Evidence of Causation—The Contribution of Life Course Research, Part II: Causation as Generative Process

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Abstract

This is the *second part in a pair of essays* on causal inference in life course research. The first part presented the dominant models of causal inference and their limitations in life course research. This essay develops the idea of "causation as generative process," offering a quite promising model for inferences in life course research.

INTRODUCTION

In the first part of a pair of essays critical issues were raised with regard to the uses and limitations of the two dominant models of causal inferences when applied in life course research (*see* Evidence of Causation—The Contribution of Life Course Research, Part I: Dominant Models of Causal Inference and Their Limitations in Life Course Research). This essay develops a third understanding of causal inference, namely, the idea of "causation as generative process" (Cox, 1990). I will develop this model step by step and, building on my previous life course research, illustrate some of the issues with application examples.

CAUSATION AS A GENERATIVE PROCESS

According to Cox (1990, 1992), it is crucial to the claim of a causal link between X and Y that there is an elaboration of an underlying, generative process existing in time and space. A causal association between X and Y must be considered as being produced by a process and is created by some (substantive) mechanism. A major shortcoming of the approaches

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of "causation as robust dependence" and "causation as consequential manipulation" is that there is no explicit notion of an underlying generative process present in these models. Thus, "causation as generative process" seems to be a necessary expansion of these two understandings of causation (Goldthorpe, 2001).

In the following, I would like to explore what the approach of "causation as generative process" has to offer to empirically working life course researchers who wish to engage in the causal analysis of dynamic systems using event history data. Event history models are linked very naturally to an understanding of "causation as generative process" because the transition rate provides a local, time-related description of how the process evolves in time (Blossfeld, Golsch, & Rohwer, 2007, p. 33). For each point in time, these models try to predict future changes of the transition rate of the dependent process on the basis of events of independent processes in the past.

Parallel and Interdependent Processes

The opportunity to be able to study parallel or interdependent processes with transition rate models is one of the most important advances of event history analysis (Blossfeld & Rohwer, 2002; Blossfeld *et al.*, 2007; Courgeau & Lelièvre, 1992; Willekens, 1991). Parallel or interdependent processes can operate at a variety of different levels. There may be interdependent or parallel processes at the level of:

- *Different Domains of an Individual's Life*. For instance, one may ask how upward and downward moves in an individual's job career influence her/his family trajectory (Blossfeld & Huinink, 1991).
- *Individuals Interacting with Each Other*, termed *Interdependent or Linked Lives* (Elder, 1987). One might study the effect of the career of the husband on his wife's labor force participation (Blossfeld & Drobnič, 2001) or how the death or migration of the head of the household impacts other family members (Courgeau & Lelièvre, 1992).
- *Intermediate Organizations.* Such as how the changing household structure determines women's labor force participation.
- *Macro Processes*. Where the researcher may be interested, for instance, in the effect of changes in the business cycle on family formation (Blossfeld & Huinink, 1991).
- *Any Combination of the Aforementioned Processes*. For example, in the study of life course, cohort, and period effects, time-dependent covariates measured at different levels must be included simultaneously (Blossfeld, 1986; Mayer & Huinink, 1990). Such an analysis combines processes at the individual level (life course change) with two kinds of

processes at the macro level: (i) variations in structural conditions across successive (birth, marriage, etc.) cohorts and (ii) changes in particular historical conditions affecting all cohorts in the same way.

In event history analysis, time-dependent covariates are often used to include the sample path of parallel processes in transition rate models. In the literature, however, only two types of time-dependent covariates have been described as not being subject to reverse causation (Blossfeld, Hamerle, & Mayer, 1989; Courgeau & Lelièvre, 1992; Kalbfleisch & Prentice, 1980; Tuma & Hannan, 1984; Yamaguchi, 1991). The first are defined time-dependent covariates whose total time path (or functional form of change over time) is determined in advance in the same way for all subjects under study. For example, process time like age or duration in a state (e.g., duration of marriage in divorce studies) is a defined time-dependent covariate because its values are predetermined for all subjects. It is the predefined onset of the process when the individual becomes "at risk" in the event history model. Thus, by definition, the values of these time-dependent covariates cannot be affected by the dependent process under study. The second type is ancillary time-dependent covariates whose time path is the output of a stochastic process that is external to the units under study. Again, by definition, the values of these time-dependent covariates are not influenced by the dependent process itself. Examples of time-dependent covariates that are approximately external in the analysis of individual life courses are variables that reflect changes at the macro level of society (unemployment rates, occupational structure, etc.) or the population level (composition of the population in terms of age, sex, race, etc.), provided that the contribution of each unit is small and does not really affect the structure in the population (Yamaguchi, 1991).

