ESSAYS ON STATIC PANEL DATA MODELS WITH DEPENDENT ERRORS: SIMULATION AND APPLICATION

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Dedication.

To our every minute supporters, Adneli, Salomon, Yemima and Marion;

and

In memory of my elder brother Madjirebaye Moundigbaye.

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Abstract.

This research aims to study the performance of a sample of linear static panel data estimators. Many panel data estimators are incorporated in econometric packages, readily available to researchers. They use different assumptions to address different aspects of dependencies in the errors, with implications for the accuracy with which both the coefficient and its variance-covariance matrix are estimated. Researchers find themselves confronted with difficulty when choosing specific estimators that best suit the data they are modelling, since no clear guidance exists to facilitate this choice. Reed and Ye (2011) attempted to provide such guidelines. After conducting Monte Carlo experiments on 11 linear static panel data estimators, they proposed a set of recommendations to be used by other researchers. In this Thesis, we first replicate their results after addressing a flaw identified in their experimental design. We improve the formulation of the original recommendations and show that the new recommendations are robust to the errors' parameters. We further use bootstrap techniques to investigate the Parks (1967) estimator, which is most efficient for certain-sized data sets, but which also has poor test size performance. The bootstrap techniques effectively remove the size distortion related to this estimator. Lessons from these two chapters are then used to model the contribution of health and education spending to economic growth in a sample of 12 African countries observed from 1999 to 2013. We find that neither public spending on education nor that on health has a significant impact on the growth rate of per worker real GDP.

Key words: panel data, dependent errors, efficiency, coverage, simulation, bootstrap, human capital investment, growth, Africa.

Chapter 1 : General Introduction.

1.1. Panel data sets: benefits and costs.

Panel data sets are records of repeated observations on multiple individuals. They have a double dimension: the number of individuals (N) and the number of times each of the individuals is observed (T). Individuals are also known as cross-sections, or (economic) units. The number of data records is not necessarily the same for all cross-sections. In fact, while balanced panel data sets are characterised by the same number of observations per unit, this is not the case with unbalanced panel data sets.[1]

The double dimension of panel data sets offers the potential to collect more data on a given topic compared with cross-sectional data sets that observe many units at a single time period, or time series data sets which observe a single unit over many time periods. Consequently, this double dimension has the potential to be a great benefit as data has become a precious tool for informed decision making. More data is associated with more robust and reliable estimation of interactions among observed variables, which is crucial in evidence based policy investigations.

However, there are costs of the double dimension of panel data sets as far as the practice of econometrics is concerned. Econometric models allow studying relationships among observed and unobserved variables on a given topic of interest. Models are simple approximations of complex dynamics that cannot be entirely described. Errors are natural parts of models in that they serve to capture some unexplained features.

The parameters of an econometric model's errors are useful in assessing its quality.

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[1] Units may disappear from the sample for many reasons: they may no longer exist, decline to continue being part of the sample, or become ineligible for the study. Our study is concerned with balanced panel data sets, though.

More specifically, the magnitude (range) and the statistical significance of explanatory variables' effects on the explained variable are both related to the characteristics of the error term. Some properties of the errors produce good results when the simplest estimation methods are employed. Such properties are desirable. However, more often, the errors' true characteristics do not fall in this category. Therefore, it is critical in econometric modelling to understand the implications of the errors' characteristics on the quality of the model's output. It is common practice among researchers to assume without rigorous verification that errors have the desirable properties. As such assumptions do not hold all the time, empirical findings based on wrong assumptions and the policy recommendations they lead to are questionable.

In the case of panel data models, errors are unlikely to exhibit simple and desirable properties. Rather, chances are high that they exhibit complex structures due to the double dimension. Heteroskedasticity, serial correlation and cross-sectional correlation could all be present, substantially increasing the number of errors' parameters and posing the problem of their accurate estimation [2]. To avoid having to estimate this large number of error parameters, unrealistic restrictions are often imposed.

This research is mostly concerned with the estimator's performance in relation with the internal structure of the errors. However, there exist other data complications that could undermine the quality of the model estimates if not adequately addressed. These additional

[2] In a balanced panel data model with N cross-sections and T time periods, a more general form of the variance covariance matrix of the error characterised by group-wise heteroskedasticity and a group-wise specific AR(1) serial correlation has $\left(\frac{N^2+3N}{2}\right)$ unique parameters to be estimated by N.T data points. If T is not sufficiently larger than N, each of these unique parameters will be inaccurately estimated by only a few data points.

sources include reverse causality, omitted variables and the measurement errors that are all causes of the estimator's bias. Measurement errors are due to misreporting of observable series or to the use of proxies for latent variables. They cause the estimator to be biased towards zero, and more so in panel data models characterized by high noise to signal ratio (Greene, 1993, Johnston and DiNardo, 1997) and could be magnified by transformations designed to accommodate heterogeneity (Mátyás & Sevestre, 2008, Biørn, 2016).

1.2. Research questions, objectives and contribution.

The problem that this research aims to address is that many ways to estimate static panel data models have been developed, based on different assumptions about the structure of the errors, having different performances and producing estimates whose finite sample properties are not well known. Our focus is specifically directed toward the group of linear statistic panel data estimators[3]. The reason for this research orientation is that these estimators are commonly used among researchers due to their accessibility via popular econometric packages. By the term accessibility, we mean both the availability of the estimators and the simplicity with which they could be used by researchers, even by those who are novices in econometrics. This simply means that these estimators constitute important policy analysis tools. Consequently, they need to be appropriately used. The mere fact that there are so many of them is indicative that none is suitable for all situations.

Our central research question is therefore "which panel estimator best fits a given research situation?" That is, how good are linear static panel estimators in specific research settings? And how do they compare to each other under various but significantly different data characteristics?

[3] Non-linear and dynamic panel data estimators exist but they are not part of the current research, our coverage of linear panel data estimators is not exhaustive either.

A number of studies have made comparative investigation of estimators. The gap this research attempts to fill is twofold. First, very few of previous studies allowed a large diversity in both the number of estimators and the number of problematic situations under which the respective performances of the studied estimators were evaluated. Secondly, very few were interested in proposing rules to guide other researchers in choosing the appropriate estimator for their specific data set.

The objective of this research is therefore to study the performance of a large number of basic linear panel data estimators under a sufficiently extended range of research situations in order to formulate some informed recommendations that researchers can use in the future in selecting the ideal estimator that suits the specific characteristics of data sets they have. By so doing, we hope to contribute to the empirical literature on comparative assessment of basic but widely accessible panel estimators based on their respective performances.

It certainly is the case that many researchers are now moving away from these basic estimators – especially the FGLS estimators - which our research focusses on towards more sophisticated estimators - including estimators for dynamic models - with improved performances. There are at least two reasons for this tendency. The first justification is the dependence of FGLS estimators' properties on their strict and unrealistic underlying assumptions. The second reason for the slowdown in the desirability of FGLS estimators stems from the fact that they do not address specific data and specification problems such as endogeneity or dynamic models that IV and GMM estimators accommodate.

However, the fact that these "old" estimators are readily accessible via popular statistical packages justifies their popularity among researchers. The exceptionally high citation of the work by Beck and Katz (1995) (over 1800 citations according to the Web of Science) in which they proposed the panel corrected standard errors (PCSE) estimator supports this view. Likewise, the comparative assessment of a large number of basic OLS and

FGLS panel estimators built in Stata or E-views by Reed and Ye (2011), henceforth RY, is getting attention among researchers with over 20 citations as reported on the Web of Science. Yet, RY recommended further research with varying structure of the errors than theirs to gather more evidence on their recommendations for estimator selection based on observable characteristics of data sets. Estimator selection under RY's recommendations are easy to implement in contrast to estimator choice under other methods that rely on non-observable properties of data such as the restrictive condition of the existence of good instruments underlying the GMM or system GMM methods. Last but not least, RY's experimental design is flawed and this only provides a significant case for a re-examination of their findings after correcting for the flaw it contains.

1.3. Methodology.

The approach in this research is based on Monte Carlo experiments followed by a practical case study. We measure two estimator performance indicators that are common in the literature to evaluate the selected estimators: coefficient efficiency and the coverage rate. The first performance measure pertains to the point value of the estimator and assesses its average variability about its mean value relative to a reference estimator. Lower measures of efficiency are associated with a higher relative quality of the estimator in comparison with the reference estimator.

The second performance measure - the coverage rate - relates to the quality of the estimated confidence interval. It assesses how often the true known value falls within the estimated confidence interval. A value for the coverage rate that is closer to the level of the confidence interval is indicative of a lower type-I error (test size) distortion.

Some key data characteristics such as the panel dimensions and measures of the degree of first order serial correlation, groupwise heteroskedasticity, and the degree of cross-sectional correlation provide useful parameters for identifying the determinants of estimator performance.

1.4. Thesis structure.

This research has six chapters. The second chapter is a replication of a previous study that carried out a performance evaluation of linear static panel data estimators with the goal of formulating recommendations on the selection of the appropriate estimator in given research situations. This research by RY resulted in a set of practical recommendations. These are presented below. This replication exercise is designed to address a flaw identified in the original study's experimental design. An unintended consequence of the Monte Carlo procedure used by RY is that it exaggerated serial correlation in their simulated explanatory variable. This exacerbated problems with the efficiency and inference properties of the estimators. As a result, there is a reasonable ground to question the recommendations their research led to. We propose to investigate whether these recommendations still hold after correcting this flaw. A robustness control of the replicated findings under the new experimental design is also conducted.

The third chapter of this thesis further investigates the Parks' (1967) estimator, one of the estimators evaluated in the chapter 2. This chapter is made necessary by the findings of the second part as discussed below. The coverage rate is the single evaluation criteriion considered in this chapter. In fact, this particular estimator performs very poorly on this criterion under the asymptotic theory adopted in the second chapter while its efficiency performance is the best. We employ the parametric and non-parametric bootstrap techniques to investigate whether they could remedy the high level distortion that characterises this estimator.

The fourth chapter constitutes a bridge between the two previous chapters and the next chapter. It sets the stage for the application of the findings of chapters 2 and 3 by providing the background information about the topic investigated in chapter 5. More specifically, this chapter first summarises the conceptual development of human capital theory and its use in macroeconomic studies of growth. A succinct review of previous empirical findings evidences the unmet expectations about the growth contributions of human capital. The chapter then briefly presents trends in Africa's economic growth and its determinants, focussing on investment and human capital.

The fifth chapter of the thesis applies the findings of chapters 2 and 3 in a study of the growth contribution of human capital investment through public spending in health and education using a sample of 12 African countries observed from 1999 to 2013. Per worker real GDP growth is related to the shares of government spending on health and education in GDP, to the ratio of private spending on health and GDP, and to further control variables chosen among variables commonly found in previous studies.

The last chapter concludes the thesis by summarising all the findings and discussions from chapters 2 to 5.

1.5. Key findings.

We present the key findings from chapters 2 to 5 below. The investigation into the reliability of recommendations in RY conducted in the first essay reveals that the flaw identified in their experimental design slightly affected their recommendations. They proposed three recommendations to guide researchers for estimator selection as follows:

Recommendation 1: *When the primary concern is efficiency and $T/N \geq 1.50$, use FGLS (Parks).*

Recommendation 2: *When the primary concern is efficiency, N > T, and HETCOEF*[4] *> 1.67, use either FGLS (Groupwise heteroskedasticity) or FGLS (Groupwise heteroskedasticity + Serial correlation).*

Recommendation 3: *When the primary concern is constructing accurate confidence intervals and RHOHAT*[5] *< 0.30, we recommend either Beck and Katz's (1995) PCSE estimator or the OLS (Heteroskedasticity + Cross-sectional dependence robust) estimator.*

One might note the incompleteness of recommendations by RY. If T/N lies between 1.0 and 1.5, or N > T but HETCOEF ≤ 1.67, recommendations 1 and 2 cannot help select the most efficient estimator. Likewise, if RHOHAT ≥ 0.30, recommendation 3 cannot be used to select the best estimator for reliable hypothesis tests.

The analysis of experimental results with the same data sets after adjusting the experimental design for the identified flaw leads to the following:

(i) Recommendations 1 and 2 by RY could be nicely combined to form a more complete single recommendation based solely on the ratio of data sets dimensions (T/N) providing our first estimator selection rule :

Rule 1: on the efficiency ground, a researcher using static panel data model should choose estimator FGLS (Parks) estimator when T/N ≥ 1.5 and FGLS (Groupwise heteroskedasticity + Serial correlation) otherwise.

(ii) Recommendation 3 by RY still holds, but the precision with which it is formulated improves with the new experimental design, leading us to the next estimator selection rule.

Rule 2: Beck and Katz's (1995) PCSE or the OLS (Heteroskedasticity + Cross-

[4] HETCOEF is a measure of the degree of heteroskedasticity referred to earlier.

[5] RHOHAT is the degree of serial correlation referred to earlier.

sectional dependence robust) estimators are best on the confidence interval accuracy ground.

To confirm how well these new rules perform, we collect new data sets and carry out new experiments with the modified experimental design. With these new data, we find that success rates in identifying the right estimator is 88.5 percent for Rule 1 and 39.3 percent for Rule 2. The lesson here is that Rule 1 is outstanding while Rule 2 is a poor one.

The result about the second rule is one of the two reasons for writing the third chapter whose key results are presented below. The other reason that it justifies the necessity of chapter 3 because, in general, when choosing estimators, researchers do not generally use different estimators for estimation and inference. It would be better to have a single estimation procedure that performed well on both estimation and inference criteria.

That the bootstrap theory produces, in general, better test decisions compared with asymptotic theory has been proven, but the extent to which this improvement takes place could not be predicted. In the third chapter, we find that the statistical test level distortion characterising the Parks estimator is not only improved, but it is completely removed by the bootstrap techniques. Both the parametric and the non-parametric bootstrap techniques perform well. However, while the former technique does so in all cases studied, with rejection rates within an acceptable range about the nominal value of five percent, the latter tends to become excessively conservative when the ratio T/N decreases. This result overlaps with findings from the second chapter. Our recommendation is to use the Parks estimator combined with the parametric bootstrap when $T > N$.

The fourth chapter reports that the growth literature develops high and positive expectations about the contribution of human capital to growth based on theoretical speculations. However, estimates of the growth contribution of various proxy measures of human capital do not confirm these expectations. Some studies find positive and significant results. Others find negative and significant results. Another group finds insignificant results, with both positive and negatives contributions. Different proxy measures, different research methods, and the poor quality of the data are key elements explaining these conflicting results. The summary of the Africa growth and human capital data shows that towards the mid-1990s, African economies escaped from a long period of economic sluggishness. This is generally attributed to improved investment, increased trade, and better governance and political stability across the continent. A slight progress in human capital accumulation is also recorded across Africa.

In chapter 5, our empirical investigation concludes that public spending on education and health are not significant growth drivers.

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Chapter 2 : Another Look at "Which Panel Data Estimator Should I Use?"

2.1. Introduction.

Modelling cross-sectional and serial dependence in panel data is motivated by strong evidence of such relationships in the context of panel models. Regular interactions among peer units such as economic agents, unobserved common shocks and factors, and the consistency of individual units' behaviour over time (adaptive decision making process) are examples of potential sources of data dependence – both among and within units – in panel data models. Even though unobserved time-constant influences can be addressed by heterogeneous parameters (intercepts and slopes), other factors may not be so readily addressed (cf. Skrondal and Rabe-Hesketh, 2008).

These complex relationships among data points violate classical econometric assumptions and need to be properly dealt with. Otherwise, there will be serious consequences including biased coefficient estimates and/or inaccurate hypothesis testing, thus generating misleading analyses and policy recommendations.

Various panel data estimators robust to serial and cross-sectional correlations have been proposed, with different underlying assumptions about the error structure. Though these necessary assumptions are critical for estimating and diagnosing panel data models, they may be considered too strong when applied to general forms of relationships in which the error terms are characterized by both serial correlation and cross-section dependence.

