

Counterfactual Graphical Models for Longitudinal Mediation Analysis with Unobserved  
Confounding

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## Abstract

Questions concerning mediated causal effects are of great interest in psychology, cognitive science, medicine, social science, public health, and many other disciplines. For instance, about 60% of recent papers published in leading journals in social psychology contain at least one mediation test (Rucker, Preacher, Tormala, & Petty, 2011). Standard parametric approaches to mediation analysis employ regression models, and either the “difference method” (Judd & Kenny, 1981), more common in epidemiology, or the “product method” (Baron & Kenny, 1986), more common in the social sciences. In this paper we first discuss a known, but perhaps often unappreciated fact: that these parametric approaches are a special case of a general counterfactual framework for reasoning about causality first described by Neyman (1923), and Rubin (1974), and linked to causal graphical models by J. Robins (1986), and Pearl (2000). We then show a number of advantages of this framework. First, it makes the strong assumptions underlying mediation analysis explicit. Second, it avoids a number of problems present in the product and difference methods, such as biased estimates of effects in certain cases. Finally, we show the generality of this framework by proving a novel result which allows mediation analysis to be applied to longitudinal settings with unobserved confounders.

*Keywords:* Causal inference, counterfactuals, mediation analysis, longitudinal studies, direct and indirect effects, path-specific effects, graphical models

## Counterfactual Graphical Models for Longitudinal Mediation Analysis with Unobserved Confounding

The aim of empirical research in many disciplines is establishing the presence of effects by means of either randomized trials, or observational studies if randomization is not possible. For example, a celebrated success of empirical research in epidemiology is the discovery of a causal connection between smoking and lung cancer (Doll & Hill, 1950).

Once the presence of an effect is established, the precise mechanism of the effect becomes a topic of interest as well. A particularly popular type of mechanism analysis concerns questions of *mediation*, that is to what extent a given effect of one variable on another is direct, and to what extent is it mediated by a third variable. For example, it is known that genetic variants on chromosome 15q25.1 increase both smoking behavior, and the risk of lung cancer (VanderWeele et al., 2012). A public health mediation question of interest here is whether these variants increase lung cancer risk by directly making the patients susceptible in some way, or whether the risk increase is driven by the increase in smoking.

In psychology, interest in mediation analysis began partly due to the influential S-O-R model (Woodworth, 1928), where causal relationships between stimulus and response are mediated by mechanisms internal to an organism, and partly due to the multi-stage causality present in many theories in psychology (such as attitude causing intentions, which in turn cause behavior in social psychology). Today, mediation questions are ubiquitous in psychology. Mediation analysis is used to explicate theories of persuasion (Tormala, Briñol, & Petty, 2007), ease of retrieval (Schwarz et al., 1991), (Tormala, Falces, Briñol, & Petty, 2007), cognitive priming (Eagly & Chaiken, 1993), developmental psychology (Conger et al., 1990), and explore many other areas. In fact, about 60% of recent papers published in leading journals in social psychology contain at least one mediation test (Rucker et al., 2011).

A standard approach for mediation analysis involves the use of (linear) structural

equation models, and the so called “difference method” (Judd & Kenny, 1981), and “product method” (Baron & Kenny, 1986). The first method, more common in epidemiology, considers an outcome model both with and without the mediator and takes the difference in the coefficients for the exposure as the measure of the indirect effect. The second method, more common in the social sciences, takes as a measure of the indirect effect the product of (i) the coefficient for the exposure in the model for the mediator and (ii) the coefficient for the mediator in the model for the outcome. These methods suffer from a number of problems. First, interpreting linear regression parameters as causal parameters is not appropriate when non-linearities or interactions are present in the underlying causal mechanism, and can lead to bias (D. MacKinnon & Dwyer, 1993), (Kaufman, MacLehose, & Kaufman, 2004). Second, it is not always the case that a regression parameter is interpretable as a causal parameter, even if the parametric structural assumptions of linearity and no interaction hold (J. Robins, 1986). Finally, these methods are not directly applicable to longitudinal settings (where multiple treatments happen over time) and assume no unmeasured confounding.

The aim of this paper is twofold. First, we describe recent developments in the causal inference literature which address the limitations of the approaches based on linear structural equations (Judd & Kenny, 1981), (Baron & Kenny, 1986). In particular, we show that the linear structural equation approach to mediation analysis is a special case of a more general framework based on potential outcome counterfactuals, developed by Neyman (1923) and Rubin (1974), and extended and linked to non-parametric structural equations and graphical models by J. Robins (1986), and Pearl (2000). We show how this more general framework avoids the difficulties of the linear structural equations approach, and has additional advantages in making strong causal assumptions necessary for mediation analysis explicit. Second, we use the counterfactual framework to develop novel results which extend existing mediation analysis techniques to longitudinal settings with some degree of unmeasured confounding.

Our argument is that to handle increasingly complex mediation questions in psychology and cognitive science, scientists must necessarily move beyond the linear structural equation approach, and embrace more general frameworks for mediation analysis. The linear structural equation approach is simply not applicable in complex data analysis settings, and careless generalizations of this approach will lead to biased conclusions.

The paper is organized as follows. In section 2, we describe mediation analysis based on linear structural equations in more detail, and describe situations where the use of this method leads to problems. In section 3, we introduce a causal inference framework based on potential outcome counterfactuals and graphical models, and show how this framework generalizes the linear structural equation framework, and correctly handles the problems described in section 2. In section 4, we describe two motivating examples involving three complications: unobserved confounding, longitudinal treatments, and path-specific effects, and show how the counterfactual framework is able to handle these complications with ease. Section 5 contains the discussion and our conclusions. The general theory necessary to solve examples of the type shown in section 4 is contained in the supplementary materials.

### Mediation Analysis Using Linear Structural Equations Models

The standard mediation setting contains three variables, the cause or treatment variable, which we will denote by  $A$ , the effect or outcome variable, which we will denote by  $Y$ , and the mediator variable, which we will denote by  $M$ . The treatment  $A$  is assumed to have an effect on both mediator  $M$  and outcome  $Y$ , while the mediator  $M$  has an effect on the outcome  $Y$ . A typical goal of causal inference is establishing the presence of the *total effect*, or just the causal effect, of  $A$  on  $Y$ . The goal of mediation analysis is to decompose the total effect into the *direct effect* of the treatment  $A$  on the outcome  $Y$ , with the *indirect* or *mediated effect* of the treatment  $A$  on the outcome  $Y$  through the mediator  $M$ .

Causal relationships in mediation analysis are often displayed by means of *causal diagrams*. A causal diagram is a directed graph where nodes represent variables of interest,

in our case the treatment  $A$ , the mediator  $M$ , and the outcome  $Y$ , and directed arrows represent, loosely, “direct causation.” The mediation setting is typically represented by means of a causal diagram shown in Fig. 1 (a).

The situation represented by this picture contains a treatment that is either randomly assigned by the experimenter, or randomized naturally. For example, genetic variants on chromosome 15q25.1 which are linked with smoking behavior and lung cancer (VanderWeele et al., 2012) can generally (modulo possibly some confounding due to population genetics) be assumed to be naturally randomized. In psychology, a randomized treatment is often a treatment or prevention program, such as drug prevention.

Another common situation assumes that the treatment is not randomized, but all causes of the treatment are observed. One example of this situation is shown in Fig. 1 (b), which contains a single observed confounder  $C$ . Extending methods described in this section to this case is straightforward.

Given the causal structure shown in Fig. 1, the statistical analysis proceeds as follows. First, the causal relationships between treatment, mediator and outcome are assumed to take the form of a causal regression model, or linear structural equation:

$$Y = \alpha_0 + \alpha_1 \cdot A + \alpha_2 \cdot M + \epsilon_y \quad (1)$$

$$M = \beta_0 + \beta_1 \cdot A + \epsilon_m \quad (2)$$

where  $\alpha_0, \beta_0$  are intercepts,  $\alpha_1, \alpha_2, \beta_1$  are regression coefficients,  $\epsilon_y, \epsilon_m$  are mean zero noise terms, and the covariance of the noise terms for  $Y$  and  $M$  is assumed to equal 0:

$$\text{Cov}(\epsilon_y, \epsilon_m) = 0.$$

For the “difference method”, a regression model for the outcome where the mediator is omitted is also included in the analysis:

$$Y = \gamma_0 + \gamma_1 \cdot A + \epsilon'_y \quad (3)$$

For binary outcomes, it is straightforward to specify alternative regression models, such as logistic regression models. However, as we shall soon see, even this simple modeling change requires care.

The total effect under these models is taken to equal to  $(\alpha_1 + \alpha_2 \cdot \beta_1)$ , and can be derived using Sewall Wright's rules of path analysis (Wright, 1921). The direct effect under these models is taken to equal to the regression coefficient  $\alpha_1$  of the treatment in the outcome model (equation 1). The "product method" (Baron & Kenny, 1986), and the "difference method" (Judd & Kenny, 1981) both aim to express the indirect effect of  $A$  on  $Y$  in terms of statistical parameters of these regression models. The product method takes as a measure of the indirect effect the product of (i) the coefficient for the treatment in the model for the mediator ( $\beta_1$  in equation 2), and (ii) the coefficient for the mediator in the model for the outcome ( $\alpha_2$  in equation 1). The difference method considers the outcome model with (equation 1) and without the mediator (equation 3), and takes the difference in the coefficients for the treatment in these two models ( $\alpha_1$  and  $\gamma_1$ ) as the measure of the indirect effect. If the outcome and mediator are continuous and there are no interaction terms in the regression model for the outcome, the two methods produce identical answers for the indirect effect (D. P. MacKinnon, Warsi, & Dwyer, 1995).

An important property in mediation analysis is the decomposition property:

$$\text{Total effect} = \text{Direct Effect} + \text{Indirect Effect} \quad (4)$$

This property allows the investigator to quantify how much of an existing total effect of treatment on outcome is due to the direct influence on the outcome, and how much is due to the influenced mediated by a third variable. Note that it is possible for the total effect to be weak or non-existent, and direct and indirect effects to both be strong. This situation can occur due to cancellation of effects. For instance, there may be a strong positive direct effect, but an equally strong negative mediated effect, resulting in a weak total effect. The

decomposition property holds for linear structural equation models with continuous outcomes, for indirect effects defined by both the product and difference methods.

The advantage of the product and difference methods is their simplicity – they rely on standard software for fitting regression models. The disadvantage is their lack of flexibility. In order to work, these methods require assumptions of linearity, no unmeasured confounding between mediator and outcome, and continuous outcomes. As we will see in the next section, careless application of these methods in settings where one or more of these assumptions are violated will result in bias, and counterintuitive conclusions.

### **Problems with the Product and Difference Methods**

With binary outcomes (D. MacKinnon & Dwyer, 1993), or interaction terms in the outcome (VanderWeele & Vansteelandt, 2009), the two methods above no longer agree on the estimate of the indirect effect. In addition, there is evidence that in the case of non-linearities or interactions in the outcome model, neither method gives a satisfactory measure of the indirect effect (VanderWeele & Vansteelandt, 2009).

Furthermore, even for the case of continuous outcome models with no interaction terms, certain underlying causal structures can make it impossible to associate any standard regression parameter with direct and indirect effects. Consider the causal diagram shown in Fig. 2. This diagram represents a situation where we have a randomized treatment  $A$  and the outcome  $Y$ , but instead of a single mediator, we have two mediating variables  $L$  and  $M$ . Furthermore, we have reasons to believe there is a strong source of unobserved confounding (which we call  $U$ ) between one of the mediators  $L$  and the outcome  $Y$ . For instance, if  $A$  represents a primary prevention program (say drug prevention), and  $M$  represents a secondary prevention program (say a program designed to increase screening rates for serious illness), then  $L$  might represent some observable intermediate outcome of people enrolled in the primary program, perhaps linked to eventual outcome  $Y$  via some unobserved measure of conscientiousness or health



consciousness. Assume for the moment that all variables are continuous, and we can model their relationships using linear regression models:

$$Y = \alpha_0 + \alpha_1 \cdot A + \alpha_2 \cdot M + \alpha_3 \cdot L + \epsilon_y \quad (5)$$

$$M = \beta_0 + \beta_1 \cdot A + \beta_2 \cdot L + \epsilon_m \quad (6)$$

$$L = \delta_0 + \delta_1 \cdot A + \epsilon_l \quad (7)$$

We model the presence of the  $U$  confounder by allowing that  $Cov(\epsilon_y, \epsilon_l) \neq 0$ , while assuming  $Cov(\epsilon_y, \epsilon_m) = 0, Cov(\epsilon_m, \epsilon_l) = 0$ . We still assume mean zero error terms. Note that though the directed arrows in the graph in Fig. 2 are causal, not all of the regression coefficients in above equations have causal interpretations. In particular,  $\alpha_1$ , and  $\alpha_3$  do not have causal interpretations, while  $\alpha_2$  does (as the direct effect of  $M$  on  $Y$ ).

