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A note on difference-in-difference estimation by Fixed Effects and OLS when there is panel non-response

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Abstract

In this note, we show that the OLS and fixed-effects (FE) estimators of the popular difference-in-differences model may deviate when there is time varying panel non-response. If such non-response does not affect the common-trend assumption, then OLS and FE are consistent, but OLS is more precise. However, if non-response is affecting the common-trend assumption, then FE estimation may still be consistent, while OLS will be inconsistent. We provide simulation as well as empirical evidence for this phenomenon to occur. We conclude that in case of unbalanced panels, any evidence of deviating OLS and FE estimates should be considered as evidence that non-response is not ignorable for the differences-in-differences estimation.

Keywords

Difference-in-difference estimation, attrition, panel estimation, balanced panel, unbalanced panel.

JEL-Classification

C21, C31.

1 Introduction

The popular Differences-in-Differences (DiD hereafter) approach is used to obtain causal estimates of a policy change that affects different subgroups at different points in time. By comparing groups affected by the reform before and after and groups unaffected by the reform before and after, and assuming that the treated and untreated groups are subject to the same time trends, the DiD approach estimates the effect of the reform. Under the common-trend assumption, by differencing, any confounding factors are removed.

Frequently authors state that estimating DiD is equivalent to estimating a fixed effects (FE hereafter) model. For instance, when estimating the effect of the "unjust dismissal" doctrine on temporary help services employment and outsourcing, Autor (2003) states on page 16: "Specifically, I estimate DiD (or more generally, FE) models of the form…" Similarly, Angrist and Pischke (2009) explain on page 227 that: "In some cases, group-level omitted variables can be captured by group-level FE, an approach that leads to the DiD strategy." Subsequently, on page 228, they state that "DiD is a version of FE estimation using aggregate data." At the end of the chapter, they explain how Besley and Burgess (2004) exploit regulatory changes across time and states to conduct a DiD design to estimate the causal effects of Indian labour regulation on business. Besley and Burgess (2004) run panel data regression for state *i* at time *t*, where the outcome variable is regressed on the regulatory measure, other state and time exogenous variables and state and year FE (pages 9 and 10). Most recently, Bedard and Kuhn (forthcoming) use a DiD research design to estimate the effects of offering a receipt that makes personalized recommendations to switch from unhealthy to healthier items at a restaurant chain on customers' choices by running a store and week FE model (page 8).

In this note, we show that the OLS and the FE estimate of the popular DiD estimation may deviate when there is time-varying panel non-response.[1] OLS on the unbalanced panel may be preferable, because it is likely to be more precise than the FE estimator (which is numerically equivalent to OLS on a balanced panel). However, if selection is affecting the common-trend assumption, in the sense that it holds in the unobservable full sample but not in the observable sample, then using the balanced sample (which corresponds to FE estimation) may (!) avoid biases due to confounding of the common support assumption. We provide simulation as well as empirical evidence for this phenomenon to occur. We conclude that in case of unbalanced panels, any evidence of deviating OLS and FE estimates should be considered as evidence that attrition is not ignorable for the DiD estimation.

2 OLS and FE estimation

We consider the most simple setting in which DiD estimation can be applied, namely the case of a binary treatment, one pre- and one-post-treatment period, and no covariates, which allows an easy and intuitive understanding of the issues at stake that will occur in the more complex models as well.

In such a setting, OLS estimation of the DiD model is usually performed by estimating a pooled model in which the regressors are a constant term, a dummy variable for (future) treatment group membership, an indicator variable for the period, as well as an interaction of the latter two variables. Thus, this is a fully interacted (saturated) regression, which is entirely nonparametric. It is numerically identical to the difference of the difference of post- and pre-treatment outcomes in the (future) treatment and non-treatment groups. In the two-period model, the FE estimator is obtained by taking first differences over time of the variables in

[1] Note that the FE estimator is only available for panel data, while the OLS DiD estimator is available for repeated cross-sections as well.

this model. Thus, it is equivalent to a cross-sectional regression of the outcome differences over time on a constant term (the former period dummy) and a treatment indicator (the former interaction term). Again, the model is fully interacted (in a trivial way) and computes the change of time of the treated minus that change of the controls.

Simple algebra shows that both estimators are numerically identical (Angrist and Pischke, 2009, p. 235) if they are using the same data (as in a balanced panel design). However, if the sample is unbalanced over time, the FE estimator still relies on the individual differences over time, thus it relies on the subset of observations that are observable in both periods. Instead, OLS estimation of the DiD model uses all observations even if they are observed only once. For this reason, the OLS version of the DiD estimator can also be applied to repeated cross-sections, while FE is not feasible in this case. Therefore, in case of an unbalanced panel, OLS and the FE estimators of the DiD model are no longer numerically equivalent.

