_{w=1}$ constitutes the field of descriptive historical studies or descriptive statistics. However, causal research goes a step further by revealing the patterns of matrices in alternative causal possible worlds. Through causal inference, it aims to infer and uncover the structures of $E_{w=2}$, $E_{w=3}$, and so on, thereby analyzing the potential historical trajectories of all causally possible object's histories. In essence, causal analysis seeks to find and elucidate the set of possible causal histories $\{E_{w=i} \mid i=1,2,3,\ldots\}$.

At the same time, causality manifests as a certain relationship between one row and another row of the matrix (this relationship still corresponds to the structure of causal possible worlds), and in a rigor definition, how one row changed by an exogenous intervention cause the change of other rows, as represented by the following equation:

$$CausalEffect = E_{w=1} - E_{w=2} = \begin{bmatrix} 0 & \ldots\ldots & 1 & 1 \\ X_{t_1} & \ldots\ldots & \ldots\ldots & X_{t_t} \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ Y_{t_1} & \ldots\ldots & \ldots\ldots & Y_{t_t} \end{bmatrix} - \begin{bmatrix} 0 & \ldots\ldots & 0 & 0 \\ X_{t_1} & \ldots\ldots & \ldots\ldots & potential(X_{t_t}) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ Y_{t_1} & \ldots\ldots & \ldots\ldots & potential(Y_{t_t}) \end{bmatrix}$$

$$= \begin{bmatrix} 0 & \ldots\ldots & 1 & 1 \\ X_{t_1} & \ldots\ldots & \ldots\ldots & X_{t_t} - potential(X_{t_t}) \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ \ldots\ldots & \ldots\ldots & \ldots\ldots & \ldots\ldots \\ Y_{t_1} & \ldots\ldots & \ldots\ldots & Y_{t_t} - potential(Y_{t_t}) \end{bmatrix}$$

The first row represents the variable whether the intervention has been made. The causal effect is represented by the difference vector between the time trend vector of the outcome variable and the potential time trend vector. In this case, since time is no longer a variable or attribute of the object, the representation of time for other variables is no longer interpreted as the causal effect of the time variable on other variables. Instead, it represents the inherent time trend possessed by the variables or the object themselves.

Let's still take the example, suppose that the grain product of the households under the land reform policy before and after the policy are 3 and 7, the grain product of the households never receive the policy before and after is 2 and 4, then we can give the causal effect and possible history matrix of the former households. That is:

$$CausalEffect = E_{w=1} - E_{w=2} = \begin{bmatrix} 0 & 1 \\ 3 & 7 \end{bmatrix} - \begin{bmatrix} 0 & 0 \\ 3 & 4+(3-2) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 2 \end{bmatrix}$$

And in this situation, the set S is the causal possible histories.

$$S = \{E_{w=1}, E_{w=2}\} = \{\begin{bmatrix} 0 & 1 \\ 3 & 7 \end{bmatrix}, \begin{bmatrix} 0 & 0 \\ 3 & 5 \end{bmatrix}\}$$

Therefore if our causal inference is right, then the world P below is not belong to the set S:

$$E_x = \begin{bmatrix} 0 & 0 \\ 3 & 7 \end{bmatrix} \notin S = \{E_{w=1}, E_{w=2}\}$$

This interpretation does not change the fundamental ideas of interventionism and the counterfactual framework. The only difference lies in objectifying time while devariablezing it, thereby allowing our causal explanations to be based on interventionism, fully considering time effects, while maintaining our intuition about causality.

VIII. Internal Validity and External Validity: Causal Studies as Fiction, History Study and Science

After the preceding discussions and groundwork, we can now delve into what causal research means and demands in different disciplinary contexts. To achieve this, we still need to clarify two central concepts: internal validity and external validity.

The concepts of internal validity and external validity were first introduced by psychologists Campbell and Stanley in their 1963 book "*Experimental and Quasi-Experimental Designs for Research*". The former concept emphasizes the reliability of causal inferences in a certain experimental study, while the latter highlights the generalizability of causal conclusions to other contexts and populations. In fact, discussions and concerns regarding internal and external validity have extended to other fields of causal analysis. Here, we still use the example of land reform in institutional economics to illustrate the discussion.

Our research on the impact of land reform on grain production is always conducted based on specific historical contexts and data. For instance, we examine the effects of the Household Responsibility System Reform of Collective Contracting and Land Tenure, implemented in certain pilot rural areas of China in 1979, on grain production. In this context, internal validity refers to the correct revelation of the causal impact of land reform on grain production, specifically measuring the differences in grain production between these villages' actual situation and the potential situation if land reform was not implemented in 1979. However, external validity asks whether the positive effect of land reform on grain production we observed can be generalized to other scenarios, such as African countries in 1979 or China in the 1950s or African in 1960......