We are interested in quantifying the direct effect of  $A$  on  $Y$ , and the effect of  $A$  on  $Y$  mediated by  $M$ . The question is, what (combination of) parameters of the regression models we specified correspond to these effects. A naive approach would be to consider a regression model in equation (5), and take the regression parameter  $\alpha_1$  associated with  $A$  as the measure of the direct effect. This approach is wrong, and will lead to bias. The difficulty with this example is that a regression coefficient of a particular independent variable  $X$  represents the extent to which the dependent variable  $Y$  depends on  $X$  given that we condition on all other independent variables. In our example, the regression coefficient for  $A$  represents dependence of  $Y$  on  $A$  given that we conditioned on  $L$  and  $M$  (we do not condition on  $U$  since  $U$  is not observed). Unfortunately, conditioning on  $L$  makes  $U$  and  $A$  dependent due to the phenomenon known as “explaining away.”

Consider a toy causal system: a light in a hallway is wired to two toggle light switches on the opposite ends of the hallway. If either of the light switches is flipped, the

light turns on. Two people, Alice and Uma, stand at opposite ends of the hallway, each near a switch. Alice sees the light turn on, and knows she did not toggle the switch. She can then conclude (“explain away” the light turning on) that Uma toggled the switch. In our graph, Alice’s switch is  $A$ , Uma’s switch is  $U$ , and the light itself is  $L$ . Conditional on  $L$ , we can learn information about  $U$  if we know something about  $A$ . In other words, conditional on  $L$ ,  $A$  and  $U$  become dependent. Of course,  $U$  is a direct cause of  $Y$ . This means that some of the variation of  $Y$  due to  $A$ , represented by the regression coefficient of  $A$  in equation (5) is actually due to the “explaining away” effect correlating  $A$  and  $U$ , which in turn correlates  $A$  and  $Y$  in a non-causal way. In particular, even if there is no direct effect of  $A$  on  $Y$ , the regression coefficient of  $A$  will not vanish in most models.

In fact, it can be shown that in examples of this sort, the presence of unobserved confounders, coupled with the “explaining away” effect will prevent us from associating any standard function of regression coefficients with causal parameters in a way that avoids bias. Furthermore, even if the correct expression for the direct effect is used (as derived in a subsequent section, and shown in equation 17), using standard statistical models in that expression can result in cases where the absence of direct effect is not possible given the model. In particular, if we use a linear regression model with no interaction terms for a continuous outcome  $Y$ , and a logistic regression model with no interaction terms for a binary mediator  $L$ , then the absence of direct effect is impossible given those models in the sense that the expression in (17) will *never* equal 0. This difficulty, which applies not only to regression models but to almost any standard parametric statistical model associated with causal diagrams such as Fig. 2, is known as the “null paradox” (J. M. Robins & Wasserman, 1997).

Finally, even if assumptions of linearity, no interaction, and no unobserved confounding hold, *no* function of the observed data will equal to either direct or indirect effect in general. In order for this equality to hold, it must be the case that error terms of the outcome and mediator model remain uncorrelated for any possible set of assignments of

independent variables to the model. This assumption is also necessary in order to derive mediation effects from double randomization studies (Word, Zanna, & Cooper, 1974) (Imai, Tingley, & Yamamoto, 2013). The assumption cannot easily be tested, and can be viewed as ruling out unobserved confounding between variables in different counterfactual situations. It will be described in more detail later. Deriving analogues of this crucial assumption in more complex settings, for the purposes of sensitivity analysis, can be challenging.

A way out of many of these difficulties involves generalizing from linear regression models to a general non-parametric framework based on potential outcome counterfactuals. This framework will be described in great detail in the next section. We will show how this framework gives a more general representation of direct and indirect effects that will happen to coincide with the results of the product and difference methods in the special case of linear regression models. We will also show how assumptions underlying mediation analysis can be clearly explained as independence statements among random counterfactual variables, displayed graphically by a causal diagram. We will discuss possible solutions to the null paradox that can be derived in this framework. Finally, the flexibility of the framework will allow us to pose more complex questions of mediation, such as “what is the effect of  $A$  on  $Y$  along the path  $A \rightarrow M \rightarrow Y$  in the graph in Fig. 2?” and answer these questions in complex settings involving multiple time-dependent treatments, and unobserved confounding.

### Potential Outcomes and Mediation

Typically, the notion of causal effect of treatment  $A$  on outcome  $Y$  refers to change in the outcome between the control group and the test group in a randomized control trial. A general representation of causality, divorced from a particular statistical model such as a regression model must capture this notion in some way. An idealized, mathematical representation of a randomized control trial captures the notion of controlling a variable by

means of an *intervention*. An intervention on  $A$ , denoted by  $\text{do}(a)$  by Pearl (2000), refers to an operation that fixes the value of  $A$  to  $a$  regardless of the natural variability of  $A$ . An intervention represents an assignment of treatment to the test group, or a decision to set  $A$  to  $a$ . The variation in the outcome after an intervention is captured by means of an *interventional distribution*, sometimes denoted by  $p(y|\text{do}(a))$ .

Crucially, intervening to force  $A$  to value  $a$  is not the same as observing that  $A$  attains the value  $a$ , that is:  $p(y|a) \neq p(y|\text{do}(a))$ . As an example: “only Olympic sprinters that can run quickly win gold medals (observation), therefore I should wear a gold medal to run faster (intervention)”<sup>1</sup>. This is the essence of the common refrain that correlation (statistical dependence) does not imply causation.

A potential outcome counterfactual refers to the value of a random variable under a particular intervention  $\text{do}(a)$  for a particular unit (individual)  $u$ , and is denoted by  $Y(a, u)$ . If we wish to average over units in a particular study, we would obtain a random variable  $Y(a)$ , representing variation in the outcome after the intervention  $\text{do}(a)$  was performed. In other words,  $Y(a)$  is a random variable with a distribution  $p(y|\text{do}(a))$ .

Assume for the moment the simplest mediation setting with variables  $A$ ,  $M$ ,  $Y$ , shown in Fig. 1, and assume the causal relationships between  $A$ ,  $M$ , and  $Y$  can be captured by structural equations shown in equations (1), and (2). The intervention  $\text{do}(a)$  in these systems of equations is represented by replacing the random variable  $A$  in each equation with the intervened value  $a$ . Alternatively, if we augment equations (1) and (2) with another equation for  $A$  itself, such as:

$$A = \epsilon_a \tag{8}$$

then the intervention on  $A$  can be represented by replacing equation (8) by another equation that sets  $A$  to a constant  $a$ . If interventions are represented in this way, then the

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<sup>1</sup>We want to thank the lesswrong.com community for this example.

total effect of  $A$  on  $Y$ , equal to  $(\alpha_1 + \alpha_2 \cdot \beta_1)$ , can be viewed as

$$\text{Total Effect} = E[Y(a = 1) - Y(a = 0)] = E[Y(1)] - E[Y(0)] \quad (9)$$

In other words, the total effect is the expected difference of outcomes under two hypothetical interventions. In one intervention,  $A$  is set to 1, and in another  $A$  is set to 0. Note that this definition is non-parametric in that it does not rely on the model for  $Y$  being a linear regression model. In fact, the definition remains sensible even if we replace the models for  $Y$  and  $M$  by arbitrary functions:

$$Y = f_y(M, A, \epsilon_y) \quad (10)$$

$$M = f_m(A, \epsilon_m) \quad (11)$$

$$A = f_a(\epsilon_a) \quad (12)$$

These models can be viewed as (non-parametric) structural equations, and are discussed in great detail by Pearl (2000). The key idea is that we assume the causal relationship between a variable, say  $Y$ , and its direct causes is by means of some unrestricted causal mechanism function  $f_y$ . These structural models can still be modeled by means of causal diagrams, but are no longer bound by linearity, lack of interactions, or other parametric assumptions.

### Direct and Indirect Effects As Potential Outcomes

Representing direct and indirect effects using potential outcomes is slightly more involved. In the case of total effects, the intuition was that  $A$  being set to 0 represents “no treatment,” while  $A$  being set to 1 represents “treatment,” and we want to subtract off the expected outcome under no treatment (the baseline effect) from the expected outcome under treatment. In the case of direct effects we still would like to subtract off the baseline,

but from the effect that considers only the direct influence of  $A$  on  $Y$  in some way.

One approach that preserves the attractive property of decomposition of total effects into direct and indirect effects proceeds as follows. We consider a two stage potential outcome. In the first stage, we consider for a particular unit  $u$ , the value the mediator would take under baseline treatment  $a = 0$ :  $M(0, u)$ . We then consider the outcome value of that same unit if the treatment was set to 1, and mediator was set to  $M(0, u)$ :  $Y(1, M(0, u), u)$ . In other words, the direct influence of  $A$  on  $Y$  for this unit is quantified by the value of the outcome in a hypothetical situation where we give the individual the treatment, but also force the mediator variable to behave as if we did not give the individual treatment. In graphical terms, this is the outcome value if active treatment  $a = 1$  is only active along the direct path  $A \rightarrow Y$ , but not active along the path  $A \rightarrow M \rightarrow Y$ , since we force  $M$  to behave as if treatment was set to 0 for the purposes of that path. If we average over units, we get a nested potential outcome random variable:  $Y(1, M(0))$ . We define the direct effect as the difference in expectation between this random variable, and the baseline outcome:

$$\text{Direct Effect} = E[Y(1, M(0))] - E[Y(0)] \quad (13)$$

Note that  $E[Y(0)] = E[Y(0, M(0))]$ . The indirect effect is defined similarly, expect we now subtract off the direct influence of  $A$  on  $Y$  from the total effect of setting  $A$  to 1:

$$\text{Indirect Effect} = E[Y(1)] - E[Y(1, M(0))] \quad (14)$$

It is not difficult to show that these definition reduce to definitions in terms of regression coefficients given in the previous sections in the special case where  $Y$  is continuous,  $f_y$ , and  $f_m$  are linear functions with no interactions, and all  $\epsilon$  noise terms are Gaussian. However, these effect definitions, known as *natural* (Pearl, 2001) or *pure* (J. M. Robins & Greenland, 1992) are the only sensible definitions of direct and indirect effects currently known that

simultaneously maintain the decomposition property (4), and apply to arbitrary functions in structural equations (10), (11), and (12).

### Assumptions Underlying Mediation Analysis

Defining the influence of  $A$  on  $Y$  for a particular unit  $u$  as  $Y(1, M(0, u), u)$  involved a seemingly impossible hypothetical situation, where the treatment given to  $u$  was 0 for the purposes of the mediator  $M$ , and 1 for the purposes of the outcome  $Y$ . In other words, this situation is a function of multiple, conflicting hypothetical worlds. In general, no experimental design is capable of representing this situation unless it is possible to bring the unit by some means to the pre-intervention state (perhaps by means of a “washout period,” or some other method). In order to express direct and indirect effects defined in the previous section as functions of the observed data, such as regression coefficients, we must be willing to make certain assumptions that make our impossible hypothetical situation amenable to statistical analysis.

A typical assumption that makes our situation tractable is expressed in terms of conditional independence statements on potential outcome counterfactuals:

$$Y(1, m) \perp\!\!\!\perp M(0) \tag{15}$$

where  $(X \perp\!\!\!\perp Y)$  stands for “ $X$  is marginally independent of  $Y$ ”, and  $(X \perp\!\!\!\perp Y|Z)$  stands for “ $X$  is conditionally independent of  $Y$  given  $Z$ .”