Since for unbalanced panel OLS and FE may give different answers, the question arise which of the two possible answers is the more reliable one. It is not possible to come up with a general answer to that question. Clearly, OLS uses more data and thus gives a more precise estimate, at least when effects are homogenous. However, if the selection process confounds the key-identifying assumptions, it may happen that the balanced panel, on which FE is based on, leads to a consistent estimator while using the unbalanced leads to an inconsistent one. Next, we formulize these arguments using a potential outcome framework, but still stick to the two-periods-two-groups model which is sufficient to illustrate the issues at stake.

2.1 The regression formulation

Denote the potential outcomes of the binary treatment D at time t as random variable Y_t^d. Y_t^d is not observed, instead we observe $Y_t = d\,Y_t^1 + (1-d)\,Y_t^0$ (capital letters denote random variables while small letters denote sample realisations or specific values of these variables). Furthermore, define time-variant treatment specific white-noise error terms by U_t^d, and a time-constant error term by C.

Next, some more structure is added to obtain the classical DiD regression representation. First, specify the potential outcomes as a linear function of stochastic components, time and treatment status:

$$Y_t^d = \alpha + \beta^1 \underline{1}(t=1) + \beta^2 D + \theta (\underline{1}(t=1)d) + DC + U_t^d .$$

$\underline{1}(t=1)$ denotes the indicator function which is one if its argument is true. β^1, β^2 and θ are unknown coefficients. It is useful for the simulation below to explicitly model the selection process into *D* as well and use this as an example for a selection process for which the time dimension of the data becomes necessary to obtain consistent estimators for the average treatment effect on the treated (ATET), i.e.:

$$D = \underline{1}\left[\gamma + \beta^1 + \beta^2 + \theta + \delta C + E > 0\right].$$

γ and δ are unknown coefficients and *E* is a white-noise error term. This model satisfies the assumptions of common trends and no initial effects for the treated, which are necessary to identify the effect of *D* on *Y* in a DiD setting (see Lechner, 2010):

No initial effects: $E(Y_0^1 - Y_0^0 \mid D=1) = 0, \quad \text{since } E(U_0^1 - U_0^0 \mid D=1) = 0.$

Common trends: $\underbrace{E(Y_1^0 - Y_0^0 \mid D=1)}_{\beta^1 \underline{1}(t=1)+E(U_1^0-U_0^0|D=1)} - \underbrace{E(Y_1^0 - Y_0^0 \mid D=0)}_{\beta^1 \underline{1}(t=1)+E(U_1^0-U_0^0|D=0)} = 0,$

since $E(U_1^0 - U_0^0 \mid D=1) = E(U_1^0 - U_0^0 \mid D=0)$.

Since U_t^d is assumed to be white noise, these conditions are fulfilled and a DiD research design identifies the ATET, i.e. θ. Note, however, that both the potential outcomes as well as the selection process depend on the unobserved fixed effect, *C*. Thus, a simple mean comparison of treated and controls will be inconsistent for the ATET.

Next, consider how the common-trend assumption implied by the above specifications depends on whether the panel data is balanced or unbalanced. To do so, consider the non-treatment outcomes only:

$$Y_1^0 = \alpha + \beta^1 + \beta^2 \; D + DC + U_1^0 , \qquad\qquad Y_0^0 = \alpha + \beta^2 \; D + DC + U_0^0 .$$

Let R_t be a variable indicating whether the potential unit is observable in period *t*. Thus in the balanced sample, which characterised by $R_1 R_0 = 1$, common trend requires that:

$$E(Y_1^0 - Y_0^0 \mid R_1 R_0 = 1, D = 1) \overset{!}{=} E(Y_1^0 - Y_0^0 \mid R_1 R_0 = 1, D = 0) \quad \Rightarrow$$
$$E(U_1^0 - U_0^0 \mid R_1 R_0 = 1, D = 1) \overset{!}{=} E(U_1^0 - U_0^0 \mid R_1 R_0 = 1, D = 0).$$

This means that the changes of the error terms over time in the observed sample must be the same for the treated and the non-treated. Note that the FE, *C*, do not play any role in this equation, because they drop out by taking differences over time.