In contrast to defined or ancillary time-dependent covariates are internal time-dependent covariates, which are often referred to as being problematic for causal analysis in event history models (Blossfeld *et al*., 1989; Courgeau & Lelièvre, 1992; Kalbfleisch & Prentice, 1980; Tuma & Hannan, 1984; Yamaguchi, 1991). An internal time-dependent covariate $YB;t$ describes a stochastic process, considered in a causal model as being the cause, that in turn is affected by another stochastic process $YA;t$, considered in the causal model as being the effect. Thus, there are direct effects in which the processes autonomously affect each other ($YB;t$ affects $YA;t$ and $YA;t$ affects $YB;t$), and there are "feedback" effects, in which these processes are affected by themselves via the respective other processes ($YB;t$ affects $YB;t$ via $YA;t$ and $YA;t$ affects $YA;t$ via $YB;t$). In other words, such processes are interdependent and form what has been called a *dynamic system* (Tuma & Hannan, 1984). Interdependence is typical at the individual level for processes in different domains of life and at the level of individuals interacting with each other (e.g., career trajectories of partners) (Blossfeld & Drobnič, 2001). For example, the empirical literature suggests that the employment trajectory of an individual is influenced by his/her marital history and marital history is dependent on the employment trajectory. In the literature, there are two central approaches to modeling these processes, what we term here as the *system approach* and the *causal approach*, with the former often used to deal with such dynamic systems.

INTERDEPENDENT PROCESSES: THE SYSTEM APPROACH

The system approach in the analysis of interdependent processes (Courgeau & Lelièvre, 1992; Tuma & Hannan, 1984) defines change in the system of interdependent processes as a new "dependent variable." Thus, instead of analyzing one of the interdependent processes with respect to its dependence on the respective others, the focus is on the modeling of a system of state variables. In other words, the interdependence between the various processes is taken into account only implicitly.

Suppose that there are J interrelated qualitative time-dependent variables (i.e., processes): $YA;t$, $YB;t$, $YC;t$, … , $YJ;t$. A new time-dependent variable (or process) Y_t, representing the system of these J variables, is then defined by associating each discrete state of the ordered J-tuple with a particular discrete state of Y_t. As shown by Tuma and Hannan (1984), as long as change in the entire system only depends on the various states of the J qualitative variables and on exogenous variables, this model is identical to modeling change in a single qualitative variable. Thus, the idea of this approach is to simply define a new joint state space, based on the various states spaces of the coupled qualitative processes, and then to proceed as in the case of a single dependent process.

Although the system approach provides insights into the behavior of the dynamic system as a whole, it has several disadvantages. First, from a causal analytical point of view, the approach presented by Courgeau and Lelièvre (1992) does not provide direct estimates of effects of coupled processes on the process under study. In other words, when using the system approach, one normally does not know to what extent one or more of other coupled processes affect the process of interest, controlling for other exogenous variables and the history of the dependent process. Since the effects can only be identified in simple models via a comparison of the constant terms of hazard rate equations, it is only possible to compare transition rates for general models without covariates (Blossfeld & Rohwer, 2002; Courgeau & Lelièvre, 1992). Second, in particular, a mixture of qualitative and quantitative processes, in which the transition rate of a qualitative process depends on the levels of one or more metric variables, turns out to be a problem in this approach. Tuma and Hannan (1984) suggest that in these situations it is not very useful. Third, this approach is also unable to handle interdependencies between coupled processes occurring in specific phases of the process (e.g., processes might be interdependent only in specific phases of the life course) or interdependencies that are dynamic over time (e.g., an interdependence might be reversed in later life phases, see Courgeau & Lelièvre, 1992), what Tuma and Hannan (1984) term *cross-state dependence*. Finally, the number of origin and destination states of the combined process Y_t, representing the system of J variables, may lead to practical problems. Even when the number of variables and their distinct values is small, the state space of the system is large. Therefore, in light of rising parameters, the event history data sets must contain a great number of events, even if only the most general models of change (i.e., models without covariates) are to be estimated. Considering these limitations, Blossfeld and Rohwer (2002) therefore suggested a different perspective in modeling dynamic systems, which they call the "causal approach."