This assumption states that if we happen to have some information on how the mediator varies after treatment is set to 0, this does not give us any information about how the outcome varies if we set the treatment to 1 and the mediator to (arbitrary)  $m$ . Note that this assumption immediately follows if we assume independent error terms in a non-parametric structural equation model defined by (10), (11), (12). This assumption

allows us to perform the following derivation:

$$p(Y(1, M(0))) = \sum_m p(Y(1, m), M(0) = m) = \sum_m p(Y(1, m)) \cdot p(M(0) = m) \quad (16)$$

This derivation expressed our potential outcome as a product of two terms, with each of these terms representing variation in a random variable after a well defined intervention. This represents progress, since we were able to express a random variable not typically representable by any experimental design in terms of results of two well defined randomized trials, one involving  $Y$  as the outcome and  $A, M$  as treatments, and one involving  $M$  as the outcome, and  $A$  as treatment.

Unfortunately, even a single randomized study can be expensive or possibly illegal to perform on people (if the treatment is harmful), let alone two. For this reason a common goal in causal inference is to find ways of expressing interventional distributions as functions of observed data. In the causal inference literature this problem is known as the *identification problem of causal effects*.

As mentioned earlier, the interventional distribution, such as that corresponding to  $Y(a)$ , namely  $p(y|\text{do}(a))$ , is not necessarily equal to a conditional distribution  $p(y|a)$ . Nevertheless, such an equality holds if there is no unobserved confounders, or common causes between  $A$  and  $Y$ . This happens to be the case in our example. In terms of potential outcomes, the lack of unobserved confounding is expressed in terms of the *ignorability assumption*

$$Y(a) \perp\!\!\!\perp A$$

In words, this assumption states that if we happen to have information on the treatment variable, it does not give us any information about the outcome  $Y$  after the intervention  $\text{do}(a)$  was performed. A graphical way of describing ignorability is to say that there does not exist certain kinds of paths between  $A$  and  $Y$ , called *back-door paths* (Pearl, 2000), in the causal diagram. Such paths are called “back-door” because they start with an arrow



pointing into  $A$ . It can be shown that if ignorability holds for  $Y(a)$  and  $A$  (alternatively if there are no back-door paths from  $A$  to  $Y$  in the corresponding causal diagram), then  $p(y|\text{do}(a)) = p(y|a)$ .

If there exist common causes of  $A$  and  $Y$  but they are observed, as is the case of node  $C$  in Fig. 1 (b), it is possible to express a more general assumption known as the *conditional ignorability assumption*

$$Y(a) \perp\!\!\!\perp A|C$$

In words, this assumption states that if we happen to have information on the treatment variable, then conditional on the observed confounder  $C$ , this information gives us no information about the outcome  $Y$  after the intervention  $\text{do}(a)$  was performed. In graphical terms, this assumption is equivalent to stating that  $C$  “blocks” all back-door paths from  $A$  to  $Y$ <sup>2</sup>. It can be shown that if conditional ignorability ( $Y(a) \perp\!\!\!\perp A|C$ ) holds, then  $p(y|\text{do}(a)) = \sum_c p(y|a, c)p(c)$ . This formula is known as the back-door formula, or the adjustment formula.

Sometimes, identification of causal effects is possible even in the presence of unobserved confounding. See the work of Tian and Pearl (2002a), Huang and Valtorta (2006), and Shpitser and Pearl (2006b, 2006a, 2008) for a general treatment of the causal effect identification problem.

In our case, the ignorability assumption for  $M(a)$  and  $A$ , as well as for  $Y(1, m)$  and  $A, M$  allows us to further express each of the terms in the product in (16) in terms of observed data as follows:

$$\sum_m p(Y(1, m)) \cdot p(M(0) = m) = \sum_m p(Y|A = 1, m) \cdot p(m|A = 0)$$

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<sup>2</sup>Pearl (1988, 2000) gives a more detailed discussion of the notion of “blocking” that has to be employed here.

Plugging this last expression into the formula (13) for direct effects gives us

$$\sum_m \{E[Y|A = 1, m] - E[Y|A = 0, m]\} p(m|A = 0)$$

This expression is known as the *mediation formula* (Pearl, 2011). Note that the mediation formula does not require a particular functional form for causal mechanisms relating  $Y$ ,  $M$  and  $A$ .

Note also that assumption (15) is untestable, since it is positing a marginal independence between two potential outcomes, one of which involves the treatment being set to 1, and another involves the treatment being set to 0. A form of this assumption is still necessary in order to equate direct and indirect effects with functions of regression coefficients in the simple linear regression setting described in previous sections, in the sense that violations of the assumption will generally prevent us from uniquely expressing a given direct or indirect effect as a function of observed data (e.g. the effect becomes *non-identifiable*.) For this reason, even in the simplest mediation problems, care must be taken to either justify assumption (15) on strong substantive grounds, perform a reasonable sensitivity analysis (Tchetgen & Shpitser, 2012a), or reduce the mediation problem to a testable problem involving interventions without conflicts (J. M. Robins & Richardson, 2010).

### Mediation with Unobserved Confounding

One of the advantages of the potential outcome framework is its flexibility. Since it does not rely on parametric assumptions, it can be readily extended to handle modeling complications. Consider again our two mediator example in Fig. 2. We mentioned in the previous section that product and difference methods will result in biased estimates of direct effects of  $A$  on  $Y$  not through  $M$ , due to a combination of unobserved confounding and the “explaining away” effect in that example. A non-parametric definition of direct effect based on potential outcomes avoids these difficulties. Our expression for direct effect

is  $E[Y(1, M(0))] - E[Y(0)]$ . Since  $A$  is randomized (there is no unobserved confounding between  $A$  and the outcome  $Y$ ), the second term can be shown to equal  $E[Y|A = 0]$ . The first term can be shown, given assumption (15), and a general theory of identification of causal effects (Tian & Pearl, 2002a),(Shpitser & Pearl, 2006b, 2008) to equal

$$E[Y(1, M(0))] = \sum_m \left( \sum_l E[Y|m, l, A = 1]p(l|A = 1) \right) p(m|A = 0)$$

The direct effect is then equal to

$$\text{Direct Effect} = \sum_m \left( \sum_l E[Y|m, l, A = 1]p(l|A = 1) \right) p(m|A = 0) - E[Y|A = 0] \quad (17)$$

while the indirect effect is equal to

$$\text{Indirect Effect} = E[Y|A = 1] - \sum_m \left( \sum_l E[Y|m, l, A = 1]p(l|A = 1) \right) p(m|A = 0)$$

It can be shown that not only do the direct and indirect effects add up to the total effect in this case, but the quantity (17) equals 0 precisely when the effect of  $A$  on  $Y$  along the arrow  $A \rightarrow Y$  is in some sense absent.<sup>3</sup> However, even though we used simple linear regression models in this example, neither of these effects reduces to any straightforward function of the regression coefficients. It is possible to express these kinds of functional as functions of regression coefficients in an appropriately adjusted model (such as the marginal structural model, which is estimated by fitting weighted regression models (J. M. Robins, Hernan, & Brumback, 2000)), or as functions of parameters in a non-standard parameterization of causal models, where statistical parameters correspond to causal parameters directly (Shpitser, Richardson, & Robins, 2011),(Richardson, Robins, & Shpitser, 2012).

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<sup>3</sup>As long as the parametric models for the functionals in the formula are general enough to avoid the “null paradox” issue. Linear regressions for all terms suffice, but a no-interaction linear regression for a continuous outcome  $Y$ , and a no-interaction logistic regression for a binary mediator  $L$  does not suffice. The general rule of thumb is the models must be general enough to permit the above mean differences to equal zero for some parameter settings.

### **Path-specific Longitudinal Mediation with Unobserved Confounding**

In the previous section we saw how the presence of unobserved confounders and multiple mediators can easily result in situations where regression coefficients cannot be meaningfully associated with direct and indirect causal effects. In this section, we consider even more complex mediation settings, which can nevertheless be handled appropriately using the potential outcome counterfactual framework representing (possibly non-linear) structural equations. We motivate the discussion with two examples, one from HIV research, and one from psychology.

The human immunodeficiency virus (HIV) causes AIDS by attacking and destroying helper T cells. If the concentration of these cells falls below a critical threshold, cell-mediated immunity is lost, and the patient eventually dies to an opportunistic infection. Patients infected with HIV with reduced T cell counts are typically put on courses of anti retroviral therapy (ART), as a first line therapy. Unfortunately, side effects of many types of ART medication may cause poor adherence to the therapy (that is, patients do not always take the medication on time, or stop taking it altogether). Side effects are often caused by toxicity of the medication, or patient's adverse reaction to the medication. Severity of the side effects is often linked to the patient's "overall health level" (ill defined, and thus not measured), which also affects the eventual outcome of the therapy (survival or death). If the ART happens to not be very effective at viral suppression, and results in patient deaths, this could be because the ART itself is not very good, or it could be due to poor patient adherence. In other words, poor outcomes of ART results in a natural mediation question in HIV research – is the poor total effect possibly due to cancellation of a strong direct effect of the medication on survival by an equally strong indirect effect of poor adherence?

The situation is shown graphically in Fig. 3. Here, we show ART taken over the course of two months, represented by two time slices. In practical studies, ART is taken over a period of years, and the number of time slices is quite large. In this graph, the ART

is represented by nodes  $A_0$  and  $A_1$ , the patient outcome by  $Y$ , patient adherence at each time slice by  $M_1$  and  $M_2$ , toxicity of the medication by  $L_1$ ,  $L_2$ , and finally the unobserved state of patient's health affecting reaction to the medication and the outcome by  $U$ . Since we are interested in the indirect effect of ART on survival mediated by adherence, we are only interested in the effect along the paths from  $A_0, A_1$  on  $Y$  which pass through  $M_1, M_2$ . These paths are shown in green in the graph.

Our second example, which is isomorphic to the HIV example above, concerns the use of prevention programs, to promote positive outcomes in vulnerable populations. Assume the primary interventions  $A_0, A_1$  involve attending a drug prevention program. Like ART in the previous example, the program is an ongoing intervention (say a monthly meeting). However, there is also a secondary intervention  $M_1, M_2$  which is meant to increase the rates of screening for serious illness such as cancer. Although the secondary intervention is not directly related to drug prevention, it is conceivable that there is a synergistic effect between the primary and secondary intervention to promote positive outcomes (say staying drug free), perhaps due to the fact that both interventions promote good habits and health consciousness. In this example,  $L_1, L_2$  are, loosely speaking, "the participant's responsiveness" which may be affected by unobserved factors involving family, friends, socioeconomic background ( $U$ ), and so on. These unobserved factors also influence the outcome. The mediation question here is quantifying the extent to which the outcome is influenced by the primary intervention itself, versus an indirect effect via the secondary intervention. The indirect effect mediated by the secondary intervention is, again, shown in green in Fig. 3.

Aside from unobserved confounding represented by  $U$ , a complication also present in the example in Fig. 2 in the previous section, what makes these examples difficult is first the longitudinal setting where treatments recur over multiple time slices, and second that we are interested in effects along a particular bundle of causal paths. In previous sections we were interested in effects either only along the direct path  $A \rightarrow Y$ , or only along all

paths other than the direct one. In these cases we are interested in some indirect paths (through  $M_1, M_2$ ), but not others (through  $L_1, L_2$ ).

In the case of multiple treatments, causal effect from these treatments to the outcome  $Y$  is transmitted along special paths called *proper causal paths* of the form  $A_k \rightarrow \dots \rightarrow Y$ , where  $A_k$  is one of the treatments, and where this path cannot intersect any other treatment other than  $A_k$  (otherwise it is really a causal path from that second treatment to the outcome). We are interested in quantifying the effect along a subset of such paths, displayed graphically as those paths consisting entirely of green arrows. Algebraically, we will denote this set of paths of interest as  $\pi$ . The proper causal paths along which the causal effect is transmitted but which do not lie in  $\pi$  is displayed graphically as those paths which contain at least one blue arrow.

### Formalization of Path-Specific Effects

Naturally, even if the statistical model associated with the causal diagram shown in Fig. 3 is given in terms of linear regressions, it is not possible to express effects of interest as simple functions of regression coefficients. However, it is possible to express these *path-specific effects* (Pearl, 2001),(Avin, Shpitser, & Pearl, 2005) in terms of potential outcome counterfactuals.

