SAS/STAT® User's Guide
Introduction to Causal Analysis Procedures

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Chapter 7
Introduction to Causal Analysis Procedures

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Overview of Causal Analysis

The study of causal relationships is one of the most important endeavors in empirical science. Knowledge of whether a *treatment* (or an *intervention*) would have a causal effect on an *outcome* enables you to make informed decisions or take actions that could lead to anticipated results about the outcome. All the following examples involve an investigation of the putative causal effect of a treatment variable on an outcome variable:

- Does smoking cause lung cancer?
- Can a new policy boost the small business economy?
- Does attending a private high school lead to greater success in college than attending a public high school?

When you use randomized controlled trials (RCTs) to study causal relationships, statistical procedures for estimating causal effects are relatively easy to apply. In a simple RCT, each subject (or research unit) is randomly assigned to either the treatment or control condition. The purpose of randomization is to make the two groups comparable by design. Then the observed differences in the outcomes between the treatment and control groups are attributed solely to the causal effects of the treatment. You can use statistical procedures such as the ANOVA, GENMOD, GLM, LIFEREG, REG, and TTEST procedures in SAS/STAT software, among others, to estimate the causal effects and test statistical significance.

But when conducting RCT is not practical, you would need to draw causal inferences from observational data or imperfectly randomized experiments. With observational data, the statistical associations among the

observed variables reflect not only causal influences but also noncausal, or confounding, factors. This is the explanation behind the maxim that association is not causation. To infer causal effects from observational data, you might need to rely on specialized methods that can somehow address the confounding associations and other causal inference issues. In this regard, several procedures available in SAS/STAT can mitigate these issues and help make valid causal inferences:

- The CAUSALGRAPH procedure applies the theory of graphical causal models to guide you with valid modeling strategies for estimating causal effects.
- The CAUSALMED procedure posits a mediator in the causal process through which a treatment causally affects an outcome, and it estimates the direct, indirect, and various causal mediation effects.
- The CAUSALTRT procedure estimates causal treatment effects by propensity score weighting, outcome regression, and doubly robust methods.
- The PSMATCH procedure provides a variety of tools for propensity score analysis and produces output data sets to which you can apply propensity score matching, weighting, and stratification methods in order to estimate causal effects.

The main features and usages of these procedures are described in the next few sections. For an introduction to causal inference with data from observational or imperfectly randomized experiments, see Berzuini, Dawid, and Bernardinelli (2012), Hernán and Robins (2020), Imbens and Rubin (2015), and Morgan and Winship (2015) and references therein.

For valid causal inference and effect estimation from data to be possible, some assumptions must be made about the statistical techniques and methods that these procedures use. These assumptions are laid out within the potential (or counterfactual) outcomes framework (Neyman, Dabrowska, and Speed 1990; Pearl 2001; Robins and Greenland 1992; Rubin 1990) or the structural causal model framework (Pearl 2009b). It is important to emphasize that these assumptions are in addition to those of standard statistical modeling, such as independent observations or distributional assumptions. It is essential for the validity of the causal inferences that are obtained through the causal procedures that these assumptions be tenable. For more information about these assumptions and the related theoretical frameworks, see the following sections for the individual procedures:

- PROC CAUSALGRAPH: “Causal Graphs and Potential Outcomes” on page 2382
- PROC CAUSALMED: “Causal Mediation Effects: Theory, Definitions, and Effect Decompositions” on page 2453
- PROC CAUSALTRT: “Causal Effects: Definitions, Assumptions, and Identification” on page 2531
- PROC PSMATCH: “Observational Studies Contrasted with Randomized Trials” on page 8372 and “Propensity Score Analysis” on page 8373

The Causal Analysis Procedures

PROC CAUSALGRAPH

The CAUSALGRAPH procedure examines the structure of graphical causal models and suggests statistical strategies or steps that enable researchers to estimate causal effects that have valid causal interpretations.

