

Time Series Cross Section Data

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Time Series Cross Section Data analysis techniques are needed for datasets consisting of a number of cross-sectional units (e.g. countries, dyads, provinces, villages) with repeated observations over time (e.g. years, months, days).

Suppose you have a dataset with 20 countries each observed over 30 years. This yields 600 observations, but in some sense this number is an artificial inflation.

Remember that the standard OLS assumption is that the error terms are independent from each other (i.i.d.). In TSCS datasets, this assumption is clearly violated for a number of reasons including but not limited to the following:

1. Observations from within the same unit over time are typically related to each other in specific ways
2. Observations from nearby units may be related to each other

*These notes are based to a large extent on Neal Beck's lecture notes. I have also borrowed from Matt Golder's lecture notes and from many of the articles and texts referenced at the end of the notes.

3. There may be differences across units that cannot be accounted for by the independent variables in the model

The old-fashioned way of dealing with these issues was to treat them as a nuisance. The new-fashioned(??) way of dealing with them is to consider them as part of the model we specify. We will usually with the latter approach.

The main issues that come up when analyzing this kind of data are as follows:

- **Between Unit Heterogeneity:** Fixed Effects, Random Effects, Random Coefficient Models
- **Time Series Issues:** Temporal Dependence, Dynamics
 - Continuous Dependent Variable
 - Dependent Variable
- **Cross-Sectional Issues:** Panel Heteroskedasticity, Spatial Correlation

1 Preliminaries

1.1 Notation

Number of cross-sectional units denoted by: N

Number of time-series units denoted by: T .

Thus, the total number of observations is NT .

In a pure cross-section dataset (e.g. a survey of N individuals), the basic model assuming one independent variable is:

$$y_i = \alpha + x_i\beta + \epsilon_i$$

In a pure time-series dataset (e.g. a series of daily world oil prices), the basic model is:

$$y_t = \alpha + x_t\beta + \epsilon_t$$

In a time series cross section dataset (e.g. a dataset consisting of N countries observed over T time periods), the basic model is:

$$y_{i,t} = \alpha + x_{i,t}\beta + \epsilon_{i,t} \tag{1}$$

where $i = 1, \dots, N$ and

$T = 1, \dots, T$

1.2 Data Structure

In TSCS data, we have multiple lines of data for each unit arranged as follows:

countryID	year	Var 1	Var 2	Var 3	Var 4
Canada	1950
Canada	1951
Canada
Canada
Canada	2000
United States	1950
United States	1951
United States
United States
United States	2000

In this case, each observation, or unit of analysis, corresponds to a country-year.

Notice how the data are stacked - they are sorted first according to cross-sectional unit and then according to time period. To run the typical TSCS commands in STATA, you will need to structure your data in this way. Some common errors to watch out for are repeated time periods within a unit and repeated units within a time period.

Once the data are structured in this way, you can specify that the data are TSCS in STATA using the command *xtset*. This will allow you to execute models and tests specific to TSCS data. For the example above, the relevant command would be:

```
xtset countryID year, yearly
```

1.2.1 TSCS vs. Panel Data

A key aspect of any dataset that must be considered is the size of N and T .

1. **Time Series Cross Sectional Data** (TSCS) refers to datasets with *large* T and small or medium sized N . Examples include CPE datasets focusing on, for example, the set of OECD countries or IR datasets with a large number of dyads observed for 50 or more years. .
2. **Panel Data** refers to datasets with *large* N but *small* T such as a repeated survey of a large number of individuals.
3. There is one other option of course! If your dataset falls in this category, you are **out of luck**. You need to collect more data!

Techniques for TSCS data allow you to leverage the large T to (among other things) model the time series structure of the data and to lend credence to your inferences through the use of fixed effects.

How large is large? T should be large enough so that averages make sense. A rough guideline is at least 10, but 20 or more is ideal.

2 Pooling/Between Unit Heterogeneity

Consider, again, Equation (1) above.

$$y_{i,t} = \alpha + x_{i,t}\beta + \epsilon_{i,t}$$

A key assumption embedded in this model is that the intercept α does not vary. This assumption is usually problematic when we think of units such as countries, dyads or provinces that usually have key fixed characteristics not accounted for by the independent variables. Running such a model amounts to "pooling" your data.