As a result, the plethora of robust panel estimators appears to be good news for researchers handling panel data sets. Yet, for researchers aware of the implications of using one robust estimator rather than another, this situation poses the problem of estimator selection. At least two motives could be invoked as evidence for this problem: (i) there is empirical evidence of performance differences among the proposed estimators, and (ii) no straightforward rule to guide researchers in the estimator selection exists. While the first motive is a direct result of differences in underlying assumptions of different estimators, the second constitutes a limit for many applied econometric investigations. In many instances, interest is mostly focussed on differences in relative performance among a limited number of estimators without an aim of developing optimal choice criteria.

A recent attempt to fill this gap was made by RY. A benefit of their study is that they provided a set of recommendations for choosing among a large number of panel data estimators. Their study has two key deficiencies. The first is that they did not include many recent panel data estimators. The second is their experimental design was flawed with potential implications on their findings. This chapter is concerned with the latter shortcoming. We intend to address this flaw and assess to what extent it impacts their key findings.

The structure of the remainder of the chapter is as follows. We review the literature on robust estimators in static linear panel models in Section 2. We then present in Section 3 the original experimental design and suggest an adjustment for the flaw it contains. Next, we replicate the experiments under the initial and the adjusted designs and present results in Section 4. We analyse the results of the two experimental designs in Section 5 in order to assess the validity of RY's (2011) findings. In Section 6, we carry out a robustness diagnosis of the conclusions under the adjusted experimental design. Section 7 concludes the chapter.

2.2. Literature review.

The effects of non-spherical errors in panel data models on the performance of estimators are well investigated and debated in the literature. A strand of the research on this topic focuses on testing for the presence of specific problems in econometric models that affect the error term (serial correlation, heteroskedasticity, and cross-sectional correlation). Another strand develops and studies the properties of coefficient estimators robust to one or a combination of deviations from standard assumptions about the models' innovations. We focus on the latter strand in this review by exclusively addressing the errors dependence in linear static panel data models.

Heteroskedascity and serial correlation are commonly addressed in static panel data by adapting the treatments used with pure cross-section or time series data based on works by Eiker (1967), Huber (1967), White (1980), Andrews (1991), Prais and Winsten (1954), and Newey and West (1987). Examples of estimators that fall in this category were proposed by Kmenta (1986) and Arellano (1987). More complex estimators robust to cross-sectional correlation have also been developed. We discuss some of these in the next paragraphs.

Zellner (1962) developed a two-step estimator of the seemingly unrelated regression equations that accommodates the cross-sectional correlation of the error term when the time dimension is large, such that for fixed cross-sectional dimension, the standard properties of time series apply. Both asymptotic and finite sample properties of this estimator have been further studied. See for instance Zellner and Huang (1962), Zellner (1963), Kakwani (1967), Kataoka (1974), Kmenta and Gilbert (1968) and Phillips (1977). Zellner and Theil (1962) extended Zellner (1962)'s original estimator to simultaneously estimate the coefficients of the system of equations in a third step. A version proposed by Parks (1967) assumes the presence of both cross-sectional and serial correlations. Stata's xtgls command produces the Parks feasible generalised least squares (FGLS) estimator. The computation of the Parks FGLS requires the estimation of a large number of parameters, thus posing the problem of precision with which these parameters can be estimated.

Other authors suggested addressing the errors' cross-sectional dependence in static panel data models by reducing them to spatial distances across units (Driscoll and Kraay, 1998; Anselin, 2013; Baltagi et al., 2013; Elhorst, 2014; Bivand and Piras, 2015). This practice has the virtue of lowering the number of parameters to estimate. Yet, the performance of the resulting estimators relies on the quality of the non-trivial distance function that is used to quantify the dependences (Corrado and Fingleton, 2012).

Another way proposed to remedy the consequences of cross-sectionally dependent errors in panel data models is the multi-factor framework that assumes time-specific common factors as a means to cut down the number of parameters (Pesaran and Smith, 1995; Bai, 2003; Coakley et al., 2006; Pesaran, 2006; Eberhardt et al., 2013; Kapetanios et al., 2011). Common factors are shocks that simultaneously affect all cross-sectional units to varying degrees (Chudick and Pesaran, 2011). This technique is common among researchers using macro panel data sets (Eberhardt and Teal, 2011). It is also prone to misspecification related to the high dimensionality reduction.

There are two other important proposed approaches that do not fall in the categories described above. Beck and Katz (1995)'s panel corrected standard errors (PCSE) adjusts the OLS estimator standard error for cross-sectional correlations[6]. Cameron et al. (2006, 2009, and 2011) developed a multi-way clustering method to compute the estimator and its variance-covariance matrix when errors are clustered.

2.3. Experimental design: old vs. new versions.

The experimental design in RY followed the traditional practice of simulation in empirical econometrics. Altogether, the experiments were implemented in the following three steps.

Step 1: In the first step, a series of dependent data are generated with pre-determined parameters, namely the data generating process (DGP), the exogenous covariates, the true coefficients, and the disturbance parameters generally provided for by the researcher. This step guarantees that the experiments are controlled.

[6] The data is first transformed using the Prais-Winsten (1954)'s method to get rid of errors serial correlation.

Step 2: In the second step, the generated dependent variable series are regressed on the same covariates, using the same model specification (DGP). The estimated parameters are stored to be analysed.

Step 3: These two first steps were iterated a large enough number of times so to allow a realistic interpretation of estimated parameters' finite properties in the third step.

In RY, the DGP was a simple static panel data model with a single covariate. One important feature of their approach is that the DGP inputs were based on real data sets. The DGP independent variable, intercept and errors' variance-covariance matrix were dataset-specific rather than guesses by the researchers as are usually used in empirical research. Concretely, four different macro-economic datasets of various characteristics (level and growth rates) and geographic coverage (US datasets at state level, and worldwide datasets at country level) are used, suggesting a rich assortment of associations among data points across and within cross-sections. These data sets are described in Appendix 2.1. This way of generating the dependent variable series forms the ground for the authors' claim that their generated datasets looked like "real-world" data.

2.3.1. Construction of data specific inputs: the original approach.

As noted above, the regressor, the intercept and the error variance-covariance matrix used to run simulations in RY were data set-specific. For each of the data sets and panel dimensions N (number of cross-sections) and T (number of time periods) respectively in the second last and last columns of Appendix 2.1, multiple static panel data fixed effects regressions with a single explanatory variable were run using contiguous data slices or windows of length T for each unit[7]. The residuals from these regressions were collected and

[7] A total maximum of 31 regressions for each set of N and T are run with each data set at this step.

used to estimate the simulation error variance-covariance matrix. The average of the dependent variable and that of the regressor across the slices (see equations (2.2) and (2.3) below) were used to calculate the DGP intercept parameter.

Model (2.1) describes the data treatment for each slice or window at this preliminary stage of the experimental design.

$$\begin{aligned}
&Y_{it} = \beta . X_{it} + u_{it}; \\
&u_{it} = \mu_i + \varepsilon_{it} \text{ or } u_{it} = \mu_i + \eta_t + \varepsilon_{it}; \\
&\varepsilon_{it} = \rho . \varepsilon_{i,t-1} + r_{it}; \\
&\boldsymbol{i} = 1,\dots,N \text{ and } \boldsymbol{t} = 1,\dots,\boldsymbol{T}.
\end{aligned} \tag{2.1}$$

where i represents the cross-sections, t represent the time, Y_{it} and X_{it} are values of the dependent and independent variables for cross-section i observed at time t, β is the slope coefficient, u_{it} is the error term including the unobserved individual fixed effects μ_i and unobserved time effects η_t, ε_{it} is the error term assumed autocorrelated of first order with the common autocorrelation ρ across time and cross-sections, and r_{it} is an error term characterised by cross-sectional correlation, but not is serially correlated.

Both the one-way and two-way error specifications above were adopted as separate experiments with each data set and for each combination of the panel data set's individual and time dimensions.

Averages of the regressands and the regressors were calculated for each individual i over the different windows as:

$$\overline{\boldsymbol{Y}} = \frac{1}{\boldsymbol{W}} \sum_{\boldsymbol{k}=1}^{\boldsymbol{W}} \boldsymbol{y}_{\boldsymbol{ik}}, \; \boldsymbol{y}_{\boldsymbol{ik}} = (\boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{k}}, \; \boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{k}+1}, \; \dots, \; \boldsymbol{Y}_{\boldsymbol{i},\boldsymbol{k}+\boldsymbol{T}-1}) \tag{2.2}$$

and

$$\overline{\boldsymbol{X}} = \frac{1}{\boldsymbol{W}}\sum_{\boldsymbol{k}=1}^{W} \boldsymbol{x_{ik}},\ \boldsymbol{x_{ik}} = (\boldsymbol{X}_{\boldsymbol{i},\boldsymbol{k}},\ \mathrm{X}_{\boldsymbol{i},\boldsymbol{k}+1},\ \ldots,\ \mathrm{X}_{\boldsymbol{i},\boldsymbol{k}+\boldsymbol{T}-1}) \qquad (2.3)$$

where W is the number of windows.

The DGP intercept is the difference $\overline{\boldsymbol{Y}}_{\boldsymbol{i}} - \boldsymbol{b}_{\boldsymbol{x}}.\overline{\boldsymbol{X}}_{\boldsymbol{i}} = \boldsymbol{b}_{\boldsymbol{0}}$ where $\boldsymbol{b}_{\boldsymbol{x}}$ is the only parameter "invented" by the researchers. The variable $\overline{\boldsymbol{X}}_{\boldsymbol{i}}$ was used by RY as the regressor for the simulated data sets.

Serial correlation coefficients of OLS residual $\hat{e}_{it}$ from the model (2.1) computed and averaged over contiguous data slices were used to Prais-transform the data in order to remove the serial correlation before re-running an OLS regression on the transformed data. The residuals of this second regression are estimates $\hat{r}_{it}$ of r_{it}. Cross-sectional correlations of residuals $\hat{r}_{it}$ are also computed and averaged across data slices.

The DGP disturbance variance-covariance matrix Ω_{NT} has the more general Parks (1967) structure. Denoting by $\bar{\Sigma}$ the average of matrices of cross-sectional correlations and $\bar{\Pi}$ the matrix of serial correlations, the expression for computing Ω_{NT} is given in equation (2.4).

$$\Omega_{NT} = \bar{\Sigma} \otimes \bar{\Pi} \qquad (2.4)$$

where

$$\bar{\Sigma} = \begin{bmatrix} \bar{\sigma}_{\varepsilon,11} & \bar{\sigma}_{\varepsilon,12} & \cdots & \bar{\sigma}_{\varepsilon,1\mathrm{N}} \\ \bar{\sigma}_{\varepsilon,21} & \bar{\sigma}_{\varepsilon,22} & \cdots & \bar{\sigma}_{\varepsilon,2\mathrm{N}} \\ \vdots & \vdots & \ddots & \vdots \\ \bar{\sigma}_{\varepsilon,\mathrm{N}1} & \bar{\sigma}_{\varepsilon,\mathrm{N}2} & \cdots & \bar{\sigma}_{\varepsilon,\mathrm{NN}} \end{bmatrix},$$

$$\bar{\Pi} = \begin{bmatrix} 1 & \bar{\rho} & \bar{\rho}^2 & \cdots & \bar{\rho}^{T-1} \\ \bar{\rho} & 1 & \bar{\rho} & \cdots & \bar{\rho}^{T-2} \\ \bar{\rho}^2 & \bar{\rho} & 1 & \cdots & \bar{\rho}^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{\rho}^{T-1} & \bar{\rho}^{T-2} & \bar{\rho}^{T-3} & \cdots & 1 \end{bmatrix},$$

and

$$\bar{\sigma}_{\varepsilon,ij} = \frac{\bar{\sigma}_{r,ij}}{1-\bar{\rho}^2}.$$

2.3.2. Experimental parameter of interest and the performance measures.

The central parameter of interest for analysis purposes in RY is the slope coefficient $\boldsymbol{b_x}$ of $\overline{\boldsymbol{X}}_{\boldsymbol{it}}$ in the DGP represented by equation (2.5).

$$\overline{Y}_{it} = \boldsymbol{b_0} + \boldsymbol{b_x}.\overline{X}_{it} + e_{it} \quad (2.5)$$

and

$$e_{it} = \boldsymbol{\rho} e_{i,t-1} + v_{it}$$

where e_{it} are a first order autocorrelated residuals whose variance-covariance matrix Ω_{NT} was described above; and v_{it} is assumed to be a white noise.

The interest lies on the relative efficiency of the estimator of the slope coefficient $\boldsymbol{b_x}$ and on the precision with which it could be estimated with regards to a number of characteristics of the DGP disturbance term. The experiments covered eleven (11) estimators of $\boldsymbol{b_x}$, all of them incorporated in Stata or Eviews. These estimators are presented in Table 2.1 and the corresponding commands in Stata or Eviews are provided in Appendix 2.2.

Denoting by L the number of trials of a given experiment, a given estimator's efficiency is computed relative to a reference estimator using the expression below.

$$efficiency = 100\frac{\sqrt{\sum_{l=1}^{L}\left[\hat{b}_k^{(l)} - b_k\right]^2}}{\sqrt{\sum_{l=1}^{L}\left[\tilde{b}_k^{(l)} - b_k\right]^2}}.$$

where $\tilde{b}_k^{(l)}$ is the value of b_k for the reference estimator (here OLS) at the l^{th} trial, $\hat{b}_k^{(l)}$ is the value of b_k for the estimator that is being compared to the reference.

Table 2.1: Features of estimators' residuals modeled.

No	**Estimator**	**Features of the residuals modeled**
	From Stata	
Estimator 1	OLS	Independent
Estimator 2	OLShet	Heteroskedasticity
Estimator 3	OLSClusti	Heteroskedasticity, serial correlation
Estimator 4	OLSClustt	Heteroskedasticity, cross-sectional dependence
Estimator 5	FGLShet	Groupwise heteroskedasticity
Estimator 6	FGLShetAR	Groupwise heteroskedasticity, serial correlation
Estimator 7	FGLSParks	Groupwise heteroskedasticity + autocorrelation + cross-sectional dependence
Estimator 8	PCSEParks	Groupwise heteroskedasticity + autocorrelation + cross-sectional dependence
	From EViews	
Estimator 9	FGLSWhiteij	Weight = Groupwise heteroskedasticity; Covariance = Heteroskedasticity, Cross-sectional dependence
Estimator 10	FGLSWhitet,	Weight = Groupwise heteroskedasticity; Covariance = Heteroskedasticity, Serial correlation
Estimator 11	FGLSWhiteii.	Weight = Groupwise heteroskedasticity; Covariance = Heteroskedasticity

Source: Table 1 in Reed and Ye (2011).

A value of efficiency greater (less) than 100 characterizes an estimator that is less (more) efficient than the reference estimator (see, for example, Beck and Katz, 1995). Likewise, a value of coverage significantly different from 95 is an indication of poor confidence interval construction.

Performance on inference was defined in RY as the 95 per cent coverage rate, measured by the percentage of times the hypothesis test of the equality between the true and experiment-based values of $\boldsymbol{b}_x$ failed to reject the null hypothesis out of the given number of trials (L).

Three main features of the generated data sets are used to analyse and interpret the experimental outcomes. These are the T to N ratio, the common first order autocorrelation coefficient and the degree of heteroskedasticity (HETCOEF) of the OLS disturbances term from model (2.5). The computation of a consistent estimate ρ (RHOHAT) of the serial correlation coefficient of the residuals follows the formula below proposed in Greene (2003, p 326).

$$\rho = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it}\hat{e}_{i,t-1}}{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{e}_{it}^{\;2}}$$

where $\hat{e}_{it}$ is the residuals series from the OLS re-estimation of the DGP equation with simulated data.

The HETCOEF parameter was determined as the ratio of the first and third quintiles of the estimates of the population variances of the residuals e_{it} from model (2.5). This indicator captures the degree of heteroskedasticity in the error term of the simulated data. Higher values of HETCOEF might be associated with higher size distortions of the hypothesis tests and the coefficients' confidence intervals due to inaccurate estimates of the coefficient's standard errors. While RY develop a measure of cross-sectional correlation, they did not relate this to estimator performance in their analysis.

