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RECENT DEVELOPMENTS IN QUANTITATIVE COMPARATIVE METHODOLOGY: THE CASE OF POOLED TIME SERIES CROSS-SECTION ANALYSIS

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INDICE

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Students of the political economy have tended to investigate relationship between institutions and economic variables by comparing observations across space or observations over time. Until recently, the space and the time domains have rarely been combinated in the comparative research. However, new quantitative methods stress sensitivity to time as well as space. Pooled time series cross-section analysis (TSCS) is probably the most important way to examine simultaneously these dimensions.

In this paper, I will try to describe the "state of the art" of this approach discussing first the characteristics of TSCS data and advantages and disadvantages of this statistical technique (Section 1). Hence, I will discuss main issues that relate to the estimation method (section 2). After that, I will address the most important problems that relate to the model specification by concentrating first on effects of the time and the space (Section 3), and then on the pooling dilemma and causal heterogeneity issue (Section 4). Finally, I will present implementations and commands in STATA software to analyze TSCS data (Section 5).

1. Advantages and Disadvantages of Pooled Analysis

Pooled analysis combines time series for several cross-sections[1]. Pooled data are characterized by having repeated observations (most frequently years) on fixed units (most frequently states and nations). This means that pooled arrays of data are one that combines cross-sectional data on N spatial units and T time periods to produce a data set of $N \times T$ observations. Here, the typical range of units of analyzed would be about 20 (if we examine developed countries), with each unit observed over a relatively long time period, like 20-50 years.

However, when the cross-section units are more numerous than temporal units (N>T), the pool is often conceptualized as a "cross-sectional dominant". conversely, when the temporal units are more numerous than spatial units (T>N), the pool is called "temporal dominant" (Stimson 1985).

Given this preamble, we can write the generic pooled linear regression model estimable by Ordinary Least Squares (OLS) procedure

$$y_{it} = \beta_1 + \sum_{k=2}^{k} \beta_k x_{kit} + e_{it} \tag{1}$$

Where i = 1,2,….; N; refers to a cross-sectional unit; t = 1,2,….; T; refers to a time period and k = 1,2,….; K; refers to a specific explanatory variable. Thus, y_{it} and x_{it} refer respectively to dependent and independent variables for

[1] Another name of pooled TSCS analysis is panel analysis, but it can be confused with panel research in survey studies.

unit i and time t; and e_{it} is a random error and β_1 and β_k refer, respectively, to the intercept and the slope parameters.[2] Moreover we can denote the $NT \times NT$ variance-covariance matrix of the errors with typical element $\mathrm{E}(e_{it}e_{js})$ by Ω.

Estimating this kind of model and some of its variants (see below), solves many problems of traditional methods of the comparative research (i.e. time series analysis and cross-sectional analysis). Several reasons support this.

The first reason concerns the "small N" problem suffered by both time series and cross-sectional analysis. The limited number of spatial units and the limited number of available data over time led data sets of these two techniques to violate basic assumption of standard statistical analysis. Most specifically, the small sample of conventional comparisons shows an imbalance between too many explanatory variables and too few cases. Consequently, within the contest of the small sample the total number of the potential explanatory variables exceeds the degree of freedom required to model the relationship between the dependent and independent variables. In contrast, thanks to pooled TSCS designs, we can greatly relax this restriction. This is because, within the pooled TSCS research, the cases are "country-year" (NT observations) starting from the country i in year t, then country i in year t+1 through country z in the last year of the period under investigation This allow us to test the impact of a large number of predictors of the level and change in the dependent variable within the framework of a multivariate analysis (Schmidt 1997, 156).

Second, pooled models have gained popularity because they permit to inquiry into "variables" that elude study in simple cross-sectional or time-

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[2] I assume the dependent variable, y, is continuous. In the case of binary

series. This is because their variability is negligible, or not existent, across either time or space. In practice, many characteristics of national systems (or institutions) tend to be temporally invariant. Therefore, regression analysis of pooled data combining space and time may rely upon higher variability of data in respect to a simple time series or cross-section design research (Hicks 1994, 170-71).

A third reason to support pooled TSCS analysis concerns the possibility to capture not only the variation of what emerges through time or space, but the variation of these two dimensions simultaneously. This is because, instead of testing a cross-section model for all countries at one point in time or testing a time series model for one country using time series data, a pooled model is tested for all countries through time (Pennings, Keman e Kleinnijenhuis 1999, 172).

Given these advantages, in the last decade pooled analysis has became central in quantitative studies of comparative political economy. Several authors have utilized pooled models to answer to classical questions of this discipline. An accumulating body of research has used this statistical technique to test the main hypothesis concerning the political and institutional determinants of macroeconomic policies and performances (Alvarez, Garrett, Lange 1991; Hicks 1991; Swank 1992). Most specifically, regarding the study of public policy, we can cite empirical works on political and socio-economic causes of the welfare state development (Pampel and Williamson 1989; Huber Ragin and Stephen 1993; Schmidt 1997). Regarding research on both economic policies and performances, researchers have tried to verify and characterize a

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dependent variable, see Beck et al. (1998).

macro-economic partisan strategy. In particular, they have shown that, once in office, different parties attempt to manage the economic cycle using the standard fiscal and monetary instruments. However, these same studies have discovered that the ability of parties to pursue their most preferred macro-economic strategies depends on institutional structures of the domestic labor market (Comptson 1997; Oatley 1998), and increasingly internationalized markets (Garrett 1998; Garrett and Mitchell 1999). Finally, several authors have utilized TSCS analysis to examine the impact of political and economic variables on the financial openness of domestic markets (Alesina et al. 1994; Quinn and Inclan 1997).

Therefore, pooled TSCS analysis is an inalienable instrument for the development of the comparative political economy. However, the popularity of this statistical technique does not depend only on its application in substantive research, but also recent papers discussing methodological issues that it implies (Stimson 1985; Hicks 1994; Beck and Katz 1995; 1996). In particular, this latter literature is more numerous now because pooled TSCS designs often violate the standard OLS assumptions about the error process.[3] In fact, the OLS regression estimates, used by social scientists commonly to link potential causes and effects, are likely to be biased, inefficient and/or inconsistent when they are applied to pooled data.[4] This is because the errors for regression

[3] For OLS to be optimal it is necessary that all the errors have the same variance (homoschedasticity) and that all of the errors are independent of each other.