2.1 Fixed Effects

One alternative to pooling is to include **fixed effects** in your model.

A fixed effect model is represented as follows:

$$y_{i,t} = \alpha + x_{i,t}\beta + \delta_1 Z_1 + \delta_2 Z_2 + \dots + \delta_n Z_{N-1} + \epsilon_{i,t} \quad (2)$$

It involves including dummy variables (Z_1, Z_2, \dots, Z_{N-1}) marking each cross-sectional unit (e.g. country). If a constant term is included, then you must include $N - 1$ dummy variables to avoid perfect collinearity.

Here, the Z_i refer to dummy variables marking each cross-sectional unit. The δ_i denote the coefficients associated with each cross-sectional unit. Thus, each cross-sectional unit (minus one) has its own intercept.

Note that Equation (1) is a restricted form of Equation (2). Equation (1) assumes that the coefficients associated with each cross-sectional unit are equal to zero or that:

$$\delta_1 = \delta_2 = \dots = \delta_{N-1} = 0.$$

Not surprisingly, if the assumption above is violated, Equation (1) generates biased estimates. As Green, Kim and Yoon (2001) note, ignoring fixed effects is a special case of the general problem of omitted variable bias.

To see how ignoring fixed effects introduces bias, consider the following scenarios and figures illustrated by Green, Kim and Yoon (2001):

Figure 1 below shows a case of pooling when there is no unmodeled heterogeneity (i.e. when the observations are homogeneous)

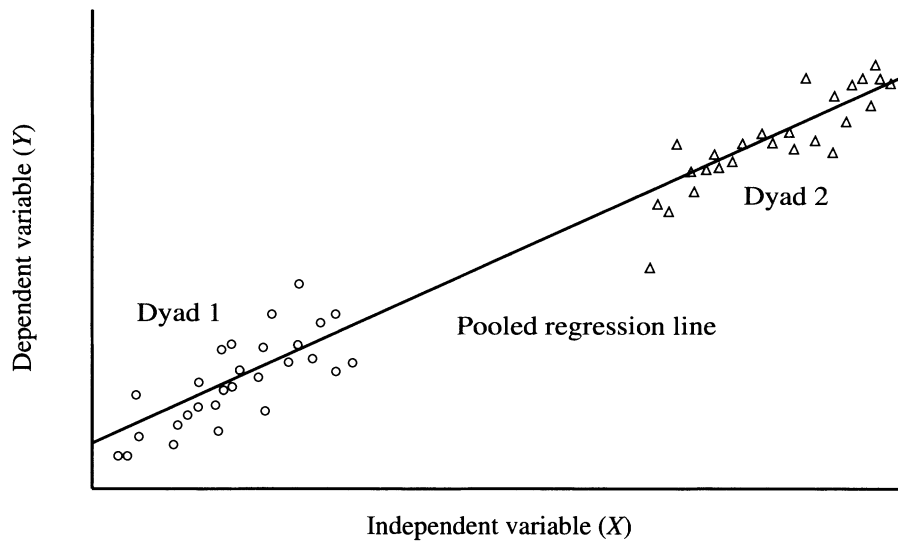


FIGURE 1. *Pooling homogenous observations*

Figure 2 below shows a case of pooling when the different cross-sectional units (in this case, dyads) have different intercepts but where the intercepts are not correlated with the independent variable X .