For the unbalanced sample, the common-trend assumption requires:

$$E(Y_1^0 \mid R_1 = 1, D = 1) - E(Y_0^0 \mid R_0 = 1, D = 1) \overset{!}{=} E(Y_1^0 \mid R_1 = 1, D = 0) - E(Y_0^0 \mid R_0 = 1, D = 0)$$
$$E(C + U_1^0 \mid R_1 = 1, D = 1) - E(C + U_0^0 \mid R_0 = 1, D = 1) \overset{!}{=}$$
$$\overset{!}{=} E(U_1^0 \mid R_1 = 1, D = 0) - E(U_0^0 \mid R_0 = 1, D = 0).$$

In this case, differencing does not eliminate the FE in the observable part of the data, because some units are only observed in the one of the two periods.

Assuming that the trend of U_t^d is independent on treatment and observability, then FE is consistent in the unbalanced panel case because it uses the balanced data only. OLS however is inconsistent. If, however, the fixed effect is unrelated to observability, i.e. $E(C \mid R_1 = 1, D = 1) - E(C \mid R_0 = 1, D = 1) = 0$, then OLS on the full data will be consistent and may be more efficient than FE (since it uses more observations than FE).

Next, again mainly for illustrative purposes, we introduce four different attrition processes and check whether they violate the common-trend assumptions in the balanced and unbalanced panel design. A natural starting point is random non-response.

R2 (random non-response in both periods): $P(R_t = 1) = p^{R2}, \forall t$.

p^{R2} is a fixed constant between 0 and 1. If the common-trend assumption holds for the full population, it also holds for the observable parts (balanced and unbalanced). This is so because the error terms are independent of the non-response process.

Next, consider a case in which the response probabilities depend on the fixed effect.

SSel (symmetric selective nonresponse): $P(R_t = 1) = \begin{cases} 1 & if\ c < 0 \\ p^S & if\ c \geq 0 \end{cases}, \forall t$.

p^S is a fixed constant between 0 and 1. In this case, the non-response probability affects a variable, *C*, that influences both treatments and outcome. However, as this happens symmetrically for both periods (and groups), we have $E(C \mid R_1 = 1, D = 1) = E(C \mid R_0 = 1, D = 1)$. Thus, common trends will hold in both responding populations if it holds in the overall population.

In the next case considered, there is full response in the pre-treatment period, but selective attrition in the post-treatment period.

AT (attrition): $P(R_1 = 1) = \begin{cases} 1 & if\ c < 0 \\ p^S & if\ c \geq 0 \end{cases}, \quad P(R_0 = 1) = 1$

In this case, the unbalanced case requires $E(C \mid R_1 = 1, D = 1) = E(C \mid D = 1)$ for common trends in the full population to imply common trends in the responding population. Clearly, AT does violate this condition. Thus, while in the balanced design OLS is consistent, in the unbalanced design OLS is inconsistent.

Finally, we consider again the case of selective non-response in both periods, but allow it to vary over time.

ASel (asymmetric selective nonresponse in both periods):

$$P(R_1 = 1) = \begin{cases} 1 & if\ c < 0 \\ p^A & if\ c \geq 0 \end{cases}, \quad P(R_0 = 1) = \begin{cases} 1 & if\ c \geq 0 \\ p^A & if\ c > 0 \end{cases}.$$

p^A is a fixed constant between 0 and 1. In this example, $E(C \mid R_1 = 1, D = 1) \neq E(C \mid R_0 = 1, D = 1)$. Thus, even if the common-trend assumption holds in the population, it does not hold in the responding unbalanced subsample. Therefore, OLS in the unbalanced sample is inconsistent. However, as in the case before, DiD estimation in the balanced sample (FE) is consistent.

3 Monte Carlo simulation

In this section, we illustrate the impact of the four non-response scenarios on OLS and FE by a small-scale Monte-Carlo simulation based on the model discussed above. To do so, assume all error terms to be standard normally distributed and the following values for the unknown coefficients:

$$\alpha = 1, \gamma = -1, \beta^1 = 2, \beta^2 = -2, \theta = 1, \delta = 5, p^{R2} = 0.7, p^S = p^A = 0.2.$$

Table 1 presents the simulation results based on a sample size of 5,000 in both periods (before non-response) with 10,000 replications for OLS and FE on the (i) the full sample ignoring nonresponse (denoted as ‘All’ in Table 1)[2], (ii) the *balanced* sample, and (iii) the *unbalanced* sample for the various types of non-responses considered above. As the estimators have enough finite sample moments in our simple setting, we present only their biases, standard deviations, and root-mean squared errors.

[2] This scenario serves only as a benchmark, because it is of course not feasible in an application.

