Glossary

AIPW estimator. See *augmented inverse-probability-weighted estimator*.

ATE. See *average treatment effect*.

ATET. See *average treatment effect on the treated*.

augmented inverse-probability-weighted estimator. An augmented inverse-probability-weighted (AIPW) estimator is an inverse-probability-weighted estimator that includes an augmentation term that corrects the estimator when the treatment model is misspecified. When the treatment is correctly specified, the augmentation term vanishes as the sample size becomes large. An AIPW estimator uses both an outcome model and a treatment model and is a doubly robust estimator.

average treatment effect. The average treatment effect is the average effect of the treatment among all individuals in a population.

average treatment effect on the treated. The average treatment effect on the treated is the average effect of the treatment among those individuals who actually get the treatment.

CI assumption. See *conditional-independence assumption*.

conditional mean. The conditional mean expresses the average of one variable as a function of some other variables. More formally, the mean of y conditional on $\mathbf{x}$ is the mean of y for given values of $\mathbf{x}$; in other words, it is $E(y|\mathbf{x})$.

A conditional mean is also known as a regression or as a conditional expectation.

conditional-independence assumption. The conditional-independence assumption requires that the common variables that affect treatment assignment and treatment-specific outcomes be observable. The dependence between treatment assignment and treatment-specific outcomes can be removed by conditioning on these observable variables.

This assumption is also known as a selection-on-observables assumption because its central tenet is the observability of the common variables that generate the dependence.

counterfactual. A counterfactual is an outcome a subject would have obtained had that subject received a different level of treatment. In the binary-treatment case, the counterfactual outcome for a person who received treatment is the outcome that person would have obtained had the person instead not received treatment; similarly, the counterfactual outcome for a person who did not receive treatment is the outcome that person would have obtained had the person received treatment.

Also see *potential outcome*.

doubly robust estimator. A doubly robust estimator only needs one of two auxiliary models to be correctly specified to estimate a parameter of interest.

Doubly robust estimators for treatment effects are consistent when either the outcome model or the treatment model is correctly specified.

EE estimator. See *estimating-equation estimator*.

estimating-equation estimator. An estimating-equation (EE) estimator calculates parameters estimates by solving a system of equations. Each equation in this system is the sample average of a function that has mean zero.

These estimators are also known as M estimators or Z estimators in the statistics literature and as generalized method of moments (GMM) estimators in the econometrics literature.

i.i.d. sampling assumption. See *independent and identically distributed sampling assumption*.

independent and identically distributed sampling assumption. The independent and identically distributed (i.i.d.) sampling assumption specifies that each observation is unrelated to (independent of) all the other observations and that each observation is a draw from the same (identical) distribution.

individual-level treatment effect. An individual-level treatment effect is the difference in an individual's outcome that would occur because this individual is given one treatment instead of another. In other words, an individual-level treatment effect is the difference between two potential outcomes for an individual.

For example, the blood pressure an individual would obtain after taking a pill minus the blood pressure an individual would obtain had that person not taken the pill is the individual-level treatment effect of the pill on blood pressure.

inverse-probability-weighted estimators. Inverse-probability-weighted (IPW) estimators use weighted averages of the observed outcome variable to estimate the potential-outcome means. The weights are the reciprocals of the treatment probabilities estimated by a treatment model.

inverse-probability-weighted regression-adjustment estimators. Inverse-probability-weighted regression-adjustment (IPWRA) estimators use the reciprocals of the estimated treatment probability as weights to estimate missing-data-corrected regression coefficients that are subsequently used to compute the potential-outcome means.

IPW estimators. See *inverse-probability-weighted estimators*.

IPWRA estimators. See *inverse-probability-weighted regression-adjustment estimators*.

matching estimator. An estimator that compares differences between the outcomes of similar—that is, matched—individuals. Each individual that receives a treatment is matched to a similar individual that does not get the treatment, and the difference in their outcomes is used to estimate the individual-level treatment effect. Likewise, each individual that does not receive a treatment is matched to a similar individual that does get the treatment, and the difference in their outcomes is used to estimate the individual-level treatment effect.

multivalued treatment effect. A multivalued treatment refers to a treatment that has more than two values. For example, a person could have taken a 20 mg dose of a drug, a 40 mg dose of the drug, or not taken the drug at all.

nearest-neighbor matching. Nearest-neighbor matching uses the distance between observed variables to find similar individuals.

observational data. In observational data, treatment assignment is not controlled by those who collected the data; thus some common variables affect treatment assignment and treatment-specific outcomes.

outcome model. An outcome model is a model used to predict the outcome as a function of covariates and parameters.

overlap assumption. The overlap assumption requires that each individual have a positive probability of each possible treatment level.

POMs. See *potential-outcome means*.

potential outcome. The potential outcome is the outcome an individual would obtain if given a specific treatment.

For example, an individual has one potential blood pressure after taking a pill and another potential blood pressure had that person not taken the pill.

potential-outcome means. The potential-outcome means refers to the means of the potential outcomes for a specific treatment level.

The mean blood pressure if everyone takes a pill and the mean blood pressure if no one takes a pill are two examples.

The average treatment effect is the difference between potential-outcome mean for the treated and the potential-outcome mean for the not treated.

propensity score. The propensity score is the probability that an individual receives a treatment.

propensity-score matching. Propensity-score matching uses the distance between estimated propensity scores to find similar individuals.

regression-adjustment estimators. Regression-adjustment estimators use means of predicted outcomes for each treatment level to estimate each potential-outcome mean.

selection-on-observables. See *conditional-independence assumption*.

smooth treatment-effects estimator. A smooth treatment-effects estimator is a smooth function of the data so that standard methods approximate the distribution of the estimator. The RA, IPW, AIPW, and IPWRA estimators are all smooth treatment-effects estimators while the nearest-neighbor matching estimator and the propensity-score matching estimator are not.

treatment model. A treatment model is a model used to predict treatment-assignment probabilities as a function of covariates and parameters.

unconfoundedness. See *conditional-independence assumption*.