[4] An unbiased estimator is one that has a sampling distribution with a mean equal to the parameter to be estimated. An efficient estimator is one that has the smallest dispersion, (i.e., one that one whose sampling distributionhas the

equations estimated from pooled data using OLS procedure and pooled data tend to generate five complications (Hicks 1994, 171-72).

First, errors tend to be no independent from a period to the next. In other terms, they might be serially correlated, such that errors in country i at time t are correlated with errors in country i at time t+1. This is because observations and traits that characterize them tend to be interdependent across time. For example, temporally successive values of many national traits (i.e., population size) tend not to be independent over time.

Second, the errors tend to be correlated across nations. They might be contemporaneously correlated, such that errors in country i at time t are correlated with errors in country j at time t. As Hicks (1994, 174) notes, we could not expect errors in the statistical model for Sweden to lack some resemblance to those for the Norway or errors for Canada and the United Stated to be altogether independent. Instead, we would expect disturbances for such nations to be cross-sectionally correlated. In this way, errors in Scandinavian economies may be linked together but remain independent with errors of North American countries.

Third, errors tend to be heteroschesdastic, such that they may have differing variances across ranges or sub sets of nations. In other words, nations with higher values on variables tend to have less restricted and, hence, higher variances on them. For example, the United Stated tends to have more volatile as well as higher unemployment rates than the Switzerland. This means that the

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smallest variance). Finally, an estimator is said to be consistent if its sampling distribution tends to become concentrated on the true value of the parameter as sample size increases to infinite (Kmenta 1986,12-3).

variance in employment rates will tend to be greater for bigger nations with large heterogeneous labor forces than for small, homogeneous nations (Hicks 1994, 172). Moreover, errors of a TSCS analysis may show heteroschesdasticity because the scale of the dependent variable, such as the level of government spending, may differ between countries (Beck and Katz 1995, 636).

Fourth, errors may contain both temporal and cross-sectional components reflecting cross-sectional effects and temporal effects. Errors tend to conceal unit and period effects. In other words, even if we start with data that were homoschedastic and not auto-correlated, we risk producing a regression with observed heteroschestastic and auto-correlated errors. This is because heteroschedasticy and auto-correlation we observe is a function also of model misspecification. The misspecification, that is peculiar of pooled data, is the assumption of homogeneity of level of dependent variable across units and time periods. In particular, if we assume that units and time periods are homogeneous in the level (as OLS estimation requires) and they are not, then least squares estimators will be a compromise, unlikely to be a good predictor of the time periods and the cross-sectional units, and the apparent level of heteroschedasticity and auto-correlation will be substantially inflated (Stimson 1985, 919).

Fifth, errors might be nonrandom across spatial and/or temporal units because parameters are heterogeneous across subsets of units. In other words, since processes linking dependent and independent variables tend to vary across subsets of nations or/and period, errors tend to reflect some causal heterogeneity across space, time, or both (Hicks 1994, 172). Therefore, this complication, like the previous one, could be interpreted as a function of misspecification. If we estimate constant-coefficients models, we cannot capture the causal heterogeneity across time and space.

In the last decade, several models have been developed to deal with these complications and different solutions have been jointed because problems usually do not appear alone. However, for reasons of the clearness, I will present the different models trying to separate various solutions utilized to deal with single problems.

In the next section, I will discuss Parks-Kmenta method and Beck and Katz ‘s (1995; 1996) proposal. They represent two different approaches to tackle the complications of serial correlation, contemporaneous correlation and heteroschedasticity (respectively problem 1, 2 and 3). After that, I will address specification problems by distinguishing between the issue of time and space effects (problem 4) and causal heterogeneity (problem 5).

2. The Estimation Issue: GLS vs. OLS

Parks-Kmenta method has been the most utilized approach for TSCS analysis in comparative political economy until the mid-nineties (see for example, Pampel and Williamson 1989; Alvarez, Garrett, Lange 1991; Hicks 1991; Swank 1992; Huber, Ragin, and Stephen 1993). Nevertheless, from those years, when the two papers of Beck and Katz (1995; 1996) suggested an alternative approach to the Parks-Kmenta method, this latter proposal has probably became the one most utilized by sociologists and political scientists (see for example, Quinn and Inclan 1997; Oatley 1998; Garrett 1998; Garrett and Mitchell 1999).

According to an historical reason, let me start by discussing the Parks-Kmenta method. This method first elaborated by Parks (1967) and then discussed by Kmenta (1971; 1986) (here referred to as Parks-Kmenta method) uses an application of the generalized least squares (GLS) estimation. The regression equation for this method may be written in the same form of the equation 1:

$$y_{it} = \beta_1 + \sum_{k=2}^{k} \beta_k x_{kit} + e_{it} \qquad (2)$$

Thus, it is an equation where a single intercept and slope coefficient are constant across units and time points. However, according to Parks-Kmenta method, this equation must be estimated by GLS because this estimation procedure is based on less restrictive assumptions concerning the behavior of regression disturbance and, thus, concerning the variance-covariance matrix, Ω, than the classical regression model (Kmenta 1986, 607). Therefore, the GLS estimation has a special interest in connection with time series and cross-section observations.

Regarding the problem of estimating parameters β of the generalized linear regression model, we can write the following expression:

$$(x'\Omega^{-1}x)^{-1}x'\Omega^{-1}y \tag{2.1}$$

This estimation is based on the assumption that the variance-covariance matrix of the errors, Ω, is known. However, since in many cases the variance-covariance matrix is unknown, we cannot use GLS but "feasible" generalized least squares (FGLS). It is "feasible" because it uses an estimate of variance-covariance matrix, avoiding the GLS assumption that Ω is known. Consequently, we need to find a consistent estimate of Ω, say, $\hat{\Omega}$, to substitute $\hat{\Omega}$ for Ω in the formula to get a coefficient estimator β (Kmenta 1986, 615). Thus we denote the FGLS estimates of β by $\hat{\beta}$.

