Applied Microeconometrics

Home assignment 1

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Abstract

This paper intends to study whether the firms which are acquired by foreign owners experience higher growth of sales than domestically-owned firms. After using the bunch of simple as well as sophisticated techniques which include matching, propensity score estimation with weightening and blocking options, the authors conclude that firms in the control group do experience higher growth. Introducing the threshold even intensifies the result above. Moreover, the framework of the potential ideal experiment is discussed.

1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Llnsales	4916	-.5697961	1.700341	-6.236795	4.85069
Lexport	4916	.5067128	.5000058	0	1
Lavwage	4916	22873.76	9960.431	2189.846	129253.8
Linnovation	4916	.3136697	.464031	0	1
Llnkapital	4916	13.75535	2.195417	6.74384	20.92299
LsalesGR	4916	.0646412	.3043649	-5.875442	5.934851
FsalesGR	4916	.0394296	.2892899	-6.105787	5.934851

Table 1: Summary statistics for control group

Variable	Obs	Mean	Std. Dev.	Min	Max
Llnsales	226	1.246542	1.339958	-1.708849	4.040571
Lexport	226	.8938053	.3087705	0	1
Lavwage	226	32877.69	11142.18	9749.479	75542.28
Linnovation	226	.4424779	.4977827	0	1
Llnkapital	226	16.25855	1.609598	9.971236	19.46721
LsalesGR	226	.0797828	.2786013	-1.463068	2.470687
FsalesGR	226	.0994009	.3104648	-.882076	3.474002

Table 2: Summary statistics for treated group

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Variable	Normalized difference
nd_Llnsales	0.839
nd_Lexport	0.659
nd_Lavwage	0.669
nd_Linnovation	0.189
nd_Llnkapital	0.92
nd_LsalesGR	0.037

Table 3: Normalized differences

Large normalized differences are incompatible with "simple" estimation techniques. Namely, when the differences exceed 0.25, linear regression with a dummy for treatment is not robust. The reason is that regression is dependent on extrapolation and hence exact specification, i.e. internal validity is questioned.

High values of the normalized differences also raise concerns for the overlap assumption. Most likely, it is not valid, so there is a need to define a subsample with this assumption satisfied. Our strategy is to delete observations with very low or very high propensity score and then assess overlapping.

2. Calculating propensity scores

In order to calculate the propensity scores the two models were used: logit and probit. For balancing property to be satisfied the additional set of polynomial terms and interactions was added. In the case of logit model it was $Llnsales * Lavwage$, $Lavwage * LsalesGR$, $Llnsales^2$ and $Lavwage^2$. In the case of probit model it was $Llnsales * Lavwage$, $Lavwage * LsalesGR$ and $Llnsales^2$.

As far as we know balancing tests consider whether the estimated propensity score adequately balances characteristics between the treatment and control group units. Since from the distributions below it can be inferred that they are quite similar, so that our results will not be too sensitive to the choice of the probability function. Let's use the probit one because of the smaller number of terms used, so that the presence in the treatment or control group should be independent of the fewer terms.

3. Regressions

In tables 4 and 5 are presented the results of the basic difference in means regression, variations of OLS-regressions and more sophisticated techniques, namely: matching (robust and bias adjusted, $m = 2$ was chosen as the one with the highest significance and the least standard error), propensity score weightening, weightening+regression and blocking+regression. From the tables below it can inferred that in general basic techniques are not significant (the significance of the second regression disappears with more controls(OLS3), while the significance of other techniques seem to be stable and the result ranges from the lowest in weightening (about 0.08) to (0.12) in another specifications.

