Dynamic panel data: A useful technique in experiments

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Abstract

Numerous experimental studies use a panel approach to analyze repeated experiments involving a large number of periods. They use “static” panel techniques and do not incorporate any temporal dependency (lags) of the dependent variable. This paper introduces dynamic panel data techniques to experimental economists. This is a standard tool in many other fields of economics and might also be useful in our discipline. It uses the lags of the dependent variable as explanatory variables. Although the coefficients on lagged dependent variables might be far from our interest, the introduction of these lags becomes crucial to control for the dynamics of the process. To show the advantages of this technique, we have compared two datasets using static and dynamic panel data. We conclude that the use of dynamic panel data models in the context of experiments allows to unravel new relationships between experimental variables and highlighting new paths in behaviors.

Keywords: dynamic panel data, experimental econometrics

JEL Classification: C91, C33, C36

I - MOTIVATION

Panel estimation methods are widely used in experimental economics. Numerous experimental studies use a panel approach to analyze repeated experiments involving a large number of periods, such as repeated public good games (see for instance, Croson et al., 2005), bidding behavior (see Rassenti et al., 2003), ultimatum games (see Botelho et al., 2005; List and Cherry, 2000; Cooper et al., 2000), among the others.

The advantage of panel data is that by using information about the intertemporal dynamics and individuals, it is possible to control for the effects of unobserved or missing variables. In experiments, this double dimension (individual/time) helps us to better capture the complexity of human behavior. For instance, Harrison (2007) shows that using panel data methods, "house money" in standard public good experiments may has an effect on behavior, in contrast to published results.

All of the above-mentioned papers have used "static" panel techniques, i.e., they have not incorporated any temporal dependency (lags) of the dependent variable. On the other hand, dynamic panel data models use the lags of the dependent variable as explanatory variables. Although the coefficients on lagged dependent variables might be far from our interest, the introduction of these lags becomes crucial to control for the dynamics of the process. The correct behavior specification lets us discover new or different relationships between the dependent and independent variables.

In this paper, we have presented this technique (Section II) as well as two examples (Section III and IV) of how results may change when the temporal structures of the dependent variable are included. Our results are detailed in Section V.

II - ECONOMETRIC TECHNIQUE

II.A - Static models

Static panel data regressions (Baltagi, 2008; Cameron and Trivedi, 2009) allow us to study individual behavior in a repetitive environment. If y_{it} is our variable of interest, then static panel data models are described by

$$y_{it} = x_{it}^{'}\beta + \alpha_i + v_{it}, \quad i = 1,...,N \text{ (individuals)}, \quad t = 1,...,T \text{ (time)}$$

where x_{it} is the *it*-th observation on *k* explanatory variables, β is the parameter vector, α_i denotes the unobserved individual-specific time-invariant effects, and the residual disturbance term v_{it} has zero mean, constant variance, and is uncorrelated across time and individuals.

Depending on the nature of α_i, two models can be distinguished:

- *Random Effect Model*: It assumes that α_i are random variables (uncorrelated with v_{it}). In these models, the regressors x_{it} are uncorrelated with individual effects α_i. We can unbiasedly, consistently, and efficiently estimate parameters β using Generalized Least Squares (GLS). Note that under the hypothesis of no correlation between regressors and individual effects, Ordinary Least Squares (OLS) estimators are unbiased and consistent, but not efficient.
- *Fixed Effects Model*: It assumes that α_i are individual fixed parameters. In these models, it is not necessary to assume no correlation between regressors and individual effects. Usually, Within Group (WG) estimators, so-called “fixed effects estimators” are used to estimate the parameters. We can obtain them with an OLS estimation of a transformation of model (1) where individual effects are removed:

$$y_{it} - \bar{y}_i = \left(x_{it} - \bar{x}_i\right)' \beta + \left(v_{it} - \bar{v}_i\right) \quad (1)$$

where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and $\bar{v}_i = \frac{1}{T}\sum_{t=1}^{T} v_{it}$. WG estimators are unbiased and consistent.

All these methods (GLS, OLS, and WG) have alternative versions that are robust under heteroskedastic disturbances (Davidson and MacKinnon, 2004). However, none of them has acceptable properties when a dynamic structure is introduced in the model.

II.B - Dynamic models

Dynamic panel data models are useful when the dependent variable depends on its own past realizations:

$$y_{it} = \gamma y_{i,t-1} + x_{it}^{'} \beta + \alpha_i + v_{it}, \quad i = 1,..., N \text{ (individuals)}, \quad t = 1,..., T \text{ (time)} \quad (2)$$

In this model, x_{it} are the regressors[1], α_i is fixed[2] individual effects, and v_{it} has zero mean, constant variance, and is uncorrelated across time and individuals.