We will use an inductive rule to construct a potential outcome representing the effect of  $A_0, A_1$  on  $Y$  only along green paths. For the purposes of this rule, we will represent values  $a'_0, a'_1$  of  $A_0, A_1$  to represent “baseline treatment” or “no treatment” (in the previous section we used 0), and values  $a_0, a_1$  to represent “active treatment” (in the previous section we used 1). This potential outcome will involve  $Y$ , and interventions on all direct causes of  $Y$  (that is all nodes  $X$  such that  $X \rightarrow Y$  exists in the graph). These interventions are defined as follows.

If the arrow  $X \rightarrow Y$  is blue, this means we are not interested in the effect transmitted along this arrow. In previous sections we represented this by considering the value of  $X$  “as

if treatment was baseline,” or  $X(0)$ . In our case we will do the same, except since we have two treatments we set them both to the baseline values  $a'_0, a'_1$ . For example,  $L_1$  and  $L_2$  are both direct causes of  $Y$  along blue arrows. This means we intervene on whatever values they would have had if  $A_0, A_1$  were set to baseline, or  $L_1(a'_0, a'_1), L_2(a'_0, a'_1)$ . If the direct cause of  $Y$  is one of the treatments  $A_0$  or  $A_1$  then we intervene to set their value to “active” if the arrow from treatment to outcome is green (e.g. we are interested in the effect), or “baseline” if the arrow is blue (e.g. we are not interested in the effect). Finally, if the direct cause of  $Y$  is not a treatment, but is a direct cause along a green arrow, we inductively set the value of that cause to whatever value it would have had under a path-specific effect of  $A_0, A_1$  on that cause. For instance,  $M_1$  is a direct cause of  $Y$  along a green arrow, which means we set the value of  $M_1$  to whatever value is dictated by the path-specific effect of  $A_0, A_1$  on  $M_1$ . To figure out what that value is, we simply apply our rule inductively from the beginning, except to  $M_1$  as the outcome, rather than  $Y$ .

Applying the first stage of our rule gives us the potential outcome

$Y(a'_0, a'_1, L_1(a'_0), L_2(a'_0, a'_1), \gamma_{m_1}, \gamma_{m_2})$ , where  $\gamma_{m_1}$  and  $\gamma_{m_2}$  are path-specific effects of  $A_0, A_1$  on  $M_1$  and  $M_2$ , respectively, along the green paths only. If we apply the rule inductively  $\gamma_{m_1}$ , and  $\gamma_{m_2}$ , and plug in and simplify, we get that our path-specific effect is the following complex potential outcome

$$Y(a'_0, a'_1, L_1(a'_0), L_2(a'_0, a'_1), M_1(a_0, L_1(a'_0)), M_2(a_1, L_2(a'_1, a'_0))) \quad (18)$$

While this expression looks algebraically complex, what it is actually expressing is a rather simple idea. We have two treatment levels: “baseline” and “active.” For the purposes of green paths, the causal paths we are interested in, we pretend treatment levels are active. For the purposes of all other paths, we pretend treatment levels are baseline. In this way, the treatment is active only along the paths we are interested in, and all other paths are “turned off.” We use this rule to select what values we intervene on, and then use these

interventions in a nested way, following the causal paths of the graph. An equivalent definition of path-specific effects phrased in terms of replacing structural equations is given by Pearl (2001).

### **The Total Effect Decomposition Property for Path-Specific Effects**

In the previous sections we defined the direct and indirect effects by taking a difference of expectations (see equations 13 and 14). We can generalize such definitions to path-specific effects to obtain a decomposition of the total effect into a sum of two terms, one representing the effect along proper causal paths in  $\pi$ , and one representing the effect along proper causal paths not in  $\pi$ .

First, assume the distribution for the nested potential outcome defining the path-specific effect along proper causal paths in  $\pi$  of  $A$  on  $Y$  is given by  $p_\pi(Y)$ . Then we have

$$\text{Effect along paths in } \pi = E[Y]_{p_\pi(Y)} - E[Y(a')] \quad (19)$$

and

$$\text{Effect along paths not in } \pi = E[Y(a)] - E[Y]_{p_\pi(Y)} \quad (20)$$

Since the total effect can be defined as  $E[Y(a)] - E[Y(a')]$ , we have

$$\text{Total Effect} = \text{Effect along paths in } \pi + \text{Effect along paths not in } \pi$$

which is an intuitive additivity property stating that the total effect can be decomposed into a sum of two terms, where one term quantifies the effect operating along a given bundle of proper causal paths  $\pi$ , and another term quantifies the effect operating along all proper causal paths other than those in  $\pi$ . Note that this property generalizes the additivity property for direct and indirect effects, where  $\pi$  was taken to mean a single arrow from  $A$  to  $Y$ .



### Path-Specific Effects as Functions of Observed Data

In the previous section we showed that a path-specific effect can be defined in terms of a nested potential outcome after we “turn off” causal paths we are not interested in. Regardless of how sensible such a definition may be, it is not very useful unless this potential outcome can be expressed as a function of the observed data, and thus become amenable to statistical analysis.

In a previous section, we showed that in order to express direct and indirect effects in terms of observed data, we needed to make an untestable independence assumption (shown in equation 15). Path-specific effects generalize direct and indirect effects, and thus require even more assumptions.

In fact, for the path-specific effect along green paths in Fig. 3, it suffices to believe the following independence claim for any value assignments  $a_0, a_1, a'_0, a'_1, l_1, l_2$ :

$$\{Y(a'_0, a'_1, l_1, l_2, m_1, m_2), L_1(a'_0), L_2(a'_0, a'_1)\} \perp\!\!\!\perp \{M_1(a_0, l_1), M_2(a_0, a_1, l_2)\} \quad (21)$$

If we believe this assumption, we can express the path-specific effect in equation 18 as

$$\sum_{l_1, l_2, m_1, m_2} p(Y(a'_0, a'_1, l_1, l_2, m_1, m_2), L_1(a'_0) = l_1, L_2(a'_0, a'_1) = l_2) \cdot \quad (22)$$

$$p(M_1(a_0, l_1) = m_1, M_2(a_1, l_2) = m_2)$$

This expression is a product of terms, where each term is a well defined interventional density (that is, there are no conflicts involving different hypothetical worlds). If we further make use of the general theory of identification of interventional densities from observed data (Tian & Pearl, 2002b), (Shpitser & Pearl, 2006b, 2008), we can express the above as follows

$$\sum_{l_1, l_2, m_1, m_2} p(Y|a'_0, a'_1, l_1, l_2, m_1, m_2) \cdot p(m_2|l_2, a_1, m_1, a_0) \cdot p(l_2|a'_0, a'_1, l_1) \cdot p(m_1|l_1, a_0) \cdot p(l_1|a'_0) \quad (23)$$

This expression is a function of the observed data.

What is left is finding an expression for the total effect of  $A_0, A_1$  on  $Y$ . It is not difficult to show that  $E[Y(a_0, a_1)] = \sum_{m_1, l_1} E[Y|m_1, l_1, a_1, a_0]p(m_1, l_1|a_0)$ . By analogy with a previous section, we can express the path-specific effect via fully green paths in  $\pi$  through  $M_1, M_2$  as a difference of expectations

$$\begin{aligned} \sum_{l_1, l_2, m_1, m_2} E[Y|a'_0, a'_1, l_1, l_2, m_1, m_2] \cdot p(m_2|l_2, a_1, m_1, a_0) \cdot p(l_2|a'_0, a'_1, l_1) \cdot p(m_1|l_1, a_0) \cdot p(l_1|a'_0) - \\ \sum_{m_1, l_1} E[Y|m_1, l_1, a'_1, a'_0]p(m_1, l_1|a'_0) \end{aligned} \quad (24)$$

while the effect via all paths that are not fully green (that is proper causal paths not in  $\pi$ ) as another difference

$$\begin{aligned} \sum_{m_1, l_1} E[Y|m_1, l_1, a_1, a_0]p(m_1, l_1|a_0) - \\ \sum_{l_1, l_2, m_1, m_2} E[Y|a'_0, a'_1, l_1, l_2, m_1, m_2] \cdot p(m_2|l_2, a_1, m_1, a_0) \cdot p(l_2|a'_0, a'_1, l_1) \cdot p(m_1|l_1, a_0) \cdot p(l_1|a'_0) \end{aligned} \quad (25)$$

These quantities can be estimated with standard statistical methods by simply positing a model for each term, for instance a regression model, estimating the models from data, and computing the estimated functional. This is the so called “parametric g-formula” approach (J. Robins, 1986). With this method, care must be taken to avoid the “null paradox” issue, as was the case with direct and indirect effects. A less straightforward approach which only relies on modeling the probability of the treatment in each times lice given the past, is to

generalize marginal structural models (J. M. Robins et al., 2000), which were originally developed in the context of estimating total effects in longitudinal settings with confounding. Another alternative is to extend existing multiply robust methods for point treatment mediation settings (Tchetgen & Shpitser, 2012b) based on semi-parametric statistics to the longitudinal setting.

### Expressing Arbitrary Path-Specific Effects in Terms of Observed Data

One difficulty with path-specific effects is that the corresponding potential outcome counterfactual is nested, and therefore complicated. On the other hand, the graphical representation of path-specific effects on a causal diagram is fairly intuitive (effect along green paths only). For this reason, it would be desirable to obtain a result which says, for a particular bundle of green paths on a particular causal diagram, whether the corresponding counterfactual can be expressed as a function of the observed data, without going into the details of the counterfactual itself. In this section we give just such a result, which generalizes existing results on path-specific effects in cases with a single treatment and no unobserved confounding (Avin et al., 2005).

We first start with a few preliminaries on graphs. We will display causal diagrams with unobserved confounding, such that those in Figs. 2 and 3 by means of a special kind of mixed graph containing two kinds of edges, directed edges ( $\rightarrow$ ), either blue or green depending on whether we are interested in the corresponding causal path, and red bidirected edges ( $\leftrightarrow$ ). The former represent direct causation edges, as before. The latter represent the presence of some unspecified unobserved common cause. For example, we represent the causal diagram in Fig. 3 by means of the mixed graph shown in Fig. 4. Note that since  $U$  links three nodes,  $L_1, L_2, Y$ , each pair of these three is joined by a bidirected arrow. We call this type of mixed graph an acyclic directed mixed graph (ADMG) (Richardson, 2009). Verma and Pearl (1990) called these types of graphs latent projections. The reason we use bidirected arrows is both to avoid cluttering the graph with potentially

many possible unobserved confounders, and because certain crucial definitions involving confounders are easier to state in terms of bidirected arrows.

A sequence of distinct edges such that the first edge connects to  $X$ , the last edge connects to  $Y$ , and each  $k$ th and  $k + 1$ th edge shares a single node in common is called a *path* from  $X$  to  $Y$ . If vertices  $X, Y$  are connected by a path of the form  $X \rightarrow \dots \rightarrow Y$ , then we say  $X$  is an ancestor of  $Y$  and  $Y$  is a descendant of  $X$ . Such a path is called directed. A path is called bidirected if it consists exclusively of bidirected edges. For an ADMG  $\mathcal{G}$  with a set of nodes  $V$ , we define a subgraph  $\mathcal{G}_A$  over a subset  $A \subseteq V$  of nodes to consist only of nodes in  $A$  and edges in  $\mathcal{G}$  with both endpoints in  $A$ . If an edge  $X \rightarrow Y$  exists,  $X$  is called a parent of  $Y$ , and  $Y$  a child of  $X$ .

**Definition 1 (district)** *Let  $\mathcal{G}$  be an ADMG. Then for any node  $a$ , the set of nodes in  $\mathcal{G}$  reachable from  $a$  by bidirected paths is called the district of  $a$ , written  $Dis_{\mathcal{G}}(a)$ .*

For example, in the graph in Fig. 4,  $Dis_{\mathcal{G}}(Y) = \{Y, L_1, L_2\}$ .