2.3.3. Criticism and adjustment of the initial experimental design.

RY's investigation resulted in practical findings which we will discuss below.

Nonetheless, we find that their experimental design is subject to criticism in connection with their construction of the independent variable used in the DGP for simulation purposes. Equation (2.3) exaggerates the degree of serial correlation in the regressor due to the fact that the averaged data slices are nested. When the error terms are serially correlated, the serial correlation in the regressor affects the variance of its OLS coefficient estimator variance. Equation (2.6) below connects the variance of the OLS slope estimator characterised by first order serial correlation of both the error term and the regressor, $\mathrm{var}(\beta_{AR(1)})$ on the one hand, and that of the usual OLS slope estimator, $\mathrm{var}(\beta_{OLS})$, on the other (see Gujarati 2004, p 452).

$$\mathrm{var}(\beta_{AR(1)}) = \mathrm{var}(\beta_{OLS})\left(\frac{1+r\rho}{1-r\rho}\right) \tag{2.6}$$

where r and ρ denote the first order serial correlation coefficients of the regressor and that of the error term, respectively.

When there is no serial correlation in the regressor, *r=0*, and $\mathrm{var}(\beta_{AR(1)}) = \mathrm{var}(\beta_{OLS})$. As *r* increases, the OLS estimate of the standard error deteriorates. Simulating values for the regressor that exaggerate the degree of serial correlation in "real world panel data sets" thus also exaggerates the bias in the estimated slope standard error. This in turn could affect conclusions about the relative performances of the respective panel data estimators, as some estimators may be more affected by this flaw than others.

We propose to adjust the experimental design for this flaw by constructing a DGP regressor without exaggerating its degree of serial correlation. Practically, we achieve this goal by randomly selecting one of the data windows used to generate the data specific parameters to substitute for the original version of the regressor. This process does not add further correlation in the regressor used for simulation purposes.

2.4. Description of replicated and redesigned experiments' output.

In RY, a total of 144 experiments were carried out with both error strictures of model (2.1). Of these experiments, 80 used data sets characterized by N≤T, and 64 were conducted with data sets where N>T. Experiments were conducted with eight different data sets, different N-T combinations formed with 6 different individual dimension (N) values (5, 10, 20, 48, 50 and 77) and 4 different time dimension (T) values (10, 15, 20 and 25). Each experiment is replicated 1000 times. The SAS/IML internal random number generation is used to generate standard normal errors to which the error structure is applied to arrive at the dependent DGP error term.

We have fully replicated the experiments twice using the same number of Monte Carlo replications (1000) and the same DGP error term generation process: (i) once with the same conditions, namely the model specifications, the experimental design, the data sets and the individual and time dimensions values specified above; (ii) and once with the sole difference in the construction of the DGP regressor used for simulation purposes that avoids exaggerating serial correlation. The results of these replications are presented below in light of the original results as published in RY.

2.4.1. The parameters of the DGP error term.

Table 2.2 describes the parameters indicative of the degree of heteroskedasticity, serial correlation and cross-sectional correlation used to study the estimators' relative performances.

It appears that these errors' parameters are well replicated under both experimental designs. This result suggests that there has not been a significant impact of the regressor serial correlation exaggeration on the errors' parameters. Consequently, differences in estimator performances in terms of efficiency or confidence interval precision, if observed, will be solely attributed to the relationship between the estimator's variance and the correlation coefficients of the regressor and the error term described in equation (2.6).

Table 2.2: Description of errors characteristics used in simulations.

		HETCOEF	RHOHATBAR	CSCORR
a. Original results in RY				
N<=T	Minimum	1.19	-0.09	0.19
	Maximum	2.31	0.79	0.89
	Mean	1.57	0.36	0.41
N>T	Minimum	1.25	-0.05	0.22
	Maximum	2.15	0.80	0.78
	Mean	1.77	0.33	0.37
b. Exact replication				
N<=T	Minimum	1.21	-0.07	0.20
	Maximum	2.34	0.78	0.90
	Mean	1.68	0.36	0.45
N>T	Minimum	1.34	-0.05	0.22
	Maximum	2.27	0.79	0.79
	Mean	1.87	0.32	0.41
c. Replication with adjustment				
N<=T	Minimum	1.21	-0.06	0.20
	Maximum	2.35	0.78	0.90
	Mean	1.68	0.36	0.44
N>T	Minimum	1.34	-0.04	0.22
	Maximum	2.25	0.79	0.79
	Mean	1.76	0.34	0.43

Source: Reed and Ye (2011) and author's calculations.

2.4.2. Relative efficiency of estimators.

Table 2.3 contains statistics about estimators' performances on the efficiency ground in three panels, corresponding to the original performances (panel a) as reported by RY, the replicated performances (panel b) with unchanged experimental design, and the redesigned performances (panel c) after reconstructing the dependent variable.

The exact replications of efficiencies are very close to the original experiments' results when considering the actual efficiency figures, or the number of experiments where OLS is less efficient. The only differences observed relate to the GLShetAR (when N>T) and the Parks (when N≤T) estimators for which slight efficiency gains are observed on the one side, and for the GLShetAR and the PCSE (N>T) estimators that dominate OLS more often on efficiency grounds in the replicated experiments.

Table 2.3: Original, replicated and redesigned relative efficiency statistics.

	Average Efficiency		Percentage of experiments where estimator is more efficient than OLS	
	N<=T	**N>T**	**N<=T**	**N>T**
a. Original results in RY				
FGLShet/FGLSW	95.2	82.9	58.8	84.4
FGLShetAR	95.1	83.1	71.3	79.7
GLSParks	73.9	--	96.3	--
PCSEParks	100.8	101.0	62.5	51.6
b. Exact replication				
FGLShet/FGLSW	95.2	82.9	58.8	84.4
FGLShetAR	95.1	82.6	71.3	81.3
GLSParks	73.7	--	96.3	--
PCSEParks	100.8	101.0	63.8	57.8
c. Replication with adjustment				
FGLShet/FGLSW	92.5	76.9	68.8	89.1
FGLShetAR	79.5	70.7	85.0	90.6
GLSParks	62.0	--	100.0	--
PCSEParks	86.4	91.8	71.3	71.9

Source: Reed and Ye (2011) and author's calculations.

However, after the DGP regressor is reconstructed, considerable efficiency gains are recorded for all estimators irrespective of whether N is larger or less than T. And the frequencies of trials where the estimators are more efficient than OLS substantially increase for all estimators. This result reveals the significance of the sensitivity of the efficiency indicator - and indirectly the quality of the slope coefficient estimate - to the degree of serial correlation in the regressor.

2.4.3. Confidence interval performance.

Table 2.4 summarises the coverage rate performance for all estimators under the original (panel a), exact replication (panel b) and the replication with adjusted experimental design (panel c). Our exact replications of confidence interval performance perfectly match the original results when the individual dimension of simulated panel data sets is not greater than the time dimension. Average coverage rates and average absolute gaps with the 95 percent theoretical threshold over all experiments are correctly reproduced for all estimators[8]. When the time dimension is dominated by the individual dimension, differences exist between replicated and original confidence internal performance, but they are within acceptable ranges. Overall, coverage rates increase by 0.9 (from 91.8 percent to 92.7 percent for OLSClusti) to 1.8 (from 74 percent to 75.8 percent for OLSClustt) percentage points while increases of the same order are observed in the gaps with the theoretical coverage level of 95 percent.

[8] It is worth noting that average $|95 - \text{Coverage}|$ is not calculated using the average coverage reported in columns 2 and 4 for a given estimator, but rather as the average of $|95 - \text{Coverage}|$ over all experiments experiments with N≤T for column 3 and with N>T for coumn 5. That's the reason why the sums of data in columns 2 and 3 on the one hand and 4 and 5 on the other are not equal to 95.

Table 2.4: Replicated and redesigned confidence interval precision. Average coverage rates and average $|95 - \text{Coverage}|$.

Estimator	N<=T		N>T	
	Coverage	|95-Coverage|	Coverage	|95-Coverage|
	a. original result in RY			
OLS	73.6	21.9	74.2	21.9
OLShet	73.7	21.8	77.9	18.8
OLSClusti	83.5	11.6	91.8	3.9
OLSClustt	72.7	22.5	74	21.3
FGLShet	69.8	25.6	72.6	22.9
FGLShetAR	86.4	9.3	88.8	7.2
GLSParks	43.3	51.7	--	--
PCSEParks	87.8	7.2	88.1	6.9
FGLSWhiteij	66.1	28.9	65.4	29.6
FGLSWhitet,	68.1	26.9	80.1	14.9
FGLSWhiteii.	69.5	25.9	72.4	23.2
	b. exact replication			
OLS	73.6	21.9	75.7	20.5
OLShet	73.7	21.8	79.3	17.5
OLSClusti	83.5	11.6	92.7	3.0
OLSClustt	72.7	22.5	75.8	19.6
FGLShet	69.8	25.6	74.1	21.4
FGLShetAR	86.4	9.3	90.2	5.5
GLSParks	43.3	51.7	--	--
PCSEParks	87.8	7.2	89.1	5.9
FGLSWhiteij	66.1	28.9	66.7	28.3
FGLSWhitet,	68.1	26.9	81.5	13.5
FGLSWhiteii.	69.5	25.9	73.9	21.7

Table 2.4 (continued).

Estimator	N<=T		N>T	
	Coverage	|95-Coverage|	Coverage	|95-Coverage|
	c. replication with adjustment			
OLS	78.0	18.0	82.1	15.2
OLShet	77.2	18.2	80.4	16.0
OLSClusti	87.6	7.7	92.1	5.1
OLSClustt	75.4	19.8	78.0	17.2
FGLShet	73.8	21.2	76.5	19.2
FGLShetAR	89.4	5.8	90.0	5.8
GLSParks	44.2	50.8	--	--
PCSEParks	91.0	4.0	92.0	3.1
FGLSWhiteij	68.3	26.7	68.7	26.3
FGLSWhitet,	73.8	21.2	81.4	13.6
FGLSWhiteii.	73.0	22.0	75.7	19.8

Source: Reed and Ye (2011) and author's calculations.

The impact of the experimental design adjustment is substantial on the accuracy of estimated confidence intervals as a result of the earlier discussed flaw. Subsequent to the adjustment, rejection rates generally increase. When N is less than or equal to T, the highest improvements are associated with the GLSWhitet, OLS, GLShet, and the OLSClusti estimators with respective gains 5.7, 4.5, 4.1 and 4.0 percentage points for these estimators calculated as differences between our replications with adjusted experimental design and exact replications. The lowest accuracy improvement (0.9 percentage point) is observed for FGLSParks (FGLS (Parks)). When N is larger than T, OLS stands out with the greatest improvement in measured accuracy, followed by the OLSClustt, GLShet and the PCSE estimators. These differences in the coverage rates indicate that on average, the impact of the regressor serial correlation exaggeration is, in many cases, substantial

2.5. Further re-examination of estimators' performances.

2.5.1. Assessment of the original recommendations.

A major question we investigate in this paper is whether the readjustment of the experimental design has altered the desirability of some estimators over others. That is, we want to examine the validity of recommendations formulated by RY after replacing their regressor contaminated with extra serial correlation following its construction by an improved regressor bearing no additional serial correlation. We achieve this purpose in this section that re-assesses the initial recommendations resulting from the original experiments.

2.5.1.1. Recommendation 1.

According to the first recommendation with the original experimental design, the FGLS (Parks) procedure is preferable when the primary concern is efficiency and $T/N \geq 1.5$. Figure 2.1 plots average efficiencies of estimators on the vertical axis against the T/N ratio on the horizontal axis under the old (panel a) and the new (panel b) experimental designs.

It clearly appears that recommendation 1 holds with both versions of the experimental design. Furthermore, our exact replication indicates that there is a cut point of T/N ratio of 1.25 from which the FGLSParks outperforms others; this ratio was 1.5 according to the original results. Additionally, under the new experimental design, when $T/N<1.5$, FGLShetAR appears dominant, leading to a complete classification of estimators when $N \leq T$. Another interesting result established with the redesigned experiments is that from T/N value of 1.5, there is a total order among the estimators with respect to the efficiency indicator as follows: OLS is the least efficient estimator, followed successively by the group of estimators FGLShet/FGLSW, PCSEParks, FGLShetAR, and lastly FGLSParks comes as the most efficient.

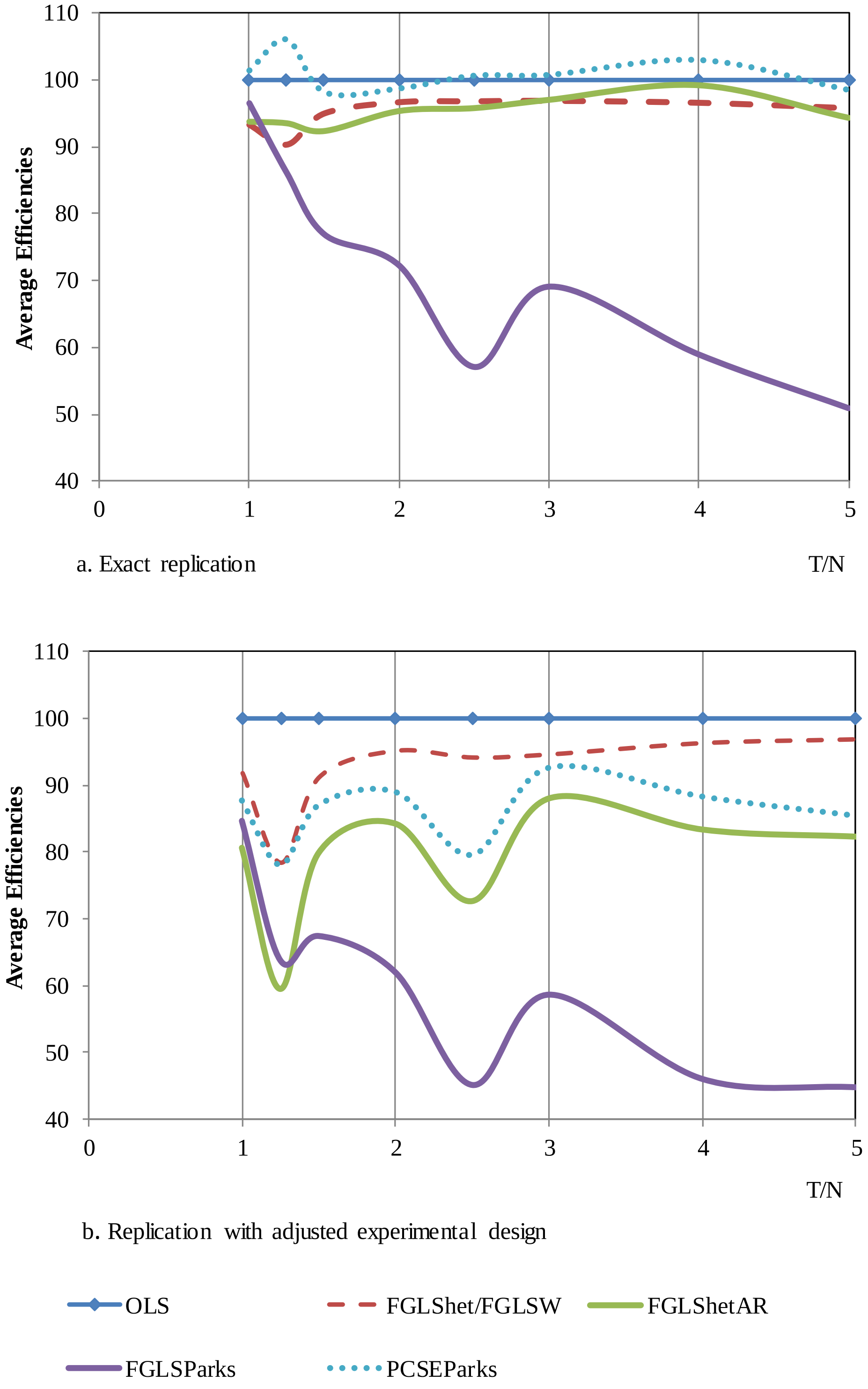


Figure 2.1: Average efficiencies of estimators when N≤T against T/N ratio.