As $y_{i,t-1}$ is correlated with α_i because $y_{i,t-1}$ is a function of α_i, GLS and OLS estimators are biased and inconsistent. WG estimators are also biased and inconsistent, because in the transformed model, when using variable deviations from mean (see equation 1), the independent variable will be endogenous ($\bar{y}_i$ is correlated with $\bar{v}_i$).

An alternative transformation to remove individual effects α_i is the so-called "first-difference" transformation:

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + \Delta x_{it}^{'} \beta + \Delta v_{it} \qquad (3)$$

Again WG and GLS estimators are inappropriate. The model suffers from an endogeneity problem, because by the dynamic structure of Equation (3), $\Delta y_{i,t-1}$ are correlated with Δv_{it} To solve this problem, Anderson and Hsiao (1982) proposed to control endogeneity using $\Delta y_{i,t-2}$ or $y_{i,t-2}$ as instruments for $\Delta y_{i,t-1}$. In fact, lagged levels of the endogenous variable *aw*, three or more time periods before, can be used as instruments (Holtz-Eakin et al., 1988), and if the panel includes three or more time periods, we will have more available instruments than unknown parameters.

Arellano and Bond (1991) proposed a method that exploits all possible instruments. Using the Generalized Method of Moments (GMM, Hansen, 1982), they obtained estimators using the moment conditions generated by lagged levels of the dependent variable $(y_{i,t-2}, y_{i,t-3}, \ldots)$ with Δv_{it}. These estimators are called difference GMM estimators.

Similar to all instrumental variables regressions, GMM estimators are unbiased. Arellano and Bond (1991) compared the performance of difference GMM, OLS, and WG estimators. Using simulations, they found that GMM estimators exhibit the smallest bias and variance.

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[1] Here x_{it} will be strictly exogenous (x_{it} are uncorrelated with v_{it} $\forall i,t$). Situations where regressors are predetermined or endogenous could also be considered.

[2] By construction, $y_{i,t-1}$ is correlated with α_i. It then makes no sense to use the random effects estimation method since one regressor is correlated with the individual effects.

II.C - Exceptions: Heteroscedasticity and time-invariant independent variables

There are two situations where the difference GMM model does not provide good estimators. This might be relevant for our experimental data.

- *Under heteroscedasticity:* When model errors are heteroskedastic, we do need a modified tool: two-step GMM estimators.[3] These estimators are robust under heteroskedasticity, but their standard errors are downwardly biased. This problem was solved by Windmeijer (2005) who proposed a correction for two-step GMM estimators.
- *When using time invariant regressors*. When a given independent variable does not change across time (e.g. gender), the variable is eliminated in Equation (3), making this method useless to estimate its associated parameter. Arellano and Bover (1995) as well as Blundell and Bond (1998) proposed an alternative method. In addition to differentiating the model equation (see Equation (3)) and using lagged levels of $y_{i,t-1}$ as instruments of $\Delta y_{i,t-1}$, they worked with the "original" model (Equation (2)) and used the difference $\Delta y_{i,t-1}$ as instruments of $y_{i,t-1}$. The estimators obtained in this way are called system GMM estimators.

Originally, this method was developed to improve the behavior of difference GMM estimators when the autoregressive parameter γ approaches unity. In this case, lagged levels of dependent variable are weak instruments. However, this method has another advantage: Time-invariant variables can be included as regressors (Roodman, 2006). In Section III we will use these estimators.

II.D - Instrument validation

Once difference or system GMM estimators are obtained, the validity of the model must be checked:

- Arellano and Bond (1991) proposed a test to detect serial correlation in the disturbances. Note that the presence of serial correlation in the disturbances affects the validity of some instruments: If v_{it} are serially correlated of order 1, then

[3] A first-step estimation is needed to obtain the covariance matrix of estimation error.

$y_{i,t-2}$ is endogenous to Δv_{it} (by the presence of $v_{i,t-1}$ in the difference), and therefore, $y_{i,t-2}$ would be an invalid instrument.

They tested serial correlation of disturbances using difference Δv_{it}, instead of level v_{it}. To test serial correlation of order 1 in levels, we must check for correlation of order 2 in differences. When the null hypothesis of this test (no serial correlation) is not rejected, validation of the instrumental variables is obtained.