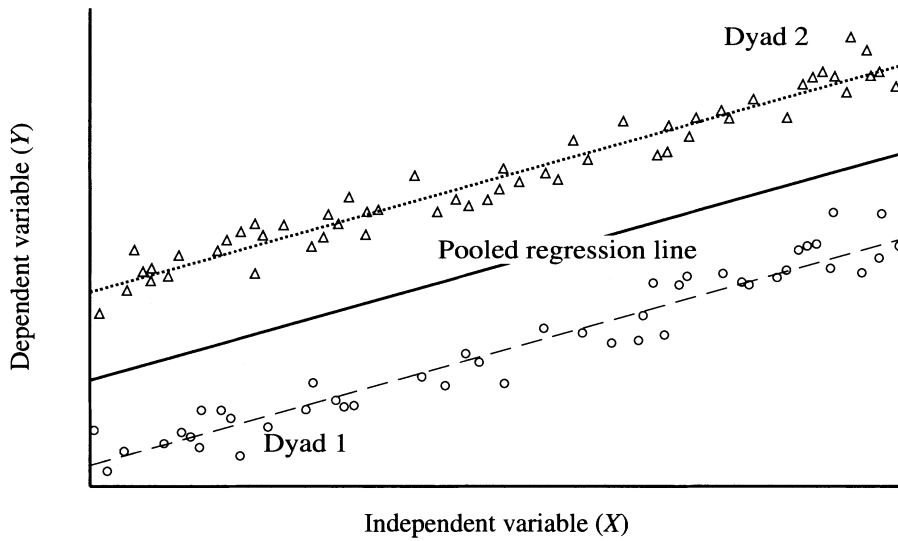


FIGURE 2. Pooling dyads with randomly varying intercepts

Figure 3 shows a case of pooling when the different cross-sectional units (in this case, dyads) have different intercepts but where the intercepts are in fact correlated with the independent variable X . Here, the pooled regression is particularly problematic since it shows that the relationship between X and Y is positive, when in fact it is negative. Because the dyad with the higher values of X also has a higher intercept, this biases the pooled regression line upwards.

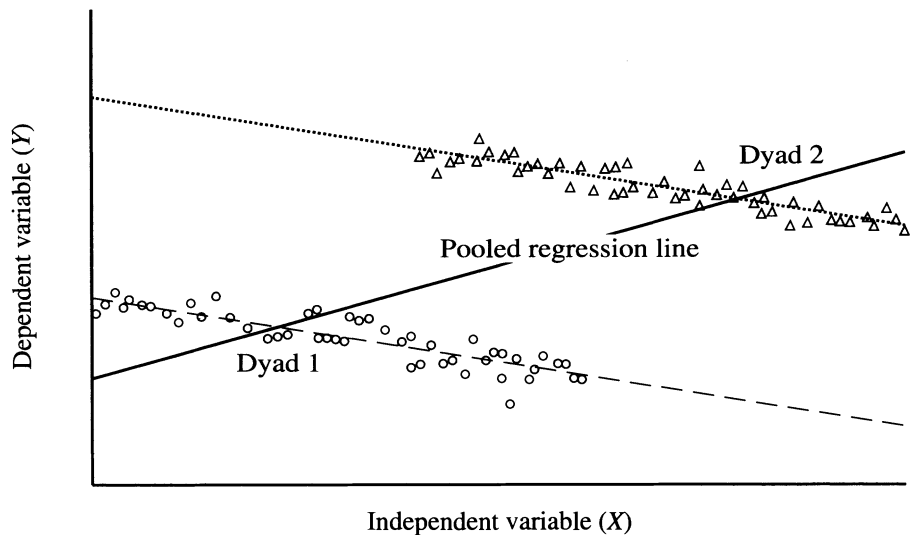


FIGURE 3. Pooling observations ignoring fixed effects

Thus, excluding fixed effect when they belong in a model leads to serious problems.

How do you know if fixed effects belong in a model? It is easy to test for fixed effects using a simple F test of joint significance. This amounts to estimating Equation (2) and then testing the following null hypothesis:

$$H_0 = \delta_1 = \delta_2 = \dots = \delta_{N-1} = 0.$$

This can be easily done in STATA using the command *testparm*.

A rejection of the null hypothesis is an indication that fixed effects belong in the model.

2.2 Cons of including Fixed Effects

Even if fixed effects belong in a model, including fixed effects can come with some serious costs.

First, including fixed effects involves using up a large number of degrees of freedom (i.e. $N - 1$) which makes estimation more difficult.