Let me now consider the problem of error complications. The Parks-Kmenta method combines the assumptions concerning serial correlation, contemporaneous correlation and panel heteroschedasticity of errors. The particular characterization of these assumptions are (Kmenta 1986, 622):

$$\mathrm{E}(e_{it}{}^{2}) = \sigma_{ii} \tag{2.2}$$

$$\mathrm{E}(e_{it}e_{jt}) = \sigma_{ij} \tag{2.3}$$

$$e_{it} = \rho_i e_{it-1} + \nu_{it} \qquad (2.4)$$

In the other words, this approach deals with errors complications by specifying respectively a model for heteroschedasticity (equation 2.2), a model for contemporaneous correlation (equation 2.3), and a model for serial correlation so called AR(1) (I.e., first-order autoregressive model), where ρ_i is a coefficients of first-order autoregressiveness . In this model we allow the value of the parameter ρ_i to vary from one cross-section unit to another(equation 2.4).

We now need to find consistent estimators of ρ_i and σ^2 (i.e., elements of the variance-covariance matrix of the errors). According to this aim, Parks-Kmenta method consists of two sequential FGLS transformations. First, it eliminates serial correlation of the errors then it eliminates contemporaneous correlation of the errors.[5] This is done by initially estimating equation 2 by OLS. The residuals from this estimation are used to estimate the unit-specific serial correction of the errors, which are then used to transform the model into one with serially independent errors. Residuals from this estimation are then used to estimate the contemporaneous correlation of the errors, and the data is once again transformed to allow for the OLS estimation with now errors without any complications.

[5] As Beck and Katz (1995, 637) note, according to Parks-Kmenta method the correction for the contemporaneous correlation of the errors automatically corrects for any panel heteroschedasticity. Consequently we need only consider corrections for contemporaneous correlation and serial correlation of errors.

Having obtained consistent estimators of ρ_i and σ^2, we have completed the task of deriving consistent estimators of elements of the Ω. Hence, by substituting $\hat{\Omega}$ for Ω, we can obtain desired estimates of coefficients and of their standard errors (Kmenta 1986, 620).

From this point Beck and Katz review the Parks-Kmenta method. They (1995, 694) claim that, while GLS are optimal proprieties for TSCS data, the really applied FGLS does not do the same. This is because, although FGLS uses an estimate of the error process, the FGLS formula for standard errors assumes that the variance-covariance matrix of the errors is known, not estimated. This is a problem for TSCS models because the error process has a large number of parameters. This oversight causes estimates of standard errors of the estimated coefficients to understate their true variability. In particular, Beck and Katz show that the overconfidence in the standard errors makes the Parks-Kmenta method unusable unless where there are more time points than there are cross-section units. In other words, t he problem of the Parks-Kmenta method is most evident for the types of TSCS data typically analyzed by political scientists and sociologists.

Here, Beck and Katz propose to use a less complex method. This because it is well known that even though OLS estimates of TSCS model parameters may not be optimal, they often perform well in practical research situations. If the errors meet one of more of the TSCS error assumptions, the OLS estimates of β will be consistent but inefficient. Moreover, it is well known that the OLS estimates of the standard errors may be highly inaccurate in such situations. Consequently, Beck and Katz propose to retain OLS parameter estimators but replace OLS standard errors with panel-corrected standard errors (PCSEs) that take into account the contemporaneous correlation of the errors and perforce heteroschedasticity. [6] However, any serial correlation of the errors must be eliminated before PCSEs are calculated. Serial correlation may be modeled by including a lagged dependent variable in the set of independent variables or corrected by estimating a model for autoregressiveness as proposed by Parks-Kmenta method. Beck et al. (1993, 946) review this latter solution. This is because it is hart to see why the parameters of the equation 2 should be constant across cross-section units, while the "nuisance" serial correlation parameters should vary from unit to unit. In a recent paper, Beck and Katz (1996) argue that seeing the serial correlation as a nuisance that obscures "the true" relationship and transforming the data to remove serial correlation, many approaches to pooled TSCS data analysis can be misleading. In other words, they argue that over-time persistence in the data constitutes substantive information that should be incorporated in the model. Therefore, they argue that it is best model dynamics via a lagged dependent variable rather than via serial correlation errors. Incorporating a lagged value of the dependent variable on the right hand side of the equation yields an explicit estimate of the extent of stickiness or persistence in the dependent variable. This allows us to stay closer to the original data than transformed data would. Consequently, we can develop the equation 1 in the following form:

[6] Beck and Katz (1995, 634) argue that since is not possible to provide analytical formula for the degree of overconfidence introduced by the Parks-Kmenta method, they provide evidences from Monte Carlo experiments using simulated data. At the same time, by using Monte Carlo analysis they show that OLS with PCSEs allow for accurate estimation of variability in the presence in the presence of the TSCS errors structures

$$y_{it} = \beta_1 + \beta_2 y_{it-1} + \sum_{k=3}^{k} \beta_k x_{kit} + e_{it} \qquad (3)$$

Where y_{it-1} stands for the first lag of the dependent variable and β_2 stands for its slope coefficient. Once the dynamics are accounted for, TSCS analysts can estimate model parameters by OLS and their standard errors by PCSEs in order to take into account contemporaneous correlation of the errors and heteroschedasticity. The correct formula for the sampling variability of OLS estimates is given by the roots of the diagonal term of the following expression (Beck and Katz 1995, 638):

$$Cov(\vec{\beta}) = (x^{'}x)^{-1}(x^{'}\Omega x)(x^{'}x)^{-1} \qquad (3.1)$$

The middle term of this equation contains the correction for the panel data. Under the conditions that the residuals are contemporaneously correlated and heteroschedastic, the matrix of covariance of the errors Ω is an NT $\times$ NT block diagonal matrix with an N $\times$ N matrix of the contemporaneous covariance, Θ along the diagonal. Thus, to estimate equation 3.1 we need a consistent estimate of Θ. Since the OLS estimates of the equation 1 are consistent, we can use OLS residuals from that estimation to provide a consistent estimate of Θ.

The idea of using OLS with PCSEs is fine and simple and has been known to have numerous applications in comparative political economy. However, as Maddala (1997, 3) argues, Beck and Katz's prescriptions are not, strictly speaking, correct. They suggest OLS estimation with panel corrected covariance matrix estimation, as suggested in their earlier paper (Beck and Katz 1995) for a model with no lagged dependent variables. With lagged dependent variables, it is well known that OLS estimators are inconsistent in the presence of serial correlation in errors. Thus the problem is not merely getting the correct standard errors but also to get consistent estimates of the parameters. In other words, the solution offered by Beck and Katz can be categorized in the “what not to do” if there are lagged dependent variables. According to Maddala their criticism of the Parks-Kmenta method is valid but not their suggested solution.