**Definition 2 (recanting district)** *Let  $\mathcal{G}$  be an ADMG,  $A, Y$  sets of nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Let  $V^*$  be the set of nodes not in  $A$  which are ancestral of  $Y$  via a directed path which does not intersect  $A$ . Then a district  $D$  in an ADMG  $\mathcal{G}_{V^*}$  is called a recanting district for the  $\pi$ -specific effect of  $A$  on  $Y$  if there exist nodes  $z_i, z_j \in D$  (possibly  $z_i = z_j$ ),  $a_i \in A$ , and  $y_i, y_j \in Y$  (possibly  $y_i = y_j$ ) such that there is a proper causal path  $a_i \rightarrow z_i \rightarrow \dots \rightarrow y_i$  in  $\pi$ , and a proper causal path  $a_i \rightarrow z_j \rightarrow \dots \rightarrow y_j$  not in  $\pi$ .*

It turns out that the recanting district criterion characterizes situations when a potential outcome counterfactual can be expressed in terms of well-defined interventions, without conflicts, as long as we assume that the causal diagram represents a set of (arbitrary) structural equations.

**Theorem 3 (recanting district criterion)** *Let  $\mathcal{G}$  be an ADMG representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A, Y$  sets of nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Then the  $\pi$ -specific effect of  $A$  on  $Y$  is expressible as a functional of interventional densities if and only if there does not exist a recanting district for this effect.*

The functional referenced in the theorem is equal to

$$\sum_{V^* \setminus Y} \prod_D p(D = d | \text{do}(E_D = e_D)) \quad (26)$$

where  $D$  ranges over all districts in the graph  $\mathcal{G}_{V^*}$ ,  $E_D$  refers to nodes with directed arrows pointing into  $D$  but which are themselves not in  $D$ , and value assignments  $d, e_D$  are assigned as follows. If any element  $a$  in  $A$  occurs in  $E_D$  in a term  $p(D = d | \text{do}(E_D = e_D))$ , then it is assigned a baseline value if the arrows from  $a$  to elements in  $D$  are all blue, and an active value if the arrows from  $a$  to elements in  $D$  are all green. All other elements in  $E_D$  are assigned values consistent with the values indexed in the summation.

The proof of this theorem is given in the supplementary materials. As an example, assume if we are interested in the effect of  $A_0, A_1$  on  $Y$  along only the green paths in the graph in Fig. 3. The set of nodes  $V^*$  in this case is just  $\{L_1, L_2, M_1, M_2, Y\}$ . There are three districts in the corresponding graph  $\mathcal{G}_{V^*}$ , which is just the graph obtained from Fig. 3 by removing  $A_0, A_1$  and all edges adjacent to these nodes. These three districts are  $\{M_1\}$ ,  $\{M_2\}$ , and  $\{L_1, L_2, Y\}$ . It is never the case that both a green and a blue arrow from  $A_0$  or  $A_1$  points to nodes in the same district such that these nodes are ancestors of  $Y$ . This means there is no recanting district for this effect, which in turn means the effect is expressible as a functional of interventional densities. We have already verified this fact in the previous section where this functional was given as equation 22, and which can be

rephrased in the  $\text{do}(\cdot)$  notation as follows:

$$\sum_{l_1, l_2, m_1, m_2} p(Y, l_1, l_2 | \text{do}(a'_0, a'_1, l_1, l_2, m_1, m_2)) \cdot p(m_1, m_2 | \text{do}(a_0, a_1, l_1, l_2))$$

which can be shown equals to

$$\sum_{l_1, l_2, m_1, m_2} p(Y, l_1, l_2 | \text{do}(a'_0, a'_1, l_1, l_2, m_1, m_2)) \cdot p(m_1 | \text{do}(a_0, l_1)) \cdot p(m_2 | \text{do}(a_1, l_2)) \quad (27)$$

which is easily verified to be an example of equation 26.

On the other hand, in either of the graphs shown in Fig. 5, the recanting district exists. In Fig. 5 (a), the district  $\{L_1, L_2, M_2, Y\}$  is recanting, since the path  $A_1 \rightarrow L_2 \rightarrow Y$  is not fully green (e.g. we are not interested in the effect along this path), while the path  $A_1 \rightarrow M_2 \rightarrow Y$  is fully green, and  $L_2$  and  $M_2$  lie in the same district. Similarly, in Fig. 5 (b), the district  $\{M_1\}$  is recanting, since the path  $A_0 \rightarrow M_1 \rightarrow L_2 \rightarrow Y$  is not fully green, while the path  $A_0 \rightarrow M_1 \rightarrow Y$  is fully green, and  $M_1$  is its own district.

The recanting district criterion generalizes an earlier result for static treatments and no unobserved confounding known as a *recanting witness*, where the “witness” is a singleton node (Avin et al., 2005). The term is “recanting” because for the purposes of one path from a particular treatment  $A_k$  the witness (or district in our case) pretends the treatment should be active, while for the purposes of another path from that same treatment  $A_k$  the witness (or district) “changes the story,” and pretends the treatment should be baseline. Identification of path-specific effects in terms of interventional distributions must always avoid this “recanting” phenomenon. Note that even in the case of multiple longitudinal treatments, the “recanting” phenomenon still involves a single treatment, but spoils the identification of the whole effect of multiple treatments.

The presence of the recanting district prevents the expression of path-specific effects in terms of either observed or interventional data in the sense that it is possible to construct two distinct causal models which are observationally and interventionally

indistinguishable, which are represented by the same causal diagram, but which disagree on the value of the path-specific effect. Furthermore, if the recanting district criterion does not exist, it is possible to characterize cases in which the expression for the path-specific effect in terms of interventional densities can be further expressed in terms of observational data.

**Theorem 4** *Let  $\mathcal{G}$  be an ADMG with nodes  $V$  representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A, Y$  sets of nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Assume there does not exist a recanting district for the  $\pi$ -specific effect of  $A$  on  $Y$ . Then the counterfactual representing the  $\pi$ -specific effect of  $A$  on  $Y$  is expressible in terms of the observed data  $p(V)$  if and only if the total effect  $p(y|do(a))$  is expressible in terms of  $p(V)$ . Moreover, the functional of  $p(V)$  equal to the counterfactual is obtained from equation (26) by replacing each interventional term in (26) by a functional of the observed data identifying that term given by Tian’s identification algorithm (Tian & Pearl, 2002a),(Shpitser & Pearl, 2006b, 2008).*

General theory of identification of causal effects states that if  $p(y|do(a))$  is identifiable in terms of observed data, then it can be expressed as the functional very similar to that in equation (26), except all variables in  $A$  are assigned “active values”  $a$ . If  $p(y|do(a))$  is identifiable from observed data, then each of the interventional terms in the functional is expressible in terms of observed data. This theorem simply states that to obtain our path-specific effect all we have to do is obtain the functional of the observed data expressing  $p(y|do(a))$ , and replace the appropriate “active values”  $a$  by “baseline values”  $a'$  in those terms of the functional which correspond to districts containing children of treatment  $A$  via blue arrows. For example, it can be shown that the total effect  $p(y|do(a_0, a_1))$  in Fig. 3 is equal to

$$\sum_{l_1, l_2, m_1, m_2} p(Y|a_0, a_1, l_1, l_2, m_1, m_2) \cdot p(m_2|l_2, a_1, m_1, a_0) \cdot p(l_2|a_0, a_1, l_1) \cdot p(m_1|l_1, a_0) \cdot p(l_1|a_0) \quad (28)$$

Replacing  $a_0$  and  $a_1$  by  $a'_0$  and  $a'_1$  in expressions for  $Y$ ,  $L_1$  and  $L_2$  (which are the only terms where the node before the conditioning bar is a child of  $A_0$  or  $A_1$  along blue arrows) yields precisely equation (23) which is the function of the observed data equal to the path-specific effect.

**Corollary 5 (generalized mediation formula for path-specific effects)** *Let  $\mathcal{G}$  be an ADMG with nodes  $V$  representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A$  be a set of nodes,  $Y$  a single node in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in  $Y$  in  $\mathcal{G}$ . Assume there does not exist a recanting district for the  $\pi$ -specific effect of  $A$  on  $Y$ . Assume  $p(y|do(a))$  is expressible as a functional  $f_{do(a)}(p(V))$  of the observed data, and the path-specific effect is equal to the functional  $f_\pi(p(V))$  obtained in Theorem 4. Then the path-specific effect along the set of paths  $\pi$  on the mean difference scale for active value  $a$  and baseline value  $a'$  is equal to*

$$\text{Effect along paths in } \pi = E[Y]_{f_\pi(p(V))} - E[Y]_{f_{do(a')}(p(V))}$$

*while the path-specific effect along all paths not in  $\pi$  on the mean difference scale is equal to*

$$\text{Effect along paths not in } \pi = E[Y]_{f_{do(a)}(p(V))} - E[Y]_{f_\pi(p(V))}$$

An example of the generalized mediation formula applied to the longitudinal mediation setting shown in Fig. 3 is shown in equation (24) for the direct effect, and equation (25) for the indirect effect. The proof of these assertions is also given in the supplementary materials.

## Conclusions

In this paper, we have shown that existing methods for mediation analysis in epidemiology and psychology literature based on the product and difference methods (Judd



& Kenny, 1981),(Baron & Kenny, 1986) and linear regression models suffer from problems in the presence of interactions, non-linearities, binary outcomes, unobserved confounders, and other modeling complications. We have described a general framework developed in the causal inference literature based on potential outcome counterfactuals, non-parametric structural equations, and causal diagrams which recovers the product and difference methods as a special case, but which is flexible enough to handle multiple types of difficulties which arise in practical mediation analysis situations.

Our paper serves two aims. We first wish to caution against careless use of mediation methodology based on linear regressions in situations where such methodology is not suitable. Such careless use may invalidate any conclusions about mediation that are drawn. Second, we want to show that appropriate use of functional models and potential outcomes is a very flexible strategy for tackling complex questions in causal inference, including mediation questions in longitudinal settings with unobserved confounding. We demonstrate this flexibility by developing a complete characterization of situations when path-specific effects are expressible as functionals of the observed data. This result paves the way for using statistical tools for answering general mediation questions in longitudinal observational studies. We argue that methods based on functional models and potential outcomes are often a more appropriate methodology in complex mediation setting than simpler methods based on linear structural equations.

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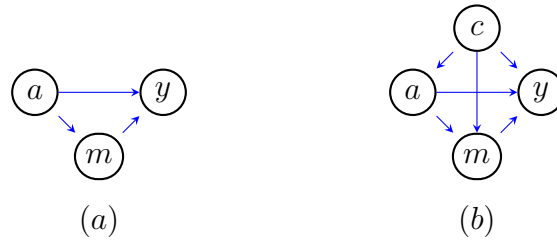
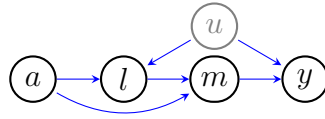
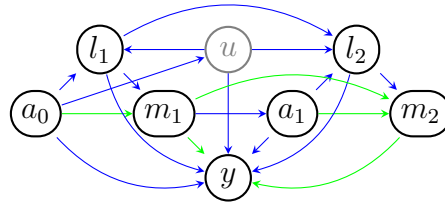


Figure 1. (a) Typical mediation setting:  $a$  is the treatment,  $m$  is the mediator,  $y$  is the outcome. (b) Mediation setting with observed confounding:  $c$  is a confounder due to being a common cause of treatment, mediator and outcome variables.



*Figure 2.* Mediation setting with an unobserved confounder  $U$ , two mediators  $L$  and  $M$ , and no direct effect of  $A$  on  $Y$ .



*Figure 3.* A longitudinal mediation setting with an unobserved confounder  $u$ , where we are interested in effects along all paths from  $A_0$  and  $A_1$  to  $Y$  only through  $M_1$  or  $M_2$ . Paths we are interested in are shown in green.



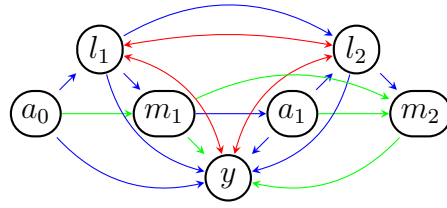


Figure 4. A mixed graph representing unobserved confounding in Fig. 3.

