

Performance Evaluation of Doubly Robust Estimators of Quantile Treatment Effects on Model Misspecification

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An important factor for evaluating policies is estimating the treatment effect, which is the impact a treatment has on an outcome. Policymakers may be interested not only in the average treatment effect, but also in the effect on the upper or lower side of the outcome distribution. The quantile treatment effect (QTE) helps evaluate the degree of effect on the lower and upper sides of the outcome distribution. A doubly robust estimator is used to estimate the QTE[1]. This estimator is less biased if either the model of the propensity score or the model of the outcome regression is correctly specified. The impact of misspecification of the propensity score model and the outcome regression model on the performance of the doubly robust estimator of the average treatment effect has been discussed[2]. By contrast, the similar impact of model misspecification on the performance of the doubly robust estimator of the QTE is not well discussed. Therefore, the relationship between model misspecification and the performances (the variance and relative bias) of the quantile treatment effect estimators is examined through numerical experiments. Details of the results are reported in the presentation.

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