Clearly, scientific research, particularly in the natural sciences, pursues external validity as much as it does internal validity. A non-repeatable experiment, even if internally valid, would have limited scientific significance. When we say gravity causes apples to fall, we do not mean that only certain apples in certain periods are affected by gravity; rather, we are stating that any apple, at any time, subjected to gravity will fall. Admittedly, social sciences, inspired by the scientific approach, also aspire for their research to have good external validity. For example, they seek to establish that education can increase income or that marketization can boost economic vitality. However, an undeniable fact is that most social research have huge problem to maintain external validity. Conclusions drawn from empirical economic papers 70 years ago, apart from methodological significance, are unlikely to be applicable to today's economic and social conditions. Furthermore, achieving convincing internal validity in empirical research and causal inference in economics and other social sciences is already a significant accomplishment, let alone expecting universal external validity.

We can still agree that the ultimate aim of social science endeavors is external validity. However, due to the historical nature of society and the challenges of causal inference in this field, many studies that make extensive efforts may only achieve internal validity. Does such research, which possesses internal validity but struggles with external validity, have academic value? I believe the answer is affirmative. This socially relevant research with internal validity represents a profound and rigorous examination of history. It reveals the causal structures and potential causal trajectories of history. Even if it lacks the universality associated with science, it provides a more meticulous understanding and impartial evaluation of historical events within a specific context. Every historical narrative inherently involves causal storytelling and metaphors of causal structures. When historical research engages in certain narratives, it already demonstrates an understanding of causality in the events being narrated. Empirical social science, with its causal inference, openly acknowledges this and enables historical causal narratives to be based on solid data rather than mere experience and induction.

Based on our previous discussions and analysis, we can understand causal research within different disciplinary contexts and assumptions. Firstly, natural sciences explore causal regularities and presuppose homogeneity of time and objects. They provide non-historical narratives that state if time and objects exhibit homogeneity, then if the intervention meets the criteria, the change in variable *X* can causally lead to a change in *Y*.

Secondly, social research, which deals with historical phenomena, cannot presuppose homogeneity of time. "Time" becomes "history" in this context. However, it does presuppose comparability among different individuals, such as the parallel trends assumption between treatment and control groups (or the continuity assumption in RD design). Therefore, it reveals the causal structures of specific historical objects. From this research perspective, history is understood not only as a series of processes in this world but also as the overall structure of causally possible histories, represented by the set $S = \{E_{w=i} \mid i=1,2,3,...\}$.

Furthermore, descriptive history or descriptive statistics even abandon the assumption of comparability between groups. Therefore, they cannot make any further causal claims. They merely reveal the linear expression of time on other variables, representing the observable world's unique history, denoted as the set $U = \{E_{w=1}\}$, where $w=1$ represents the unique observable history of reality we live in.

What's more, fictional stories also describe possible worlds. For example, historical science fiction presents alternative historical trajectories based on certain historical events occurring or not occurring. However, such descriptions lack causal foundations. Thus, the set of possible histories they depict is much larger than the set of causally possible histories. We denote the set of possible histories described by fictional stories as P.

In summary, the relationships between the following sets describe the aforementioned ideas: $U \subset E \subset P$. The study of *E* is not equal to the study of pure science and is also not equal to the study of *U* or *P*. So now we reveal the meaning of causal analysis in historical social studies.

IX.Conclusion

The core argument of this paper discusses various points of attention regarding the comprehensive consideration of time variables when using interventionism to understand causal analysis in the social sciences. It emphasizes that in cases where historical time effects exist, it is impossible to directly achieve a realistic and satisfactory intervention. A proper intervention must appeal to possible causal worlds and naturally lead to a framework of potential outcomes, and the methods of randomized experiment and quasi-experiment provides the way to infer the potential outcomes.

By analyzing good controls and bad controls, the paper points out how the understanding of time variables as controlled variables can potentially introduce bias and influence causal analysis. Also, the paper examines the consequences of treating time as a variable within the interventionist framework. It concludes that time variation itself is a valid intervention and that time variables causally affect all other variables. To make transformation of such understanding which may seem counterintuitive in order to realign with our intuitive, it requires adjusting the object of causality and incorporating time into the consideration of causal object itself.

Overall, I believe interventionism remains a sound analytical framework and a good criterion for judging causality. However, considering its rigor and the historical nature of the social sciences, we must demand proper intervention to control for time effects, effectively equivalently expressed in the framework of potential outcomes. These efforts indicate that we have already treated potential outcomes and causally possible worlds as something meaningful and existing, and a strict description of causality depicts the structure of causally possible histories, encompassing the object-in-time across various causally possible worlds as a whole.

Therefore, the mission of causal science as historiography is, based on the rigor of its methods and judgments, to infer other possible worlds and potential histories from a single observed time trend in reality. In this sense, causal science as historiography constructively understands history by using causal inference to construct counterfactual causal worlds and potential histories that hold causally. This approach allows us for grasping the structure of history in a more profound and rigorous manner, distinct from natural science or pure-science oriented social science research, descriptive history, or purely made-up fictional narratives.

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