2.5.1.2. Recommendation 2.

In their second recommendation, RY advised using estimators FGLShet/FGLSW or FGLShetAR to best optimize efficiency when N>T and HETCOEF>1.67. We are able to confirm this recommendation with our exact replication. Figure 2.2 (Panel a) provides evidence for these preferences in absolute terms. The two conditions hold for a total of 46 experiments of which roughly two thirds indicate that FGLShetAR is more efficient than the group of estimators FGLShet/FGLSW, but these estimators are all strictly preferred to PCSEParks and the OLS.

However, subsequent to the correction of the experimental design, no strict preference for a given estimator is revealed over all the experiments with N>T and RHOHAT>1.67. The number of experiments that meet these requirements remains the same, and is split the following way with respect to the efficiency performance criteria: PCSEParks outperforms all others in 4 cases; it dominates the group of estimators FGLShet/FGLSW in 13 cases and FGLShetAR in 4 cases. While the graphical representation reveals a close proximity between estimators FGLShet/FGLSW and FGLShetAR, the performance of the group of estimators at least dominates that of FGLShetAR in only 15.2 percent of the cases (7 experiments out of 46).

Therefore, only FGLShetAR stands out as the best. The elimination of extra serial correlation introduced in the regressor affects this recommendation by making less recommendable estimators FGLShet/FGLSWas best estimators on efficiency grounds when N>T.

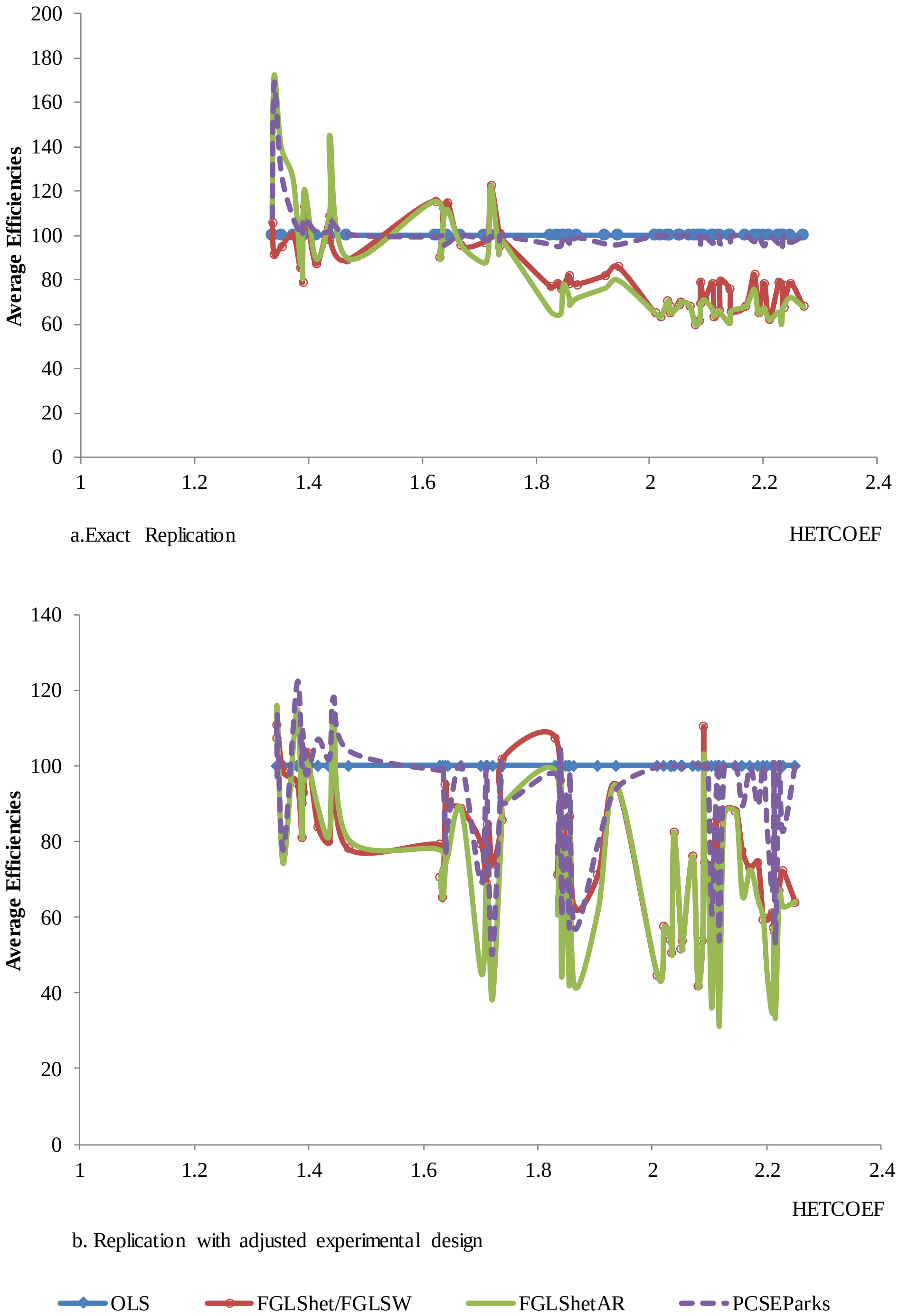


Figure 2.2: Average efficiencies of estimators when N≤T (vertical axis) against HETCOEF ratio (horizontal axis).

This conclusion aligns with the summaries of Table 2.3 showing the smaller average efficiency coupled with the number of times FGLShetAR is preferred over OLS. It is worth noting that the order for both indicators is reversed for the group of estimators FGLShet/FGLSW and FGLShetAR post-correction for the DGP regressor extra serial correlation.

2.5.1.3. Recommendation 3.

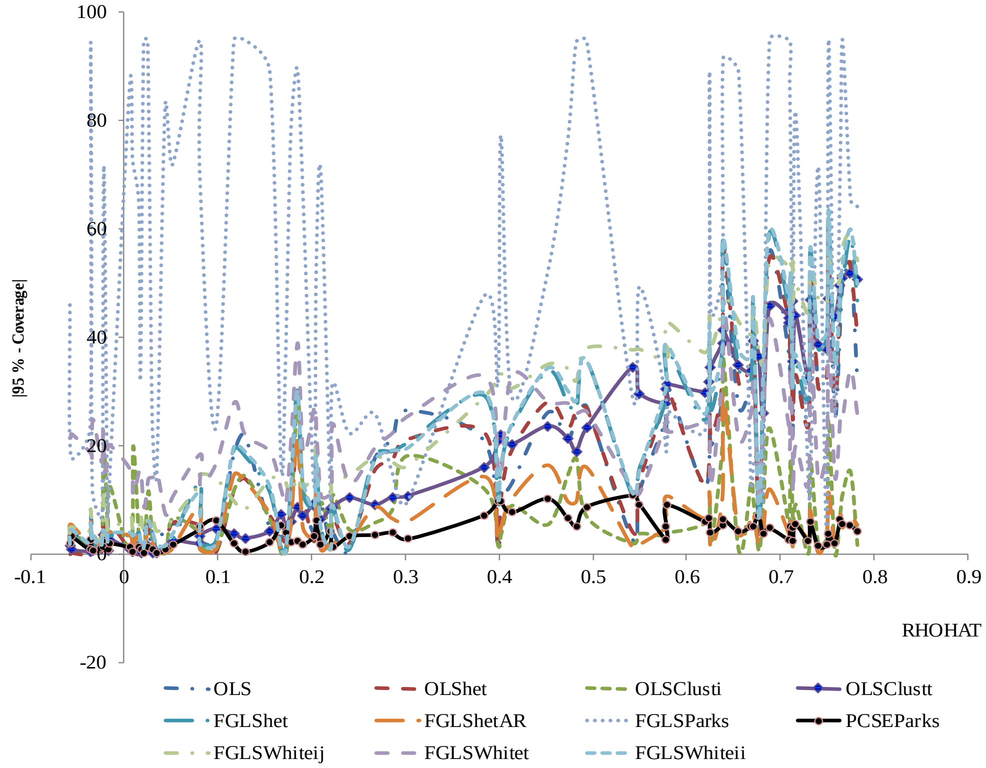
Recommendation 3 of the original research chooses PCSEParks and OLSClustt as best performers for constructing confidence intervals when RHOHAT<0.30. Two indicators are used to measure the performance of estimators with respect to the confidence interval. These are the coverage rate and the absolute coverage gap with the 95 percent threshold discussed earlier. The second indicator fills the gap that characterizes the first due to the coverage level averaging by capturing the mixed effects of over-rejection and under-rejection in experiments for a given estimator.

According to Table 2.5 and Figure 2.3, recommendation 3 selects the same estimators under both replication experimental designs with some variations. For RHOHAT<0.30, there is a substantial gain in confidence interval accuracy for PCSEParks with the experimental design change, making it the best estimator to recommend when N≤T and the closest substitute for OLSClustt when N>T. In the meantime, the confidence interval precisions for estimators OLShet and OLSClusti which were the closest to that of OLSClustt under the initial experimental design significantly deteriorate subsequent to the amendment.

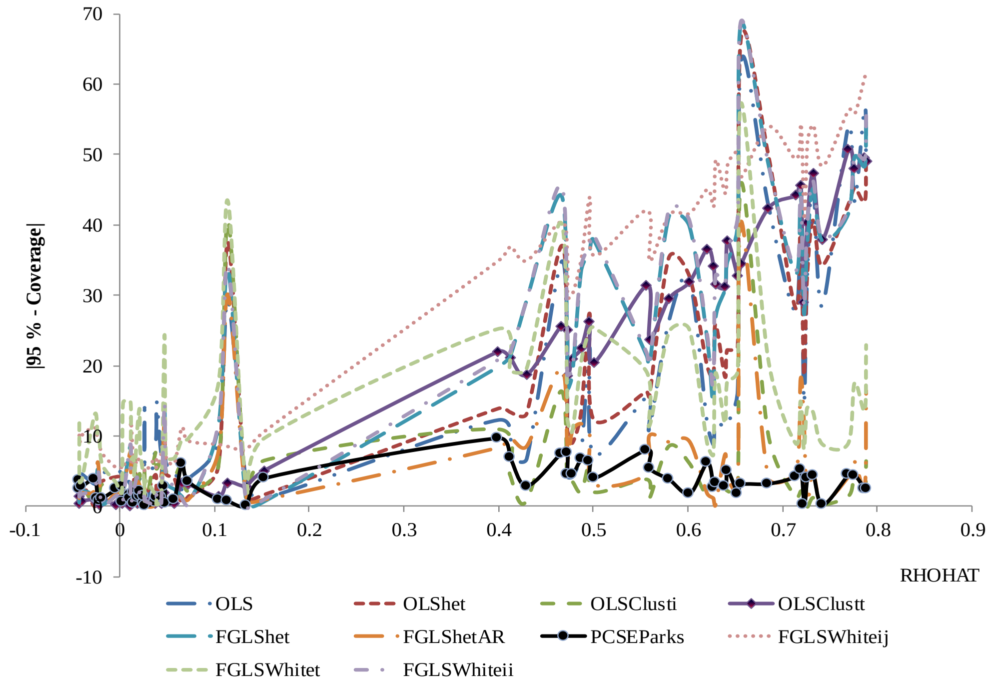
Table 2.5: Average absolute coverage gap with 95 percent when RHOHAT<0.30.

Estimator	RY results		Exact replications		Replications with adjustment	
	N<=T	**N>T**	**N<=T**	**N>T**	**N<=T**	**N>T**
OLS	5.2	4.0	5.1	3.9	6.1	5.8
OLShet	4.5	1.8	4.5	1.8	4.9	4.0
OLSClusti	9.9	1.5	9.9	1.5	6.5	4.8
OLSClustt	3.7	1.4	3.7	1.4	3.8	1.3
FGLShet	6.3	2.1	6.3	2.1	6.4	3.7
FGLShetAR	4.9	2.0	4.9	2.6	4.4	3.4
GLSParks	47.9	--	47.9	--	49.4	--
PCSEParks	3.1	2.4	3.1	2.4	2.3	1.8
FGLSWhiteij	8.6	6.9	8.6	6.9	9.4	7.8
FGLSWhitet,	19.9	6.4	19.9	6.4	17.7	8.8
FGLSWhiteii.	6.4	2.1	6.4	2.1	6.8	3.8

Source: Reed and Ye (2011) and author's calculations.



a. N≤T



b. N>T

Figure 2.3: Efficiencies vs. error term serial correlation indicator (RHOHATBAR) under the adjusted experiments.

2.5.2. Further implications of the redesign of experiments.

We found that for the individual dimension not greater than the time dimension (N≤T), FGLShetAR and FGLSParks are the best performers respectively when T/N<1.5 and when T/N≥1.5. More interestingly, we also found that based on the T-N ratio, the efficiency of FGLShetAR is outstanding when N>T as shown on Figure 2.4. This implies that taking out the HETCOEF indicator would allow formulating a more compelling recommendation for selecting the most efficient estimator for panel datasets characterized by N>T.

The above findings about the first two recommendations imply that a single recommendation solely based on the T/N ratio would more effectively combine these two as follows: When the primary concern is efficiency, (i) choose FGLShetAR when T/N<1.5, and (ii) choose FGLSParks when T/N≥1.5.

2.6. Robustness diagnosis of new recommendations.

Our objective in this section is to assess how robust to error dependence parameters our new versions of the recommendations are. To do this, we collect a new set of data sets and implement the experiments using the adjusted design. We first analyse the aggregated output to investigate whether or not the recommendations are confirmed with the new data sets. We then consider a disaggregated analysis to assess how likely a researcher is to make a right selection based on these recommendations.

2.6.1 Data description.

The aim of the data description is twofold. In the first step, we discuss the sources of the new data sets and clarify the necessary treatments to arrive at the versions of data used for our purpose. Then, we analyse the parameters of the errors produced with these new data sets.

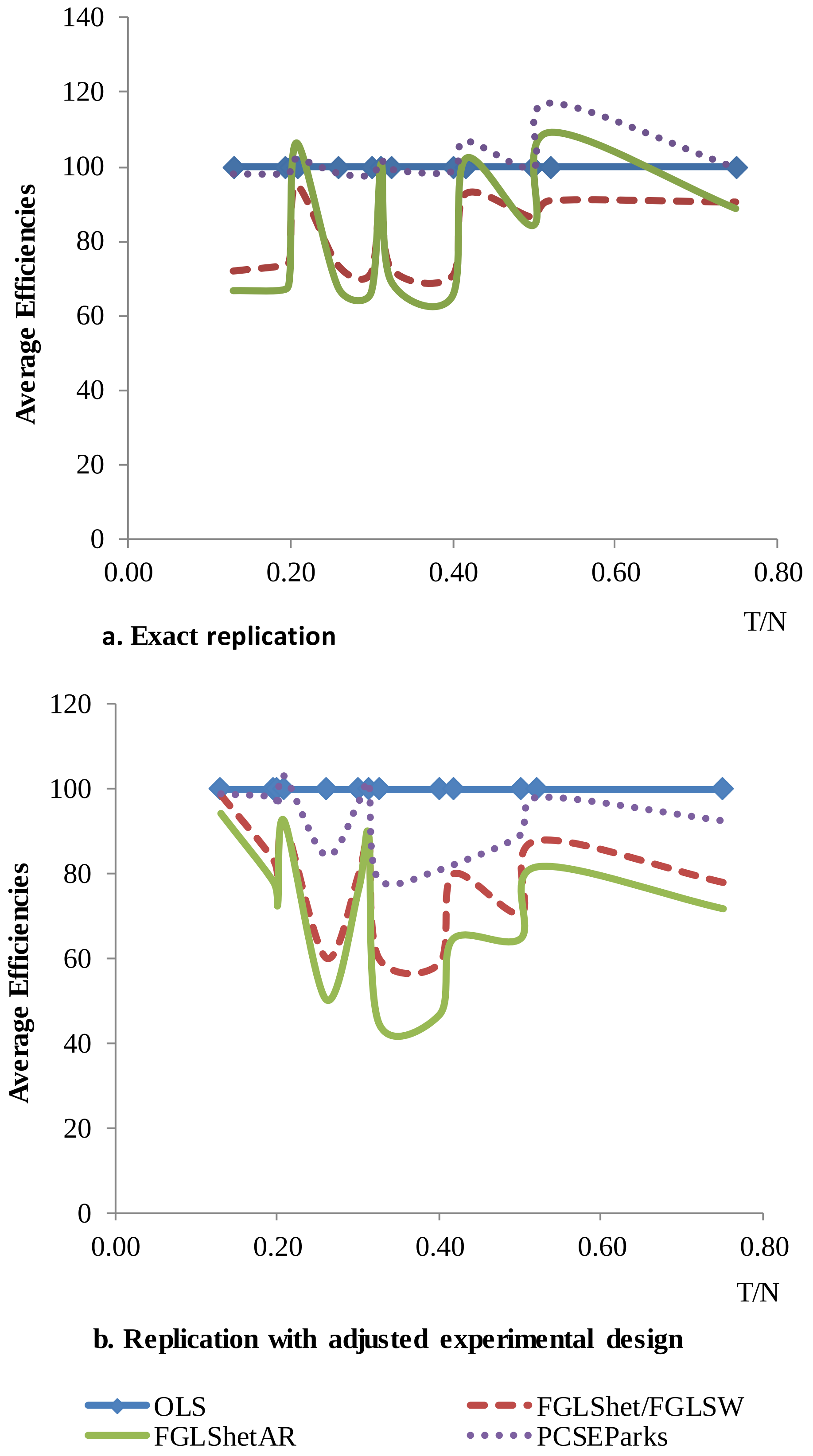


Figure 2.4: Comparison of efficiencies using the T/N ratio when N>T.