The issues occur if we have (1) variables that do not change over time or (2) variables that change very slowly. Variables of type (1) will be dropped from your model when you include fixed effects because they will be perfectly collinear with the fixed effects. The coefficients on variables of type (2) will be very hard to estimate precisely. Potential solutions are offered by Plumper and Troeger (2007) and Beck (2001).

2.3 Random Effects

Another approach to dealing with between unit heterogeneity is to include random effects. The key assumption made in random effects models is that **the unit-specific effects are uncorrelated with the independent variables**. If this assumption is true, then OLS will yield unbiased, consistent estimates (see Figure 2 of Green, Kim and Yoon (2001) above). But the estimated standard errors will be too small because, with a random effects model, we are ignoring the fact that observations within the same unit are correlated.

Consider a reformulation of Equation (1) where we now have:

$$y_{i,t} = x_{i,t}\beta + (\alpha + u_i) + \epsilon_{i,t} \quad (3)$$

The component u_i is the random error specific to the i th cross-sectional unit and is constant through time.

Thus, the error term of the random effects model can be written as:

$$\eta_{i,t} = u_i + \epsilon_{i,t}$$

The random effects model relaxes the OLS assumption of no correlation between errors within a cross-sectional unit and allows for the situation where:

$$Cov(\eta_{i,t}, \eta_{i,s}) = \sigma_u^2 \text{ when } t \neq s.$$

The random effects model can be easily implemented in STATA using the following command:

```
xtreg depvar indepvar1 indepvar2 ..... , re
```

You can test whether random effects belong in your model using the **Breusch and Pagan Lagrange Multiplier Test** which is easy to implement in STATA (The STATA command is *xttest0* after estimating a random effects model in STATA).

The null hypothesis under the Breusch Pagan test is:

$$H_0 : \sigma_u^2 = 0 \text{ or that } Corr[\eta_{i,t}, \eta_{i,s}] = 0$$

The alternative hypothesis is:

$$H_A : \sigma_u^2 \neq 0.$$

The resulting test statistic of the Breusch and Pagan Lagrange Multiplier Test is distributed as Chi-Squared with one degree of freedom.

There are several assumptions embedded in a random effects model, but the key ones are:

A. The unit specific effects are uncorrelated with the independent variables.

$$Cov[u_i, x_{i,t}] = 0$$

B. There is no correlation between the errors across units. $Cov(\eta_{i,t}, \eta_{i,s}) = 0$ for all t and s if $i \neq j$.

The good news is that you can test Assumption (A) above using a Hausman specification test. (The STATA command is *hausman*).¹

Under the null hypothesis that Assumption (A) is true, the fixed effects and random effects models are both consistent, but the random effects are more efficient. (This is because FEs use up degrees of freedom).

Under the alternative hypothesis that $Cov(u_i, x_{i,t}) \neq 0$, the fixed effects estimator is consistent (because it does not assume that $Cov[u_i, x_{i,t}] = 0$), but the random effects estimator is not.

If the Hausman test does not reject the null hypothesis, it is advisable to use a random effects model since this will be more efficient than a fixed effects model. If

¹To carry out this test in STATA, you will need to estimate both a fixed effects model and a random effects model in STATA using the command *xtreg* with the appropriate modification. You would then need to store each of the results under the names *fixed* and *random* respectively. The command is *estimates store fixed*. You would then carry out the hausman specification test by typing *hausman fixed random*. The order is important since the first model is consistent under both the null and alternative, while the second model is efficient under both the null and alternative.

the null is rejected, however, it is advisable to use a fixed effects model since a random effects model would be inconsistent.

2.4 Random Coefficient Models

A more flexible approach and one that is increasingly becoming the most preferred by many researchers is a random coefficient model (RCMs). This allows for heterogeneity of the coefficients as well as the intercepts in a nice way.

RCMs are a special case of a multi-level model. You have already covered multi-level models, so we will not go into more detail here. For more on this refer to: Beck and Katz (2007) or Beck's lecture notes.