Interdependent Processes: The Causal Approach

The underlying idea of the causal approach for analyzing interdependent processes can be outlined as follows (Blossfeld & Rohwer, 2002). Based on theoretical reasons, the researcher focuses on one of the interdependent processes and considers it as the dependent one. The future changes of this process are linked to the present state and history of the entire dynamic system as well as to other exogenous variables (Blossfeld, 1986; Blossfeld & Huinink, 1991). Thus, in this approach, the variable Y_t, representing the system of joint processes at time t, is not used as a multivariate dependent variable. Instead, the history and the present state of the system are seen as a condition for change in (any) one of its processes. The question of how to give a more precise formulation for the causal approach remains. The following ideas may be helpful.

Causes and Time-Dependent Covariates

As discussed in the first of the two essays, Holland (1986) developed the idea that causal statements imply counterfactual reasoning: If the cause had been different, there would have been another outcome, at least with a certain probability. However, the consequences of conditions that could be different from their actual state are obviously not empirically observable. This means that it is simply impossible to observe the effect that would have happened on the same unit of analysis, if it were exposed to another condition at the same time.

To find an empirical approach to examine longitudinal causal relations, Blossfeld and Rohwer (2002) suggested the examination of conditions that actually do change in time, controlling for other factors. These changes are characterized as events or transitions. More formally, an event is specified as a change in a variable, and this change must happen at a specific point in time. The most obvious empirical representation of causes is therefore in terms of quantitative or qualitative variables that can change their states over time. These kind of variables link very naturally to the concept of time-dependent covariates in event history analysis. The role of a time-dependent covariate in this approach is to indicate that a (qualitative or metric) causal factor has changed its state at a specific time and that the unit under study is exposed to another causal condition. From this point of view, it seems somewhat misleading to regard whole processes as causes. Rather, only events or changes in state space can sensibly be viewed as possible causes.

Time and Casual Effects

Consequently, we do not suggest that process $YA;t$ is a cause of process $YB;t$, but that *a change* in $YA;t$ could be a cause (or provide a new condition) of *a change* in $YB;t$. Or, more formally: $\Delta YA;t \rightarrow \Delta YB;t'$, $t < t'$, meaning that a change in variable $YA;t$ at an earlier time t is a cause of a change in variable $YB;t'$ at a later point in time, t'. Of course, it is not implied that $YA;t$ is the only cause which might affect $YB;t'$. We speak of causal conditions to stress that there might be, and normally is, a quite complex set of causes (Marini & Singer, 1988). Thus, if causal statements are studied empirically, they must intrinsically be related to time, which relates to three important aspects of "causation as generative process".

First, to speak of a change in variables necessarily implies reference to a time axis. We need at least two points in time to observe that a variable has changed its value. Of course, at least approximately, we can say that a variable has changed its value at a specific point in time. Therefore, we use the following symbols to refer to changes in the values of the time-dependent variable $\Delta YA;t$ and the state variable $\Delta YB;t'$ at time t. This leads to the important point that causal statements relate changes in two (or more) variables, if we think in terms of "causation as generative process."

Second, we must consider time ordering, time intervals, and apparent simultaneity. Time ordering assumes that cause must precede the effect in time: $t < t'$, in the formal representation given above, an assumption which is generally accepted (Eells, 1991, Chapter 5). As an implication, the "causation as generative process" approach must specify a temporal interval between the change in the variable representing a cause and the corresponding effect (Kelly & McGrath, 1988). The finite time interval may be very short or very long but can never be zero or infinity (Kelly & McGrath, 1988). In other words, in time-continuous event history models, there can never be simultaneity of the causal event and its effect event.