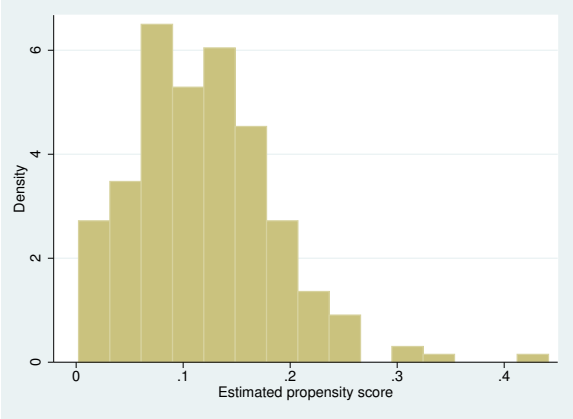
Variables	(1) Difference in means	(2) OLS1	(3) OLS2	(4) Weightening and regression
Llnsales		-0.0105	-0.00990	-0.0261***
		(0.00675)	(0.00704)	(0.00348)
Lexport		0.00147	0.00385	0.0223***
		(0.00907)	(0.00893)	(0.00795)
Lavwage		5.26e-07	4.08e-07	1.20e-06***
		(5.18e-07)	(5.43e-07)	(4.01e-07)
Linnovation		0.0176**	0.0222***	-0.0930***
		(0.00825)	(0.00849)	(0.00736)
Llnkapital		0.00602	0.00578	0.0192***
		(0.00490)	(0.00508)	(0.00260)
LsalesGR		-0.0552	-0.0575	0.0461***
		(0.0774)	(0.0803)	(0.0112)
Llnsales_own			-0.0192	
			(0.0183)	
Lexport_own			-0.139	
			(0.137)	
Lavwage_own			1.40e-06	
			(1.74e-06)	
Linnovation_own			-0.0716**	
			(0.0322)	
Llnkapital_own			0.00333	
			(0.0116)	
LsalesGR_own			0.0510	
			(0.101)	
own	0.700s	0.0567**	0.131	0.0817***
	(0.0210)	(0.0222)	(0.189)	(0.00692)
Constant	0.0394***	-0.0641	-0.0602	-0.252***
	(0.00413)	(0.0714)	(0.0741)	(0.0361)
Observations	5,142	5,142	5,142	9,694
R-squared	0.002	0.008	0.010	0.040

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

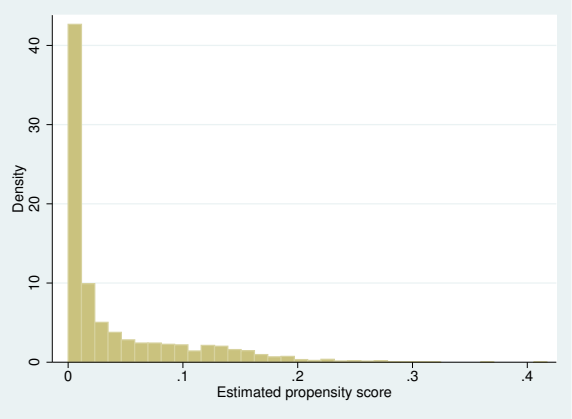
Table 4: Results of the regressions: the whole sample

Method	Result of estimation
Matching (m=2)	0.1259735
Propensity score weighting	0.07904711
Blocking+ regression	0.1138645

