AEPP Final Project

In this project, three different econometric methods were used to determine the effect of mothers smoking during pregnancy on the birth weight of the child: randomised control trial (RCT), simple linear regression and propensity score matching (PSM).

Randomised Control Trial (RCT)

A RCT is a trial in which subjects are assigned to two groups- the treatment group, in which the intervention is administered, and the control group, which does not introduce any new changes. Ideally, subjects in both groups should be balanced in terms of confounding variables that might play a role in influencing the outcome. In this experiment, the intervention is the use of cigarettes while pregnant. The control group consists of mothers who did not smoke while pregnant. For the results to be optimal, there should be no more general underlying differences between the two groups- subjects should be evenly distributed with respect to income, education level, etc.

Methodology

First, proportionality was checked. It was found that there were 178 subjects in the treatment group, and 222 in the control group, indicating a fairly good ratio.

Next, balance was checked by taking the average of all subjects in both groups with respect to other independent variables. The data set was found to be unbalanced in all respects. In the control group, average education of the mother was 12.5 years, average father's education was 13.6 years, average per capita income was 56,575 currency units and the average wellness level of the mother was 159. In contrast, the treatment group showed that average education of the mother was 7 years, average father's education was 6.3 years, average per capita income was 26,158 currency units and the average wellness level of the mother was 113. Thus, it was found that in the treatment group, families were likely to be poorer, less educated and less healthy on average. This indicates imbalance.

Finally, the average treatment effect was calculated by taking the difference of the average birth weight of the child in both groups. It was found that children of mothers who smoke during gestation weighed 59 grams less on average than children whose mothers did not smoke (Treatment group weight = 226 gm, Control group weight = 258 gm).

Merits

One of the key merits of RCTs is the direct establishment of a cause-and-effect relationship. In our study, it was possible to assess the direct result of smoking on the birth weight of a child by looking at the average weight at birth in both the treatment and control groups and comparing the findings. The treatment and control groups could be easily compared to one another by isolating the treatment. RCTs should also ideally help reduce selection bias through the process of random allocation. The accurate calculation of average birth weight would have been optimised if both groups were adequately balanced in terms of confounding variables. Thirdly, when a sample size is large enough, it helps circumvent committing type 1 or type 2 errors. By having a fair and large proportion of subject in both groups, the risk of rejecting the null or alternate hypothesis incorrectly was minimised.

Demerits

A lack of balance was the most detrimental factor in the study. The fact that the treatment group, on average, had poorer, less educated and less healthy mothers, opened the door to selection bias. It is safe to infer that, women who earn relatively less and have left school at an early age will be more likely to smoke while pregnant due to being inadequately informed about the damaging effects. Therefore, it is more probable that mothers who fulfil these criteria will be more likely to populate the treatment group. Furthermore, it is very possible that lower incomes and education levels would have enhanced the ill-effects of smoking on birth weight. Malnutrition and a lack of healthcare due to these underlying variables might also contribute to a lower birth weight.

Linear Regression

A linear regression attempts to bring out a statistically significant correlation between a dependent variable and one or more independent variables. In this study, three linear regressions were performed to see which variables had a significant impact on the birth weight of the child.

Methodology

The three linear regression models conducted may be summarised as follows:

1. Reg0 (Bivariate)
   Yi (Child birth weight) = X0 + X1 (Mother smoking) + ui
   It was found that even though smoking had a statistically significant impact on child birth weight, the model could be further improved by adding new variables, considering that this model accounted for only 31.7% of the impact.

2. Reg1 (Multivariate)
   Yi (Child birth weight) = X0 + X1 (Mother smoking) + X2 (Mother education) +X3 (Mother health) + X4 (Monthly income) + ui
   It was found that even though mother's education was the only statistically insignificant variable, the model could be explained relatively more using these factors.

3. Reg2 (Multivariate)
   Yi (Child birth weight) = X0 + X1 (Mother smoking) + X2 (Mother education) +X3 (Mother health) + X4 (Father edu) + X5 (Father Smoking) + X6 (Monthly income) + ui
   It was found that many variables, such as father smoking and education, had a largely insignificant impact on the birth weight.