Table 1: Results of simulations for ATET (θ)

	Random			Symmetric selective			Attrition			Asymmetric selective		
Sample	Bias	Std.	RMSE	Bias	Std.	RMSE	Bias	Std.	RMSE	Bias	Std.	RMSE
All *(OLS=FE)*	-0.2	4.6	4.6	-0.2	4.6	4.6	-0.2	4.6	4.6	-0.2	4.6	4.6
Balanced (OLS=FE)	-0.3	5.8	5.8	0.0	9.8	9.8	-0.8	6.1	6.2	1.0	8.4	8.5
Unbalanced (OLS)	-0.5	4.6	4.7	-0.0	7.5	7.5	-18.6	5.6	19.4	23.5	6.5	24.3

Note: As FE and OLS estimation on the balanced (and the overall) sample are numerically identical, they are subsumed under the heading of 'Balanced' (which also subsumes FE estimation in the unbalanced sample) and 'All'. OLS in the unbalanced sample is denoted by 'Unbalanced'. All values are multiplied by 100. True effect is 1 (100). Treatment share is 50%. N = 5,000 (all). 10'000 replications.

These simulations reflect the general statements before with respect to biases and efficiency gains. They also show that biases that occur in the unbalanced samples could be substantial and by far outweigh the respective efficiency gains coming from using more data.

4 Application

In this section, we provide empirical evidence illustrating on how OLS and FE estimators may differ in an unbalanced sample. To do so, we use the data of Fernandez-Kranz and Rodriguez-Planas (2013).[3] They estimate the impact of a November 1999 Spanish labor law on the employment outcomes of childbearing-aged women. The law granted all workers with children younger than 7 years old protection against a layoff if the worker had previously asked for a work-week reduction due to family responsibilities. As only mothers took advantage of these flexible-work arrangements, the paper analyzes whether this law led employers to replace childbearing-aged women by men. The data used are quarterly longitudinal Social Security data beginning with the first quarter of 1996 and ending in the last quarter of 2010. The balanced sample is composed of individuals observed every quarter 1996 - 2010.

4.1 DiD estimation results for FE and OLS

Table 2 presents OLS and FE DiD estimates of the effects of this law on three different employment outcomes using the balanced sample (columns 1 and 2) and the OLS estimate of

[3] The most recent version of the paper can be found at https://sites.google.com/site/nuriarodriguezplanas/ .

the unbalanced sample (columns 5 and 6).[4] Columns 3 and 4 show the outcomes for the unbalanced observations, excluding those in the balanced sample. Each row displays the effects of the reform on the likelihood of: (i) holding a permanent contract at time *t*, (ii) holding a fixed-term contract at time *t*, and (iii) not-working at period *t*.[5]

Table 2: Effects of the 1999 Law on Childbearing-aged Women's Employment Outcomes (comparison group: childbearing-aged men), 1996-2010

	Balanced Sample		Unbalanced Observations (excludes individuals in BS)		Unbalanced Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variables	FE	OLS	FE	OLS	FE	OLS
Permanent work at *t*	-0.015*	-0.015*	-0.043***	-0.000	-0.037***	-0.036***
	(0.009)	(0.009)	(0.016)	(0.017)	(0.008)	(0.009)
Pre-99 mean probability	0.694	0.694	0.377	0.377	0.580	0.580
Fixed term work at *t*	-0.029***	-0.029***	-0.021***	-0.064***	-0.020***	-0.035***
	(0.007)	(0.007)	(0.015)	(0.016)	(0.007)	(0.008)
Pre-99 mean probability	0.147	0.147	0.298	0.298	0.201	0.201
Not working at *t*	0.044***	0.044***	0.064***	0.065***	0.058***	0.072***
	(0.007)	(0.007)	(0.012)	(0.013)	(0.006)	(0.006)
Pre-99 mean probability	0.158	0.158	0.324	0.324	0.217	0.217
# of observations	257,400	257,400	267,602	267,602	525,002	525,002
# of individuals	4,290	4,290	8,535	8,535	12,825	12,825

Note: Individuals born between 1965 and 1970 out of a sample comprising 4% of the working population in Spain. All models have an indicator for being a woman (treatment), a post-1999 dummy, and the interaction between these two variables, the level of education, a linear time trend, age and the regional unemployment rate. Numbers in parentheses are robust standard errors allowing for intra cluster (individual) correlation. *** Significant at the 1% level. ** … 5% level. * … 10% level. Clustered standard errors are in parentheses.

As expected OLS and FE estimates using the balanced sample are identical. However, when we use the unbalanced panel this is no longer true for two out of three outcomes. Comparing columns 5 and 6 we observe that FE and OLS estimates of the reform on the likelihood of having a fixed-term contract and not working differ, with the size of the OLS coefficient being larger in absolute value.