- The Sargan test (Sargan, 1958) verifies the validity of instrument subsets. It is based on the observation that residuals should be uncorrelated with instruments (null hypothesis). When this hypothesis is not rejected, the validation of instrumentals is obtained.

III - Example 1: Guillen P., Fatás, E. and Brañas-Garza, P. (2010)

Guillen et al. (2010) reported evidence about cooperative behavior in a repeated public goods game. Subjects played 10 periods in groups of four players with constant group composition. So in the jargon of experimental economists, this is a "partners" design. In each period, players decided on how much to allocate to a public account (between 0 and 50 units). The sum of contributions of the four players was multiplied by two and equally split between them. The subjects played 10 additional periods after a surprise restart, where the group composition remained the same as in the first 10 periods. Hence, this is the classical example of a lab experiment where subjects play for several rounds and have a feedback after each decision.

Their study explored two main treatments: the baseline (which is identical to Croson et al., 2005) and the threat. Under the threat treatment, the subjects were informed that there was a positive probability that they would play with a computer simulated subject that would cooperate until any group member contributed less than 45 units. The experiment was conducted at the LINNEX (Valencia) with 60 subjects.

Using individual contributions as the dependent variable (y_{it}), they proposed a static panel data model where the explanatory variables were the *Period* and a dummy representing the *Threat* treatment:

$$y_{it} = \beta_0 + \beta_1 \cdot Period_t + \beta_2 \cdot Threat_i + \alpha_i + v_{it}, \ i = 1,...,60 \quad t = 1,...,10$$

To estimate this model, they used random effects GLS regression with cluster-robust standard errors.

Columns a.1 and b.1 in Table 1 replicate results shown in the original paper. They found a positive and significant effect of the threat on cooperative behavior. This was not only true for the first 10 rounds, but also for the second 10 rounds after the surprise restart.

Columns a.2 and b.2 in Table 1 show the dynamic panel data estimations. It must be noted that the dummy *Threat* is time-invariant. As we explained in Section II, since difference GMM estimators remove this type of variable, we used system GMM estimators. To control for heteroskedasticity, we used the two-step version with the Windmeijer correction. We have also presented the associated *p* values for the Arellano-Bond serial correlation (of order 2 in difference) test and the Sargan test. The validity of the instruments has not been rejected.

Table 1: Estimated parameters

	First 10 periods		Last 10 periods	
	a.1	a.2	b.1	b.2
γ	-	**0.30 (0.00)**	-	**0.35 (0.00)**
$Period_t$	**-2.47(0.00)**	**-1.61 (0.00)**	**-2.60 (0.00)**	**-1.04 (0.00)**
$Threat_i$	**12.44 (0.00)**	-13.18 (0.35)	**14.94 (0.00)**	**26.52 (0.01)**
β_0	**29.51 (0.00)**	**31.51 (0.00)**	**29.02 (0.00)**	**15.43 (0.03)**
AB serial correlation test	-	0.66	-	0.59
Sargan test	-	0.06	-	0.19
Instruments	-	46	-	52
N	600	540	600	600
Technique	*SPD*	*DPD*	*SPD*	*DPD*

p-value in parenthesis

Now we will compare the results obtained with static and dynamic panel data methods. How do the results change due to the new methodology?

- Along the first 10 periods, it can be observed that the dummy *Threat* is not significant ($Threat_i=-13.18;\ p=0.35$). There is not a treatment effect. Once we capture the dynamics in behavior, this dummy is not significant.

- After the surprise restart, we found a very interesting result. Once all the players have already learnt to play the game, then the *Threat* dummy becomes highly significant and its coefficient doubles its value ($Threat_i=26.52;\ p=0.01$).

Additionally, we obtained precious information from the autoregressive structure of behavior. The significant and positive value of the AR(1) coefficient[4] indicates that although the trend (*Period* variable) is negative, the slope is smoothed by the positive coefficient γ.

Therefore, the use of a dynamic panel data model allows us to properly identify the treatment effects and understand how these effects change across time and after a surprise restart.

IV - EXAMPLE 2: BRAÑAS-GARZA, P., BUCHELI, M. AND T. GARCÍA-MUÑOZ (2011).

Brañas-Garza et al. (2011) reported a Dictator game with 88 dictators taking each of 16 decisions about how to allocate 10 bills of 20 Uruguayan pesos (around 10 American dollars) between themselves and a random and unknown recipient. The authors assumed that the decisions are uncorrelated because there was no feedback throughout the game and only one of them (randomly chosen) was implemented at the end.