Therefore, although the Beck-Katz approach has been heavily applied in comparative research, the estimation debate could not be conclusive yet. However, since Beck-Katz argument addresses the problem of standard error inflation and, hence, to avoid calling something significant when it might not be, let me now discuss the inference issue in comparative research.

Tests of statistical significance are generally used in regression analysis to evaluate the reliability of estimation results. These tests calculate the probability that a random sample in which the regression coefficients are as estimated could be drawn from a parent population in which the regression coefficient was zero. However, for TSCS data sets,used in comparative research, the countries and years under investigation are not a representative sample of a larger population of countries and years. They are the population. This means that regression estimate of the population regression is a coefficient of itself. Therefore, once we have carry out the regression therefore we know whether the population parameter is zero (or not) without the need for recourse to probability theory (Comptson 1997, 741-2). Nevertheless, as Western and Jackman (1994, 412-3) suggest, we can adopt a Bayesian approach of statistical inference rather than the conventional statistical inference to address this problem. In fact, the comparative researchers' discomfort with frequentistic inference is well founded because is not applicable to a no stochastic setting. It is simply irrelevant for this problem to think of observations as drawn from a random process when further realizations are impossible in practice, and lack meaning even as abstract propositions. In contrast, the Bayesian model of the statistical inference is a valid solution to this problem of the comparative research. This is because the probability is conceived subjectively as characterizing a researcher's uncertainty about the parameters of statistical model rather than a fact characterizing an object n the external world. Consequently, for the Bayesian approach it is not relevant that data are not generated by a repeatable mechanism such as coin flip.

3. Time and Space Effects

As we argued above, error complications can be also caused by model misspecifications. If we assume that the level of the dependent variable is homogeneous across time periods and units, we risk that error contains both temporal and cross-section components reflecting, respectively, time effects and cross-section effects. In particular, if different time periods and cross-section are consistently higher or lower on the dependent variable, the common intercept β_1 estimated in OLS regression will be a average of all time period and units that may not be representative for any one of the single groups of observations.

To deal with this problem, we can use either the covariance model or the error component model. Both these models use a varying intercept term in order to capture the differences in behavior over time and space (Judge et al. 1985, 519). Consequently, for both models, we can write the following equation:

$$y_{it} = (\beta_1 + \mu_i + \lambda_t) + \sum_{k=2}^{k} \beta_k x_{kit} + e_{it} \tag{4}$$

With intercept $\beta_{1it} = \beta_1 + \mu_i + \lambda_t$. Where β_1 is the "mean intercept", μ_i represents the unit effects and λ_t represents time effects. However, if we are interested in stable difference across cross-section units only, we use the μ_i term and drop the λ_t from the equation. Alternatively, if we are interested in change over time only, we use λ_t and drop the μ_i term from the equation.

If the term μ_i and λ_t are fixed, the equation 4 is a covariance model (or a dummy variable model). Conversely, when they are random, it is an error component model. In other words, in the case of covariance model, the specific characteristic of a cross-section units and of a time period are parameters; but, using error component model the specific characteristic of a cross-section units and of a time period are normally distributed random variables. Thus, in the statistical literature, the error component model is kwon as a random effect model, and the covariance model is referred to as a fixed effect model.

The reasoning underlying the covariance model is that in specifying the regression model we have failed to include relevant explanatory variables that do not change over time and/or others that do not change across cross-section units, and hence the inclusion of dummy variables is a cover-up of our ignorance (Kmenta 1986, 633). Conversely, the reasoning underlying the error component model is that the relevant explanatory variables that we have omitted random variables and, thus, μ_i and/or λ_t are drawn from a normal distribution.

Regarding the covariance model as one with a varying intercept appears reasonable because we address the unit and/or the period effects through the ad hoc addition of dummy variables for cross-section units and/or time periods. On the other hand, regarding error component model as one with a varying intercept could appear arbitrary (Judge et al 1985, 522). In fact, it could also be viewed as one where all coefficients are constant and the regression disturbances are composed by three independent models (one component associated with the time, one component associated with the space and the third associated with both dimensions) (Kmenta 1986, 633). Consequently, for the error component model we can reparameterize the equation 4 in the following form:

$$y_{it} = \beta_1 + \sum_{k=2}^{k} \beta_k x_{kit} + e_{it} \tag{4.1}$$

Where $e_{it} = \mu + \lambda_t + \omega_{it}$ and μ_i are random over cross-section, λ_t are random over time and ω_{it} are random over space and time. The three components, μ_i, λ_t, and ω_{it} are normally distributed and each has properties like those assumed for OLS regression. Each component also has a constant error variance such that the variance for the summary error e_{it} is constant, or homoschedastic. Thus, this model cannot deal with the heteroschedatic error complication (Hicks 1994, 177). Moreover, each component is also free of autocorrelation. However, despite to this apparent neglect of problem of autoregressiveness, a coefficient of correlation between of a given cross-section unit at two different point of time (between e_{it} and e_{is}) is implied by the formulation of this model At the same time, the error component model address the contemporaneous correlation of the error by including a coefficient of correlation between the disturbance of two different cross-sectional units at a given point of time (between e_{it} and e_{is}) (Kmenta 1986, 625-26).

Therefore, using this kind of unrestrictive assumption concerning the disturbance, the most appropriate estimation procedure for the error component model is the GLS (and most specifically FGLS) method recommended by Parks-Kmenta approach. In contrast, the alternative method prescribing the

OLS with PCSEs is not especially appropriate for the error component model. In fact, given that the error component model is heavily used in cross-sectional dominant data set, Beck and Katz (1995, 645) do not consider this model. Their proposal is limited to temporally dominant models.

Alternatively, for the covariance model, we can use either Beck-Katz approach or Parks-Kmenta method. In this case the disturbance e_{it} is supposed to satisfy the assumption of the classical linear regression model. Moreover, as Beck and Katz (1995, 645) note, this model presents no special problems, especially when it is utilized in a temporally dominant model and it is allowed intercepts to vary by unit only. This is because the number of unit-specific dummy variables required is not large and, thus, the fixed effects do not use an absurd number of degree of freedom.

However, we could allow e_{it} to be autoregressive and heteroschedastic, and then use the GLS (FGLS) estimation procedure for a covariance model (Kmenta 1986, 630). In other words, the Parks-Kmenta method can be made to address the unit and period effects through the ad hoc addition of dummy variables for cross-section units, time periods, or both (Hicks 1994, 175).