2.6.1.1. Data sources and treatment.

Our data sets come from five different data sets used in different researches identified in Table 2.6. Columns of this table contain the studies references, while its rows summarize some of the characteristics of our final data sets. Except the data sets from Biagi et al. (2012) which we used without any modification, others resulted from treatments of the author's original data sets. For the treatments, we essentially eliminated missing values and resized the data dimensions to arrive at balanced panel data sets with at least 25 time periods and the maximum number possible of cross-sections. Our dependent variables were used as such in initial works, and our regressors were used by respective authors in respective researches with other covariates, including year and/or individual dummies. The statistical significance of a given explanatory variable in the original research is an essential selection criterion. The Nunn & Qian (2014) study is the only one for which the explanatory variable is non-significant. However, the non-significance of the regressor is irrelevant for the purposes of our Monte Carlo study.

For each data set, all cross-products of corresponding sample N and sample T values listed in Table 2.6 were used with all estimators studied in this chapter. There are two exceptions to this rule. The first is related to the Parks estimator, which requires that the time dimension is at least as large as the individual dimension. The other exception relates to the rounding errors that did not allow the Cholesky decomposition of the error variance - covariance matrix generated with the data from Kerstinmg & Kilby (2014) for two sets of dimensions combinations. This error occurred with the two-way error specification for (N,T) = {(50,10), (50,20)}. Accounting for all data sets, we obtain a total of 172 successful experiments, of which 92 were conducted with N≤T and 80 carried out with N>T.

Table 2.6: Sources and description of new data sets.

	Kerstinmg & Kilby (2014)	Bruckner (2013)	Casper & Tufis (2003)	Biagi et al. (2012)	Nunn & Qian (2014)
Cross-sections	World countries	World countries	World countries	Italian States	World countries
N	108	44	52	95	98
T	25	25	26	19	36
Dependent variable	Gross Aid Disbursement as Share in GDP (Germany Aid Allocation)	Net Official Development Aid	Vanhanen's Democracy Index	Crime per 100000 inhabitants	Any Conflict
Regressor	Freedom House Score	Real Per Capita GDP Growth	Primary education enrolment (share of population)	Tourists arrivals per square kilometre	US-Wheat Aid (1000 MT)
Sample N	5, 10, 20, 50, 77	5, 10, 20, 44	5, 10, 20, 50	5, 10, 20, 50, 77	5, 10, 20, 50, 77
Sample T	10, 15, 20, 25	10, 15, 20, 25	10, 15, 20, 25	10, 15, 19	10, 15, 20, 25
Estimator	OLS	OLS	OLS	OLS	OLS
Coefficient reference	Table 6; 3rd column; 2nd row	Table 1; 3rd column; 1st row	Table 1; 2nd column; 5th row	Table 4; 1st column; 5th row	Table 2; 1st column; 1st row

Source: Author.

2.6.1.2. Error Structures from the data sets.

In this sub-section, we present the characteristics of error terms constructed from the data sets to serve as inputs in the experiments. These characteristics are measures of heteroskedasticity (HETCOEF), serial correlation (RHOHAT) and cross-sectional correlation (CSCORR) as defined in RY. Table 2.7 contains these error parameters for original data sets used in RY and our new data sets. Significant differences between error structures from the original and new data sets are observed as we observe higher and erratic levels of the heteroskedasticity indicator and lower overall level of cross-sectional correlation in the new error structures. The difference in heteroskedasticity pattern offers an ideal opportunity to re-assess the impact of this data feature on estimators' relative efficiencies that we fail to obtain with the prior set of data with the corrected version of experiments. Conversely, serial correlation figures do not display significant differences between the 2 sets of data apart from the stronger negative autocorrelation coefficients that characterizes some of the new data sets.

Table 2.7: Characteristics of error parameters with new and original data sets.

		HETCOEF	RHOHATBAR	CSCORR	HETRANGE
New data sets					
N≤T	Minimum	1.26	-0.43	0.22	0.03
	Maximum	40.21	0.73	0.61	2.90
	Mean	3.86	0.32	0.36	0.53
N>T	Minimum	1.47	-0.23	0.23	0.05
	Maximum	34.91	0.73	0.49	3.55
	Mean	6.16	0.36	0.34	0.67
Original data sets					
N≤T	Minimum	1.21	-0.06	0.20	0.00
	Maximum	2.35	0.78	0.90	3.44
	Mean	1.68	0.36	0.44	0.82
N>T	Minimum	1.34	-0.04	0.22	0.01
	Maximum	2.25	0.79	0.79	3.37
	Mean	1.76	0.34	0.43	0.95

Source: Author's calculations.

2.6.2. Analysis of experimental results.

2.6.2.1. Estimators' relative efficiencies.

Average efficiency figures are reported in Table 2.8. They indicate that the best estimator is, on average, FGLShetAR (OLS with groupwise heteroskedastic and first order serially correlated errors) irrespective of the relative order of N and T. This estimator also presents the highest indicator of the frequency of its dominance over the OLS when N≤T and shares this top position with FGLShet (OLS with groupwise heteroskedastic errors) with respect to the same criterion when N>T. The highest average efficiency indicative of poor relative performance is recorded for the PCSE estimator, which also appears to be the least often preferred to the standard OLS.

Table 2.8: Estimators' average efficiencies over estimators.

Estimator	Average Efficiency		Percentage of times the estimator is more efficiency than OLS	
	N≤T	N>T	N≤T	N>T
FGLShet/FGLSW	64.5	55.4	93.5	98.8
FGLShetAR	56.5	49.7	98.9	98.8
GLSParks	60.3		96.7	
PCSEParks	90.7	91.8	79.3	82.5

Source: Author's calculations.

2.6.2.2. Selection rule of estimator based on efficiency.

Based on the above analysis, one would recommend the selection of FGLShetAR as the best on efficiency grounds if the analysis is restricted to the average values of efficiency. However, Figure 2.5 shows evidence of the superiority of the Parks estimator for experiments where T/N>1.5. In fact, averaging efficiencies over estimators has masked disparities related to a key experimental parameter, the T/N ratio. So, using the data sets dimensions ratio, the new data sets lead to the same selection rule based on estimator efficiency as the original data sets.

The investigation of the relationship between the measure of heteroskedasticity and the estimators' efficiency-based relative performance reveals two different situations for respective cases where N>T and N≤T. RY based their second recommenation on the measure of heteroskedasticity when N>T. But we can see from Figure 2.6 that when N>T, FGLShetAR is dominant irrespective of the level of heteroskedasticity.

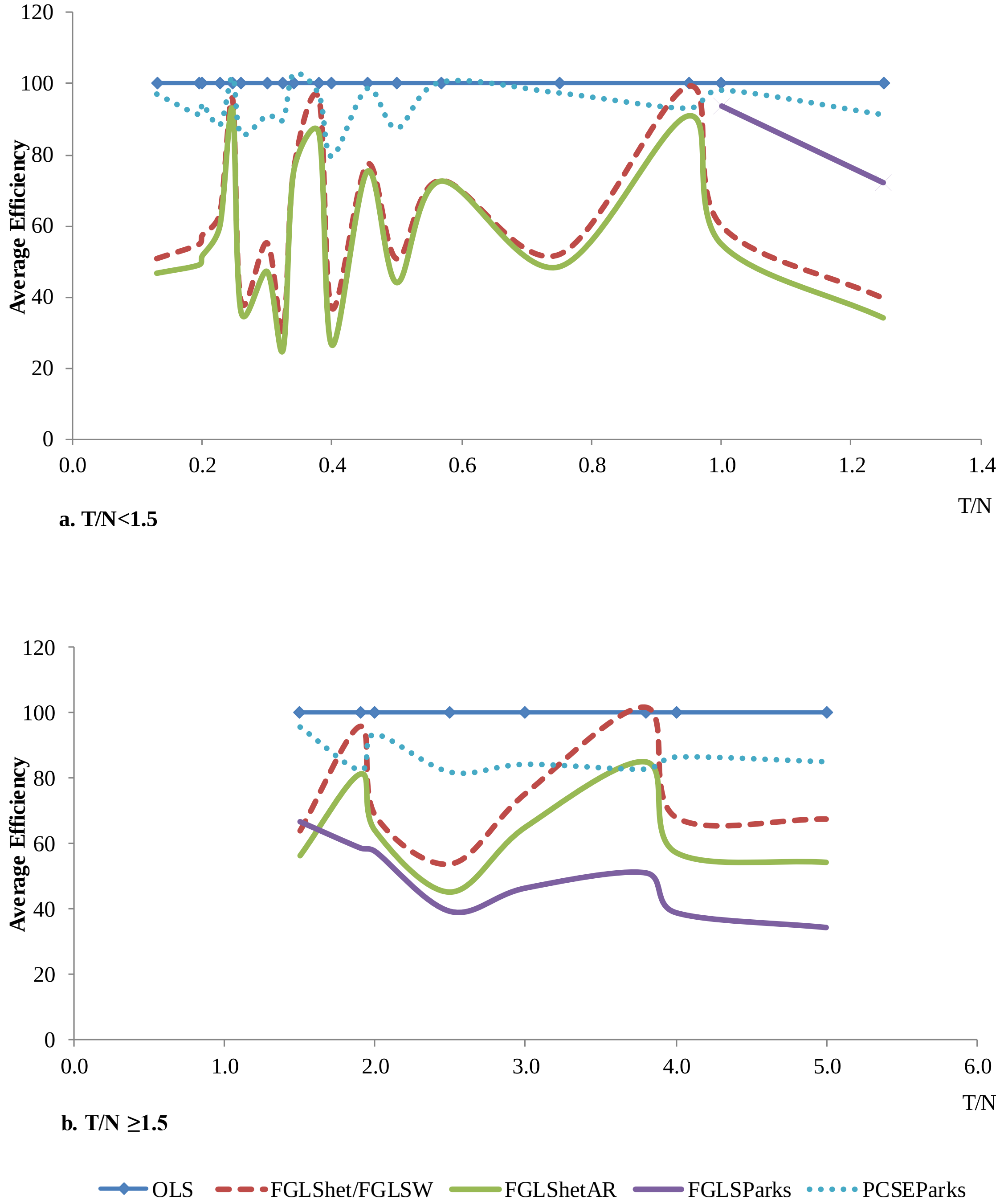


Figure 2.5: Relative average efficiencies of estimators over T/N ratio.

In fact, in just one experiment PCSEParks (Beck and Katz PCSE) dominates FGLShetAR. This again provides ample evidence against of using the measure of heteroskedasticity to recommend a choice of estimator on the efficiency ground. We also found this result with the original data sets used in RY after the adjustment of the experimental design.

Turning to the experiments where $N \leq T$, HETCOEF could not be used to formulate a consistent recommendation to select the best estimator with the lowest efficiency score. Data indicate that for lower values of HETCOEF (below 1.77), Park's estimator is often suprior and for higher values of HETCOEF (above 1.77), FGLShetAR is the most frequently dominant. The problem with this use of HETCOEF is that the related recommendation is not consistently valid. None of the estimator preferences over the given ranges of HETCOEF are absolute. Of 42 experiments for which HETCOEF falls in the above defined lower range, the Parks estimator shows itself superior 34 times, and FGLShetAR only 5 times. On the other hand, of 50 experiments for which the measure of heteroskedasticity falls in the upper range, FGLShetAR dominates 37 times and the Parks estimator 12 times. Given this lack of consistency of the finding based on HETCOEF, we conclude that the safest data characteristic to base the choice of the most efficient estimator on is the ratio T/N, which results in a complete and consistent selection rule. This result too, was established with data sets used in RY.

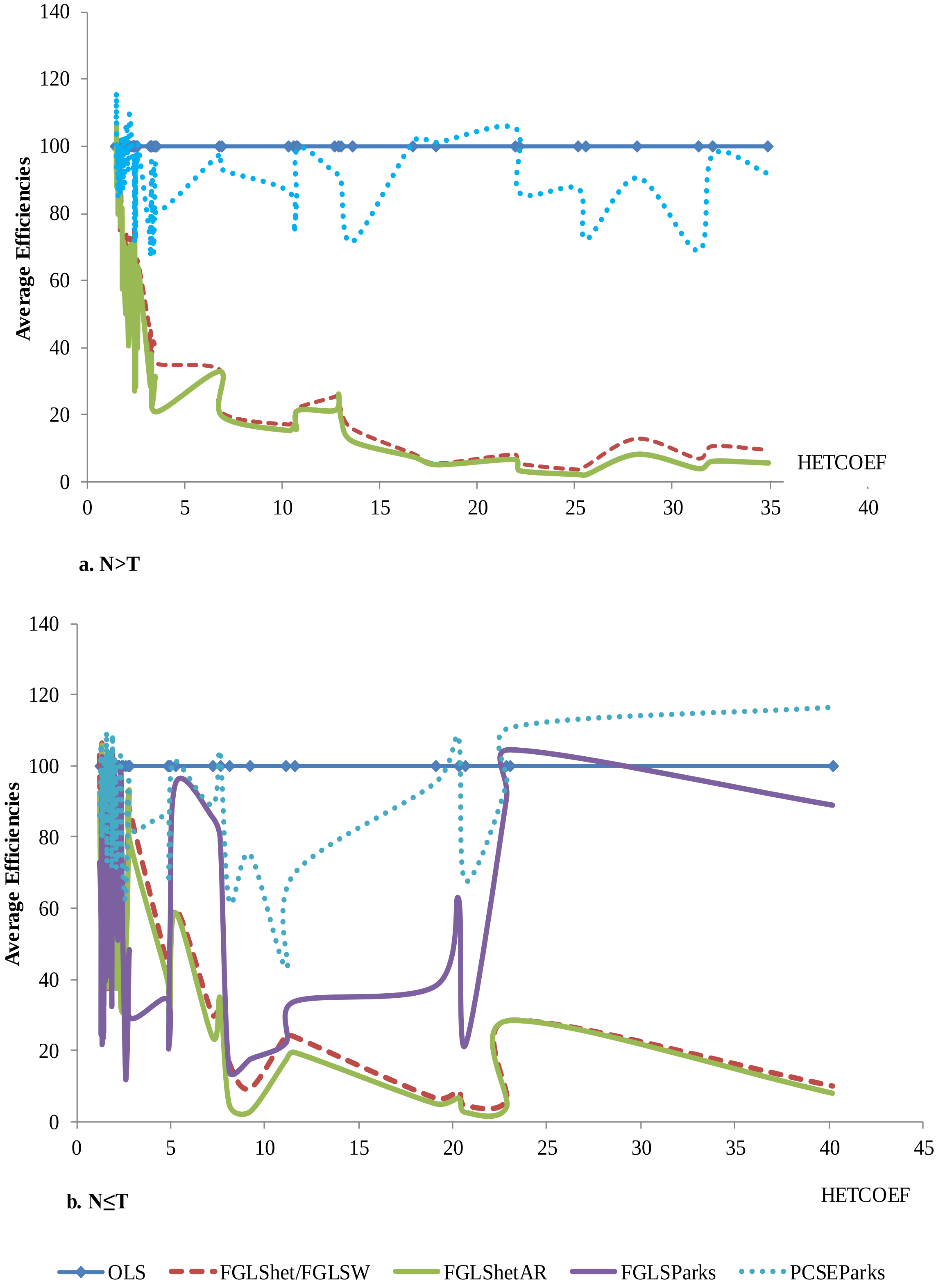


Figure 2.6: Relationship between estimator efficiency and HETCOEF.