All the games were identical in format, but framed. Besides a blind (baseline) game, they used three types of frames to generate 15 different environments that vary according to the information given about gender, income (poor/rich), and political preferences (right/left). Dictators were matched with a different recipient every single round, which is what

[4] We tested for higher order correlation, but it was not significant.

experimental economists call a "random strangers" design, and the 16 tasks were presented to each subject in a different random order.

Using individual donations as the dependent variable (y_{ij}), they used a dynamic panel data model to estimate the donation in period *t*:

$$y_{it} = \gamma \cdot y_{i,t-1} + x_{it}^{'} \cdot \beta + \alpha_i + v_{it}, \quad i = 1,...,88 \;\; t = 1,...,16$$

where α_i is the fixed individual effects, the regressors x_{it} are three treatment dummies and a temporal trend (*Period*), and all regressors were strictly exogenous.

To estimate this model, they used two-step[5] difference GMM estimators with the Windmeijer correction. The results are presented in Table 2, columns a.2 and b.2 (the difference between these two models is the temporal trend that is included only in column b.2). To test for the validity of the instrument, *p* values of Arellano-Bond serial correlation test (of order 2 in difference) and Sargan test were presented, and the validity was not rejected.

WG estimators provide a consistent estimator of static fixed effects models:

$$y_{it} = x_{it}^{'} \cdot \beta + \alpha_i + v_{it}, \quad i = 1,...,88 \quad t = 1,...,16$$

Columns a.1 and b.1 in Table 2 show the results of the static model[6].

As in the previous example, we compared the results from static and dynamic approaches:

- In models where the *Period* variable was included (e.g. a.1 and a.2), we found that the trend was never significant, but the dummies (treatments) were.
- In dynamic models (e.g. a.2 and b.2), time series of donations followed a stationary AR(1) process with a negative coefficient.

Why is this important? The latter signifies that in the subsequent periods, donations move around their mean, but display a very noisy behavior, constantly crossing their mean level. Hence, experimental subjects tend to balance in each round what they did in the previous round.

[5] To control for possible heteroskedasticity

[6] To avoid heteroskedasticity, cluster-robust standard errors are used

The use of dynamic panel data makes it possible to uncover a result favoring an equalization behavior. The pattern of donations over time emerges as the result of a systematic equalization process: Moral licensing (being selfish after having been altruist; Merrit et al., 2010) or cleansing (altruistic after selfish; Sachdeva et al., 2009). However, the use of a static setting does not allow unraveling this result.

Table 2: Estimated parameters

	a.1	a.2	b.1	b.2
γ	-	**-0.07 (0.03)**	-	**-0.09 (0.00)**
Period	0.07 (0.67)	0.19 (0.43)	-	-
Treatment 1	**15.67 (0.00)**	**12.28 (0.00)**	**15.62 (0.00)**	**12.07 (0.00)**
Treatment 2	**15.80 (0.00)**	**13.21 (0.00)**	**15.76 (0.00)**	**13.11 (0.00)**
Treatment 3	**15.27 (0.00)**	**14.54 (0.00)**	**15.20 (0.00)**	**14.71 (0.00)**
β_0	**45.54 (0.00)**	**45.16 (0.00)**	**46.24 (0.00)**	**48.08 (0.00)**
AB serial correlation test	-	0.49	-	0.42
Sargan test	-	0.83	-	0.80
Instruments	-	44	-	43
N	1402	1220	1402	1220
Technique	*SPD*	*DPD*	*SPD*	*DPD*

p-value in parenthesis

IV - DISCUSSION

We have shown that the use of dynamic panel data models in the context of experiments allows unraveling new relationships between experimental variables and highlighting new paths in behaviors.

Dynamic panel data techniques allow controlling the dynamics of the process introducing in the regression equation temporal dependency (lags) of the dependent variable. Although the coefficients on lagged dependent variables might be far from our interest, the presence of these lags in the regression equation discovers new or different results. In our first example (section III), we discover that the treatment effect is different after a surprise restart. This result is not unraveled when static panel data method is used. The second example (section IV), the use of dynamic panel data techniques allows to uncover an unexpected result: subjects equalize behavior across repetitions.

One critical issue in these methods is the choice of the number of instruments to be used. These estimators generate moment conditions with the instrument count being quadratic in T. This may cause several problems in finite samples (Roodman, 2006). First, a finite sample may lack adequate information to effectively estimate such a large matrix and, second, the bias present in all the instrumental variables regressions becomes more pronounced as the instrument count rises. There is no general rule in the literature about how many instruments to use. Roodman (2006) offers a useful piece of advice: The instruments count must be smaller than the individual units in the panel.

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