Causal models are encoded in the form of directed acyclic graphs (DAGs) (Pearl 2009a, b), which are the primary input for the procedure. In the following example, you input a causal model in the MODEL statement and inquire about the identification conditions for the causal effect of PFAS on Duration in the IDENTIFY statement:

```
proc causalgraph;
   model "MyModel"
      Age    ==> Parity PFAS Education,
      Parity ==> PrevBF Duration PFAS,
      PrevBF ==> PFAS Duration,
      PFAS   ==> Duration,
      Education ==> Duration Employment PFAS BMI Alcohol Smoking,
      Employment ==> Duration PFAS BMI Alcohol Smoking,
      BMI Alcohol Smoking ==> Duration;
   identify PFAS ==> Duration;
run;
```

PROC CAUSALGRAPH interprets and encodes the (causal) directional relationships among the variables that you specify in the MODEL statement. It then applies the causal DAG theory to determine appropriate statistical strategies that you can use to estimate the causal effect of PFAS on Duration. For example, PROC CAUSALGRAPH outputs the valid sets of covariates that you can use for adjustments in outcome regression analysis or for matching in propensity score analysis. By using regression adjustment or propensity score matching techniques to estimate the target causal treatment effects, you can minimize the biasing effects due to the confounding covariates.

PROC CAUSALGRAPH provides a number of criteria for identifying causal treatment effects:

- constructive backdoor criterion
- backdoor criterion
- parents-of-treatment criterion
- parents-of-outcome criterion
- joint ancestor criterion
- instrumental variables

To identify the sets of adjustment covariates or instrumental variables, you can either request that the procedure list these sets (as in the preceding example) or test the validity of the sets that you specify. For more information about different criteria of identification, see the METHOD= option in Chapter 37, "The CAUSALGRAPH Procedure."

PROC CAUSALGRAPH supports the specification of multiple models, multiple treatments, and multiple outcomes. Other main features of PROC CAUSALGRAPH include the following:

- identification of joint causal effects from multiple treatments on multiple outcomes
- enumeration of all the observationally testable assumptions that are encoded by a causal model
- listing of causal and noncausal treatment-to-outcome proper paths
- ability to import and export saved models
- ODS graphics to visualize causal models

For more information about PROC CAUSALGRAPH, see Chapter 37, "The CAUSALGRAPH Procedure," and Thompson (2019).

PROC CAUSALMED

The CAUSALMED procedure estimates causal mediation effects in situations where the observed effects might have been confounded, such as in observational studies.

In causal mediation analysis, a treatment variable T is posited to causally affect an outcome variable Y through a mediation process that is reflected by the values of a mediation variable M. The total causal effect of T on Y is decomposed into two parts:

- an indirect effect through the mediation process, denoted as $T \rightarrow M \rightarrow Y$
- a direct effect not through the mediation process, denoted as $T \rightarrow Y$

To estimate causal mediation effects, PROC CAUSALMED uses the regression adjustment approach proposed by Valeri and VanderWeele (2013) and VanderWeele (2014). For a comprehensive review, see VanderWeele (2015). In this approach, you specify parametric models for the outcome variable and the mediator variable. In addition, confounding covariate effects are dealt with during model estimation.

For example, the following statements specify a causal mediation analysis in which you investigate the causal effects of the treatment variable Smoking (smoking behavior of mother) on the outcome variable Death (infant death):

```
proc causalmed data=birthwgt;
   class LowBirthWgt Smoking Death AgeGroup Race Drinking;
   mediator LowBirthWgt = Smoking;
   model Death = LowBirthWgt | Smoking;
   covar AgeGroup Race Drinking;
run;
```

You specify the outcome regression model in the MODEL statement and the mediation model in the MEDIATOR statement. Together, these models specify that the causal effect of Smoking on Death is mediated by the mediator variable LowBirthWgt (low birth weight) and that the interaction effect, as well as the main effects of Smoking and LowBirthWgt, is included in the outcome model. In addition, you specify in the COVAR statement that the covariates AgeGroup, Race, and Drinking might have confounded the

observed effects. These confounding effects would then be adjusted for when PROC CAUSALMED fits the outcome and mediator models and estimates various causal mediation effects.

The main results from PROC CAUSALMED include the total effect of T on Y, the natural indirect effect of T on Y that is mediated by M, the natural direct effect of T on Y that is not mediated by M, and the percentage of total effect that is due to mediation. Standard errors for these estimates are computed by analytic formulas or bootstrapping.