Table 5: Results of estimation: the whole sample

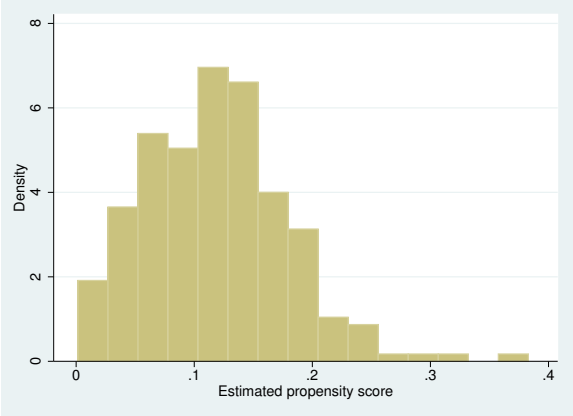


(a) treated group

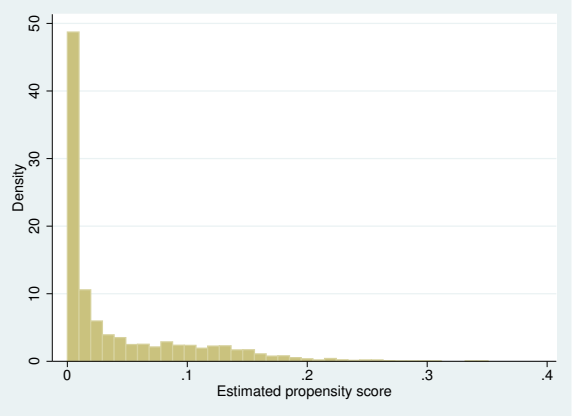


(b) control group

Figure 1: Propensity scores for Logit: whole sample



(a) treated group



(b) control group

Figure 2: Propensity scores for Probit: whole sample

As for the comparison of techniques, advantages of matching are that it is easy to implement and robust. However, it creates bias and inefficiency. The method of propensity score weighting is also easy to implement and can give better results for high-dimensional X, however, problem of functional form can arise. Also, his estimator can be sensitive to the estimation method of the propensity score and it is asymptotically inefficient. The third estimator is very robust. It is consistent if either regression model or propensity score is specified correctly. The same can be said about blocking + regression technique. It is also consistent in both situation and it is more robust than each blocking and regression methods.

4. Resampling

Normalized differences have decreased. However, for Llnsales, Lavwage and Llnkapital they are still higher than 0,25. To exclude the concern about overlapping it is recomended to try smaller sample (for example, exclude observations which has pscore higher than 0,9 or lower than 0,1).

Variable	Obs	Mean	Std. Dev.	Min	Max
Llnsales	2555	.5937273	1.373021	-2.992961	4.85069
Lexport	2555	.790998	.4066754	0	1
Lavwage	2555	28273.44	9974.624	5240.588	84664.3
Linnovation	2555	.3913894	.4881567	0	1
Llnkapital	2555	15.20508	1.864134	9.228281	20.92299
LsalesGR	2555	.0732732	.2558907	-1.258664	5.235402
FsalesGR	2555	.0395629	.2847675	-6.105787	5.934851

Table 6: Summary statistics for control group for subsample

Variable	Obs	Mean	Std. Dev.	Min	Max
Llnsales	220	1.313354	1.294127	-1.708849	4.040571
Lexport	220	.9136364	.2815409	0	1
Lavwage	220	33332.4	10919.92	10868.3	75542.28
Linnovation	220	.45	.4986283	0	1
Llnkapital	220	16.33159	1.563939	9.971236	19.46721
LsalesGR	220	.0803413	.2786903	-1.463068	2.470687
FsalesGR	220	.0975849	.3115249	-.882076	3.474002

Table 7: Summary statistics for treated group for subsample

Variable	Normalized difference
nd_LlnsalesSS	0.381
nd_LexportSS	0.248
nd_LavwageSS	0.342
nd_LinnovationSS	0.084
nd_LlnkapitalSS	0.463
nd_LsalesGRSS	0.019

Table 8: Normalized differences in subsample

Overall, the results are qualitatively the same in comparison with second point, that's why probit model will be chosen again as the basic one. The results of the regressions are also qualitatively the same with the increase of the ranges of the results: now the effect of being in the treatment group ranges from 0.05 to almost 0.13.

5. Rationality behind using methods in part 3

Matching is known to be an easy and robust method. Nevertheless, it leads to a bias and it lacks efficiency. Generally, the propensity score estimation is easy to implement, but is not asymptotically efficient. Regression is a simple estimation method, which is not robust in the pres-

Variables	(1) Difference in means	(2) OLS1	(3) OLS2	(4) Weightening and regression
Llnsales		-0.0105	-0.00990	-0.0261***
		(0.00675)	(0.00704)	(0.00348)
Lexport		0.00147	0.00385	0.0223***
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		(0.00825)	(0.00849)	(0.00736)
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		(0.00490)	(0.00508)	(0.00260)
LsalesGR		-0.0552	-0.0575	0.0461***
		(0.0774)	(0.0803)	(0.0112)
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LsalesGR_own			0.0510	
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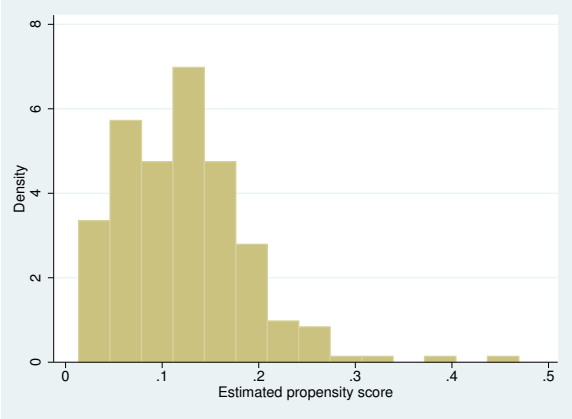
own	0.700s	0.0567**	0.131	0.0817***
	(0.0210)	(0.0222)	(0.189)	(0.00692)
Constant	0.0394***	-0.0641	-0.0602	-0.252***
	(0.00413)	(0.0714)	(0.0741)	(0.0361)
Observations	5,142	5,142	5,142	9,694
R-squared	0.002	0.008	0.010	0.040

