Final exam : report and comment on our simulations

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Abstract

In this final exam we use simulations to investigate the effect of a selection bias. The original project is to estimate the effect of grid connectivity on electricity prices

1 Project presentation

The original project on which this final exam relates is an estimation of the effect of grid connectivity on the electricity prices. This design comes from the master thesis project of one of us and relies on the outage database of the ENTSOE[1]. Outages exogenously reduce the available transfer capacities for electricity trade between countries, and therefore is used as a explaining variable in the following panel regression :

$$P_{it} = \beta_0 + \beta_1 NewNTC_{it} + \beta_2 X_{it} + C_i + Y_t + \epsilon \quad (1)$$

Where $NewNTC$ is the explaining variable, X a set of controls and C_i and Y_t are time and countries fixed effects.

This design assumes that the newNTC database depends on outages that are themselves exogenous with respect to wholesale electricity price. However, since most of the outage on the European network are due to maintenance there is a risk that Transfer System Operators choose in some extent the date of the outages in relation to covariates that are linked to price (for exemple consumption). In this case, the previous suffers from endogeneity that could result in a bias in the estimate.

The exercice we perform on R is to simulate an alternative Data Generating process with a selection effect leading to endogeneity, and to compute the bias due the wrong model. We built a several step data generating process :

1. We simulate distributions for prices and net transfer capacities on the basis of existing data from the ENTSOE
2. We compute a NewNTC statistic that modify that is based on the NTC distribution but is correlated with observed prices : $NewNTC = NTC + \gamma P$
3. We redefine prices thanks to the following data generating process : $P = \beta_0 X + \beta_1 New_N TC$

In our simulation the True data generating process is therefore based on newNTC. But the model that we will estimate uses NTC as explaining variable. There is therefore a bias that is revealed by the simulation.

We test four different models :

1. Data generating process with daily data (means of hourly data)
2. Data generating process directly with hourly data (and hourly fixed effects)
3. Data generating process with differentiate controls among two countries : the values of the control variable are not the same for both countries

[1]European Network of Transfer System Operators

4. Data generating process with some kind of seasonality : a categorical variable differentiates cold months from hot months

These for different all give the same kind of results : without surprise estimating the wrong model gives on average the wrong result. The distribution is not centered on the True effect as can be seen on the following graph.

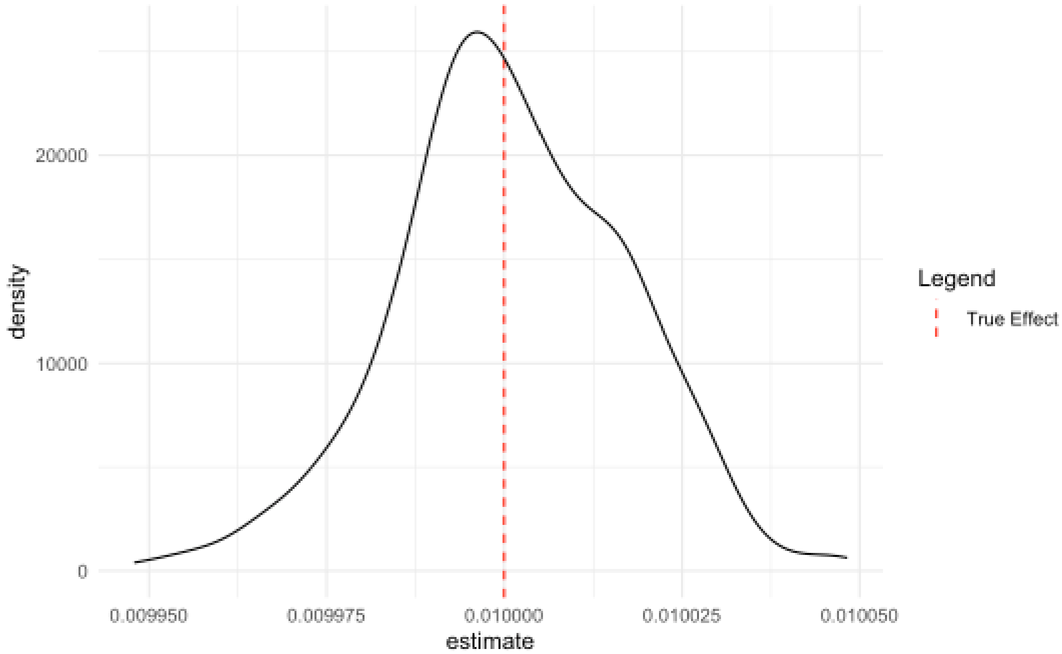

Figure 1: Distribution of estimates after repeating 400 times the model (1).

We then perform other test on the data generating process :

1. Power calculation for every previous dataset
2. Try to perform a random shock on the dataset to see if a strong variation of price on a few observations is likely to cause a additional bias in the estimate.
3. Adding a propensity score of outage for every observation : we estimate a logit model that gives for each hour a probability to face a maintenance as a function of some exogenously defined characteristics (weather, grid quality...).

None of the additionnal test we ran gave any results that are worthy of being signaled. The bias is observed in every situation.