Finally, let me briefly discuss the problem of the choice between these models. Since assuming unit and/or time period effects to be fixed or random is not obvious, the estimation procedure could not be chosen accordingly (Judge et al.1985, 527). For example, consider a research where the dependent variable, in additional to explanatory variables, is affected by a variable which varies across units yet remains constant over time (as usually happens in political economy research). Here, the inference concerning coefficients of relevant explanatory variables could be unconditional with the respect to other variables, or it could be conditional on the other variables. The advantage of using the error component model is that we save a number of degree of freedom and, then, obtain more efficient estimates of the regression parameters. The disadvantage of using the error component model is that if the cross-section characteristic is correlated with included explanatory variables, the estimated regression coefficients are biased and inconsistent. The advantage of the covariance model is that it protects us against a specification error caused by such a correlation, but its disadvantage is a loss of efficiency due to the increased number of parameters to be estimated. Therefore, the crucial consideration is the possibility of a correlation between cross-sectional and/or time period characteristics and included explanatory variables (Kmenta 1986, 634).

If there is doubt about the correlation between the cross-sectional characteristic and the included explanatory variables, we may carry out a test of the null hypothesis that not such correlation exists against the alternative hypothesis that there is a correlation. For this purpose we can use the Hausman's test. Under the null hypothesis that $\mathrm{E}(x_{it}\mu_i) = 0$ the GLS estimator of β of the random effect model should not be very different from the least squares estimator of β of the fixed effects model. Provided no other classical assumption is violated, a statistically significant difference between these two estimators indicates that $\mathrm{E}(x_{it}\mu_i)$ is different from zero (Kmenta 1986, 635). This test is formally a test of equality of the coefficients estimated by the fixed and the random effect estimator. If the coefficients differ significantly, either the model is misspecified or the assumption that the random effect μ_i are correlated with the regressor x_{it} is incorrect.

Nevertheless, since for several political economy models the fixed effects cause serious econometric problems, the issue created becomes fixed effects vs. no fixed effects, and not fixed effects vs. random effects. This is so because these cases have many independent variables that change slowly over time, and then the fixed effects are highly collinear with some of them. Consequently, in many political economy researches, the analysts tend to not control for country fixed effects (Beck 2000, 5). Nevertheless, Garrett and Mitchell (1999, 19) consider this a mistake. This is because if a regressor varies only little over time, but greatly across countries, and if the inclusion of country dummy has a substantial effect on the direction, magnitude, or statistical significance of the variable, the appropriate response is not to exclude the country dummies. Rather, the analyst should conclude that the relevant variable is part the underlying historical fabric of a country that affects the dependent variable and that is not captured by any of the time and country-varying regressors. When these fixed effects are taken into account, the apparent effect of year-to-year fluctuations in the variable could well be very different than when country dummies are not included.

4. Pooling Dilemma and Causal Heterogeneity

These models do not address the problem 5. They do not consider that the error tends to be nonrandom across spatial and/or temporal units because parameters (like the underlying processes that they reflect) are heterogeneous across subsets of units. In fact, for the fixed effect model, the random effect model and the simpler pooled model, the slope coefficients are assumed to be equal over time and space. The homogeneity of slope coefficients is often an unreasonable assumption (Maddala et al. 1997, 90).

The solution frequently suggested is to apply a preliminary test of significance to test the equality of the coefficients and decide not to pool if this hypothesis is rejected and to pool if this hypothesis is not rejected. Consequently, the question becomes: to pool or not to pool? The question is whether to estimate the models separately for different cross-section units or for different time series, or to estimate the model by pooling the entire data set and, thus, by estimating a model with coefficients that are constant across units and time periods (Maddala 1991, 302).

Kittel's proposal concerns these two extreme cases of complete homogeneity and complete heterogeneity. He (1999, 232-43) argues that the constant coefficient model in TSCS analysis (without any inclusion of fixed or random effects) represents the combined average partial effect for both time and space. It does not yield information about the relative contribution of two dimensions to its value. In other words, without additional analysis the question of the whether cross-country differences or cross-specific developments account for the variation goes unanswered. Consequently, to inspect the development of the relation over time, we estimate repeated cross-section regression analysis. In particular, by estimating yearly cross-sectional models, we can evaluate whether the relationship between the dependent variable and independent variables changes over the period investigated or whether it remains constant as the constant coefficient model prescribes. A second method of validating pooled coefficients compares the time series of the countries analyzed. Since in the comparative political economy research several explanatory variables tend to vary across countries, but are constant or change within many countries, we cannot assess the relationship of the time series dimensions. However, this indicates as a further restriction to the sensitive use of the constant coefficient approach to the pooling. Being based on mostly constant data in the time series dimension, the pooled coefficients of these variables rely almost completely on the cross-section dimension.

Therefore, according to Kittel (1999, 232-3), these problems do not mean that pooling is not worth the effort. They simply point to the proviso that the data set should be analyzed with care and that reporting pooling coefficients in the pooling constant coefficients model without further evaluation of the relative contributions of the space and time dimensions to the coefficients can lead to unwarranted conclusions.

However, between these two extreme cases of the complete homogeneity of the constant coefficient model and of the complete heterogeneity of the separate estimation of cross-section or time series coefficients, there are more appropriate intermediate solutions. The problem with these two estimation methods of either pooling the data or obtaining separate estimates for each cross-section or time series is that both are based on extreme assumptions. The parameters are assumed to be all the same or all different in the each cross-section and/or time series. The truth probably lies somewhere in between.. The parameters are not exactly the same, but there is some similarity between them (Maddala et al. 1997, 91). One way of allowing for the similarity is to assume that the parameters all vary over time or/and units. However, in this paper I will concentrate only on the cross-section heterogeneity. This is because, although they are not significantly applied in the comparative research yet, they represent critical methodological issues regarding the pooled analysis. From a substantive perspective, a key idea of comparative research is that causal process varies across countries. The fundamental problem in the comparative research contextual explanation where the differences in the causal processes within countries are related to characteristics that varies across countries. This contextual idea is expectably relevant to the comparative political economy. In this area cross-national variation in economic relationships originated with enduring institutional differences (Western 1998, 1255). Therefore, with causal heterogeneity depending on cross-national variation in the institutions, model with slope coefficients that vary over cross-sectional units provide a closer fit between institutional theory and model specification. Consequently, we assume that response of the dependent variable y_{it} to an explanatory variable x_{kit} is different for different units, but for a given cross-section it is constant over time. The equation for this kind of models may be written as;