2.6.2.3. Confidence interval accuracy.

With the original data sets, the PCSE estimator and OLSClustt (OLS plus cross-sectional correlation errors) had superior performance in constructing more accurate confidence intervals. The recommendation related to this criterion was confirmed for the measure of serial correlation RHOHAT less than 0.3, and the rule was to use the PCSE estimator when N is not larger than T, and OLSClustt or the PCSE again when N is strictly larger than T. However, the results with the new data sets reported in Table 2.9 maintain only the preference for PCSEParks (PCSE) no matter the T/N ratio and for the same range of RHOHAT. The average absolute difference between the coverage rates of the comparison of the true estimated slope to the true slope and the 95 percent theoretical threshold is below 2 for this estimator for all experiments satisfying RHOHAT<0.30. With this cut point of RHOHAT values, OLSClustt does not produce more accurate confidence intervals. Rather, with the new data sets, we found that for N>T, OLSClustt competes well with the PCSE when RHOHAT<0.20 where respective averages of absolute coverage gap values are 1.1 and 0.9.

There is another major finding with the new data sets that seems to generalize the preference for the PCSE estimator on average and across all values of RHOHAT. Statistics summarized in Table 2.10 show that the confidence intervals constructed with the PCSE procedure remain consistently close to the 95 percent expected theoretical threshold. This estimator results in a lower average coverage gap value, the smallest maximum value, the smallest inter-quartile range (IQR) and the smallest standard deviation both when N≤T and when N>T.

Table 2.9: Average absolute coverage rates deviation from 95 percent when RHOHAT<0.30.

	New data sets		**Original data sets**	
Estimator	N≤T	N>T	N<=T	N>T
OLS	6.1	5.4	6.1	5.8
OLShet	4.7	5.2	4.9	4.0
OLSClusti	3.9	4.8	6.5	4.8
OLSClustt	4.5	2.6	3.8	1.3
FGLShet	5.6	4.4	6.4	3.7
FGLShetAR	3.4	3.5	4.4	3.4
GLSParks	54.2	--	49.4	--
PCSEParks	1.8	1.7	2.3	1.8
FGLSWhiteij	11.9	12.4	9.4	7.8
FGLSWhitet,	18.8	9.5	17.7	8.8
FGLSWhiteii.	8.8	6.3	6.8	3.8

Source: Author's calculations.

This result is attractive for its implication regarding the use of serial correlation as an estimator selection criterion. In fact, it suggests that, given the data sets used for the experiments, no matter the implied values of the RHOHAT parameter of the errors, the PCSE procedure always results in the most accurate confidence intervals. Therefore, the error parameter RHOHAT does not influence the selection of the procedure that improves the accuracy of confidence intervals. This result poses a real challenge to the finding on the use of the degree of serial correlation in the original data sets.

A further investigation of data reveal two outliers in the coverage gaps for OLSClusti (OLS plus heteroskedastic and first order serially correlated errors) for N>T which had affected the related mean and other statistics in Table 2.10. These outliers need to be addressed in order to get meaningful statistics for comparison purposes between this estimator and any other estimator. We adopt two distinct treatments for these outliers with effects on all estimators.

Table 2.10: Description of absolute coverage rates deviation from 95 percent over all experiments.

Estimator	N≤T					N>T				
	Minimum	Maximum	IQR	Mean	Standard Deviation	Minimum	Maximum	IQR	Mean	Standard Deviation
OLS	0.1	46.1	21.7	16.5	12.9	0.1	50.5	16.4	13.0	11.7
OLShet	0.0	40.9	25.3	16.5	12.2	0.1	43.4	14.2	14.2	10.8
OLSClusti	0.1	41.8	4.7	5.8	7.4	0.1	39.4	2.4	3.7	6.1
OLSClustt	0.0	41.7	17.9	15.3	11.9	0.0	38.0	13.4	15.6	10.5
FGLShet	0.0	43.1	24.0	17.4	13.4	0.1	46.4	23.9	16.9	14.0
FGLShetAR	0.0	13.8	4.4	5.0	3.3	0.2	11.4	3.0	3.8	2.4
GLSParks	2.1	95.0	70.1	53.4	34.3	--	--	--	--	--
PCSEParks	0.0	8.2	3.1	2.8	1.9	0.1	7.3	2.4	2.5	1.8
FGLSWhiteij	4.0	52.4	19.0	24.5	13.1	3.0	56.5	18.4	27.1	13.5
FGLSWhitet,	1.4	62.9	9.3	21.3	10.6	0.0	36.2	7.6	11.6	7.0
FGLSWhiteii.	0.3	46.6	19.6	20.9	12.7	0.8	51.6	20.9	19.8	13.6

Source: Author’s calculations.

Note: The number of observations is, respectively 92 for N≤T and 80 for N>T.

The first treatment consists in omitting the experiment trials for which these outliers occur. For the second treatment, we omit experiment trials with the entire data set for which the outliers are observed, namely the data used in Nunn and Qian (2014). For each treatment, we reproduce the average gap indicators of Table 2.10. Results of the post-treatment of outliers reported in Table 2.11 provide ample evidence that the precision with which confidence intervals are constructed is the same with Estimators 3 and 8. So again, the main finding this adds to the analysis above is that we could interchangeably use Estimators 3 or 8 had we aimed for an accurate confidence interval. But it still rules out the use of measured serial correlation to arrive at such a preference.

2.6.3. Micro-level diagnosis of recommendations.

2.6.3.1. The importance of micro-level diagnosis.

The typical choice problem for a researcher will be based on a single data set with specific data dimension values N and T. Therefore, it is worth investigating the validity of the recommendations discussed so far on the basis of a single data set at a time, and by considering independently each set of data dimension combinations used in the experiments. We carry out this investigation by producing and analysing disaggregated performances for each of the new data sets described in Table 2.6. A benefit from such an analysis would be its ability to remove the effects of averaging indicators to produce the recommendations, thereby leaving us with more realistic performance indices for each estimator given the data sets we have. This alternative for robustness control allows assessing the recommendations in terms of the ability to lead to right choices through a success rate indicator.

Table 2.11: Description post treatment of outliers of absolute gaps between coverage rates and the 95 percent threshold for N>T.

Estimator	Treatment 1					Treatment 2				
	Minimum	Maximum	IQR	Mean	Standard Deviation	Minimum	Maximum	IQR	Mean	Standard Deviation
OLS	0.1	50.5	16.7	13.0	11.8	0.2	50.5	20.1	14.4	12.7
OLShet	0.1	43.4	14.4	14.2	10.9	0.1	43.4	17.5	15.5	11.9
OLSClusti	0.1	10.9	2.3	2.7	2.2	0.1	10.9	2.2	2.5	2.2
OLSClustt	0.0	38.0	13.2	15.8	10.6	0.0	38.0	13.5	17.8	11.1
FGLShet	0.1	46.4	24.0	17.2	14.0	0.2	46.4	19.6	21.5	13.2
FGLShetAR	0.2	11.4	3.1	3.8	2.5	0.2	11.4	3.5	3.9	2.7
GLSParks	0.1	7.3	2.4	2.5	1.8	0.2	7.3	2.8	2.9	1.8
PCSEParks	3.0	56.5	18.3	27.3	13.6	3.0	56.5	10.4	30.3	14.0
FGLSWhiteij	0.0	36.2	7.8	11.7	7.0	3.4	36.2	8.2	12.8	7.0
FGLSWhitet,	0.8	51.6	20.6	20.2	13.6	0.8	51.6	19.3	23.2	13.9

Source: Author' calculations.

Note: the number of observations is, respectively 78 for treatment 1 and 60 for treatment 2.

The level of aggregation in the performance indicators is restricted to the two versions of the model error term specification (one version with only individual fixed effects and the other with both individual and time fixed effects). The total number of N-T combinations with all 5 new data sets is 87, of which 46 cases where N≤T. Furthermore, 28 experiments are associated with RHOHAT<0.30, of which 17 fall in the case where N≤T.

2.6.3.2. Defining predicted and realised best estimators.

We define the predicted best estimators on (i) efficiency and (ii) accuracy of confidence intervals as those estimators that the two new versions of recommendations would lead the researcher to choose. Predicted best estimators are selected according to the observed characteristics of the data set he/she has (based on T/N ratio or RHOHAT value).

In contrast, realised best estimators are those that perform best in the experiments. Contrary to predicted best estimators, realised best estimators are not known a priori based on data characteristics. A successful prediction of the best estimator occurs when the predicted best estimator is the same as the realised best estimator. Prediction success rates are defined as the frequency of successful predictions with regards to each recommendation. These are analysed below to gauge the robustness of the recommendations.

2.6.3.3. Diagnosis of recommendations.

We analyse below the statistics on the micro-performance of estimators for each performance criteria toward assessing the precision the recommendations. These statistics are visually represented in Figure 2.7.

2.6.3.3.1. Recommendation for efficiency based selection.

According to this recommendation, the predicted best estimator is the Parks FGLS if T/N>1.5, and the FGLS with groupwise heteroskedastic and first order serially correlated errors which has the OLS with groupwise heteroskedastic error as the closest substitute. The overall success rate for this recommendation is about 89 percent. This high total performance is explained by a good performance in the group of experiments where N≤T (76.1 percent) and an almost perfect prediction in the group of experiments with N>T (97.6 percent).

Furthermore, the performance of this recommendation could be reinforced by looking closely at the order of estimators' performance indicator figures. For 3 (N, T) combinations, the efficiencies of the realised and predicted estimators efficiencies are strikingly close ((54.55, 54.61), (88.38, 88.53), and (94.36, 95.06)). If these cases with small differences between the efficiencies of best predicted and realised estimators are taken as successful predictions, we obtain a total success rate of 92 percent for this recommendation due to fully accurate predictions when N>T and an improved 84.8 percent success in the performance of the recommendation when N≤T.

2.6.3.3.2. Recommendation for confidence interval precision selection.

Unlike the first rule about the efficiency that fares well in light of the performance presented above, the rule 2 for the selection of the estimator based on the confidence interval criterion has a very poor performance. It allows to choose the PCSEParks and the OLSClustt as best alternative performers for constructing confidence intervals when RHOHAT<0.30. To start with, the rule does not apply for more than half of the total experiments conducted, as the condition on the RHOHAT coefficient is satisfied for only 28 experiments out of 87[9].

[9] Experiments here consisted of two sub-experiments conducted with the same data set, the same data

Plus, of these experiments a decision could be made, the overall success rate of decisions falls far below 50 percent. The prediction power with N>T (55 percent success) is far better than that with N≤T (nearly 30 percent success).

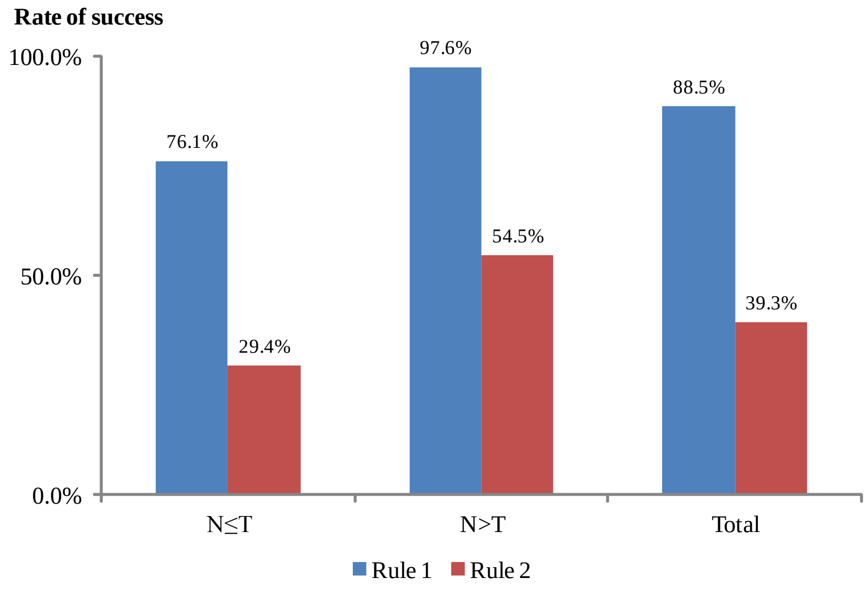


Figure 2.7: Success rates for rule 1 and rule 2 with new data sets.

2.7. Concluding remarks.

Researchers using econometric models implicitly need to support their theoretical analyses by summarizing relationships among series of relevant data. One important concern is to correctly summarize these relationships. This requires accounting for the characteristics of their data sets in light of the underlying assumptions of econometric models that guarantee good performance on estimation and inference. Many estimators have been made available and incorporated in statistical packages, but their performances on different data

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dimensions (T and N), but using two versions of DGP parameters with (i) only cross-sectional fixed effects and (ii) both cross-sectional and year fixed effects.

characteristics differ according to the treatment of data by underlying procedures and the types of data relationships they accommodate. This complicates an a priori selection of the best estimator to match specific data sets a given user of econometrics is analyzing. This difficulty is accentuated in the context of panel data models characterized by a much larger number of relationships among variables. Estimator selection appears thus to be one of the key determinants of an econometric model's performance.

RY attempted to empirically provide researchers with recommendations for choosing the best estimator among a set of commonly used estimators based on the data sets they had available by deploying a Monte Carlo simulation method. Their research resulted in a set of practical recommendations for econometric practitioners. They based their recommendation on the following data set characteristics: the ratio T/N, the severity of heteroskedasticity (HETCOEF), and the degree of serial correlation (RHOHAT) in the OLS residuals. They did not find that measured cross-sectional correlation was useful for identifying best performance.

However, it appears that their experimental design contained a flaw whose implications for the recommendations are investigated in this paper. The serial correlation in the regressor they used in their Monte Carlo experiments was inadvertently exaggerated. After adjusting for this flaw, we find the following:

(i) HETCOEF, which is one of the data characteristics used for recommendations in RY appears to be irrelevant for this purpose;

(ii) A single complete recommendation could be formulated from the panel data sets dimensions ratio (T/N) in place of two incomplete recommendations based on T/N ratio for the one while the other combines the HETCOEF indicator to the T/N ratio;

(iii) While recommendation 3 still holds post experimental design adjustment, the success of the recommendation is improved, making it more straightforward compared to its initial version.

We then carried out sensitivity analyses of these new findings using new data sets. The same experiments conducted after correcting for the experimental design were reproduced with these new data sets. After examining the experimental outcome, we note that some of the findings with the original data could be validated, while one major finding is not reproducible with the new data. A key original finding was that, in the group of estimators studied, the choice of the dominant estimator in efficiency grounds could be well done using the data dimensions ratio (T/N). We were able with the new data sets to validate the revised formulation of the combination of recommendations 1 and 2 in RY related to the efficiency of estimators. Thus, we conclude that there is strong evidence in favour of the recommendation that researchers who are interested in the most efficient estimator should (i) select the FGLS estimator with groupwise heteroskedastic and first order serially correlated errors if $T/N < 1.5$; and (ii) select the Parks estimator if $T/N \geq 1.5$.