3 Time Series Issues

Let us go back, again, to the basic OLS model.

$$y_{i,t} = \alpha + x_{i,t}\beta + \epsilon_{i,t}$$

A key assumption of this model is that: $Cov(\epsilon_{i,t}, \epsilon_{i,s}) = 0$ where $t \neq s$. Obviously, this assumption is problematic since we expect events and phenomena to be correlated across time.

Why might errors be correlated across time? There are features of the world that are unobserved (i.e. not included in the model) that change slowly over time. If we

had perfect data availability (a utopian scenario), would we still need to model time dependence?

It is useful to introduce some additional notation here pertaining to the lag operator L .

$$L.y_t = y_{t-1}$$

$L^2.y_t = y_{t-2}$ and so on.

It is also useful to introduce the first difference operator D or Δ :

$$D.y = y_t - y_{t-1} \quad (\Delta y = y_t - y_{t-1})$$

This will be useful when we consider how to approach time series issues in STATA.

3.1 Continuous Dependent Variable

3.1.1 Huberized Standard Errors/Clustering

Clustering or **Huberizing** the standard errors allows for the errors of observations within a single cross-sectional unit to be correlated and, for TSCS data, it is often used to deal with temporal dependence. Clustering amounts to an *ex post* fix of the standard errors and, thus, will affect your standard errors but not your coefficients.

A common approach used in the political science literature is to simultaneously deal with non-independence of observations within a cross-sectional unit as well as panel heteroskedasticity by estimating a regression model in STATA using Huber-White standard errors (also known as heteroskedastic-consistent clustered

standard errors). If your cross-sectional unit is country (countryID), the command in STATA is:

```
reg y x1 x2....., robust cluster(countryID)
```

Compared to the standard OLS variance covariance matrix given above, the *robust cluster* command does the following:

- 1) It allows the error variance for each cross-sectional unit to be different. (i.e. the diagonal terms are σ_i^2 (where i is the cross-sectional unit) rather than σ^2 .)
- 2) It allows the covariance between the error terms within the same unit to be non-zero (e.g. $\sigma_{i,t,t+1} \neq 0$; $\sigma_{i,t,t+2} \neq 0$ etc.)

It retains the assumption that there is no correlation between errors across units (i.e. $\sigma_{i,j,t} = 0$ for any t for all $i \neq j$.)

Why use clustering? Clustering is easily implemented in a maximum likelihood framework where dealing with temporal dependence in other ways becomes complicated. If you do not deal with temporal dependence in any other way, you should at least use clustering as it is generally the more conservative approach **in expectation, but not necessarily in practice!**

3.1.2 Serial Correlation: AR1 Error Model

A model with an AR1 error process or, equivalently, first order serial correlation is specified as follows:

$y_{i,t} = \alpha + x_{i,t}\beta + \epsilon_{i,t}$ where

$\epsilon_{i,t} = \rho\epsilon_{i,t-1} + \nu_{i,t}$ where $-1 < \rho < 1$.

Similarly,

$\epsilon_{i,t-1} = \rho\epsilon_{i,t-2} + \nu_{i,t-1}$

Thus, making the necessary substitutions in the equation above for $\epsilon_{i,t}$ we get:

$\epsilon_{i,t} = \rho^2\epsilon_{i,t-2} + \rho\nu_{i,t-1} + \nu_{i,t}$

We can similarly substitute for $\epsilon_{i,t-2}$ and so on. We quickly see that this is a model of exponential decay when $\rho < 1$. The current error is a function of the previous errors weighted by an exponentially declining factor.

It is easy to estimate an AR1 error model using STATA.² However, as Beck (1996) argues, there is seldom any reason to prefer a model with serial correlation which treats temporal dependence as a nuisance to a lagged dependent variable (LDV) model which does not.

Note that ρ is restricted to being less than 1 which means we are in the world of a **stationary time-series**. Intuitively, this refers to a situation where effects exponentially decay over time and where the time-series never wanders too far from the mean. Occasionally, one encounters a situation where $\rho > 1$ which forces us to enter the more complicated world of **non-stationary time-series**.³ Intuitively, a

²One way to do this is to implement the Prais-Winsten procedure described in Neal Beck's notes on continuous time series. The STATA command to implement this procedure is *prais* which can be run with TSCS data.