Some Effects Take Place Almost Instantaneously

However, some effects may occur in a time interval that requires small time units (e.g., μs) or are too small to be measured by any given methods, so that cause and effect seem to occur at the same point in time. Apparent simultaneity is often the case where temporal intervals are relatively crude such as, for example, yearly data. For example, the events "first marriage" and "first childbirth" may be interdependent, but whether these two events are observed simultaneously or successively depends on the degree of temporal refinement of the scale used in making the observations. Other effects need a long time until they start to occur. Marini and Singer (1988), for example, discuss the gap between mental causal priority and observed temporal sequences of behavior. Thus, there is a delay or lag between cause and effect (Figure 1) that must be specified in an appropriate model of "causation as generative process." Unfortunately, in most of the current social science theories and interpretations of research findings, this interval is left conceptionally unspecified.

This leads to the third point of "causation as generative process": temporal shapes of the unfolding effect. This means that there might be different shapes of how the causal effect Y_t unfolds over time (Figure 1). While the problem of time-lags is widely recognized in the social science literature, only little attention has been given to the temporal shapes of effects (Kelly & McGrath, 1988). Researchers (using experimental or observational data) often seem to either ignore or be ignorant about the fact that causal effects could be highly time dependent, which, of course, is an important aspect of "causation as generative process." For instance, in Figure 1a, there may be an immediate impact of change that is then maintained (this obviously is the idea underlying the approaches of "causation as robust dependence" and "causation of consequential manipulation" because there is no explicit notion of an underlying generative process present in these models). Or, the effect could occur with a lengthy time-lag and then become time invariant (Figure 1b). The effect could start almost immediately and then gradually increase (Figure 1c), or there may be an almost all-at-once increase that reaches a maximum after some time and then decreases (Figure 1d). Finally, there could exist a cyclical effect pattern over time (Figure 1e). Thus, based on these examples, it is clear that we cannot rely on the assumption of eternal, time-less laws but have to recognize that the causal effect may change during the development of

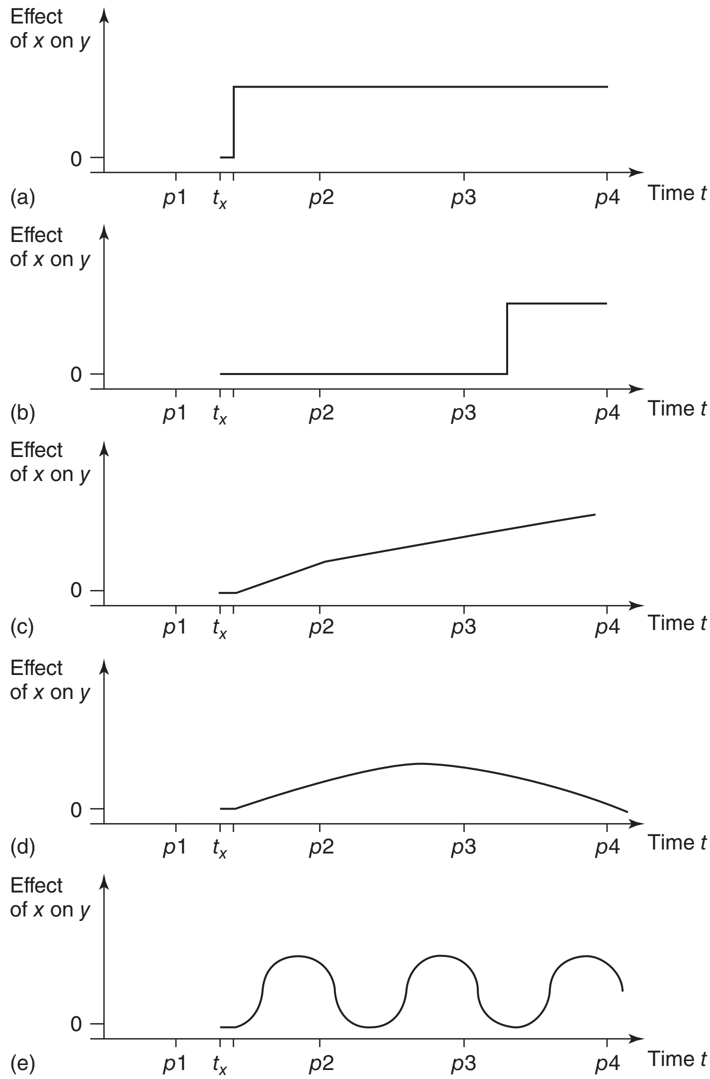

Figure 1 Hypothetical temporal lags and effect shapes. (a) Effect occurs almost immediately and is then time constant. (b) Effect occurs with a certain time-lag and is then time-constant. (c) Effect occurs almost immediately and then increases continuously. (d) Effect occurs almost immediately, rises monotonically at first, then declines, and finally disappears. (e) Effect occurs almost immediately and oscillates over time.