PROC CAUSALMED supports binary and continuous variables for the mediator and the following combinations of data type and model for the outcome response:

- continuous outcomes that are fitted by linear models
- time-to-event outcomes that are fitted by accelerated failure time or Cox proportional hazards models
- count data that are fitted by Poisson or negative binomial models
- binary outcomes that are fitted by generalized linear models with log or logit links

Other main features of PROC CAUSALMED include the following:

- estimation of the controlled direct effect, portion eliminated, percentage due to interaction, and various types of mediation effects and percentages
- computation of various two-way, three-way, and four-way effect decompositions of causal mediation effects
- estimation of conditional causal mediation effects for the subgroups of interest

For more information about PROC CAUSALMED, see Chapter 38, "The CAUSALMED Procedure," and Yung, Lamm, and Zhang (2018)

PROC CAUSALTRT

The CAUSALTRT procedure estimates the average causal effect of a binary treatment T on a continuous or discrete outcome Y, where the observed effect might have been confounded, such as in observational studies.

Two types of modeling are used in PROC CAUSALTRT. One is outcome modeling by a generalized linear model. The other is propensity score modeling of the treatment variable by a logistic regression model (Guo and Fraser 2015; Imbens and Rubin 2015). For example, the following statements specify both outcome and treatment modeling for estimating the causal treatment effect of Drug on Diabetes (both are assumed to be binary here):

```
proc causaltrt data=drugs;
   class Gender;
   psmodel Drug = Age Gender BMI;
   model Diabetes = Age Gender BMI;
run;
```

In the PSMODEL statement, you specify that the treatment variable is Drug and the corresponding propensity score model contains Age, Gender, and BMI as predictors of the treatment variable. The propensity scores in this model refer to the probabilities of drug use in individuals. In the MODEL statement, you specify that the outcome is Diabetes, which is modeled by Age, Gender, BMI, and Drug. Notice that the treatment effect of Drug on Diabetes is made implicit here. With the modeling of both the outcome and propensity scores, PROC CAUSALTRT uses a doubly robust estimation method (Lunceford and Davidian 2004) to estimate the potential outcome means, the average causal treatment effect, and their standard errors.

In fact, depending on whether or not you specify the effects on the right-hand side of the equal sign in the PSMODEL and MODEL statements, PROC CAUSALTRT estimates causal treatment effects by four different types of methods:

- specification of effects in both the PSMODEL and MODEL statements: doubly robust methods such as the augmented inverse probability weighting method and the inverse probability weighted regression adjustment method
- specification of effects only in the PSMODEL statement: three types of inverse probability weighting methods—basic, with ratio adjustment, and with ratio and scale adjustments
- specification of effects only in the MODEL statement: regression adjustment method
- specification of effects in neither the PSMODEL nor MODEL statement: unadjusted effect by computing the observed outcome mean difference between the treatment and control groups

The CAUSALTRT procedure can estimate two types of causal effects: the average treatment effect (ATE) and the average treatment effect for the treated (ATT). However, not all estimation methods can estimate both types of causal effects.

Other main features of PROC CAUSALTRT include the following:

- a class of generalized linear models for modeling continuous and binary outcomes
- asymptotic and bootstrap methods for computing standard errors and confidence intervals
- diagnostic plots for the propensity score model, including various plots of propensity scores or weights
- output data sets for propensity scores, inverse probability weights, and the predicted potential outcomes

For more information about PROC CAUSALTRT, see Chapter 39, "The CAUSALTRT Procedure," and Lamm and Yung (2017).

PROC PSMATCH

The PSMATCH procedure provides a variety of tools for propensity score analysis (Rosenbaum and Rubin 1983). It outputs data sets that contain pertinent propensity score information that you can use in subsequent outcome analyses to estimate causal effects.

PROC PSMATCH conducts propensity score analysis of a binary treatment variable T (say, T=1 indicates the treatment level), which is posited to have a causal effect on an outcome variable Y. You fit a propensity score model to the data so as to predict the propensity scores from a set of pretreatment (or baseline) characteristics. A commonly used form of the propensity score model is logistic regression, which is also assumed by PROC PSMATCH. For an introduction to propensity score analysis, see Guo and Fraser (2015).