³A situation where $\rho = 1$ is referred to as a "random walk".

non-stationary time series process is one in which very distant shocks persist to the present rather than dying out.⁴

The subsequent discussion is relevant for stationary time-series processes. For most political science/political economy applications, Beck and Katz (2011) recommend using stationary time series methods such as the ones discussed below even when series appear to display high levels of persistence over time. For further discussion of this rationale see Beck and Katz (2011).

3.1.3 Testing for Serial Correlation

It is always a good idea to test for serial correlation. There a number of possible tests but an intuitive and general test is the **Breusch-Godfrey Lagrange Multiplier Test** which can be implemented by hand in STATA. The null hypothesis for this this test is that there is no autocorrelation. The alternative hypothesis is that the residuals follow an $AR(P)$ or $MA(P)$ process where P refers to the number of lags.

The test can be carried out by regressing the OLS residuals on the lagged residual(s) and the original independent variables and noting down the R^2 from this regression. For example, if you were interested in testing for first order serial correlation (i.e. $P = 1$), you would regress $\epsilon_{i,t}$ on $\epsilon_{i,t-1}$ and the other independent variables and obtain the R^2 . The test statistic is TR^2 where T is the number of time periods in your dataset and R^2 is as specified above.

⁴See Matt Golder's notes on Stationary Time Series for visual representations of these processes.

The resulting test statistic is distributed as Chi-Squared with P degrees of freedom.

3.1.4 Modelling Temporal Dependence

A lagged dependent variable model is:

$$y_{i,t} = \alpha + x_{i,t}\beta + y_{i,t-1}\gamma + \epsilon_{i,t}$$

Recall that the AR1 error model is:

$$y_{i,t} = \alpha + x_{i,t}\beta + \nu_{i,t} + \rho\epsilon_{i,t-1}$$

since:

$$\epsilon_{i,t} = \nu_{i,t} + \rho\epsilon_{i,t-1}$$

Also, note that:

$$y_{i,t-1} = \alpha + x_{i,t-1}\beta + \epsilon_{i,t-1} \text{ which means that } \epsilon_{i,t-1} = y_{i,t-1} - \alpha - x_{i,t-1}\beta.$$

Thus, substituting for $\epsilon_{i,t-1}$ in the first equation for the AR1 model, we get:

$$y_{i,t} = (\alpha - \rho\alpha) + x_{i,t}\beta + \rho y_{i,t-1} - x_{i,t-1}\beta\rho + \nu_{i,t}.$$

The Auto-Regressive Distributive Lag (ADL) Model nests both the AR1 error model and the LDV model and is:

$$y_{i,t} = \alpha + x_{i,t}\beta + \rho y_{i,t-1} - x_{i,t-1}\gamma + \nu_{i,t}.$$

In other words, the AR1 error model and the LDV model are special cases of the ADL model.

This means that it is preferable to start with the ADL model and test from general to specific. In particular, you should:

1. Start with the ADL setup.
2. Test the following null hypotheses: (1) $\gamma = 0$ (2) $\gamma = -\beta\rho$.
3. If you cannot reject (2) then the AR1 model might be appropriate. If you cannot reject (1), the LDV model might be appropriate. If you reject both, use the ADL model.

An alternative approach is the Error Correction (EC) Model which is:

$$\Delta y_{i,t} = \Delta x_{i,t}\beta - \phi(y_{i,t-1} - x_{t-1}\gamma) + \nu_{i,t}$$

where Δ is the first difference operator described above. To derive the EC model from the ADL model, subtract $y_{i,t-1}$ from both sides of the ADL model to get a first difference of y on the left hand side and add and subtract $\beta x_{i,t-1}$ from the right hand side to get a first difference of x in the equation. The EC model models a change in the dependent variable as a function (ϕ) of the degree to which the variables are out of equilibrium plus a function (β) of a change in the independent variables.

Each of the above models assumes something different about how y adjusts in response to a permanent one unit change in x . We will examine this more closely in the homework assignment where we will plot how y changes in response to a change in x in each type of model.