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

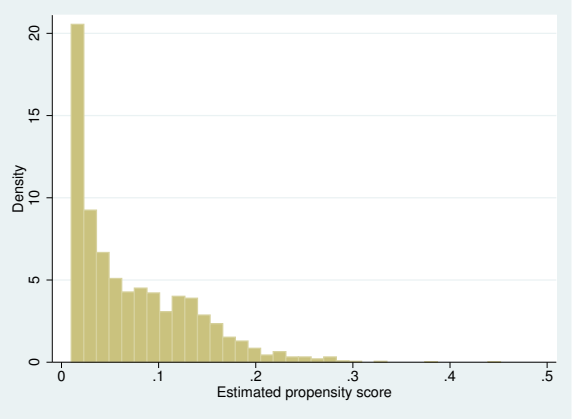
Table 9: Results of the regressions: the subsample

Method	Result of estimation
Matching (m=4)	0.1252293
Propensity score weighting	0.0506077
Blocking+ regression	0.1245755

Table 10: Results of estimation: the subsample

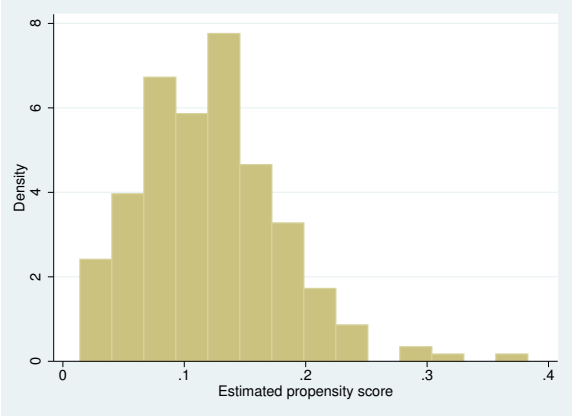


(a) treated group

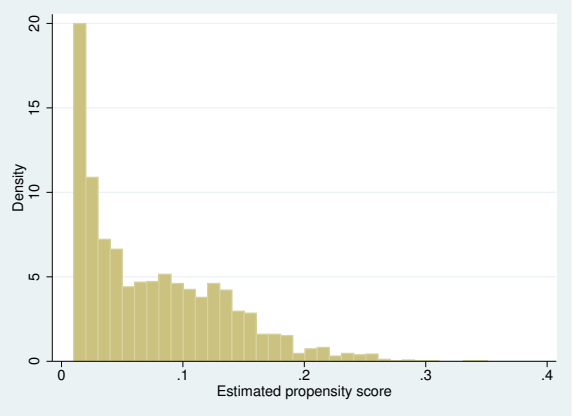


(b) control group

Figure 3: Propensity scores for Logit: subsample



(a) treated group



(b) control group

Figure 4: Propensity scores for Probit: subsample

ence of large differences between the groups. Unfortunately, this issue is not resolved even when we allow for different regression coefficients for treated and controls. Using mixed estimation methods including regression and and propensity score analysis have a benefit of double robustness. Those techniques alone would require the correctly postulated models. When the approach is mixed, the correct specification of only one of the models is sufficient.

It is not reasonable to assume that the foreign ownership is assigned randomly. In some cases the foreign ownership is associated with good performance of a company, which is attractive to foreign investors. Typically, there are little incentives for an investor to purchase a badly-performing foreign company. Hence, the selection bias is present.