For example, the following statements specify a propensity score analysis of the treatment variable Music (which indicates musical training in subjects):

```
proc psmatch data=School;
   class Music Gender;
   psmodel Music = Gender Absence;
   match method=optimal;
   output out(obs=match)=OutMatch;
run;
```

In the PSMODEL statement, the propensity score model specifies that the probability of receiving musical training is determined by the pretreatment characteristics Gender and Absence. In the MATCH statement, you request an optimal one-to-one matching of subjects between the treated and control groups. PROC PSMATCH then selects subsets of observations from the original data so that the selected observations in the treated and control groups match their propensity score distributions as closely as possible.

In the OUTPUT statement, you request that PROC PSMATCH output a data set called OutMatch. This output data set contains the original data as well as information about the matched subjects. For the current example, PROC PSMATCH creates a weighting variable named _MATCHWGT_ to indicate the matched subjects. You can then use this data set to estimate the causal treatment effect of Music on the outcome variable of interest.

For example, you can use PROC TTEST to estimate the causal treatment effect of Music on GPA (representing academic performance) and to test the statistical significance of the estimated causal effect by specifying the following statements:

```
proc ttest data=OutMatch;
   class Music;
   var GPA;
   weight _MATCHWGT_;
run;
```

PROC PSMATCH implements various propensity score methods, which are summarized as follows:

- propensity score matching method: PROC PSMATCH outputs matched observation weights for all subjects; subjects that are not matched are indicated by zero weights. Each set of matched subjects in the treated and control groups is also indicated by distinct identification numbers.
- propensity score weighting method: PROC PSMATCH outputs weights that are computed on the basis of the predicted propensity scores for all subjects.

- propensity score stratification method: PROC PSMATCH outputs stratum identification numbers for subjects. It also provides stratum weights that you can use to combine causal effect estimates from separate outcome analyses for the strata that PROC PSMATCH creates.

In all these propensity score methods, PROC PSMATCH outputs weights that you need to use in subsequent outcome analyses for estimating causal treatment effects. In addition, PROC PSMATCH computes different types of weights that are appropriate for computing the average treatment effect (ATE) and the average treatment effect for the treated (ATT), respectively.

A very important step in propensity score analysis is to evaluate the balance in covariates after you fit a propensity score model. PROC PSMATCH provides many numerical and graphical tools that you can use to assess the balance, including these:

- standardized mean differences between treated and control groups in the covariates
- percentage reductions of absolute mean differences after matching or weighting
- comparisons of distributions of covariates and propensity scores before and after matching or weighting

When you apply a propensity score–based adjustment method that is derived from a good propensity model, you expect good balance between the treated and control groups for all pretreatment covariates. If you are not satisfied with the covariate balance, refitting the propensity score model by other statistical strategies would be needed.

Other main features of the PSMATCH include the following:

- input of propensity scores that are estimated by methods outside PROC PSMATCH (for more information about inputting propensity scores, see the PSDATA statement of Chapter 101, "The PSMATCH Procedure")
- various matching methods: greedy nearest-neighbor matching, optimal matching, and matching with replacement

For more information about PROC PSMATCH, see Chapter 101, "The PSMATCH Procedure," and Yuan, Yung, and Stokes (2017).

Using the Causal Analysis Procedures

The causal analysis procedures that are described in this chapter help solve different kinds of causal inference problems. Certainly, this does not mean that you would use only one of these procedures exclusively. This section discusses how you might use these causal analysis procedures together and how these procedures work with other procedures to facilitate causal effect estimation.

Using PROC CAUSALGRAPH before Using Other Causal Analysis Procedures

Loosely speaking, being able to identify a causal effect means that you have a *valid* statistical strategy that infers or estimates the causal effect from the data, whether you collect them from observational studies or randomized experiments. When you use the CAUSALTRT or CAUSALMED procedure to estimate various types of causal effects or when you use the PSMATCH procedure to conduct propensity score modeling for matching, weighting, or stratification, you essentially assume the identification of the causal effect in question.

Practically, the identification assumption in these procedures is about whether you have measured and included a valid set of covariates in the regression model of the outcome variable and/or in the propensity score model for the treatment variable. In many situations, researchers might simply assume that a set of background (pretreatment) characteristics is a valid set of covariates in the model(s).