As with the original data, experiments based on the new data sets result in the inconsistency of the use of the degree of heteroskedasticity to select an estimator for desirable efficiency. When $T>N$, the Parks estimator has shown superior on the efficiency criterion independently of the degree of heteroskedasticity of the generated error terms.

The last key implication of the sensitivity analysis is the alteration of the recommendation regarding the accuracy of the confidence interval. We were unable to confirm the ability of the serial correlation parameter in helping to select the estimator that produces the most accurate confidence interval. Here again, one estimator stands as the best on this criterion for estimator performance. However, this conclusion remains weak as experimental results show that its relative performance is sensitive to specific data sets, and different combinations of dimensions within a particular data set.

Taking stock of all the above, we conclude that though error parameters are critical in assessing the performance of the estimators investigated, some estimators are robust across different types of error behaviours when it comes to efficiency, but not for accuracy of confidence intervals. The need to have a robust procedure for constructing hypothesis tests is the motivation for the next chapter.

Lastly, we want to wrap up this chapter with a note on research situations that our findings could apply to in light of the nature of the data sets we used for experiments. All experiments were conducted with macro panel datasets with numbers of cross-sections ranging from 5 to 77 and time periods ranging from 5 to 25. Generalising our findings in such a limited coverage of data dimensions combinations context to all panel data sets is not possible. Therefore, we advise that further research using panel data sets with dimensions combinations outside those of our data to confirm the findings is needed before any generalisation is allowed in due course. In other words, while researchers using long and thin panel data sets could find our findings useful, those in possession of short and wide panel data sets from surveys with complex design for instance should avoid using our recommendations before additional research is done with such data.

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Appendices.

Appendix 2.1: Description of Rend and Ye (2011) datasets.

Dataset	*Source*	*Dependent Variable*	*Independent Variables*	*N*	*T*
1	Penn World Table	Log of real GDP	Ratio of government expenditures to GDP Country fixed effects	5, 10, 20, 50, 77	5, 10, 15, 20, 25
2	Penn World Table	Real GDP growth	Ratio of government expenditures to GDP Country fixed effects	5, 10, 20, 50, 77	5, 10, 15, 20, 25
3	Reed (2008)	Log of real state PCPI	Tax Burden State fixed effects	5, 10, 20, 48	5, 10, 15, 20, 25
4	Reed (2008)	Real state PCPI growth	Tax Burden State fixed effects	5, 10, 20, 48	5, 10, 15, 20, 25
5	Penn World Table	Log of real GDP	Ratio of government expenditures to GDP Country fixed effects Time fixed effects	5, 10, 20, 50, 77	5, 10, 15, 20, 25
6	Penn World Table	Real GDP growth	Ratio of government expenditures to GDP Country fixed effects Time fixed effects	5, 10, 20, 50, 77	5, 10, 15, 20, 25
7	Reed (2008)	Log of real state PCPI	Tax Burden State fixed effects Time fixed effects	5, 10, 20, 48	5, 10, 15, 20, 25
8	Reed (2008)	Real state PCPI growth	Tax Burden State fixed effects Time fixed effects	5, 10, 20, 48	5, 10, 15, 20, 25

Source: Reed and Ye (2011).

Appendix 2.2: List and Description of Panel Data Estimators.

Estimator	***Package***	***Command***
OLS	Stata	command = **xtreg**
OLShet	Stata	command = **xtreg** options = **robust**
OLSClusti	Stata	command = **xtreg** options = **cluster(**name of cross-sectional variable)
OLSClustt	Stata	command = **xtreg** options = **cluster(**name of time period variable)
FGLShet	Stata	command = **xtgls** options = **corr(independent) panels(heteroscedastic)**
FGLShetAR	Stata	command = **xtgls** options = **corr(ar1) panels(heteroscedastic)**
GLSParks	Stata	command = **xtgls** options = **corr(ar1) panels(correlated)**
PCSEParks	Stata	command = **xtpcse** options = **corr(ar1)**
FGLSWhiteij	EViews	GLS Weights = **Cross-section weights** Coef covariance method = **White cross-section**
FGLSWhitet,	EViews	GLS Weights = **Cross-section weights** Coef covariance method = **White period**
FGLSWhiteii	EViews	GLS Weights = **Cross-section weights** Coef covariance method = **White (diagonal)**

Source: Table 1 in Reed and Ye (2011).

Chapter 3 : Bootstrap Methods for Inference in the Parks Model.

3.1. Introduction.

The Seemingly Unrelated Regression (SUR) in general and panel data models in particular may be characterised by contemporaneously and serially correlated errors. Among the estimators accommodating these features of the disturbances, the Parks' (1967) estimator was shown to be unbiased (Magnus, 1978, Andrews, 1987) and efficient for both large and small sample sizes. Examples of empirical research supporting the efficiency of the Parks estimator include Kmenta and Gilbert (1970), Guilkey and Schmidt (1973), and more recently RY.

The major criticism directed to the Parks' (1967) estimator is that it produces negatively biased coefficient standard errors (Kmenta and Gilbert, 1970, Beck and Katz, 1995), due to the fact that estimates of the error variance-covariance matrix rather than the true values are used to compute the estimator's variance-covariance matrix. Freedman and Peters (1984) showed that in such circumstances, estimator variances are underestimated. This bias could be amplified by the large number of error parameters to be estimated with the Parks estimator (Reed and Webb, 2009). The Parks model consequently tends to result in smaller confidence intervals and over-rejection of the null hypothesis. Using Monte Carlo experiments, Beck and Katz (1995) reported that overconfidence with the Parks model could be severe unless T>>N. Consequently, they suggested an alternative to the Parks estimator, known as the "panel corrected standard errors" (PCSE). The PCSE expressly corrects the contemporaneous correlations estimated from the OLS residuals using Prais-Winsten transformed data. It considerably reduces the bias, and certainly does better than the Parks estimator in correcting the size distortion.

However, in the presence of non-spherical disturbances, most popular robust estimators, including the Beck and Katz's (1995) PCSE, fail to completely eliminate the level of distortion. Statistical hypothesis testing still suffers from a residual bias. Hence, it seems legitimate to reinvestigate the Parks efficient estimator using alternative testing methods such as bootstrap or jackknife techniques. We do this in this chapter by conducting hypotheses tests on the Parks estimator using bootstrapped critical values. This is achieved by re-sampling the residuals of the Parks estimator with SUR residuals. Both parametric and non-parametric re-sampling techniques are investigated. Results show that bootstrapped critical values of test statistics are well above the corresponding asymptotic critical values. Moreover, Monte Carlo experiments show a far better performance of the bootstrap based tests relative to the asymptotic theory based.

The remainder of the chapter is structured as follows. In Section 2, we summarize the literature on bootstrap techniques. Section 3 presents the model. Section 4 discusses the practice of hypothesis testing using parametric and non-parametric bootstrap techniques. The application of these techniques is carried out in Section 5. Section 6 discusses the Monte Carlo technique and implements it to illustrate the lessons drawn from the bootstrap techniques implementation. In Section 7, we control the robustness of the bootstrap and Monte Carlo experiments. Section 8 summarizes the main findings of the chapter.

3.2. Literature review.

Asymptotic inference in econometrics is based on the assumption that the limiting distribution of some empirical statistic of interest is well approximated by some standard distribution such as the standard normal distribution, the student distribution, or a chi-squared distribution. Even though such approximation works well for large sample sizes, most empirical studies in the economics field are constrained by data and use relatively small samples. Implementing asymptotic inference to perform statistical hypothesis tests in these studies using small sample size data sets would be inappropriate as the finite sample distributions of the statistics of interest might not – and are not expected to – be close enough to their corresponding asymptotic standard distributions. In the context of regression analysis, non-spherical errors that cause the variance covariance matrix of estimators to be biased constitute another reason asymptotic theory inference does not perform well.

To remedy the shortfall of the asymptotic theory inference theory, Quenouille (1949, 1956) and Tukey (1958) introduced the jackknife technique to estimate the bias and the variance of a statistic of interest. Miller (1974) surveyed early contributions to the development of the jackknife technique.

Later, Efron (1979) proposed the bootstrap technique as a more general empirical technique for statistical inference comprising the jackknife technique. Provided that the test statistic of interest is pivotal[10] under the null hypothesis, its bootstrap distribution converges to the true sample distribution[11]. See for instance Efron (1987), Hall (1988), Hall and Wilson (1991), Beran (1988), Horowitz (1994) and Davidson and MacKinnon (1999) for discussions about the importance of bootstrapping pivotal statistics. Bootstrap inference bases hypothesis test decisions upon the sample distribution of a sufficiently long series of asymptotically pivotal test statistics. The parameters of the data generating process for the replication of this series are allowed to satisfy the null hypothesis as suggested by Fisher and Hall (1990), and Hall and Wilson (1991) among others. Monte Carlo experiments produced smaller errors in the rejection probability relative to tests based on asymptotic theory in support of the theoretical analyses (see for instance Flachaire, 1999 and Lee, 2014).

The superior performance of bootstrap methods in reducing the size distortion of tests is

[10] A statistic is pivotal when its distribution does not depend on unknown parameters.

[11] MacKinnon (2002) suggested that even when the test statistic is not pivotal, a bootstrap based test would lead to a much more correct decision than a test based on an asymptotic distribution.

not necessarily achieved at the expense of the power of the tests. Research findings rather support that there are instances where the size and the power of tests are improved together (see for instance Beran, 1986, Davidson and MacKinnon, 1996, Mantalos and Shukr, 1996, Lin, Long & Ou, 2011). Bickel and Ren (1996 and 2001), Politis and Romano (1996), and Paparoditis and Politis (2005) and others provided theoretical evidence of this view.

Bootstrap inference has proven especially successful in regression analysis, where its superior performance in conducting statistical hypothesis tests has been demonstrated relative to asymptotic theory. In this context, there is first the sample size problem mentioned above that could affect the quality of standard asymptotic tests in conjunction with the convergence rate of test statistics. This concern with respect to the sample size applies to the bootstrap testing method as well especially when the test statistic is only asymptotically pivotal and its estimation thus falls short to be pivotal in a small sample size. In such case, the bootstrap test is not valid as the test statistic does depend on unknown population parameters. Yet, it is believed that relative to the asymptotic theory, the performance of a bootstrap based test under such a circumstance would still be better (see for instance Beran, 1988, Hall, 1992, and Davidson and MacKinnon, 1999).

The second problem of asymptotic tests relates to complex data structures - such as endogeneity sources or dependent disturbances - that could sharply deviate from standard assumptions necessary for accurate estimates and associated variance-covariance matrices upon which test statistics depend. This matters for the precision of asymptotic theory based tests as approximations of test statistics' distributions with standard distributions assume that the statistics themselves do not suffer from such empirical estimation problem. As discussed in the previous two chapters, error dependence is a rather frequent feature of panel data sets justifying the poor hypothesis test performances of estimators we examined in chapter 2. For this reason, it could be reasonably expected that bootstrap techniques designed to address data dependence can lead to significant improvements of test sizes in panel data regression analysis, provided that the structure of the data dependence under the null hypothesis is preserved by the bootstrap data generating process (MacKinnon, 2002).

Many bootstrap techniques were developed, some of which are applicable to independent data while others accommodate data dependencies. Surveys of bootstrap methods for dependent data are contained in Bühlmann (2002), Horowitz (2003), Politis (2003), Härdle et al. (2003) and MacKinnon (2006) among others. Chang (2004), Herwartz (2006), Shao (2011), Gonçalves and Vogelsang (2011) are examples of empirical studies applying bootstrap techniques to dependent data and obtaining hypothesis tests size improvement effects. Hounkannounon (2011) conducted an extensive survey of available bootstrap techniques and their applications in panel data models. He and other contributors including Kapetanios (2008), Andersson and Karlsson (2001) also showed that resampling methods could produce efficient panel estimators even with dependent data.

We propose to apply the bootstrap method to the Parks model using Zellner's (1962) SUR residuals. This model is presented in the next Section.

3.3. Model Description.

The description of the Parks model with SUR residuals that follows is inspired by Guilkey and Schmidt (1973, Appendix A) and Judge et al (1985, 485-487), Messemer (2003), and Messemer and Parks (2004). The model specification, its estimation and the implementation of the parametric and non-parametric bootstrap techniques for the statistical hypothesis test are discussed in turn.

3.3.1. Specification.

Each of the equations (3.1) and (3.2) below describes the SUR model with N equations and T observations per equation.

$$y_i = X_i\beta_i + e_i \text{, i = 1, 2, …, N,} \tag{3.1}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} X_1 & & & \\ & X_2 & & \\ & & \ddots & \\ & & & X_N \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_N \end{bmatrix}. \tag{3.2}$$

where y_i, X_i, β_i, and e_i are respectively (Tx1), (Txk), (kx1), and (Tx1) arrays using balanced panel data with the same number of variables for each cross-section[12]. The above could be more compactly summarized by equation (3.3).

$$y = X\beta + e. \tag{3.3}$$

where y, X, β and e are respectively (NTx1), (NTxNk), (Nkx1), and (NTx1) matrices. Besides, it is assumed that the expected value of the idiosyncratic disturbance is zero and that its variance-covariance matrix has a more general form with non-contemporaneous covariance and auto-covariance terms possibly taking on non-null values, such that:

E[e] = 0 and E[ee'] = Ω.

For each cross-section i in equation (1), $e_{(i)} = (e_{i1}, e_{i2}, \ldots, e_{it}, \ldots, e_{iT})'$ is assumed to satisfy the following condition:

$$e_{it} = \rho_i e_{i,t-1} + v_{it},\ t = 2, \ldots, \text{T.}, \tag{3.4}$$

Letting $\mathrm{v}_{(t)} = (\mathrm{v}_{1t}, \mathrm{v}_{2t}, \ldots, \mathrm{v}_{Nt})'$, and $V = \{v_{(t)}\}$, it is further assumed that:

$$\mathrm{E}\left[\mathrm{v}_{(t)}\right] = 0;$$

and

[12] The data need not be balanced or have the same number of variables for cross-sections for the method presented to work. We adopt those for both simplicity and for our specific purpose in doing this in conducting this investigation.

$$E[VV'] = \Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1N} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \cdots & \sigma_{NN} \end{bmatrix}, \text{ for all t } = 1, 2, \ \ldots, \ \text{T}. \tag{3.5}$$

3.3.2. Generalised least squares estimation.

If Ω, the variance-covariance matrix of the error term is known, then the SUR generalised least squares (GLS) estimator is defined as:

$$\beta = (X'\Omega^{-1}X)^{-1}(X'\Omega^{-1}y). \tag{3.6}$$

However, there are 2 difficulties with this GLS estimator. The first is the large dimension of Ω, which is an (NTxNT) array, making its inversion computationally intensive and prone to rounding errors. The second problem is that in general, the exact value of Ω is not directly revealed to researchers by the data. Due to these two problems, an empirical researcher must implement feasible generalised least squares (FGLS) instead of GLS, in which the individual elements of Ω are estimated. The Parks FGLS estimator is an alternative estimator of β that mitigates some of these difficulties. Its implementation is presented below.

3.3.3. The Parks feasible generalised least squares estimation.

The Parks FGLS estimator with SUR residuals is implemented in 5 steps as below:

i. Implement SUR with contemporaneously correlated disturbances.

- Estimate equation (3.3) using ordinary least squares and collect the residuals to compute the contemporaneous variance-covariance matrix Σ_{OLS}.

$$\Sigma_{OLS} = \frac{1}{T} E_{OLS}^{'} E_{OLS},$$

where E_{OLS} is a TxN matrix whose columns are made of individual OLS errors.