social processes. Since the approaches of "causation as robust dependence" and "causation of consequential manipulation" do not have an explicit idea of an underlying generative process in time and space, it might happen that the timing of observations in observational or experimental studies (see, e.g., the arbitrary chosen observation times p2, p3, or p4 in Figure 1) lead to completely different empirical evidences for causal relationships.

The Principle of Conditional Independence

We consider here only interdependent processes that are not just an expression of another underlying process so that it is meaningful to assess the properties of the two processes without regarding the underlying one (control variable approach). This means, for instance, that what happens next to $YA;t$ should not be directly related to what happens to $YB;t$, at the same point in time, and vice versa. This condition, which we call *local autonomy* (Pötter & Blossfeld, 2001), can be formulated in terms of the uncorrelatedness of the prediction errors of both processes, $YA;t$ and $YB;t$, and excludes stochastic processes that are functionally related.

Combining the ideas mentioned above, a causal view of parallel and interdependent processes becomes easy, at least in principle. Given two parallel processes, $YA;t$ and $YB;t$, a change in $YA;t$ at any (specific) point in time t' may depend on the history of both processes up to but not including t'. Or stated in another way: what happens with $YA;t$ at any point in time t' is conditionally independent of what happens with $YB;t$ at t', conditional on the history of the joint process $Y_t = (YA;t, YB;t)$ up to, but not including, t'. Of course, the same reasoning can be applied if one focuses on $YA;t$ instead of $YB;t$ as the "dependent variable." This is the principle of conditional independence for parallel and interdependent processes.

The same idea can be developed more formally. Beginning with a transition rate model for the joint process, $Y_t = (YA;t, YB;t)$ and assuming the principle of conditional independence, the likelihood for this model can be factorized into a product of the likelihoods for two separate models: a transition rate model for $YA;t$ which is dependent on $YB;t$ as a time-dependent covariate, and a transition rate model for $YB;t$ which is dependent on $YA;t$ as a time-dependent covariate. Estimating the effects of time-dependent (qualitative and metric) processes on the transition rate can be easily achieved by applying the method of episode splitting (Blossfeld & Rohwer, 2002; Blossfeld *et al.*, 1989).

This result has important implications for the modeling of event histories. From a technical point of view, there is no need to distinguish between defined, ancillary, and internal covariates because all of these time-dependent covariate types can be treated equally in the estimation procedure. A distinction between defined and ancillary covariates on the one hand and internal covariates on the other is, however, sensible from a theoretical perspective because only in the case of internal covariates does it make sense to examine whether parallel processes are independent, whether one of the parallel processes is endogenous and the other ones are exogenous, or whether parallel processes form an interdependent system (i.e., they are all endogenous).

Joint Determination of Interdependent Processes

The principle of conditional independence implies that the prediction errors (or residuals) of the correlated processes *YA;t* and *YB;t* are uncorrelated, given the history of each process up *t* and the covariates. In practice, however, there may be time-invariant unmeasured characteristics that affect both *YA;t* and *YB;t* leading to a residual correlation between the processes. In that case, we say that the two processes are jointly determined by some unmeasured influences. Suppose, for example, that we are interested in studying the relationships between employment transitions and fertility among women. We might expect that a woman's chance of making an employment transition at *t* would depend on her childbearing history up to *t* (e.g., the presence and age of children) and that her decision on whether to have a(nother) child at *t* would depend on her employment history up to *t*. There may be unobserved individual characteristics, fixed over time, that affect the chances of both an employment and a fertility transition at *t*. For example, more "career-minded" women may delay childbearing and have fewer children than less "career-minded" women. In the absence of suitable measures of "career-mindedness," this variable would be absorbed into the residual terms of both processes, leading to a cross-process residual correlation. If the residual correlation cannot be explained by time-dependent and time-invariant covariates, the two processes should be modeled simultaneously, and multiprocess models (Lillard & Waite, 1993) have been developed for this purpose.