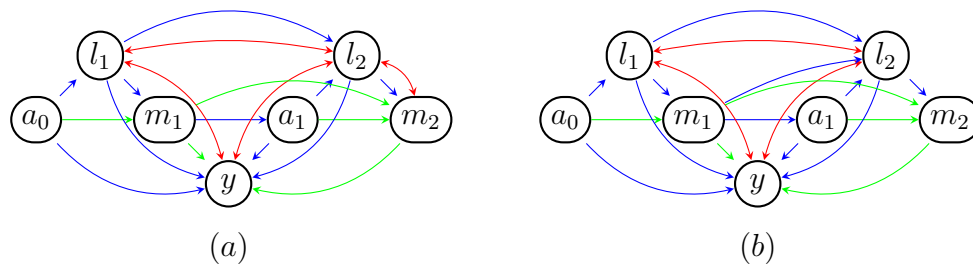


Figure 5. Two variations on the graph in Fig. 4 where the path-specific effect of  $A_0, A_1$  on  $Y$  along the green paths is not identifiable from observational (or even interventional) data. (a) The presence of an unobserved parent of  $L_2$  and  $M_2$  spoils identification. (b) If  $M_1$  is a direct cause of  $L_2$ , the effect along green paths is not identifiable.

# Counterfactual Graphical Models for Longitudinal Mediation Analysis with Unobserved Confounding – Supplementary Material

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## A Overview

Here we give a complete theory underlying our reported results. We proceed as follows. We first describe some background terminology on graphs, potential outcomes, and causal inference. We then give a formal definition of path-specific effects for multiple treatments, and multiple outcomes in causal diagrams where some nodes are possibly unobserved. This is one of the most general settings for mediation problems. In particular, it subsumes longitudinal mediation settings with unobserved confounding. We do not, however, handle issues that arise due to selection bias, measurement error, and model misspecification bias. These difficulties are very general in causal inference and statistics itself, and handling them in mediation settings is a topic of future work. We then give a formula which expresses a path-specific effect in terms of interventional densities if the recanting district does not exist for the effect, in accordance with Theorem ?? . We then prove that if such

a district does not exist, then the formula is indeed correct (the “if”, or soundness part of Theorem ??). We then show that if a recanting district does exist, then it is possible to construct two causal models which agree on the causal diagram, and all interventional densities, but disagree on the path-specific effect of interest. This implies the path-specific effect cannot be expressed as a functional of interventional densities for all causal models which induce a particular diagram (the “only if” or completeness part of Theorem ??). Finally, we give the proofs of Theorem ??, and Corollary ??.

## A.1 A Note on Notation

We will use a somewhat different notation in this supplement from that found in the main body of the paper, for the following reasons. In this paper, we need to clearly distinguish mathematical objects along the following three axes: graphical (nodes) vs statistical (variables), singletons vs sets, and values vs variables. In simple examples such as those found in the main body of the paper, the singleton/set distinction did not really arise, and it was clear from context whether graphical or statistical concepts were discussed. Then values can be distinguished by lower case letters, while variables can be distinguished by upper case letters. In the supplement, where we develop a general mathematical theory underlying the examples, this option is no longer open to us – the uppercase/lowercase Roman notation is simply ambiguous when all three distinctions need to be drawn.

The paper must satisfy conflicting notation goals: we want to both make the main body of the paper accessible, and conform to existing notation in mediation papers, and at the same time to make the mathematical portion of the paper unambiguous and clear. The change of notation satisfies these two goals, although it makes the mapping of the main body of the paper to the supplement somewhat harder. To assist this mapping, we restate all main results in the supplement with the new notation. With that said, the notation used in this supplement will be as follows. Vertices in a graph  $\mathcal{G}$  will be denoted by lower case letters:  $w$ . Sets of

vertices will be denoted by upper case letters:  $W$ . A random variable corresponding to a vertex  $w$  will be denoted  $X_w$ , or sometimes subscripted:  $X_1, \dots, X_n$ . A set of random variables corresponding to a set of vertices  $W$  will be denoted by  $X_W$ . A value assignment to a random variable  $X_w$  will be denoted by  $x_w$ . A value assignment to a set of random variables  $X_W$  will be denoted by  $x_W$ .

We will consider sets of random variables  $X_{v_1}, \dots, X_{v_n}$ , and joint probability distributions  $p(x_{v_1}, \dots, x_{v_n})$  over these sets.

## A.2 Graphs, Counterfactuals, and Structural Models of Causality

A directed graph is a graph containing vertices (or nodes) and directed arrows connecting pairs of vertices. If vertices  $w, y$  in a graph  $\mathcal{G}$  are connected by a directed edge  $w \rightarrow y$ , we say  $w$  is a parent of  $y$  and  $y$  is a child of  $w$ . A sequence of nodes such that every  $k$ th and  $k+1$ th node in the sequence are connected by an edge, and no node occurs more than once in a sequence is called a *path*. If vertices  $w, y$  are connected by a path of the form  $w \rightarrow \dots \rightarrow y$ , then we say  $w$  is an ancestor of  $y$  and  $y$  is a descendant of  $w$ . A directed graph is acyclic if no node is its own ancestor. We abbreviate directed acyclic graphs as DAGs. For a given node  $w$  in  $\mathcal{G}$ , we denote its sets of parents, children, ancestors and descendants as  $Pa_{\mathcal{G}}(w)$ ,  $Ch_{\mathcal{G}}(w)$ ,  $An_{\mathcal{G}}(w)$ ,  $De_{\mathcal{G}}(w)$ , respectively. The “genealogic relations” on sets of vertices are defined by taking unions, for instance for a set  $W$ ,  $An_{\mathcal{G}}(W) = \bigcup_{w_i \in W} An_{\mathcal{G}}(w_i)$ .

A Bayesian network is a DAG  $\mathcal{G}$  which contains  $n$  nodes,  $\{v_1, \dots, v_n\} = V$ , and a set of random variables  $X_{v_1}, \dots, X_{v_n}$ , one for each vertex in  $\mathcal{G}$ , forming a joint probability distribution  $p(x_{v_1}, \dots, x_{v_n})$  with a certain property linking the distribution and the graph. This property is called the Markov factorization property:

$$p(x_{v_1}, \dots, x_{v_n}) = \prod_{i=1}^n p(x_{v_i} \mid x_{Pa_{\mathcal{G}}(v_i)})$$

This factorization is equivalent to the local Markov property which states that

each  $X_{v_i}$  is independent of  $X_{V \setminus (De_{\mathcal{G}}(v_i) \cup Pa_{\mathcal{G}}(v_i))}$  conditional on  $X_{Pa_{\mathcal{G}}(v_i)}$ , and in turn equivalent to the global Markov property defined by d-separation [1], which states, for any disjoint sets of vertices  $W, Y, Z$  in  $\mathcal{G}$ , that if all paths of a certain type from nodes in  $W$  to nodes in  $Y$  are “blocked” by nodes in  $Z$  in  $\mathcal{G}$ , then  $X_W$  is independent of  $X_Y$  given  $X_Z$  in  $p(x_{v_1}, \dots, x_{v_n})$ . A Bayesian network is thus a statistical model in that its Markov properties define a set of probability distributions.

A statistical graph model can further be considered a causal model if we can meaningfully talk about interventions on variables. An intervention on  $A$ , denoted by  $do(X_A = x_A)$  (which we will shorten to  $do(x_A)$ ), is an operation that sets the variables  $X_A$  to values  $x_A$ , regardless of the usual behavior of  $X_A$  given by the observable joint distribution  $p$ . Effects of such interventions on other variables in the system will represent causal effects. A statistical model defined by a DAG  $\mathcal{G}$  is causal if for every such  $do(x_A)$ ,

$$p(x_{V \setminus A} \mid do(x_A)) = \prod_{v_i \notin A} p(x_{v_i} \mid x_{Pa_{\mathcal{G}}(v_i)})$$

Informally, this formula asserts that whenever we intervene on a set of variables  $X_A$ , we remove from the Markov factorization all terms  $p(x_a \mid x_{Pa_{\mathcal{G}}(a)})$ , for all  $a \in A$ . This is known as the truncation formula [7],[2], or the g-formula [4]. This formula implies, in particular, that for any  $X_a$ ,  $p(x_a \mid do(x_{Pa_{\mathcal{G}}(a)})) = p(x_a \mid x_{Pa_{\mathcal{G}}(a)})$ .

The intuition for the g-formula is that in a causal model the parents of every variable are that variable’s *direct causes*. These direct causes determine with what probability a variable assumes its values in the model. By intervening on a variable, we force it to attain a particular value, independently of the usual influence of direct causes. For this reason, we “drop out” the term which links the direct causes and the variable from the Markov factorization.

We denote a random variable  $X_y$  in a causal model after  $do(x_A)$  has been performed by the notation  $X_y(x_A)$ . Such a variable is called a potential outcome, or a counterfactual variable. An assumption very commonly made in causal inference is

the so called consistency assumption, which states that if we observed variables  $X_A$  attain a value  $x_A$ , then for any  $X_Y$ , the variable sets  $X_Y$  and  $X_Y(x_A)$  are the same. This assumption is crucial in that it allows us to link outcomes under hypothetical interventions with outcomes seen in observational studies where no interventions were in fact performed.

In order to express natural direct and indirect effects in terms of interventional distributions, it was necessary to assume independence of counterfactual variables which lie in different hypothetical worlds. This is not a testable assumption, since no possible experiment we could perform can falsify it. Nevertheless, there is one type of causal model that implies such assumptions in a plausible way. This causal model is the so called *non-parametric structural equation model* [2] (sometimes abbreviated as an NPSEM, although from this point on we will refer to this model simply as a functional model.) This model is a graphical model which consists of a distribution  $P(x_{v_1}, \dots, x_{v_n})$  that factorizes according to a DAG  $\mathcal{G}$  such that every intervention can be expressed in terms of the g-formula, and the consistency assumption is true for every counterfactual. In addition, we assume that every observable variable  $X_{v_i}$  is causally determined from its direct causes  $X_{Pa_{\mathcal{G}}(v_i)}$  (plus possibly a single unobserved cause only of  $X_{v_i}$  and no other variable) via some unknown function or causal mechanism. A functional model for the simple mediation setting is shown in equations (??), (??), and (??).

Because of these functions, this functional model can be viewed as a kind of “stochastic circuit” with variables representing wires, and functions representing logic gates that determine the voltage at a particular wire in terms of other wires in the circuit, with a few specific wires allowed to be randomized. On the one hand, the model may seem quite reasonable, since many data generating processes in nature can be naturally thought of as such circuits (at least on the level of Newtonian physics). On the other hand, the model implies that for every  $X_w, X_y$ , it is the case that  $X_w(x_{Pa_{\mathcal{G}}(w)})$  is independent of  $X_y(x_{Pa_{\mathcal{G}}(y)})$ , for any value assignments  $x_{Pa_{\mathcal{G}}(w)}, x_{Pa_{\mathcal{G}}(y)}$ , even if  $Pa_{\mathcal{G}}(w)$  and  $Pa_{\mathcal{G}}(y)$  have nodes in common, and these

nodes are set to conflicting values by  $x_{Pa_{\mathcal{G}}(w)}$  and  $x_{Pa_{\mathcal{G}}(y)}$ . For this reason, these kinds of functional models are sometimes considered too strong [3]. In the remainder of the supplement, we will assume our graphs represent functional models, with a warning that without assuming such strong models directly, or at least certain cross-world independences such models imply, none of the identification results presented in this paper are valid.

### A.3 A General Definition of Path-Specific Effects

We define path-specific effects in the general case of multiple treatments  $\{a_1, \dots, a_k\} = A$  and multiple outcomes  $\{y_1, \dots, y_m\} = Y$ . We will consider two sets of values for  $A$ , the treatment values  $\{x_{a_1}, \dots, x_{a_k}\} = x_A$  and reference values  $\{x_{a_1}^*, \dots, x_{a_k}^*\} = x_A^*$ . We will be interested in effect of the set  $X_A$  on the set  $X_Y$  along a set  $\pi$  of directed paths from nodes in  $A$  to nodes in  $Y$ . As described in the main body of the paper, our convention will be that if an arrow is a part of some path in  $\pi$ , it is shown in green, otherwise it is shown in blue.

We now show how to translate path-specific effects along a given set of paths into counterfactual form. The resulting counterfactual, denoted by  $X_Y(\pi(x_A), x_A^*)$ , will be defined inductively.

