

Using Propensity Scores to Adjust For Treatment Selection Bias

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ABSTRACT

Estimating the effect of drug treatment on outcomes requires adjusting for many observed factors, particularly those influencing drug selection. This paper demonstrates the use of PROC LOGISTIC in creating propensity scores to address such potential treatment selection bias. In this example using a pharmacy claims database, this method evaluates the probability of patients being included in five treatment groups and calculates weights based on factors hypothesized to influence treatment selection. A propensity score-weighted regression model is then fitted to compare the outcome of adherence between groups and to study the possible predictors of adherence.

INTRODUCTION

A limitation of observational studies is the lack of treatment assignment. This can lead to large differences in treatment groups that should be adjusted for to reduce selection bias and better clarify the effect of treatment. Regression adjustment, matching, and stratification using propensity scores are widely used techniques to compare groups, usually comparing a treatment group to a non treatment group. The purpose of this paper is to provide an example of using propensity score regression adjustment to balance five treatment groups.

DESCRIPTION OF STUDY

In this study, we identified patients using lipid lowering and antihypertensive therapy from a large pharmacy claims database. Patients were categorized into five treatment groups with the main objective of comparing compliance and adherence rates. Compliance was measured as the proportion of days a medication was supplied over a 180 day period. Adherent patients were identified as those reaching a threshold of 80% compliance. Demographic variables (age, gender) and previous medication use was measured in a 6 month baseline period prior to treatment.

Table 1 describes the treatment groups. PROC GLM was used to compare groups. For most covariates, there were significant differences among treatment groups ($p < .0001$).

Table 1. Unadjusted Demographic and Baseline Measures

UNADJUSTED VALUES		A	B	C	D	E	p-value
Member Count		434	1,064	971	850	1,228	
Age	Mean	57.2	61.8	62.3	61.7	63.9	<.0001
	SD	13.1	13.5	13.0	13.1	12.8	
Female	%	39.8%	50.3%	48.4%	53.8%	53.1%	<.0001
HMO Business Type	%	78.3%	75.2%	68.2%	68.4%	50.8%	<.0001
Open Formulary	%	73.0%	53.1%	53.7%	47.5%	49.3%	<.0001
# of baseline drugs	Mean	3.9	3.7	3.7	3.1	3.1	<.0001
	SD	3.7	4.1	4.3	4.1	4.2	
Maintenance Medication Refill %	%	38.8%	33.7%	33.8%	26.0%	26.8%	<.0001
ACE Inhibitor	%	21.4%	21.2%	21.0%	15.7%	15.3%	<.0001
Beta-blocker	%	16.5%	20.0%	20.3%	12.0%	13.3%	<.0001
Diuretic	%	4.1%	6.1%	6.9%	4.8%	5.4%	0.1813
ARB	%	18.8%	9.1%	10.5%	6.2%	7.8%	<.0001
Coronary Vasodilator	%	4.8%	6.2%	6.3%	6.2%	4.3%	0.1348
Digoxin	%	1.1%	1.0%	2.1%	1.7%	1.7%	0.2876
Platelet Aggregation Inhibitor	%	4.3%	4.3%	4.5%	2.8%	3.3%	0.2398
Diabetes	%	14.9%	16.1%	16.5%	12.5%	15.0%	0.1500
Antidepressant	%	13.1%	12.6%	11.6%	9.6%	9.6%	0.0518

CREATING PROPENSITY SCORES

The propensity score is the conditional probability of each patient receiving a particular treatment based on pre-treatment variables. Using the LOGISTIC procedure, propensity scores were calculated based on the 15 covariates listed in Table 1. The objective was to balance the treatment groups so to reduce bias of treatment selection and obtain better idea of treatment effect on the outcome of compliance. The generalized logit function is specified in the LINK option to contrast the reference group to the other four groups and the RSQUARE option assesses the amount of variation explained by the independent variables. The propensity score is output to data set named ps.

```
proc logistic data=ccb;
model cohort = age female pre_drgcnt hmo f_open ace betab diur arb nitrate
antiplatelet cvddig diabetes antidepressant maintrefillratio
/link=glogit rsquare
output out = ps pred = ps;
run;
```