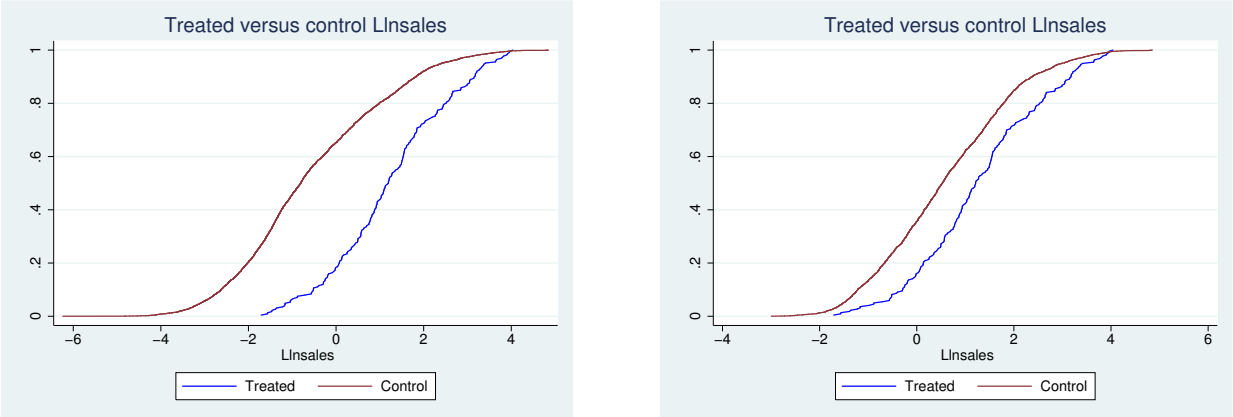
In the case of difference in means (3a) the selection bias is defined as:

$$SB = E[Y_i(0)|W_i = 1] - E[Y_i(0)|W_i = 0]$$

SB is likely to have a positive sign, since the foreign investors would choose to purchase firms with better performance. Moreover, like presented in the assignment foreign firms may give access to their distribution channels which is a comparative advantage in comparison with the domestic ones.

6. Unconfoundedness

This assumption is not directly testable. It states that the conditional distribution of the outcome under the control treatment, $Y_i(0)$, given receipt of the active treatment and given covariates, is identical to the distribution of the control outcome given receipt of the control treatment and given covariates, and the same for the outcome given the active treatment $Y_i(1)$. Since the data are uninformative about the distribution of the control outcome $Y_i(c)$ for those who received the active treatment (those with $W_i = t$), and about the distribution of the active treatment outcome given receipt of the control treatment, the data cannot directly provide evidence on the validity of the unconfoundedness assumption. Nevertheless, there are indirect ways of assessing the unconfoundedness assumption in some settings. One of the methods tells us that unconfoundedness is directly connected with the overlapping assumption of covariates. If they don't overlap a lot, we don't believe in it. However, as it can be seen from Figure 5 and Figure 6, the overlap for Llnsales and Lavwage (another variables also however not all graphs are presented) is high enough, moreover after introducing threshold (if overlap is weak,than subsample is a good idea to satisfy overlapping in order to precisely estimate a treatment effect on some subpopulation)the overlapping increases. Hence, it is naturally to believe in unconfoundedness.

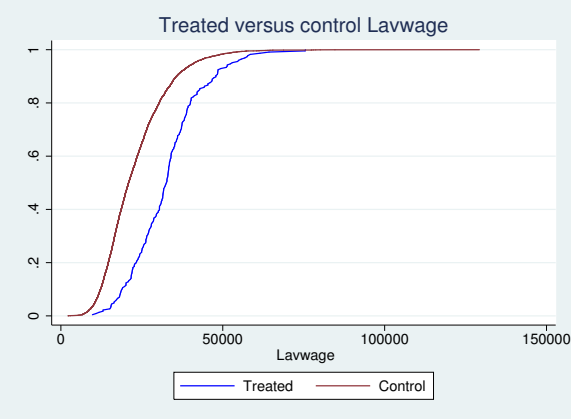


(a) the whole sample

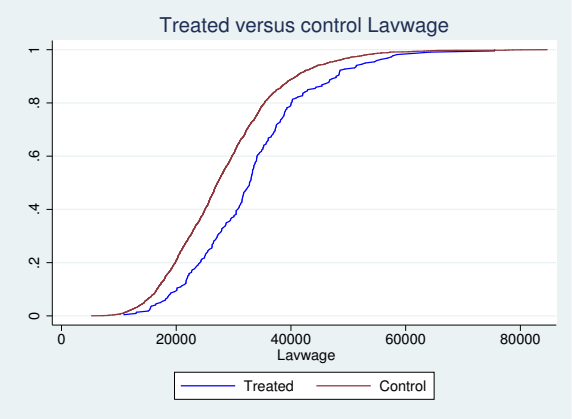
(b) the subsample

Figure 5: Empirical distributions of Llnsales in treatment and control groups

However, if we have an identification-greek friend who does not believe in the unconfoundedness we are trapped with the problem of the selection bias.



