

# A Case Application of Propensity Score Matching in MTM Outcomes Evaluation at Retail Pharmacy

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# Introduction

Propensity Score Matching (PSM) is widely used in observational studies. The basic idea of PSM is to match an untreated group to the treated group and the treatment effect is simply estimated as the difference between the average outcomes of two balanced groups. It is obviously important that the propensity score model balances the covariates. But how do we ensure that all covariates relevant to the study are incorporated into the model?

The current paper attempts to address this very issue by way of a case application, in which we examined multiple baseline study outcomes to verify that the PSM model is correctly specified with all relevant covariates. Conventionally, when a study involves multiple outcomes, PSM is performed for each individual outcome. In our current case application, a single PSM was done for multiple study outcomes. We then check for balance in all study outcomes at baseline, between the treated and un-treated groups, after propensity score matching. A correctly specified PSM model should balance all study outcomes at baseline.

### Methods

A medication therapy management program at a national retail pharmacy chain provides its patients comprehensive medication review (CMR) to promote safe and effective use of medications. A retrospective cohort study with a propensity matched control was conducted to evaluate the effects of CMR on brand to generic drug savings, medication adherence and immunization rates among the study subjects. The treatment group consisted of patients who had at least one completed CMR between January 2011 and June 2011. The control group consisted of patients who received no CMR and had at least one prescription filled at the retail pharmacy chain between January 2011 and June 2011. A 3.5% random sample (1,482,330 patients) was drawn from an enterprise data warehouse to serve as the pool for the control group.

#### Initial PSM Model

The initial PSM model to balance baseline covariates includes the following baseline covariates: Age, Gender, Co-pay, Total Drug Cost, Average Cost per Rx, Number of Therapeutic Classes, Insurance Plan, Average Community Income and Community Race Composition. A caliper matching algorithm was used to match the control group to the treatment group on a 1-to-1 ratio without replacement. The algorithm adjusts the caliper width from 4 to 1 decimal places so that it finds the "best" match first and the "next-best" match second. In the event of multiple matches, the algorithm randomly selects a control for the treatment.

A quick check of baseline study outcomes revealed that even though the propensity score model balanced the baseline covariates, it did not balance the baseline outcomes generic dispense rates (GDR). As was shown in Table 1, the baseline GDR for the treatment group was nearly twice that of the control group after propensity score matching.

Table 1: Baseline Generic Dispense Rate after Initial Propensity Score Matching

Group	# Patients	Baseline Generic Dispense Rate	P-value
Treatment	1367	11.7%	
Control	1383	6.7%	<.0001

# Final PSM Model

We could incorporate baseline GDR into the propensity score model to force a baseline GDR balance. However, to do so would most likely require us to do a separate propensity matching for each study outcome. In addition, just because one baseline outcome is balanced does not necessarily mean the model is correctly specified with all relevant covariates. It's important to try to uncover any additional confounders that might not have been considered in the model and could potentially affect the study outcomes.

A closer examination of the data revealed that the index dates, which defined GDR baselines for the two groups, were not balanced. We then added the index month in the propensity model, re-matched the two groups and checked the baseline GDR again. As was shown in Table 2, the baseline GDR now appeared to be balanced. We then checked the baseline Pneumovax and Zoster immunization rates (Table 2) and, again, they appeared to be balanced between the two groups. Lastly, we checked the baseline medication adherence as measured in proportion of days covered (PDC) for five select drug categories (Table 2) and, once again, they appeared to be balanced between the two groups.

# Results

Table 2: Baseline Study Outcomes after Final Propensity Score Matching

Outcome Metrics	Treatment Group		Control Group		
Canaria diamana Data	N	Rate	N	Rate	P-value
Generic dispense Rate	1,501	11.70%	1,481	10.90%	0.36
	Treatment Group		Control Group		P-value
Pneumovax immunization Rate	N	Rate	N	Rate	i -vaiuc
	7,142	0.30%	7,142	0.30%	0.75
	Treatment Group		Control Group		P-value
Zoster immunization Rate	N	Rate	N	Rate	i -vaiuc
	7,142	0.40%	7,142	0.40%	1
Proportion of Days Covered (PDC)	Treatment Group		Control Group		n voluo
Proportion of Days Covered (PDC)	N	PDC	N	PDC	p-value
ANTIDIABETICS	3,320	0.87	2,008	0.87	0.87
ANTIHYPERLIPIDEMICS	3,792	0.89	2,745	0.9	0.24
ANTIHYPERTENSIVES	3,693	0.91	2,814	0.91	0.82
BETA BLOCKERS	2,205	0.91	1,782	0.9	0.19
CALCIUM CHANNEL BLOCKERS	1,500	0.92	1,137	0.92	1
OVERALL	14,510	0.9	10,48 6	0.9	0.3

#### Conclusion

The propensity score model balanced all the study outcomes on top of the covariates, which, to a degree, validated the model. We were able to conduct the study as if it were a pseudo randomized study with just a single matching to evaluate multiple outcomes.

## Reference

Lori S. Parsons, "Performing a 1: N Case-Control Match on Propensity Score", May 2004, SUGI29