Unobserved Heterogeneity

Since observational data are often highly selective, life course researchers attempt to identify and then to represent all these important variables in their estimation models. Unfortunately, we are not always able to include all important factors in our analytical models. One reason is the limitation of available longitudinal data sets. Furthermore, we often do not know what is important. So what are the consequences of this situation? Basically, there are two aspects to be taken into consideration. The first one is well known from "causation as robust dependence." Because our covariates are often correlated, the parameter estimates depend on the specific set of covariates included in the model. Every change in this set is likely to change the parameter estimates of the variables already included in previous models. Thus, as in the "causation as robust dependence" approach, the way to proceed is to estimate a series of models with different specifications and then to check whether the estimation results are stable or not. Since our theoretical models are often quite weak (Sørensen, 2009), this procedure can provide some insights into what may be called *context sensitivity* of causal effects in life course research.

Second, changing the set of covariates in a transition rate model will very often also lead to changes in the time-dependent shape of the transition rate. A similar effect occurs in traditional regression models: Depending on the set of covariates, the empirical distribution of the residuals changes. However, as opposed to regression models, where the residuals are normally only used for checking model assumptions, in transition rate models, the residuals become the focus of modeling. In fact, if transition rate models are reformulated as regression models, the transition rate becomes a description of the residuals, and any change in the distribution of the residuals becomes a change in the time-dependent shape of the transition rate (Blossfeld *et al*., 2007). Consequently, the empirical insight that a transition rate model provides for the time-dependent shape of the transition rate more or less depends on the set of covariates used to estimate the model. So, the question is whether a transition rate model can provide at least some reliable insights into a time-dependent transition rate.

The transition rate that is estimated for a population can be the result (a mixture) of quite different transition rates in the subpopulations. What are the consequences? First, this result means that one can "explain" an observed transition rate at the population level as the result of different transition rates in subpopulations. Of course, this will only be a sensible strategy if we are able to identify important subpopulations. To follow this strategy, one obviously needs observable characteristics to partition a population into subpopulations. Although there might be unobserved heterogeneity (and we can usually be sure that we were not able to include all important variables), just to make more or less arbitrary distributional assumptions about unobserved heterogeneity will not lead to better models. On the contrary, the estimation results will be more dependent on assumptions than would be the case otherwise (Lieberson, 1985). Therefore, I would like to stress the view that the most important basis for any progress in model building is sufficient and appropriate data.

There remains the problem of how to interpret a time-dependent transition rate from a causal view. The question is: Can time be considered as a proxy for an unmeasured variable producing a time-dependent rate, or is it simply an expression of unobserved heterogeneity, which does not allow for any substantive interpretation? There have been several proposals to deal with unobserved heterogeneity in transition rate models, which cannot be developed here (Blossfeld *et al*., 2007; Tuma & Hannan, 1984). Furthermore, fixed-effects methods have become increasingly popular in the analysis of event history data in which repeated events are observed for each individual. They make it possible to control for all stable characteristics of the individual, even if those characteristics cannot be measured (Allison, 1996; Steele, 2003; Yamaguchi, 1986; Zhang & Steele, 2004). All these models broadly enrich the spectrum of models and can be quite helpful in separating robust estimation results (i.e., estimation results that are to a large degree independent of a specific model specification) and "spurious" results, which might be defined by the fact that they heavily depend on a specific type of model.

CONCLUSIONS

The causation as generative process approach has the comparative advantage that it focuses our thoughtful consideration on the theoretical and statistical elaboration of an underlying, generative causal process, existing in time and space, including also actors who make decisions within changing social contexts. One major shortcoming of current life course research is that our applications are only based on observed life course behavior. If we only record the time order of behavioral events without taking into account the timing of decisions, this could lead to a reversal of the order of (causal and effect) events. Thus, life course research, which aims to model causation as a generative process, has to develop prospective designs that collect actor's objectives and decisions in addition to information on behavioral events.

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