Let  $V^* = An(Y)_{\mathcal{G}_A}$ , where  $\mathcal{G}_A$  is a subgraph of  $\mathcal{G}$  containing all vertices other than  $A$ , and all edges between these vertices which occur in  $\mathcal{G}$ . Fix a node  $s$  in  $V^*$ , and let  $Pa_s = Pa_{\mathcal{G}}(s)$ . Let  $B$  be the set of nodes  $t \in Pa_s$  such that the arrow  $t \rightarrow s$  is green. For each such  $t$ , let  $X_t(\pi(x_A), x_A^*)$  be the inductively defined path-specific effect of  $X_A$  on  $X_t$  along  $\pi$ . Then the path-specific effect of  $X_A$  on  $X_s$  along  $\pi$  is defined as

$$X_s(X_{B \setminus A}(\pi(x_A), x_A^*), X_{Pa_s \setminus (B \cup A)}(x_A^*), x_{A \cap B}, x_{(A \cap Pa_s) \setminus B}^*)$$

The path-specific effect  $X_Y(\pi(x_A), x_A^*)$  is defined to be the joint distribution over  $X_{y_1}(\pi(x_A), x_A^*), \dots, X_{y_m}(\pi(x_A), x_A^*)$ .



## A.4 A Restatement of the Main Results

In this section, we restate the main definition of the recanting district and the three main results of the paper in terms of the notation used in this supplement.

**Definition 1 (recanting district)** *Let  $\mathcal{G}$  be an ADMG,  $A, Y$  sets of nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Let  $V^*$  be the set of nodes not in  $A$  which are ancestral of  $Y$  via a directed path which does not intersect  $A$ . Then a district  $D$  in an ADMG  $\mathcal{G}_{V^*}$  is called a recanting district for the  $\pi$ -specific effect of  $A$  on  $Y$  if there exist nodes  $z_i, z_j \in D$  (possibly  $z_i = z_j$ ),  $a_i \in A$ , and  $y_i, y_j \in Y$  (possibly  $y_i = y_j$ ) such that there is a proper causal path  $a_i \rightarrow z_i \rightarrow \dots \rightarrow y_i$  in  $\pi$ , and a proper causal path  $a_i \rightarrow z_j \rightarrow \dots \rightarrow y_j$  not in  $\pi$ .*

**Theorem ?? (recanting district criterion)** *Let  $\mathcal{G}$  be an ADMG representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A, Y$  sets of nodes nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Then the  $\pi$ -specific effect of  $A$  on  $Y$  is expressible in terms of interventional densities if and only if there does not exists a recanting district for this effect.*

**Theorem ??** *Let  $\mathcal{G}$  be an ADMG with nodes  $V$  representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A, Y$  sets of nodes nodes in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in a node in  $Y$  in  $\mathcal{G}$ . Assume there does not exist a recanting district for the  $\pi$ -specific effect of  $A$  on  $Y$ . Then the counterfactual representing the  $\pi$ -specific effect of  $A$  on  $Y$  is expressible in terms of the observed data  $p(x_V)$  if and only if the total effect  $p(x_Y | do(x_A))$  is expressible in terms of  $p(x_V)$ . Moreover, the functional of  $p(x_V)$  equal to the counterfactual is obtained from equation (??) by replacing each interventional term in (??) by functional of the observed data identifying that term given by Tian's identification algorithm [8],[5], [6].*

**Corollary ?? (generalized mediation formula for path-specific effects)** *Let  $\mathcal{G}$  be an ADMG with nodes  $V$  representing a causal diagram with unobserved confounders corresponding to a structural causal model. Let  $A$  be a set of nodes,  $y$  a single node in  $\mathcal{G}$ , and  $\pi$  a subset of proper causal paths which start with a node in  $A$  and end in  $y$  in  $\mathcal{G}$ . Assume there does not exist a recanting district for the  $\pi$ -specific effect of  $A$  on  $y$ . Assume  $p(x_y|do(x_A)) = f_{do(x_A)}(p(x_V))$ , and the path-specific effect is equal to the functional  $f_\pi(p(x_V))$  obtained in Theorem ??. Then the path-specific effect along the set of paths  $\pi$  on the mean difference scale for active values  $x_A$  and baseline values  $x_A^*$  is equal to*

$$\text{Effect along paths in } \pi = E[X_y]_{f_\pi(p(x_V))} - E[X_y]_{f_{do(x_A^*)}(p(x_V))}$$

*while the path-specific effect along all paths not in  $\pi$  on the mean difference scale is equal to*

$$\text{Effect along paths not in } \pi = E[X_y]_{f_{do(x_A)}(p(x_V))} - E[X_y]_{f_\pi(p(x_V))}$$

## A.5 The Soundness Proof

We first show soundness, namely that if a recanting district does not exist, then the path-specific counterfactual is identifiable from interventional distributions. We also give an expression for this counterfactual in terms of interventional densities.

Let  $\{v_1, \dots, v_m\} = V^* = An(Y)_{\mathcal{G}_A}$ . Consider the counterfactual joint probability  $p(X_{y_1}(\pi(x_A), x_A^*) = x_{y_1}, \dots, X_{y_m}(\pi(x_A), x_A^*) = x_{y_m})$ , representing the path-specific effect of  $A$  on  $Y$  along paths in  $\pi$ .

“Unrolling” this counterfactual, we get the following formula:

$$\sum_{x_{V^* \setminus Y}} p(X_{v_1}(x_{Pa_{\mathcal{G}_{V^*}}(v_1)}) = x_{v_1}, \dots, X_{v_m}(x_{Pa_{\mathcal{G}_{V^*}}(v_m)}) = x_{v_m}) \quad (1)$$

where each value assignment  $x_{Pa_{\mathcal{G}_{V^*}}(v_i)}$  is consistent with  $x_{v_1}, \dots, x_{v_m}$  and  $x_{V^* \setminus Y}$ , and the values of  $X_A$  given by the effect definition (that is if there is a green arrow from  $a \in A$  to  $v_i$ , then  $x_{Pa_{\mathcal{G}_{V^*}}(v_i)}$  assigns to  $X_a$  the treatment value  $x_a$  rather than the reference value  $x_a^*$ ).

One of the assumptions that functional DAG models make is that absence of a directed arrow from  $a$  to  $y$  implies fixing all observable parents of  $X_y$  renders the resulting counterfactual  $X_y(x_{Pa_{\mathcal{G}}(y)})$  independent of any counterfactual  $X_a(\cdot)$ , and that fixing  $X_a$  will not change  $X_y(x_{Pa_{\mathcal{G}}(y)})$ .

This in turn implies that in a marginal of a functional DAG model represented by an ADMG  $\mathcal{G}$ , for any two counterfactuals  $X_z(x_{Pa_{\mathcal{G}}(z)}), X_w(x_{Pa_{\mathcal{G}}(w)})$ , if there is no bidirected arrow from  $z$  to  $w$  in  $\mathcal{G}$ , then  $p(X_z(x_{Pa_{\mathcal{G}}(z)}), X_w(x_{Pa_{\mathcal{G}}(w)})) = p(X_z(x_{Pa_{\mathcal{G}}(z)})) \cdot p(X_w(x_{Pa_{\mathcal{G}}(w)}))$ . Further, any graphical independence model, including models induced by functional DAGs obey a property called compositionality. A counterfactual version of compositionality states that for any sets of counterfactual variables  $(X_A(x_{S_A}) \perp\!\!\!\perp X_Y(x_{S_Y}) \mid X_Z(x_{S_Z}))$  and  $(X_W(x_{S_W}) \perp\!\!\!\perp X_Y(x_{S_Y}) \mid X_Z(x_{S_Z}))$  hold, then  $(X_A(x_{S_A}) \cup X_W(x_{S_W}) \perp\!\!\!\perp X_Y(x_{S_Y}) \mid X_Z(x_{S_Z}))$  also holds.

These properties imply the that formula 1 is equivalent to the following formula

$$\sum_{x_{V^* \setminus Y}} \prod_{v_1, \dots, v_k \in D \in \mathcal{D}(\mathcal{G}_{V^*})} p(X_{v_1}(x_{Pa_{\mathcal{G}_{V^*}}(v_1)}) = x_{v_1}, \dots, X_{v_k}(x_{Pa_{\mathcal{G}_{V^*}}(v_k)}) = x_{v_k}) \quad (2)$$

where  $\mathcal{D}(\mathcal{G}_{V^*})$  is a set of districts in  $\mathcal{G}_{V^*}$ . This is a decomposition of formula 1 into a set of terms, one for each district in  $\mathcal{G}_{V^*}$

Finally, since all interventional values  $x_{Pa_{\mathcal{G}_{V^*}}(v_i)}$  for  $X_{v_i}$  involve either assignments to  $A$  or assignments to variables which appear in the district, and moreover, the intervened on values  $x_{Pa_{\mathcal{G}_{V^*}}(v_i)}$  are consistent with the assigned values

$x_{v_j}$  ( $j \neq i$ ) for variables in the district, we can use the consistency assumption to conclude formula 2 is equivalent to formula 3.

$$\sum_{x_{V^* \setminus Y}} \prod_{D \in \mathcal{D}(\mathcal{G}_{V^*})} p(X_D = x_D \mid \text{do}(x_{Pa_{\mathcal{G}_{V^*}}(D) \setminus D})) \quad (3)$$

where  $x_{Pa_{\mathcal{G}_{V^*}}(D) \setminus D}$  is a value assignment to  $Pa(D)_{\mathcal{G}_{V^*} \setminus D}$  consistent with  $x_{V^* \setminus Y}$  and assignments to  $X_A$  given by the effect.

This establishes our result.

## A.6 The Completeness Proof

Next, we show completeness, namely that if a recanting district exists, then the path-specific effect given by a counterfactual distribution

$p(X_{y_1}(\pi(x_A), x_A^*), \dots, X_{y_m}(\pi(x_A), x_A^*))$  is not identifiable. The proof will proceed as follows.

We will first show if there exists a recanting district  $D$  (for a particular  $a \in A$ ) then the following counterfactual probability  $\gamma_1$  is not identifiable from  $P_* = \{p(X_{V \setminus W} \mid \text{do}(x_w)) \mid W \subseteq V\}$  in the graph  $\mathcal{G}_{D \cup \{a\}}$ :

$$\gamma_1 = \sum_{x_{v_i}: v_i \in D \setminus rh(D)_{\mathcal{G}_{D \cup \{a\}}}} p(X_{v_1}(x_{Pa_{\mathcal{G}_{D \cup \{a\}}}(v_1)}) = x_{v_1}, \dots, X_{v_k}(x_{Pa_{\mathcal{G}_{D \cup \{a\}}}(v_k)}) = x_{v_k})) \quad (4)$$

where  $\{v_1, \dots, v_k\} = D$ ,  $rh(D)_{\mathcal{G}_{D \cup \{a\}}} = \{v_i \in D \mid Ch(D)_{\mathcal{G}_{D \cup \{a\}}} \cap D = \emptyset\}$ , and  $x_{Pa_{\mathcal{G}_{D \cup \{a\}}}(v_i)}$  for every  $v_i \in D$ , is a value assignment defined as follows.

It's an assignment of values to  $Pa_{\mathcal{G}_{D \cup \{a\}}}(v_i)$  that are consistent with  $x_{v_i}$  (values being summed and assigned) for nodes in  $Pa(v_i)_{\mathcal{G}_{D \cup \{a\}}} \setminus \{a\}$ . If  $a \in Pa_{\mathcal{G}_{D \cup \{a\}}}(v_i)$ , the assignment assigns to  $a$  the treatment value  $x_a$  if the arrow from  $a$  to  $v_i$  is green, and the reference value  $x_a^*$  otherwise (note that by assumption there exists both a green arrow from  $a$  to a node in  $D$ , and a blue arrow from  $a$  to a node in  $D$ ).

After showing the non-identifiability of  $\gamma_1$ , we show the non-identifiability of a

related counterfactual  $\gamma_2$ , defined as follows.