Next a propensity score weight, also referred to as the inverse probability of treatment weight (IPTW), is calculated as the inverse of the propensity score.

```
data ps_weight;
set ps;
ps_weight=1/ps;
if cohort =_level_;
run;
```

As of now the weights are based on the entire study group and would give more weight to the smaller treatment groups. A SQL procedure creates a weight that reflects the sample size for each of the treatment groups.

```
proc sql;
create table ps_weight_adj as
select *, (count(*)/4547)*ps_weight as ps_weight_adj
from ps_weight
group by cohort;
quit;
```

Table 2 describes the treatment groups based on the propensity score weights. The effect of the propensity score weights was to balance the groups. Comparisons among treatment groups found no significant differences, with exception to the diuretic covariate.

Table 2. Propensity Score Weighted Demographic and Baseline Measures

PROPENSITY SCORE WEIGHTED VALUES		A	B	C	D	E	p-value
Member Count		434	1,064	971	850	1,228	4,547
Age	Mean	62.6	61.6	62.1	62.0	61.6	0.6203
	SD	13.8	13.5	13.1	13.0	13.2	
Female	%	52.7%	49.9%	50.3%	49.6%	50.9%	0.8539
HMO Business Type	%	67.5%	66.7%	66.0%	66.4%	67.0%	0.9769
Open Formulary	%	54.5%	53.6%	52.6%	53.1%	53.5%	0.9730
# of baseline drugs	Mean	3.8	3.5	3.5	3.5	3.6	0.6102
	SD	3.7	4.0	4.2	4.3	4.3	
Maintenance Medication Refill %	%	33.9%	30.8%	30.8%	31.5%	30.9%	0.6252
ACE Inhibitor	%	19.0%	18.6%	18.7%	19.5%	19.0%	0.9882
Beta-blocker	%	20.5%	16.2%	16.4%	16.8%	16.8%	0.3324
Diuretic	%	10.5%	5.7%	5.6%	5.7%	5.9%	0.0035
ARB	%	9.4%	9.8%	9.3%	9.7%	9.7%	0.9941
Coronary Vasodilator	%	6.4%	5.6%	5.6%	5.9%	5.3%	0.9310
Digoxin	%	1.5%	1.5%	1.5%	1.5%	1.4%	0.9999
Platelet Aggregation Inhibitor	%	3.9%	3.8%	3.8%	3.7%	3.7%	0.9999
Diabetes	%	18.1%	15.3%	15.1%	14.9%	16.0%	0.5930
Antidepressant	%	12.6%	11.3%	11.0%	11.0%	11.6%	0.9166

PROPENSITY SCORE WEIGHTED OUTCOME MODEL

Next, a propensity score-weighted logistic regression model was fitted to compare the outcome of adherence. Table 3 shows the comparisons of treatment groups. A second model was run to assess the diuretic covariate.

```
proc logistic data=ps_weight_adj descending;
class cohort / param=glm ;
model pdc_bothmeds_80= cohort /rsquare
weight ps_weight_adj;
format cohort cohortreg.;
run;
```

Table 3. Propensity Score Weighted Outcome Models

Effect	Odds Ratio	95% Confidence Limits	p-value	Effect	Odds Ratio	95% Confidence Limits	p-value
B vs. A	0.823	0.658 - 1.029	0.0869	B vs. A	0.815	0.652 - 1.019	0.0726
C vs. A	0.706	0.563 - 0.886	0.0026	C vs. A	0.699	0.557 - 0.877	0.0020
D vs. A	0.867	0.688 - 1.092	0.2254	D vs. A	0.858	0.681- 1.082	0.1959
E vs. A	0.726	0.583 - 0.903	0.0040	E vs. A	0.719	0.577 - 0.895	0.0031
				Diuretic	0.818	0.641 - 1.044	0.1061

CONCLUSION

This paper presents a scenario where compliance outcomes are compared among five treatments groups using an inverse propensity score weighted logistic regression model. This is an additional method that can be used in conjunction with other regression adjustment techniques to reduce bias and better describe the effect of treatment.

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