Assessing the Causal Link between the Minimum Legal Drinking Age and Motor Vehicle Accidents

ECON 615 Term Paper

Daniel Yang

Introduction

In 2011, Carpenter and Dobkins compiled a literature review in the *Journal of Economic Perspectives* regarding the role of the minimum legal drinking age (MLDA) in the USA and it's impact among youths and young adults. The minimum legal drinking age is commonly framed as a dichotomous discussion - detractors often consider the 21-year MLDA as too high in the qualified sense of what constitutes an adult right, that culturally similar countries have a lower MLDA of 18, and most importantly the effectiveness of these kinds of laws when it comes to reducing adverse societal impacts (Carpenter and Dobkins, 2009). Beginning in the 70s, several states experimented with lowering the MLDA, which offers an opportunity to study the policy effects of government intervention. In their paper, the authors evaluate these effects in part by analyzing the changes in mortality rates that are linked to alcholic consumption. Our focus in this paper is the replication of the differences-in-differences method employed for such analysis.

Data

The original dataset analyzed by Carpenter and Dobkins contained information on state, year, mortality rates (in 100 000s), cause of mortality and a 'legal drinking ratio'. The last variable represents the proportion of 18-20 year olds that are legally able to drink at a specific state and time, and so accounts for the fact that not every state that chose to lower the MLDA uniformly lowered to 18 years old. We turn our attention to mortality rates specific to motor vehicle accidents, as that cause of death is likely the most compelling from a causal point of view. This dataset was sourced from the National Vital Statistics System and the Fatality Accident Reporting System. Unfortunately, attempts to recover this particular dataset failed. As a result, an alternative dataset was used to approximate the results, the same one that Angrist and Pischke (2014) chose as a case study for the same topic in their textbook[1]. All 51 states[2] were used, over the period of 1970-1983, for a total of 714 data points. The key difference between the datasets are the time periods chosen (the original dataset is from 1975-1993).

Econometric Model

The model in the paper is a panel regression of the following form:

$$Y_{st} = \beta \text{MLDA}_{st} + \theta_s + \mu_t + \psi_{st} + \varepsilon_{ist}$$

The model chosen to replicate the results *in general*[3] is that of the difference in differences design:

$$Y_{st} = \alpha + \delta_{DD}\text{MLDA}_{st} + \sum_{k=\text{Alaska}}^{\text{Wyoming}} \beta_k \text{State}_{ks} + \sum_{i=1970}^{1983} \lambda_i \text{Year}_{it} + \psi_{st} + \varepsilon_{st}$$

The above model can be interpreted in the following manner: Y is the mortality rate, α is the intercept term, δ is the parameter for MLDA (the proportion of 18-20 year olds that are legally able to drink), β_k are the dummy variables that captures the state effects, λ_i are the dummy variables that captures the time effects, and ψ is the interaction between state and year. In the paper, a form of RDD was also carried out to provide alternative estimates:

$$y = \beta_0 + \beta_1 \text{MLDA} + \beta_2 \text{Birthday} + f(\text{age}) + \varepsilon$$

Where $f(\cdot)$ is a quadratic function. This regression model was included for the sake of completion *and not analysis.*

[1] Probably, the primary data source is the same (National Vital Statistics)
[2] Includes the district of Columbia
[3] We actually consider 4 variants to this model in the Analysis portion

Results

We consider four kinds of models based on the DID design described earlier: the OLS model without ψ, the OLS model with ψ, the weighted model without ψ, and the weighted model with ψ. Clustered standard errors by state population were chosen to be included. We present the findings of our estimates in the table below:

Table 1: Point estimates for the effect of MLDA on mortality rates

Model	Point Estimate	Clustered SE
No Trend, No Weight	7.59	2.50
Trend, No Weight	6.64	2.66
No Trend, Weight	7.50	2.27
Trend, Weight	6.46	2.24

All models find MLDA to be significant. We find that on average, a lower MLDA resulted in an increase of 6-7 motor vehicle accident fatalities per 100 000. Including the interaction term modestly increases standard errors, while considering a weighted model substantially decreases standard errors. With a different dataset, we would not be able to recover the same parameter and SE as the paper. However, we can happily report that the point estimates and standard errors matches the case study results, which is really the intended goal (as the dataset corresponds to the case study).

Discussion and Limitations

One important aspect of econometric analysis we have yet to address is that of checking model assumptions. Indeed, it seems out of order that we have actually conducted the analysis first prior to checking the assumption of the DID model - particularly the common trend assumption. But by including ψ, the state-specific linear time trend effect, we are capturing any sharp deviations in the trend of a treated group, even if trends are not parallel. Since there is not much difference between the models with and without ψ, we conclude our findings are not spurious. Another potential issue is the difference in how all states chose to implement changes to their MLDA[4]. This forces us to use a more complex model than the parsimonious binary model. As a result, it may be more favourable to consider an RDD model instead - far less model coefficients to estimate.

Conclusion

Our findings, while not matching the exact estimates in the paper, leads to the same conclusion that a lower MLDA is linked to higher fatalities. As the identification strategy is through the difference in differences method, we feel justified in saying we recovered the *causal effect*. As to whether or not we *ought* to increase the MLDA to decrease fatalities is outside the scope of what the original paper strives to answer - as a result, we make no attempt either. Our findings do match the results in the case study, which lends a lot of credence to the analysis.

References

1. Carpenter, Christopher, and Carlos Dobkin. "The minimum legal drinking age and morbidity in the United States." Review of Economics and Statistics 99.1 (2017): 95-104.

2. Carpenter, Christopher, and Carlos Dobkin. "The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age." American Economic Journal: Applied Economics 1.1 (2009): 164-82.

3. Angrist, Joshua D., and Jörn-Steffen Pischke. Mastering'metrics: The path from cause to effect. Princeton University Press, 2014.

[4] An unfortunate side effect is that it makes graphical depictions of the data trends very difficult (if not straight up impossible) to implement

Appendix

Below are the codes used to generate the results in the paper.

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library(multiwayvcov)

load(file = “deaths.rda”) #DID

dtypes <- c(“all” = “All deaths”, “MVA” = “Motor vehicle accidents”, “suicide” = “Suicide”, “internal” = “All internal causes”)

deaths = mutate(deaths, year_fct = factor(year)) data = filter(deaths, year <= 1983, agegr == “18-20 yrs”, dtype == “MVA”)

mod = lm(mrate ~ 0 + legal + state + year_fct, data = data) vcov_firm <- cluster.vcov(mod, data$state) coeftest(mod, vcov_firm)

model2 = lm(mrate ~ 0 + legal + year_fct + state + state:year, data = data) coeftest(model2, vcov.= vcovHC(model2, type = “HC3”)) vcov_firm <- cluster.vcov(model2, data$state) coeftest(model2, vcov_firm)

model3 = lm(mrate ~ 0 + legal + state + year_fct, data = data, weights = pop) vcov_firm <- cluster.vcov(model3, data$state) coeftest(model3, vcov_firm)

model4 = lm(mrate ~ 0 + legal + year_fct + state + state:year, data = data, weights = pop) coeftest(model4, vcov.= vcovHC(model4, type = “HC3”)) vcov_firm <- cluster.vcov(model4, data$state) coeftest(model4, vcov_firm)

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