Fix  $Y' \subseteq Y$ , such that all nodes in  $rh(D)_{\mathcal{G}_{D \cup \{a\}}}$  are ancestral of  $Y'$  in  $\mathcal{G}_{V^*}$ , and for no subset of  $Y'$  is this true. For every node  $r$  in  $rh(D)_{\mathcal{G}_{D \cup \{a\}}}$  pick a node  $y_r \in Y'$  such that there is a directed path  $\pi_r$  from  $r$  to  $y_r$ . Let the set of nodes in every such path be equal to  $W^*$ . Let  $\mathcal{G}^*$  be a subgraph of  $\mathcal{G}_{V^*}$  containing nodes in  $D \cup W^*$ . Then we will show a counterfactual probability  $\gamma_2$  is not identifiable from  $P_*$  in  $\mathcal{G}^*$ , where  $\gamma_2$  is defined as

$$\gamma_2 = \sum_{x_{v_i}: v_i \in (D \cup W^*) \setminus Y'} p(X_{v_1}(x_{Pa_{\mathcal{G}^*}(v_1))} = x_{v_1}, \dots, X_{v_l}(x_{Pa_{\mathcal{G}^*}(v_l))} = x_{v_l}) \quad (5)$$

where  $\{v_1, \dots, v_l\} = D \cup W^*$ , and  $x_{Pa_{\mathcal{G}^*}(v_i)}$  is defined as before.

Having shown  $\gamma_2$  is not identifiable in  $\mathcal{G}^*$  from  $P_*$ , we then have two models  $M_1, M_2$  which agree on  $P_*$  but disagree on  $\gamma^*$ . We then note that augmenting  $M_1, M_2$  with additional variables can result in models  $M'_1, M'_2$  that induce  $\mathcal{G}$ , and such that  $\gamma_2$  is a marginal distribution of the counterfactual  $\gamma$  in these models. This will imply  $\gamma$  is not identifiable from  $P_*$  in  $\mathcal{G}$ , which was what we wanted to show.

**Lemma 2** *The counterfactual  $\gamma_1$  given in equation 4 is not identifiable from  $P_*$  in  $\mathcal{G}_{D \cup \{a\}}$ .*

*Proof:* Pick two nodes in  $D$ ,  $v_1, v_2$  such that  $a$  has a green arrow to  $v_1$ , and a blue arrow to  $v_2$ . Assume without loss of generality that  $a$  only affects those two nodes in  $D$ . Assume, also without loss of generality, that every node in  $D$  has at most one child (other arrows are vacuous).

We now construct two functional models,  $\mathcal{M}_1$  and  $\mathcal{M}_2$ , which both agree on  $P_*$ , both induce  $\mathcal{G}_{D \cup \{a\}}$ , but which disagree on  $\gamma_1$  as defined. In these models, every observable variable is binary. Every bidirected arc corresponds to an unobserved binary variable with two children. In  $\mathcal{M}_1$ , for every observable node, its value is determined by the bit parity function of its parents (both observed and unobserved).

For  $\mathcal{M}_2$ , for every observable node, its value is determined by the bit parity function of its parents, except the functions determining the values of  $v_1, v_2$  do not take the value of  $a$  into account. The distributions over unobserved nodes is the same in both models, and is uniform.

We now show the two models have the desired properties. That both models induce  $\mathcal{G}_{D \cup \{a\}}$  is clear. Next, we show  $\mathcal{M}_1$  and  $\mathcal{M}_2$  agree on  $P_*$ .

By construction, both models agree on  $p(x_a)$ . We next show both models agree on  $p(x_D \mid \text{do}(x_a))$ . It's not difficult to show (following the proof of Theorem 17 in [6]) that  $p(x_D \mid \text{do}(x_a)) = p(x_D)$  is a uniform distribution in  $\mathcal{M}_2$  over assignments  $x_D$  such that  $x_{rh(D)_{\mathcal{G}_{D \cup \{a\}}}}$  has even bit parity. In fact, the same proof shows the same for  $p(x_D \mid \text{do}(a))$  in  $\mathcal{M}_1$ . This implies that  $p(x_{D \cup \{a\}}) = p(x_D \mid \text{do}(x_a))p(x_a)$  is the same in  $\mathcal{M}_1$  and  $\mathcal{M}_2$ . Furthermore, for any partition  $(Z_1, Z_2)$  of  $Z = (D \cup \{a\})$ , it is either the case that  $Z_1 \subset D$ , or  $p(x_{Z_1} \mid \text{do}(x_{Z_2})) = p(x_{Z_1 \setminus \{a\}} \mid \text{do}(x_{Z_2 \cup \{a\}}))p(x_a)$ . In the former case we have two causal submodels derived from  $\mathcal{M}_1, \mathcal{M}_2$  which agree on functions and distributions of unobserved variables, and which have the observed distribution  $p(x_D \mid \text{do}(x_a))$ . This implies  $\mathcal{M}_1$  and  $\mathcal{M}_2$  must agree on  $p(x_{Z_1} \mid \text{do}(x_{Z_2}))$ . In the latter case, the decomposition of the effect, and the previous argument implies our conclusion.

Finally, we must show  $\mathcal{M}_1$  and  $\mathcal{M}_2$  disagree on  $\gamma_1$ .

In  $\mathcal{M}_2$ ,  $\gamma_1$  is a distribution over nodes in  $R = rh(D)_{\mathcal{G}_{D \cup \{a\}}}$ . By assumption, the values of the variables in set  $X_R$  can be viewed as giving the bit parity of each unobserved value, counted twice. This implies  $\gamma_1$  assigns probability 0 to any value assignment to  $X_R$  with odd bit parity, and a uniform distribution to even bit parity assignments. What we must now show is that  $\gamma_1$  is a different distribution in  $\mathcal{M}_1$ . Indeed, in  $\mathcal{M}_1$  the values of the variables in set  $X_R$  can be viewed as giving the bit parity of each unobserved value, counted twice, plus 1 (because  $a$  has exactly one directed path to  $R$  in  $\mathcal{G}_{D \cup \{a\}}$  where  $a$  takes on value  $x_a = 1$ , and exactly one directed path to  $R$  in  $\mathcal{G}_{D \cup \{a\}}$  where  $a$  takes on value  $x_a = 0$ ). This implies  $\gamma_1$  assigns probability 0 to any value assignment to  $X_R$  with even bit parity, and a

uniform distribution to odd bit parity assignments.

The constructed models  $\mathcal{M}_1, \mathcal{M}_2$  induce non-positive probabilities  $p(x_{D \cup \{a\}})$ . It is not difficult to augment these models to create a pair of new models  $\mathcal{M}'_1, \mathcal{M}'_2$  such that  $p(x_{D \cup \{a\}})$  in the new models is positive, and the models agree on  $P'_*$  (the set of interventional distributions in these new models) and disagree on  $\gamma_1$ .

We construct  $\mathcal{M}'_1, \mathcal{M}'_2$  by adding a new unobserved binary parent for every node in  $R$ , with a distribution  $\{\epsilon, 1 - \epsilon\}$ , where  $\epsilon$  is a very small positive real number. Clearly,  $\mathcal{M}'_1, \mathcal{M}'_2$  agree on any member of  $P'_*$  involving nodes in  $(D \cup \{a\}) \setminus R$ . Note that any member  $P'_j$  of  $P'_*$  involving nodes  $R' \subseteq R$  in  $\mathcal{M}'_1, \mathcal{M}'_2$  is a function of some interventional distribution over parents of  $R'$ , the distribution  $P(x_{U_R})$  over unobserved parents  $U_R$  of  $R$  added to  $\mathcal{M}'_1, \mathcal{M}'_2$ , the functions determining the values of  $R$  in  $\mathcal{M}'_1, \mathcal{M}'_2$ , and the distribution over original unobserved nodes in  $\mathcal{M}'_1, \mathcal{M}'_2$ . Since  $\mathcal{M}'_1, \mathcal{M}'_2$  agree on all these objects, they must agree on  $P'_*$ .

By construction, the probability of  $\gamma_1$  in  $\mathcal{M}'_2$  assigns low but non zero probabilities to odd bit parity assignments to  $X_R$ , while the probability of  $\gamma_1$  in  $\mathcal{M}'_1$  assigns low but non zero probabilities to even parity assignments to  $X_R$ . Since  $\epsilon$  can be made arbitrarily small, this implies  $\mathcal{M}'_1, \mathcal{M}'_2$  disagree on  $\gamma_1$ .

This concludes our proof.  $\square$

**Lemma 3** *The counterfactual  $\gamma_2$  shown in equation 5 is not identifiable from  $P_*$  in  $\mathcal{G}^*$ .*

*Proof:* Without loss of generality, assume every node in  $\mathcal{G}^*$  has at most one child. Then we augment  $\mathcal{M}'_1, \mathcal{M}'_2$  constructed in the proof of Lemma 2 by adding a binary node for every vertex in  $\mathcal{G}^*$ , but not  $\mathcal{G}_{D \cup \{a\}}$ . We let each such node obtain its value from the bit parity of its parents in  $\mathcal{G}^*$  (without adding unobserved parents). Call the resulting models  $\mathcal{M}''_1, \mathcal{M}''_2$ .

Every node added to  $\mathcal{M}''_1, \mathcal{M}''_2$  forms its own district, and for every such node  $w$ , the distribution  $p(x_w \mid \text{do}(x_{Pa(w)_{\mathcal{G}^*}}))$  is the same in  $\mathcal{M}''_1$  and  $\mathcal{M}''_2$  by construction. This implies  $\mathcal{M}''_1, \mathcal{M}''_2$  agree on  $P''_*$ . But by construction we also obtain

that  $M''_1, M''_2$  disagree on  $\gamma_2$ .

As before, the constructed models  $M''_1, M''_2$  do not yield positive observable distributions. We augment our models and create a new pair of models  $\mathcal{M}_1^*, \mathcal{M}_2^*$  which induce positive observable distributions, which agree on  $P_*$  and disagree on  $\gamma_2$ . To do so, we add for every node in  $W^* \setminus rh(D)_{\mathcal{G}^*}$  a new binary unobserved parent with probabilities  $\{\epsilon, 1 - \epsilon\}$ , where  $\epsilon$  is a very small positive real number. Since every node  $w$  in  $W^* \setminus rh(D)_{\mathcal{G}^*}$  is its own district, by construction  $\mathcal{M}_1^*, \mathcal{M}_2^*$  agree on  $p(x_w \mid \text{do}(x_{Pa_{\mathcal{G}^*}(w)}))$ , which implies  $\mathcal{M}_1^*, \mathcal{M}_2^*$  agree on  $P_*$ .

The probability of  $\gamma_2$  in  $\mathcal{M}_2^*$  then assigns a small but positive probability to any even bit parity assignment to  $Y'$ , while the probability of  $\gamma_2$  in  $\mathcal{M}_1^*$  assigns a small but positive probability to any odd bit parity assignment to  $Y'$ . Since  $\epsilon$  can be made arbitrarily small, this implies  $\mathcal{M}_1^*, \mathcal{M}_2^*$  disagree on  $\gamma_2$ .

This establishes our result.  $\square$

**Lemma 4** *The counterfactual  $\gamma$  is not identifiable from  $P_*$  in  $\mathcal{G}$ .*

*Proof:* This can be easily established by augmenting models  $\mathcal{M}_1^*, \mathcal{M}_2^*$  constructed in the previous Lemma with enough extra nodes to enlarge  $\mathcal{G}^*$  to  $\mathcal{G}$ . These extra nodes will be fully jointly independent of each other and nodes in  $\mathcal{G}^*$ . (That is, any edge connecting to such nodes in  $\mathcal{G}$  will be vacuous in our augmentation of  $\mathcal{M}_1^*, \mathcal{M}_2^*$ . It's clear from this construction that the resulting augmented models agree on  $P_*$ , disagree on  $\gamma$ , and induce a positive observable distribution.

This establishes completeness of the criterion.  $\square$

## A.7 Remaining Proofs

We first prove Theorem ?? . If the recanting district does not exist for a given path-specific effect of  $A$  on  $Y$  along paths in  $\pi$ , then the corresponding counterfactual is identifiable from interventional densities via equation (3). A general theory of identification [8],[5], [6] states that if a causal effect  $p(x_Y \mid \text{do}(x_A))$  is expressible as a function of  $p(x_V)$  in all causal models inducing  $\mathcal{G}$ , then it can be expressed as



a functional almost identical to equation (3) in this supplement, except all values of  $A$  in the functional are  $x_A$ . The conclusion immediately follows. Corollary ?? follows immediately from Theorem ??, and definitions in equations (??) and (??).

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