3.1.5 The Inclusion of a Lagged Dependent Variable with Fixed Effects

When analyzing TSCS data we will often want to include a lagged dependent variable along with fixed effects. It has been shown, however, that the inclusion of fixed effects in a model with a lagged dependent variable introduces bias into the coefficient estimates.⁵ It has been shown that this bias is of order $\frac{1}{T}$ and, hence, decreases, as T gets large.

Based on simulations they ran, Beck and Katz (2011) recommend using OLS when T is large enough (i.e. 20 or more) rather than alternative approaches. Other approaches include using Generalized Method of Moments (GMM) as described by Wawro (2002).

3.2 Binary Dependent Variable

A binary dependent variable is one which takes a value of either 0 or 1. Just as with a continuous dependent variable, we would expect TSCS data with a binary dependent variable to show temporal dependence.

Note, however, that using a lagged dependent variable in a BTSCS model is not the same as using LDV in a continuous TSCS model. To see this, we need to introduce the Markov transition framework.

⁵According to Beck and Katz (2011, p342), this bias arises because centering all variables by country introduces a correlation between the centered lagged dependent variable and the centered error term.

3.3 Markov Transition framework

A first-order Markov process assumes that whether or not the dependent variable is a 0 or 1 at time t is a function only of the value of the dependent and independent variables at time $t - 1$.

With this assumption, we would estimate two different probits (or logits) depending on the prior state:

$$P(y_{i,t}|y_{i,t-1} = 0) = Probit(x_{i,t}\beta)$$

$$P(y_{i,t}|y_{i,t-1} = 1) = Probit(x_{i,t}\alpha).$$

Note that we are allowing for the effects of the independent variables to differ depending on the prior state.

We can combine these two separate equations into one model as follows:

$$P(y_{i,t} = 1) = Probit(x_{i,t}\beta + y_{i,t-1} * x_{i,t}\gamma)$$

where $\gamma = \alpha - \beta$.

You can test the hypothesis that the prior state does not matter by testing $\gamma = 0$.

A model with a lagged dependent variable is a special case of the above combined model which assumes that the only thing that differs according to the prior state is the intercept. This is an assumption that should be tested.

3.4 Duration Data framework

Beck, Katz and Tucker (1998) observe that binary TSCS data (BTSCS data) are equivalent to grouped duration data.

Consider an example in which an “event” or “failure” is a conflict and the length of time in between is a “spell” of peace.

BTSCS data are “grouped” in the sense that we only know whether a unit has failed in some discrete time interval (e.g. a year).⁶

Note that in this set-up we need to separate out conflict onset and conflict duration and not lump them together in the same model. In the former case, a “failure” would be defined as the onset of conflict whereas in the latter, a “failure” would be defined as the onset of peace.

Recall (from last week?) that the hazard probability refers to the probability of “dying” (or failing) in time t given alive at the start of the interval t .

Estimating the probability of failure using ordinary logit (or probit) assumes that the hazard is time invariant:

$h_{i,t} = h(\mathbf{x}_{i,t})$. (Notice the lack of subscript on the hazard function on the right hand side of the equation).

To allow for duration dependence, we need to estimate a binary model in which:

$h_{i,t} = h_t(\mathbf{x}_{i,t})$. (Notice the subscript on the hazard function on the right hand side

⁶This is as opposed to a continuous duration model in which a unit can fail at any time.

of the equation. This implies that the hazard function varies with time.).

How should the hazard function vary with time? Beck suggests a simple approach of allowing for different intercepts at each time point.

$$h_{i,t} = a_t + h(\mathbf{x}_{i,t})$$

which would be estimated by including period dummies in the relevant model for a binary dependent variable. The dummies would be included to reflect the time since the last “failure” or “event”. Here, an example would help:

Let $y_{i,t}$ be a dummy variable coded 1 if Country 1 if experiencing conflict in the given year and 0 otherwise.

countryID	year	$y_{i,t-1}$	Time	α_1	α_2	α_3	α_4
Country1	1950	1	1 ⁷	1	1	0	0
Country1	1951	0	1	1	0	0	0
Country1	1952	0	2	0	1	0	0
Country1	1953	0	3	0	0	1	0
Country1	1954	1	4	0	0	0	1
Country1	1955	1
Country1	1956	1

Thus, time refers to the number of years since the last “event” and a separate dummy variable is included to denote the number of years lapsed. Note that in this case we are interested in conflict onset, so the observations from 1955 and 1956 will be dropped from our analysis.