2 Simple Logit model on an outage dummy

The idea of this section was to add some insights about how we could calculate an hourly probability of maintenance on the grid. We use a binary logit model to achieve this. The quarto document attached to this report contains the detail of the code

3 Effective sample approach

In this section, we tried to evaluate wether or not an unequal distribution across the panel sample can lead to an unequal wight of each country in the sample. The idea is the following : the explaining variable used in the estimation is the reduction in Net Transfer Capacity due to outage, therefore the precision of the estimate depends on the available variability in the in NTC and is higher if the grid face a lot of outages. The original goal was to estimate how the difference in quality that reflects in the difference in the frequency of outages leads to an unequal weight of the different countries in the final estimate.

Such a result is key when there are heterogeneous effects since the inequality of weight would lead in this case to a bias average treatment effect estimate.

We didn't have time to perform all of what we programmed. The only simulation we succeeded in this section consist in computing an estimate with randomly generated distribution for dependent and explaining variable, then looking at the distribution of standard errors when we let the variance of the explaining variable -linked to the outage frequency- vary. The simple code we wrote could very much be improved. The result is surprising since the standard error varies in a close, defined interval, as can be seen on this graph :

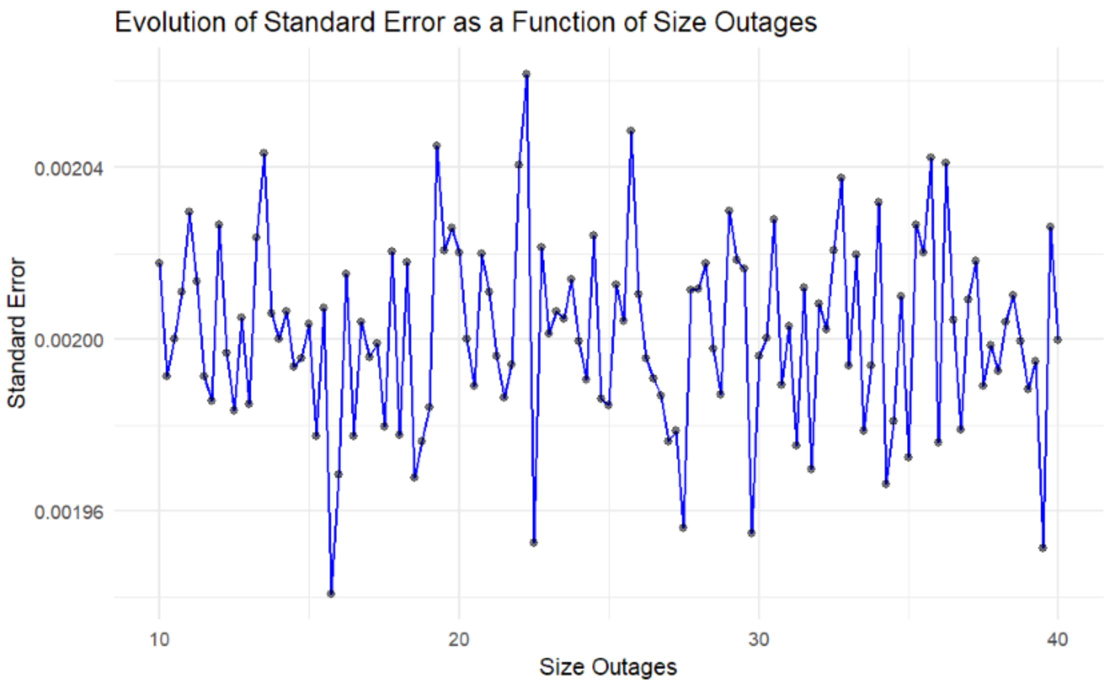

Figure 2: Evolution of standard error as a function of size outages

To get a more relevant estimate (even if we would first have to think about what was wrong in our original idea) would be to calculate a whole set of estimates for each value of the explaining variable in order to have a more accurate vision of the distribution of computed standard errors.

We tried to make the data generating process more complex but we were not able to produce a functional code. We planned to :

1. Improve the code to compute a simulation of the DGP on a set of countries with 10 000 observations for each country : the same DGP is applied for every country but the variability of the explaining variable varies across the panel varies among countries.

2. Run an estimation on the whole sample and compute a true effective sample statistic that quantify the weight of each country in the final estimation. The share of each country in the effective sample is expected to be positively correlated with the variability of the explaining variable, therefore the number of outges

3. The next step is to quantify the possible bias this inequality in the effective sample may induce : let's suppose the effect is heterogeneous and is positively correlated with grid quality and

therefore to the outage. The estimation will then give a higher weight to countries with a high effect size. If the panel is very imbalanced due to a high variability of grid outages it could lead to strong bias, the average treatment would be biased toward the specific effect of some countries in the sample.

Conclusion

We realize that the final result we get is not satisfying since the DGP is not complex enough to give a convincing idea of the estimation constraints. We probably made mistakes while evaluating what was actually possible to do given our time constraints and R skills. The simulation approach gives a lot of liberty to the researcher, which can lead to drowning in the infinite range of possibilities, distributions and parameters to explore.