(a) the whole sample



(b) the subsample

Figure 6: Empirical distributions of Llnsales in treatment and control groups

It seems that more advanced techniques (like matching) tend to mitigate the effect of the selection bias, but not change its direction. Consequently, the direction will be the same in all three cases. Otherwise, it means that the way of estimation defines the sign of bias which is meaningless.

7. Ideal experiment

As an ideal experiment, which however can not be conducted in real life, we suggest dividing the company into 2 parts when it is going to be acquired by foreign investor. One will be acquired by investor, another one will stay under control and ownership of the domestic owner. If we forget about realism, for the ideal experiment companies should be randomly assigned to the investors. Then we will achieve internal validity without control variables. If companies can not be assigned randomly and investors decide, which company to buy, we will take companies, which are going to be acquired. To satisfy internal validity we should carefully divide the company so that the parts stay equal in all characteristics. Doing this we will have the same company in both states (as treated and controlled). In the experiment we will take companies from the E.U. to decrease external validity, but to be able to construct a model. If we take only Spain we will not be able to extend the results on other countries. If we take the whole world there will be too many unobservable factors and almost certainly unconfoundedness will not hold. To avoid the effect of being observed the owner of each part will be kept secret. Nevertheless, we will not be able to gain perfect external validity. The first problem is small sample: the number of companies to be acquired is limited, also, it will be impossible to separate some companies into equal parts (for example, small companies with few employees, each doing unique work). The second problem, even if we take EU the results will not hold for the rest of the world.

We can consider a quasi-experiment, which is more realistic, but has more problems. We will

take some highly competitive industries, define a long list of characteristics and for each acquired company we will find not acquired one with almost equal characteristics. There will be less internal validity, because companies are not absolutely the same and will be much less external validity. First of all, we will take only some industries of Spain, so we can not extend the results even on the other industries in Spain. If we take countries other than Spain, internal validity will suffer.

Conclusion

In the paper, we have attempted to estimate the effect of foreign ownership of firms on their sales dynamics, The employed dataset contains a cross-section fo observations from Spain. Upon observing the normalized differences, we concluded that the distance between the control and treated firms is too high to be measured by simple techniques and to satisfy overlapping assumption. Nevertheless, we have studied the whole sample by analyzing difference and means, running OLS with different coefficients for the control and treatment groups as well as using several robust approaches. Firstly, we use matching method, which is unfortunately biased and inefficient. Next, we compute propensity score and weight the observations; again, it is not efficient asymptotically. Finally, we combine two methods based on proponsity score – weighting and blocking – with regression that includes dummy for the treatment status. The latter methods are known in the literature as "soubly ronust", but they still partly inherit the drawbacks of those techniques involved. In a word, we estimate the effect several robustt ways to offset their deficiencies.

While the original sample does not possess the "good" properties needed for a valid average treatment effect estimation, we cut the observations whose propensity score is lower than 0.01 or higher than 0.99. After that, we obtain lower normalized differences, which are still not as small as they could be for us to feel safe. In the further research it may be useful to define even smaller subsample, but now it is beyond the scope of our interest. We repeat the estimation procedures for the subsample and find probably more valid estimators of the effect.

Next, we discuss the reasonableness of the key assumptions and, in particular, conclude that unconfoundedness is a credible thing to believe in this setup. We do not stop here and further describe an ideal experiment (and a quasi-experiment) that would ensure both unconfoundedness, overlapping and discuss the validity issues. The greates validity challenge is the external one, as the nature of different economies (EU, for instance) generate a lot of unobservable characteristics that complicate the process of estimation. Ideally, each economic region would require a separate study of the effect of interest.