⁷This is a case of left censoring. See below.

One can test whether the dummy variables belong in the model (i.e. whether there is duration dependence) using a standard F test in which the null hypothesis is that all the period dummies (i.e. $\alpha_1, \alpha_2, \dots$ are 0).

Including the period dummy variables often uses up a large number of degrees of freedom. Beck, Katz and Tucker (1998) observe that this does not usually have much of an effect on estimating the coefficients on the key independent variables, but may lead to problems estimating the period dummies themselves. An alternative approach is to use *cubic splines* which are essentially smoothed functions of the "Time" variable above. For more information on splines, see Beck, Katz and Tucker (1998).

What is the appropriate model for binary dependent variables? It can be shown that a Cox proportional hazard model for grouped duration data is mathematically equivalent to a conditional logit model which involves using a *cloglog* function or "link"⁸ rather than a *logit* function/link. Beck and Katz (1998) observe that, in practice, there is almost no difference between these models when failure rates are below 50% and recommend using logit in these situations for practical reasons.

Additional problems arise with these kind of data (e.g. how to deal with multiple failures, left censoring etc.) See Beck, Katz and Tucker (1998) for recommendations for how to deal with these issues.

⁸This terminology comes from the Generalized Linear Model approach.

4 Cross-Sectional Issues

4.1 Panel Corrected Standard Errors (PCSEs)

A key assumption entailed in OLS is that the off-diagonal terms of the variance-covariance matrix are 0.

A standard error matrix for OLS looks like this:

$$V_{NT \times NT} = \begin{bmatrix} \sigma^2 & 0 & . & . & . & . & 0 \\ 0 & \sigma^2 & . & . & . & . & 0 \\ 0 & . & \sigma^2 & . & . & . & 0 \\ 0 & . & . & . & . & . & 0 \\ 0 & . & . & . & . & 0 & \sigma^2 \end{bmatrix}$$

One reason this assumption is unlikely to hold true for TSCS data is that there may be a contemporaneous correlation of errors across cross-sectional units. In this case, OLS is still consistent but the regular OLS standard errors are incorrect since they incorrectly estimate the sampling variability.

PCSEs leave the coefficient estimates intact and fix the standard errors to allow for contemporaneous correlation of errors (i.e. $Cov(\epsilon_{i,t}, \epsilon_{j,t}) \neq 0$ for $i \neq j$).

PCSEs, however, assume that:

1. There is no temporal dependence in the errors. (i.e. $Cov(\epsilon_{i,t}, \epsilon_{i,t+1}) = 0$)
2. The covariance between errors of a pair of cross-sectional units (e.g. countries) remains the same over time. (e.g. $Cov(\epsilon_{i,t}, \epsilon_{j,t})$ is the same for all t .)

PCSEs use the OLS estimates of the errors to generate estimates of the relevant covariances (i.e. $Cov(\epsilon_{i,t}, \epsilon_{j,t})$). This works because, despite contemporaneous correlation, the OLS estimates are still consistent.

4.2 Modeling Spatial Dependence

PCSEs treat spatial dependence between observations as a nuisance. As an alternative, one could model the spatial dependence between units. Spatial econometrics has become an important way of analyzing interdependence amongst observations from “nearby” cross-sectional units. Beck, Gleditsch and Beardsley (2006) note that one could not only incorporate geographic notions of distance but also political economy notions of distance such as extent of trade between countries. In such models, it is typically assumed that the structure of dependence between observations is known by the researcher.

There are a number of possible specifications: a spatially lagged error model, the spatially autoregressive model and so on. These are conceptually relatively easy to understand, but in practice often hard to implement. See Beck, Gleditsch and Beardsley (2006) for more details on this.

5 References

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