$$y_{it} = \sum_{k=1}^{k} \beta_{ik} x_{kit} + e_{it} \tag{5}$$

$$= \sum_{k=1}^{k} (\beta + \alpha_{ki}) x_{kit} + e_{it}$$

In contrast to previous equations I no longer treat the constant term differently from the other explanatory variables. $\beta = (\beta_1 .....\beta_k)$ can be viewed as the common-mean coefficient vector and $\alpha_i = (\alpha_{1i} .....\alpha_{ki})$ as the individual deviation from the common mean. When β_{ki} are treated as fixed and different constants, equation 5 can be viewed as the seemingly unrelated regression model. Conversely, when β_{ki} are treated as random parameters, equation 5 is equivalent to the random coefficient model (Judge et al. 1985, 538-9; Hsiao 1986, 130-1).

The seemingly unrelated regression model treats each cross-section and the time series within that cross-section as a separate equation that is unrelated to any other cross-section (and time series within the cross-section) in the pooled data set. Most specifically, this model is interpretable as a series of a nation specific regression analysis that utilizes contemporaneous cross-equation error correlations among the error of a system of equation to improve the efficiency of the equation's estimates (Sayrs 1989, 39; Hicks 1994, 181).

The random coefficient model is due to Swamy (1970). This model assumes that each β_i are drawn from a common normal distribution In other words, $\beta_i = \beta + \alpha_i$ are treated as random, with a common mean. The model set up is:

$$\beta_i \sim (\beta ; I^{\wedge}) \tag{5.1}$$

$$E(\alpha_i \alpha_j) = E[(\beta - \beta_i)(\beta - \beta_j)] = 0 \qquad \text{if } i \neq j \tag{5.2}$$

$$E(x_{it}\alpha_i) = E[x_{it}(\beta - \beta_i)] = 0 \tag{5.3}$$

$$E(e_{it}e_{jt}) = \sigma_{ij} \qquad \text{if } I=j \tag{5.4}$$

$$E(e_{it}e_{jt}) = 0 \qquad \text{if } i \neq j \tag{5.5}$$

This set up assumes that the β_i are drawn from a common normal distribution (with mean β and variance covariance $I^{\wedge}$) where each of the drawns are independent from each other as well as of the x_{it}'s. This set up allows for the components of β_i to be correlated and also allows panel heteroschedasticity. Moreover, the set up can include dynamics modeled with a lagged dependent variable, but without serial correlation of error (Hsiao 1985, 131; Beck and Katz 1996b, 3).

In this model, we will determine the mean β from which we can estimate cross-sectional individual β_i. Without going into details, to estimate the mean β and its standard errors ,we can use FGLS. Conversely, the estimates of β_i are a weighted combination of the OLS estimates of β_i and the common estimate of β. The weights of two these estimates are a function of the estimated variability of the β_i's.

But, which of these models is the more appropriate for the comparative political economy? Can students of this discipline use the random coefficients model? Hsiao (1986, 136) concludes that the question of whether β_i should be assumed fixed and different or random and different depends on whether we are making inferences conditional on the individual characteristics or making unconditional inferences on the population characteristics. In the former cases, fixed-coefficients model should be used. In the latter cases, the random coefficients model should be used.

Such a conclusion indicates that the random coefficients model is appropriate for panel studies in survey research rather than for comparative TSCS analysis. This is because in the panel data the observed “people” are of no interest *per se*, with all of inferences of interest being to the underlying population that was sampled. TSCS data show the opposite situation. Here, all inferences of interest are conditional on the observed units (Beck 2000, 3)

However, one way to avoid this problem is to use Bayesian approach. As Beck and Katz (1996, 5) suggest, the advantage of Bayesian linear hierarchical model is that the randomness resides in the parameters, and not the units. Hence, the distinction between fixed and sampled units is no longer relevant. This approach yields identical results to the random coefficients model. Here, we have a prior on the variability of the β_i's, which looks like equation 5.1. This assumes that β_i are “exchangeable”, since a priori we cannot distinguish between the units other than through the covariates. The Bayesian approach lets the data choose the prior using the estimated structure of $I^{\wedge}$ as the prior of parameter variability. However, from the Bayesian perspective letting the data choose the prior appears a bit odd. Bayesians have prior beliefs about the diversity of β_i. Thus, these priors can be combined with the observed data (via likelihood function) to produce a new, posterior, set of beliefs about the β_i. The prior which is represented by $I^{\wedge}$, is based on the analyst's belief about the world rather than a parameter to be estimated. The prior $I^{\wedge}$ than can be combined with the OLS estimates of β_i.

However, the Bayesian hierarchical model can be made more useful for comparative research by allowing the β_i to be a function of the other unit variables, which allow modeling differential effects as a function of different institutions. In fact, as Western (1998, 1241) notes, in the Beck and Katz's (1996b) model institutional effect and the issue of contextual explanation are omitted. Consequently, one can allow the β_i to be function of other unit variable, z_i, which allows for modeling effects as a function of differing institutions. Most specifically, to allow the chance for the contextual variation, we can rewrite the model for a single country as follows:

$$y_{it} = \beta_1 + \beta_2 y_{it-1} + \beta_{3i} x_{kit} + e_{kit} \tag{6}$$

Hence, variation in the time series coefficients is written as a function of time invariant institutional condition,

$$\beta_{1i} = \phi_{11} + \phi_{12} z_i + \delta_{1i} \tag{6.1}$$

$$\beta_{2i} = \phi_{21} + \phi_{22} z_i + \delta_{2i} \tag{6.2}$$

$$\beta_{3i} = \phi_{31} + \phi_{32} z_i + \delta_{3i} \tag{6.2}$$

The subscripts on the ϕ coefficients indicate that the institutional effects are constant across countries. This hierarchical model can be written as a single equation with interaction terms by substituting equation 6.1, 6.2, and 6.3 in equation 6 (Western 1998, 1237):

$$y_{it} = (\phi_{11} + \phi_{12} z_i + \delta_{1i}) + (\phi_{21} + \phi_{22} z_i + \delta_{2i}) y_{it-1} + (\phi_{31} + \phi_{32} z_i + \delta_{3i}) x_{it} + e_{it}$$

(6.1)

$$= \phi_{11} + \phi_{12} z_i + \phi_{21} y_{it-1} + \phi_{31} x_{it} + \phi_{22} z_i y_{it-1} + \phi_{32} z_i x_{it} + (\delta_{1i} + \delta_{2i} y_{it-1} + \delta_{3i} x_{it} + e_{it})$$

This model is identical to the usual single-equation regression with interaction term except that the error term has a more complicated structure. Here, it includes two sources of uncertainty, e and δ, and with random coefficients on the linear term only. Since the time series coefficients have a stochastic component, δ, we can consider these stochastic components as drawn from a single population distribution shared by all the countries under study.