In conclusion, Reg1 included variables that helped explain a relatively greater part of the difference in child birth weight. Thus the model was optimised.

Merits

Through these models we were able to assess and compare the impact of several independent variables on the dependent variable, and see which one had the greatest/least influence. We were also able to effectively weed out irrelevant or insignificant variables such as father's education and smoking habits, and to identify outliers.

Demerits

Even after optimising the model it was found that the included variables could account for only 33% of the difference in birth weights. This would lead to omitted variable bias, and overestimating the impact of several independent variables on the average birth weight. Secondly, it was found that heteroskedasticity exists in the model, thus rendering it an inaccurate determination of the impact of smoking on birth weight, as error terms are unevenly placed along the line. Finally, the assumption of no multicollinearity was not satisfied, as factors such as the mother's smoking habits and education levels seem to be correlated.

Propensity Score Matching

Propensity score matching is a method by which similar observations are paired with one another according to certain baseline features to limit selection bias. The propensity score acts as a leveller. In our study, it was observed that there is a systematic baseline difference between treated and untreated subjects, stemming from the fact that mothers with certain incomes and education levels are more likely to administer the treatment, i.e. cigarettes during pregnancy. If we assigned a propensity score to each subject, it would help eliminate the difference in these characteristics, as mothers in a certain set of scores would have similar incomes and education levels. Therefore, a method is used whereby variables affecting the treatment itself, and not the outcome, are accounted for.

Methodology

Three generalised linear models were used, and can be summarised as follows:

1. Pscores Model = Mother Smoking ~ Mother edu + Mother health + Father edu + Father smoking + Monthly income

2. Pscores Model 1 = Mother Smoking ~ Mother edu + Mother health + Father edu + Monthly income

3. Pscores Model 2 = Mother Smoking ~ Mother health + Father edu + Father smoking + Monthly income

Of these, it was found that the first model had the lowest AIC of -34, thus making it the most accurate and suitable model. It was also observed that the lower the level of education, health of the mother, and monthly income, the higher the chance of the subject being placed in the treatment group, and vice versa.

Then, a propensity score matrix was created to allot scores to each subject in order to see the probability of each being placed in either the treatment or the control group.

New sets were created, as subjects were matched with one another depending on their propensity scores in order to minimise selection bias and even out the differences in baseline characteristics.

Summaries of the matched and original data sets were compared. It was found that there was not much improvement in mean difference. Finally, the average treatment effect was calculated by subtracting the mean of the birth weight in the control group from that in the treatment group. The mean difference was -62.42, suggesting that a child in the treatment group would weigh an average of 62 grams less than a child in the control group. This result was validated by a linear regression model.

Merits

The PSM method tries to eliminate underlying differences in the treatment and control group in order to optimise the accuracy of the calculated treatment effect. In our study, a propensity score table was created in order to group women with similar incomes, education and health levels. This would isolate the administration of the treatment as much as possible.

Demerits

The PSM method relies heavily on variables other than the treatment in order to allocate propensity scores to subjects. However, the model can be prone to inaccuracies if there are crucial variables left out. We have observed in the linear regression model, that all the variables mentioned take into account only 33% of the model. Grouping subjects by propensity scores dependent on factors that may not play such a large role can damage the model. Secondly, the matching process weeds out many subjects that do not have a close match. This makes the subset even smaller in order to achieve balance. In our model, there were 44 unmatched subjects in the treatment group. This number makes up a considerable proportion, and can lead to bias.

Conclusion

Taking into account the merits and demerits of each method, the propensity score matching method might be the most suitable for such an experiment. Though there is a chance of omitted variable bias, other underlying factors are largely controlled for, thus isolating the treatment effect as much as possible. The randomised control trial does display selection bias. The linear regression model is largely impractical due to the amount of multicollinearity present among variables. The propensity score method takes into account these biases and tries to iron out the differences as much as possible by pairing up observations with similar scores.