However, from the perspective of causal graph theory, the inclusion of all presumed background characteristics might not be an efficient or even valid modeling strategy to estimate causal effects. The primary purpose of PROC CAUSALGRAPH is to find valid modeling strategies or test the validity of a proposed strategy. When researchers can qualitatively specify the data generating process (including unmeasured variables and/or latent constructs) that explains how the treatment and outcome variables are related in the data, PROC CAUSALGRAPH can output valid measured covariate sets for regression adjustment or propensity score modeling.

Therefore, when you can reasonably assume the qualitative structure of the underlying data generating process, it is recommended that you use PROC CAUSALGRAPH to study the identification of causal effects before you use other causal analysis procedures. For illustrations of such a practice, see the examples in Thompson, Lamm, and Yung (2020) and Example 2 in Lamm, Thompson, and Yung (2019).

Using PROC PSMATCH Repeatedly to Ensure Proper Covariate Balancing

You use a propensity score model to estimate the probability that an individual receives a treatment. Then you use the estimated probabilities to create a matched, weighted, or stratified data set to which you apply a subsequent outcome analysis to estimate the causal effect of interest. Thus, a valid propensity model and an appropriate propensity score–based adjustment is critical to a valid estimation of the causal effect.

Checking covariate balance that results from a propensity score–based method (matching, weighting, or stratification) is perhaps the most common practice to justify the appropriateness of the propensity score–based adjustment. Although PROC PSMATCH provides many numerical and graphical tools for checking covariate balance, you can apply only a single logistic regression to model the propensity scores in a given analysis. If the covariate balance is not satisfactory, you might want to try other propensity score models that can lead to better covariate balancing. There are several possibilities for exploring suitable propensity score models:

- Add higher-order effects to the existing logistic regression of propensity scores.
- Replace the covariates in the existing logistic regression of propensity scores with a new set of covariates.
- Model the propensity scores by a technique other than logistic regression, possibly with a new set of covariates and/or a new set of covariate effects.

You can use PROC PSMATCH to explore the first two possibilities, but you must rely on other statistical procedures to explore the third possibility. Fitting a propensity score model in an external procedure might also be necessary when there is complete or quasi-complete separation of the data and the maximum likelihood estimates for the logistic regression model do not exist or are not unique.

When these other procedures produce the estimated propensity scores, you can input the propensity scores into PROC PSMATCH by specifying the PSDATA statement. PROC PSMATCH then examines the covariate balance by using these input propensity scores and completes the remaining tasks of the specified propensity score analysis. For illustrations of using the PSDATA statement, see Example 101.8 of Chapter 101, "The PSMATCH Procedure," and Example 1 of Lamm, Thompson, and Yung (2019).

Using PROC CAUSALTRT or PROC PSMATCH to Estimate Causal Effects

Both PROC CAUSALTRT and PROC PSMATCH use the logistic regression model to conduct propensity score analyses. If you specify the same propensity score model for these two procedures, you will get the same set of model fitting results and hence the same set of estimated propensity scores. Both procedures enable you to estimate the average treatment effect (ATE) and the average treatment effect for the treated (ATT). In addition, both procedures provide numerical and graphical tools for examining covariate balancing. Nonetheless, the two procedures have several distinct features that would suit different modeling situations.

You should consider using PROC CAUSALTRT in the following situations:

- You have a reliable outcome model to use for estimating causal effects by either an outcome regression method or a doubly robust method (for more information, see the METHOD= option and the MODEL statement in Chapter 39, "The CAUSALTRT Procedure").

- You are confident about the appropriateness of the specified propensity score model and want to estimate the standard errors of causal effects by taking the estimation of propensity scores into account.

You should consider using PROC PSMATCH in the following situations:

- You need to use the propensity score matching or stratification method (for more information, see the MATCH statement and the STRATA statement in Chapter 101, "The PSMATCH Procedure").
- You need to explore different propensity score models to achieve adequate covariate balance before conducting an outcome analysis (for more information, see the section "Using PROC PSMATCH Repeatedly to Ensure Proper Covariate Balancing" on page 144).

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