Therefore, the random coefficients model and, in particular, Bayesian hierarchical model indicate that one of the most important issues of the TSCS methodological research is to carefully the model specification. These models can represent a solution to the trade-off between the institutional approach of the political economy and model specification.

5. Pooled TSCS analysis in STATA software

Finally, this section presents some implementations and commands in STATA software to analyze TSCS data. Several econometric packages for pooled models are now widely available (SAS and SHAZAM). However, I will consider STATA only, assuming that the reader is familiar with the basics of this statistical software.

The “xt” series of STATA commands provide tools for analyzing cross-sectional time series data sets. Cross-sectional time series (longitudinal) data sets are of form x_{it}, where x_{it} is a vector of observations for unit i and time t. The particular commands as such “xtreg”, “xtgls” and “xtpcse” allow us to estimate the majority of pooled models discussed in this paper. Since TSCS data sets are characterized by both unit i and time t dimensions, corresponding STATA options are usually required to estimate pooled models using these commands. The option “i( )” sets the name of the variable corresponding to the unit. The option “t( )” sets the name of the variable corresponding to the time index t (STATA 1999, 317). Given that in the comparative analysis these variables are often represented by “country” and “year”, in the next examples I will use these variable names. Moreover, for expository purpose, let me suppose that we have data of the following form: y (dependent variable), and x1, x2, x3 (respectively, 1st predictor, 2nd predictor and 3rd predictor).

The simplest model estimable via OLS procedure (related to equation 1) can be obtained by using the STATA command “regress” by typing:

```
. regress y x1 x2 x3
```

Hover, as noted, TSCS designs often violate the standard OLS assumptions, first we need to consider STATA implementations concerning Parks-Kmenta method and Beck-Katz approach. Regarding the Parks-Kmenta approach, the “xtgls” command estimates models using FGLS procedure. This command allows estimation in presence of AR(1) autocorrelation within units, cross-sectional correlation and/or heteroschedasticity across units. In other words, the model related to the equation 2 can be estimated by “xtgls” STATA command and the assumptions concerning the panel heteroschedasticity, contemporaneous correlation and serial correlation can be obtained by specifying particular options (STATA 1999, 360-69). The heteroschedastic models obtained by specifying by:

```
. xtgls y x1 x2 x3, i(country) panels(heteroschedastic)
```

However, we may wish to assume that the error terms are correlated in additional to having different variances. Hence, we must specify:

```
. xtgls y x1 x2 x3, i(country) t(year) panels(correlated)
```

Finally, “xtgls” allows different options so that you may assume serial correlation within units. If we assume a serial correlation where the correlation parameter is common for all units, we must specify the following command:

```
. xtgls y x1 x2 x3, i(country) t(year) corr(ar1)
```

Conversely, if we assume that each group has errors that follow a different autoregressive process, we must use:

. xtgls y x1 x2 x3, i(country) t(year) corr(psar1)

Obviously, these options can be combined according to our assumption about the error term.

Regarding Beck-Katz proposal, “xtpcse” command produces panel corrected standard error (PCSE) estimates for TSCS linear models. This command produces OLS estimates of the parameters when no autocorrelation is specified. [7] In computing the standard errors and the variance-covariance estimates, the disturbances are, by default, assumed to be heteroschedastic and contemporaneously correlated across units. However, in order to compute PCSEs, STATA must be able to identify the units to each which observation belongs and also be able to match the time periods across the units. Thus, we tell STATA how to do this matching by specifying the time and the unit variables using the following command:

. tsset country year, yearly

Hence, to estimate a model related to the equation 3, we must to type:

---

[7] “xtpcse” command is implemented in the updated of STATA 6.0. Conversely, STATA 6.0. Without any update allows producing OLS parameters with

. xtpcse y ly x1 x2 x3

Where ly stands for a lagged dependent variable of one year. It can be obtained by typing:

. generate ly = y[_n-1]

Let me now consider fixed and random effect models. For both these models we can refer to the equation 4 when includes the unit effect term and drops the time effect term. In fact, STATA considers the case in which fixed and random effect model include the unit effects only. The command to estimate this models is "xtreg" (STATA 1999, 420-40). In particular, to obtain an OLS fixed effect model, we must to type:

. xtreg y x1 x2 x3, fe

Conversely, to obtain a GLS random effect model, we must type:

. xtreg y x1 x2 x3, re

After "xtreg, re" estimation we can obtain the Hausman test by typing:

. xthaus

PCSES by specifying "xtgls" with the "ols" or "pcse" option (STATA 1999, 364).

However, the dummy variables are not included in the outputs corresponding to these STATA commands. But, since fixed effect regression is supposed to produce the same coefficient estimates as standard error as ordinary regression when dummy variables are included for each units, to obtain an output including dummy variables we must type:

. xi: regress y x1 x2 x3 i.country

Where “xi” command allows us to create dummy variables. Consequently, by using this command with either “xtgls” or “xtpcse” respectively Parks-Kmenta method or Beck-Katz approach can be made to address unit effects.

Let me now consider the models with slope coefficients that vary across units, represented by equation 5. The STATA command to estimate a seemingly unrelated regression model is “sureg”. However, in order to estimate a simultaneous equation model using “sureg”, we should first reshape our data (STATA 1999, 415). In other words, we need to convert our data from “long to “wide” form by typing:

. reshape y x1 x2 x3, i(year) j(country)

Hence, we can estimate a seemingly unrelated regression model by typing:

. sureg (y1 x11 x21 x31) (y2 x12 x22 x32) (y3 x13 x23 x33)

Where the numbers 1, 2, 3 associated to the variables y x1 x2 x3 represent the different countries of an example with three cases only.