[4] The analysis focuses on private sector wage and salary workers and prime childbearing-aged individuals defined as men and women between 23 and 44 years old (both included), given that they are most at-risk of being potentially eligible. See the working paper for thorough details on the data.

[5] These are stock probabilities as opposed to flow probabilities, that is, we do not condition on employment status at *(t-1)*.

4.2 Why are the FE and OLS DiD estimation results different?

As explained earlier, asymmetric selective attrition pre- versus post-reform across treatment and comparison groups would lead to different OLS and FE DiD estimates. Table 3 explores whether asymmetric selective attrition based on observables is an issue in this example. To do so, Table 3 presents estimates of a probit model with as dependent variable a dummy equal 1 if the individual is in the balanced panel and 0 otherwise. This dependent variable is regressed on the post-reform dummy, all other covariates used in Table 2 (including the post-reform dummy interacted with all other covariates, and the gender dummy interacted with all other covariates). If the triple interactions (between the interaction of gender and post-reform with the other covariates) are statistically significant and different from zero, they would provide evidence of asymmetric selective attrition pre- and post-reform by treatment status (gender), which would bias the OLS estimates. The coefficients with **Φ** indicate that the difference between the treatment groups versus comparison groups is statistically significant at the 10% confidence level.

According to Table 3, having a permanent contract increases the likelihood of being in the balanced panel, both for men and women, but this likelihood is larger after the reform and more so for men than for women. Similarly, lower educated men are more likely to be in the balanced panel and this is more so after the reform. In contrast, the opposite is true for women with only primary education (our least educated group). Finally, being older increases the chances of being in the balanced panel, but this likelihood is greater for men than women after the reform. Hence, Table 3 shows that there is asymmetric selective attrition pre- versus post-reform across treatment and comparison groups. Finally, the differential effect of the post-1999 dummy between men and women is explained by the fact that after the reform many more women enter the labor market than men as the reform made it more attractive for women to try to get a permanent contract.[6]

Table 3: Comparing the covariates in the balanced and unbalanced samples: Marginal effects of pooled sample probit analysis for females and males

	Males	Females
Post99	-0.755***Φ (0.014)	-0.063*Φ (0.034)
Permanent at t Pre99	0.286***¥ (0.005)	0.288***¥ (0.004)
Permanent at t Post99	0.412***Φ (0.002)	0.362***Φ (0.002)
Non-Work at t Pre99	0.027***¥ (0.010)	0.024***¥ (0.007)
Non-Work at t Post99	0.069*** (0.005)	0.065*** (0.003)
Less than Secondary Education Pre99	0.081***Φ¥ (0.006)	-0.072***Φ¥ (0.006)
Less than Secondary Education Post99	0.147***Φ (0.002)	-0.127***Φ (0.002)
Secondary Education Pre99	0.137***Φ¥ (0.006)	0.039***Φ¥ (0.006)
Secondary Education Post99	0.212***Φ (0.003)	0.066***Φ (0.003)
Trend Pre99	-0.065***Φ¥ (0.002)	-0.073***Φ¥ (0.002)
Trend Post99	-0.060***Φ (0.000)	-0.046***Φ (0.000)
Age Pre99	0.024***¥ (0.001)	0.025***¥ (0.001)
Age Post99	0.048***Φ (0.000)	0.021***Φ (0.000)
Unemployment Rate Pre99	0.001***Φ¥ (0.000)	0.006***Φ (0.000)
Unemployment Rate Post99	0.003***Φ (0.000)	0.006***Φ (0.000)

Note: The table shows the probit marginal effects coming from a regression of BALANCED against the full set of covariates, where BALANCED is a dummy indicator that takes 1 if the observation belongs to the balanced sample. Individuals born between 1965 and 1970 out of a sample comprising 4% of the working population in Spain. The reference state is college degree working under a fixed term contract *** Significant at the 1% level, ** … 5% level. * … 10% level. Clustered standard errors are in parenthesis. **Φ** indicates that the treatment versus control group difference of the value of the coefficient is statistically different from zero at the 10% or higher confidence level. ¥ indicates that the Post99 versus Pre99 difference of the coefficient is statistically different from zero at the 10% confidence level.

5 Conclusion

In this note, we argue that OLS and FE estimators of the popular DiD model may deviate when there is time varying panel non-response. We illustrate both the occurrence and magnitude of this phenomenon using simulations and an empirical application. Our research highlights that in case of unbalanced panels, any evidence of deviating OLS and FE estimates should be considered as evidence that attrition is not ignorable for the DiD estimation.

[6] The ratio of men in the balanced to unbalanced samples is between 1.6 and 2.6 before and after the reform, while for women it is 1.8 before the reform but 0.6 after the reform.

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