Conversely, to estimate a random coefficient model, we do not need to reshape our cross-sectional time series data set. To obtain such a model it is enough typing the following command:

.xtrchh y x1 x2 x3, i(country) t(year)

STATA uses FGLS procedure to estimate random coefficients models, as suggested by Swamy (1971), assuming that all coefficients are drawn from a common multivariate normal distribution.[8] The requirement of the random coefficients model that that all variables) with random coefficients) vary within units, may cause difficulty for comparative politics applications. where it is frequently the case that some important variables are time invariant national characteristics (Beck and Katz 1996b, 9). Nevertheless, STATA does not allow assuming that the coefficients of some variables are fixed.[9]

Finally, regarding hierarchical models, software is now available (Western 1998, 1244). An extensive review of five packages for hierarchical modeling is reported by Kreft et al. (1994). In additional to specialized software, routine can also be found in the general statistical software SAS and S-PLUS (see Pinheiro and Douglas 2000).

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[8] Such a procedure can cause some problems to estimate the variance matrix of the error. For full details see Beck (2000, 19-20).

[9] Conversely, LIMPDEP 7.0. allows the investigator to specify whether variables have fixed or random coefficients (see Greene 1995).

Bibliography:

Alesina A., Grilli V. and Milesi-Ferretti G. M., 1994,
The Political Economy of Capital Controls, in L. Leiderman and A. Razin, (edited by), Capital Mobility, Cambridge, Cambridge University Press.

Alvarez M., Garrett G., and Lange P., 1991,
Government Partnership, Labour Organization and Macroeconomic Performance: 1967-1984, in American Political Journal Review, 85, pp. 539-556.

Beck N., 2000,
Issues in the Analysis of Time-Series Cross-Section Data in the Year 2000, University of California, Manuscript.

Beck N. and. Katz J.N, 1995,
What To Do (and Not To Do) with Time-Series Cross-Section Data, in American Political Journal Review, 89, pp. 634-647.

Beck, N. and Katz J.N, 1996,
Nuisance vs. Substance: Specifying and Estimating Time-Series-Cross-Section Models, Political Analysis, 6, 1-36.

Beck, N. and Katz J.N., 1996b,
Lumpers and Splitters United: The Random Coefficients Model, Presented at the annual meeting of the Methodology Political Group, Ann Arbor, Michigan.

Beck, N. and Katz J.N., 1998,
Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable, in American Journal of Political Sciences, 42(4), pp. 1260-1288.

Beck, N, Katz J.N., Alvarez M., Garrett G., and Lange P., 1993,
Government Partisanship, Labor Organization, and Macroeconomic Performance: A Corrigendum, American Political Journal Review, 67(4). pp. 945-948

Compston H., 1997,
Union Power, Policy-Making and Unemployment in Western Europe:1972-1993, in Comparative Political Studies, 30(6), pp. 732-751

Garrett, G., 1998,
Partisan Politics in the Global Economy, Cambridge, Cambridge University Press.

Garrett, G. and Mitchell D., 1999,
Globalization and the Welfare State, Yale University, Manuscript.

Hicks A., 1991,
Union, Social Democracy, Welfare and Growth, Research in Political Sociology, 5, pp. 209-234

Hicks A., 1994,
Introduction to Pooling, in T. Janoski and A. Hicks (edited by), The Comparative Political Economy of the Welfare State, Cambridge University Press

Hsiao C., 1986,
Analysis of Panel Data, Cambridge University Press

Huber E., Ragin C., and Stephens J.D., 1993,
Social Democracy, Christian Democracy, Constitutional Structure, and the Welfare State, American Journal of Sociology, 99(3) pp. 711-749

Judge G.G., Griffiths W.E., Hill R.C., Lutkepohl H. and Lee T-C., 1985,
The Theory and Practice of Econometrics, New York, Wiley, 2nd Ed

Kittel B., 1999,
Sense and Sensitivity in Pooled Analysis in Political Data, in European Journal of Political Research, 35(2), pp. 225-253

Kmenta, J., 1986,

Elements of Econometrics. New York: Macmillan; London: Collier Macmillan, 2nd Ed.

Maddala, G.S., 1994,
To Pool or Not to Pool: That is the Question, in Maddala G.S. ,(edited by), Econometric Method and Applications, Edward Elgart

Maddala, G.S., 1997,
Recent Developments in Dynamics Econometric Modeling: A Personal Viewpoint, Ohio State University, Manuscript.

Maddala, G.S., H. Li, R.P. Trost and F. Joutz (1997),
'Estimation of Short-Run and Long-Run Elasticities of Energy Demand From Panel Data Using Shrinkage Estimators, Journal of Business Economics and Statistics, 15, pp. 90-100

Oatley T., 1993,
How Constraining is Capital Mobility? The Partisan Hypothesis in an Open Economy, in American Journal of Political Sciences, 43(4) pp. 1003-1027

Pampel F.C. and Williamson G.B., 1989,
Age, Class, Politics and the Welfare State, Cambridge, Cambridge University Press

Parks R.W., 1966,
Efficient Estimation of a System of Regression Equation When Disturbance are Both Serially and Contemporaneously Correlated, in Journal of the American Statistical Association, 62, 500-509

Pennings P., Keman H. and Kleinnijenhuis: J., 1999,
Doing Research in Political Science: An Introduction to Comparative Methods and Statistics, Sage,

Quinn, D. P. and Inclan, C., 1997,
The Origins of Financial Openness, in American Journal of Political Sciences, 41(3), pp. 771-813

Sayrs, L.W., 1989,
Pooled Time Series Analysis, Sage Publications

Schmidt M.G., 1997,
Determinants of Social Expenditure in Liberal Democracies, in Acta Politica, 32(2) pp. 153-173

Stimson, J.A., 1985,
Regression in Space and Time: A Statistical Essay, in American Journal of Political Sciences, 29(4) pp. 914-947

Swamy P.A.P.V. 1970,
Efficient Inference in a Random Coefficients Regression Model, Econometrica, 32, pp. 313-323

Swank D.H., 1992,
Structural Power and Capital Investment in the Capitalists Democracies, in American Political Journal Review, 86, pp. 38-54

Western, B., 1998,
Causal Heterogeneity in Comparative Research: A Bayesian Hierarchical Modeling Approach, in American Journal of Political Sciences, 42(4), pp. 1233-1259.

Western B. and Jackman S., 1994,
Bayesian Inference for Comparative Research, American Political Journal Review, 88(2), pp. 412-423