- Construct the OLS residuals full variance-covariance matrix as a block diagonal matrix.

$$\Omega_{OLS} = \Sigma_{OLS} \otimes I_{(T)} . \tag{3.7}$$

- The SUR estimate with contemporaneously correlated errors is given by:

$$\beta_{SUR} = [X'(\Sigma_{OLS}^{-1} \otimes I_{(T)})X]^{-1}[X'(\Sigma_{OLS}^{-1} \otimes I_{(T)})y] . \tag{3.8}$$

ii. Use errors from the SUR model with contemporaneously correlated errors to estimate the first-order serial correlation coefficient for each equation in system (3.1).

$$\varepsilon = y - X\beta ; \tag{3.9}$$

and

$$\rho_i = \frac{\sum_{t=2}^{T} \varepsilon_{it}\varepsilon_{i,t-1}}{\sum_{t=1}^{T-1} \varepsilon_{it}^{2}} . \tag{3.10}$$

- For t = 2, 3, …, T, and for each i, transform y_i and X_i series using ρ_i.

$$y_i^{\bullet} = P_{0i} y_i \quad and \quad X_i^{\bullet} = P_{0i} X_i \ , \tag{3.11}$$

where

$$P_{0i} = \begin{bmatrix} -\rho_i & 1 & 0 & \cdots & 0 \\ 0 & -\rho_i & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -\rho_i & 1 \end{bmatrix} .$$

- Regress $y_i^{\bullet}$ on $X_i^{\bullet}$ using OLS and collect the residuals to compute the estimate Σ of the contemporaneous variance-covariance matrix Σ .

$$\Sigma = \frac{1}{T-1} E^{'} E ,$$

where E is a (T-1)xN matrix whose columns are OLS residuals from the regression of

$y_i^{\bullet}$ on $X_i^{\bullet}$.

iii. Construct the full transformation matrix P, such that:

$$P\Omega P' = \Sigma \otimes I_{(T)}. \tag{3.12}$$

P has the form:

$$P = \begin{bmatrix} P_{11} & 0 & \cdots & 0 \\ P_{21} & P_{22} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ P_{N1} & \cdots & P_{N1} & P_{NN} \end{bmatrix}, \tag{3.13}$$

where

$$P_{ii} = \begin{bmatrix} \alpha_{ii} & 0 & 0 & \cdots & 0 \\ -\rho_i & 1 & 0 & \ddots & \vdots \\ 0 & -\rho_i & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -\rho_i & 1 \end{bmatrix}; \tag{3.14}$$

$$P_{ij} = \begin{bmatrix} \alpha_{ij} & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}; \tag{3.15}$$

$$A = \begin{bmatrix} \alpha_{11} & 0 & \cdots & 0 \\ \alpha_{21} & \alpha_{22} & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ \alpha_{N1} & \alpha_{N2} & \cdots & \alpha_{NN} \end{bmatrix}. \tag{3.16}$$

where A is defined as the product $H'(B)^{-1}$, B and H are upper triangular matrices satisfying $H'H = \Sigma$, $B'B = V_0$, and V_0 is the contemporaneous variance-covariance matrix of the error term ε and is defined as below. By construction, the matrix A contains initial parameters ensuring the stationarity of the error term in equation (3.1).

$$V_0 = \begin{bmatrix} \frac{\sigma_{11}}{1-\rho_1^2} & \frac{\sigma_{12}}{1-\rho_1\rho_2} & \cdots & \frac{\sigma_{1N}}{1-\rho_1\rho_N} \\ \frac{\sigma_{21}}{1-\rho_2\rho_1} & \frac{\sigma_{22}}{1-\rho_2^2} & \cdots & \frac{\sigma_{2N}}{1-\rho_2\rho_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sigma_{N1}}{1-\rho_N\rho_1} & \frac{\sigma_{N2}}{1-\rho_N\rho_2} & \cdots & \frac{\sigma_{NN}}{1-\rho_N^2} \end{bmatrix}. \quad (3.17)$$

It follows that:

$$\Omega^{-1} = P'(\Sigma^{-1} \otimes I_{(T)})P \quad . \quad (3.18)$$

iv. Apply P to transform y and X and use OLS on the transformed data to get the Parks estimator of the SUR model with contemporaneously and first order serially correlated errors.

$$y^* = Py \, . \quad (3.19)$$

$$X^* = PX \, . \quad (3.20)$$

$$\beta_{Parks} = [X^*{}'(\Sigma^{-1} \otimes I_{(T)})X^*]^{-1}[X^*{}'(\Sigma^{-1} \otimes I_{(T)})y^*] \, . \quad (3.21)$$

A consistent estimator of the covariance matrix of β_{Parks} is

$$V(\beta_{Parks}) = [X^*{}'(\Sigma^{-1} \otimes I_{(T)})X^*]^{-1} . \quad (3.22)$$

3.3.4. Hypothesis testing: Bootstrap vs. asymptotic critical values.

3.3.4.1. Test statistic, its distribution and test level distortion.

Let R and r be restriction arrays of respective dimensions qxNk and qx1 where q is the number of restrictions, such that:

$$R\beta_{Parks} = r \, . \quad (3.23)$$

This relationship broadly defines the hypothesis test of q joint restrictions on linear combinations of estimated coefficient parameters. The test statistic is given by equation (3.24).

$$g = [R\beta_{Parks} - r]'[RV(\beta_{Parks})R'][R\beta_{Parks} - r] \qquad (3.24)$$

The asymptotic distribution of g is Chi-square with q degrees of freedom. However, inference using the Parks estimator that is based on the asymptotic distribution of the test statistic over-rejects the null hypothesis in finite samples. We expect the bootstrap-based test to reduce this size distortion.

3.3.4.2. Implementation of the parametric bootstrap technique.

The parametric bootstrap technique is implemented by following 7 steps as described below in order to preserve the dependent structure of the errors.

i. Run the unrestricted model and compute the test statistic g using equation (3.24).

ii. Run the restricted model under the null hypothesis to get $\tilde{\beta}$, Σ, $\tilde{H}$ and $\tilde{A}$, then use the residuals to estimate the individual autocorrelation coefficients and form the diagonal matrix of autocorrelations.

$$\tilde{\Phi} = \begin{bmatrix} \tilde{\rho}_1 & & & 0 \\ & \tilde{\rho}_2 & & \\ & & \ddots & \\ 0 & & & \tilde{\rho}_N \end{bmatrix}$$

iii. Generate a sample of the dependent variable under the restriction (H_0) using $\tilde{\beta}$ plus the error term constructed in three steps as below:

a. Draw a NxT matrix $U = \{u_{(t)}\}$ consisting of random normal variables;

b. Pre-multiply U by the transpose of $\tilde{H}$ to construct the random disturbances, $V = \{v_{(t)}\}$ that preserve the covariance matrix Σ.

c. Use $\tilde{A}$ and $\tilde{\Phi}$ to transform the columns of V to construct the correlated error term $E = \{e_{(t)}\}$.

$$e_{(1)} = \tilde{A}^{-1}.v_{(1)} \text{ and } e_{(t)} = \tilde{\Phi}.e_{(t-1)} + v_{(t)} \text{ for t = 2, 3, …, T.}$$

iv. Compute the Parks estimator using the generated dependent variable and the initial set of regressors, and compute the bootstrap statistic $g_{boot,i}$ using equation (3.24).

v. Repeat steps ii through iv a sufficient number of times and store the resulting statistics, $g_{boot,i}$.

vi. Use the quantile g_{boot} of the stored bootstrap statistics to serve as the statistic to compare against the test statistic g.

vii. If $g \geq g_{boot}$, then reject the null hypothesis.[13]

3.3.4.3. Description of the non-parametric bootstrap technique.

The steps required to implement the non-parametric bootstrap technique are similar to the steps for the parametric bootstrap technique with exceptions at steps ii and iii. At step ii, one needs to collect the disturbance term of the restricted model and transform it in a TxN matrix $\tilde{E} = \{\tilde{e}_{(t)}\}$. This matrix is then converted into the untransformed matrix $\tilde{U}$ from which one operates a selection with replacement to form the random error term. This conversion is done by reversing the order of sub-steps in step 3 by the following transformations:

$\tilde{v}_{(1)} = \tilde{A}\tilde{e}_{(1)}$;

[13] In this research, we use the percentile-t method discussed in Bickel and Freedman (1981) and Efron (1981), which is more general in the sense that it could be applied to inference about a single parameter as well as a linear combination of parameters. However, we acknowledge the existence of refinement inference methods proposed by Efron (1982, 1987) and others for adjusting the confidence interval in single parameter inference settings.

$$\tilde{v}_{(t)} = \tilde{e}_{(t)} - \tilde{\Phi}\tilde{e}_{(t-1)} \text{ for } t = 2, 3, \ldots, T;$$

$$\tilde{U} = (\tilde{H}')^{-1}\tilde{V}.$$

Apart from the differences described for steps ii and iii, all other steps of the parametric bootstrap apply identically to the non-parametric bootstrap technique.

3.4. Illustration of the bootstrap technique.

3.4.1. Data and estimation.

To implement the bootstrap method described above, we use the Grunfeld time-series cross-section investment data set with 10 firms used in Hill et al. (2008). This data set contains observations of 3 variables on 10 US firms over 20 years, from 1935 to 1954. The dependent variable and two explanatory variables are, respectively, (1) the gross investment in plant and equipment, (2) the value of common and preferred stock, and (3) the stock of capital, all measured in constant US dollars of 1947.

We first use this data set with all 10 firms and 20 time periods. And then, we change the number of firms and the time period to study the behaviour of the estimator for different values of the ratio T by N. For this purpose, we use 5 and 7 firms with the full time period; and then we reduce the time period to 11 and use respectively 2, 5 and 10 firms. By reducing the time period, we intend to meet two specific needs. In fact, this will allow the assessment of the performance of the Parks estimator with SUR residuals (i) with small sample sizes, and (ii) when the ratio T by N is very close to 1. It is worth noting that performance is measured here by the accuracy of the estimator's confidence interval.

Table 3.1 presents the individual first-order autocorrelation coefficients for values of the time and individual dimensions described above. It indicates that the unit specific autocorrelations are not particularly high. The last two rows contain the test statistic and the p-value of hypothesis tests that all correlation coefficients in a given column are jointly equal to 0. One could see that in three cases (the last three columns) where respectively 2, 5 and 10 firms are observed in 11 years (from 1935 to 1945) the null hypothesis is rejected at the 10 percent confidence level. In the three other cases, the null hypothesis is rejected at the 5 percent level.

Table 3.1: Individual autocorrelation coefficients.

	T = 20 (1935- 1954)			**T = 11 (1935 - 1945)**		
Firms	**N = 5**	**N = 7**	**N = 10**	**N = 2**	**N = 5**	**N = 10**
General Motors	0.432	0.493	0.535	0.560	0.563	0.565
US Steel	0.450	0.466	0.536	0.285	0.360	0.417
General Electric	0.499	0.489	0.513		0.304	0.271
Chrysler	0.014	0.026	0.034		-0.393	-0.438
Atlantic Richfield	-0.211	-0.169	-0.201		-0.201	-0.218
IBM		0.102	0.163			0.133
Union Oil		0.122	0.120			-0.295
Westinghouse			0.373			0.295
Goodyear			0.357			-0.418
Diamond Match			0.487			-0.159
q-statistic	**13.647**	**15.072**	**28.454**	**4.344**	**8.074**	**13.169**
p-value	**0.018**	**0.035**	**0.002**	**0.114**	**0.152**	**0.214**

Source: Author's calculations.

3.4.2. Test statistic and critical values.

We test 3 restrictions using both parametric and non-parametric methods. First, we test the significance of the first slope of the first equation. We then test the difference between the first slope in the first equation and the first slope in the second equation. Lastly, we test (i) the difference between the first slope in the first equation and the first slope in the second equation, and (ii) the second slope in the first equation and the second slope in the second equation. For illustration, when N = 2, the restriction matrices for these tests are:

$$R_1 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0 & 1 & 0 & 0 & -1 & 0 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 \end{bmatrix}$$

Table 3.2 contains the test statistics calculated according to equation (3.24), the asymptotic and the bootstrapped critical values. The statistics g1, g2, and g3 are respectively associated with restrictions represented by matrices R_1, R_2 and R_3 used for matrix R in equations (3.23) and (3.24). Asymptotic distributions for these statistics are respectively χ_1^2 for g1 and g2, and χ_2^2 for g3. Two observations are in order with respect to the figures in this table. First, it is the case that both parametric and non-parametric bootstrapped critical values are well above the corresponding asymptotic statistics. This suggests that the type-I error will be less frequent in tests using the two former statistics rather than the asymptotic statistics. Second, it could be observed that the parametric and non-parametric bootstrapped critical values are close for a given test. These two observations translate into different rejection decisions for the 12 tests in Table 3.2 when using the asymptotic critical values of the test statistic (12 rejections), the parametric (8 rejections) and the non-parametric (9 rejections) bootstrapped critical values. The following lesson emerges from these test results:

Lesson 1: ***The number of rejections of the null hypothesis is higher when using the asymptotic critical values, and approximately the same for the parametric and non-parametric bootstrapped critical values.***

The implication of this first lesson is that the bootstrap techniques could be used with the Parks model to correct the size distortion of hypothesis tests. What cannot be inferred from the results in the table is the extent to which this approach corrects size distortion. To investigate this aspect, we conduct Monte Carlo experiments in the next section.

Table 3.2: Empirical, asymptotic and bootstrapped critical values.

N	Test statistic		Asymptotic critical value	Bootstrapped critical values	
				Parametric	Nonparametric
	T = 20				
5	g1 =	32.214	3.841	9.039	8.861
	g2 =	1.226	3.841	7.917	8.949
	g3 =	1.340	5.991	12.697	12.007
7	g1 =	42.713	3.841	11.293	10.893
	g2 =	2.073	3.841	13.024	13.040
	g3 =	2.553	5.991	16.958	16.605
10	g1 =	50.709	3.841	14.712	16.562
	g2 =	12.274	3.841	16.605	21.097
	g3 =	17.278	5.991	25.589	28.742
	T = 11				
2	g1 =	23.949	3.841	10.618	13.912
	g2 =	22.572	3.841	13.043	14.332
	g3 =	23.049	5.991	22.058	23.970
5	g1 =	23.729	3.841	17.605	20.020
	g2 =	31.911	3.841	21.870	23.322
	g3 =	32.489	5.991	30.337	30.333
10	g1 =	23.937	3.841	55.571	54.644
	g2 =	39.472	3.841	43.376	115.260
	g3 =	41.234	5.991	64.960	82.175

Source: Author's calculations.

3.5. Monte Carlo evidence of the level distortion remediation.

3.5.1. Monte Carlo experiments implementation.

We provide Monte Carlo evidence of the test level distortion correction with the Parks estimator by using the same data set and its sub-sets used in the previous section. We use three null hypotheses corresponding to the three restrictions represented by the matrices R_1, R_2 and R_3. That is, we start off with the estimated coefficients using the Parks model with SUR first order auto-correlated residuals.

The Monte Carlo experiments are implemented in 6 steps:

i. choose parameters for the model satisfying the null hypothesis;

ii. generate a sample data set;

iii. using the generated data set, test the null hypothesis using critical values from the χ_q^2 distribution with a nominal level of significance, α;

iv. from the generated data, apply the bootstrap technique to get the bootstrapped critical values and then proceed with the test;

v. repeat ii through iv to get L (L = 1000 in our case) Monte Carlo samples, and decisions based on asymptotic critical values and bootstrapped critical values;

vi. compare the frequencies of rejection in the Monte Carlo samples between them and with the nominal level of the test (0.05 in our study).

We then impose three sets of restrictions:

- the first slope of the first equation is set to 0;
- the first slope of the first equation is set to the value of the first slope of the second equation; and
- the first and second slopes of the first equation are set equal to the first and second slopes of the second equation, respectively.

3.5.2. Monte Carlo experiments report.

The rejection rates of the true null hypotheses described above are summarized in Table 3.3 below. They are reported in the last three columns and are expected to be comparable to the nominal level reported in the third column in the ideal world. Column 4 contains the rejection rates corresponding to the type-I error when the asymptotic critical values are used for the tests. As expected, it confirms the over-rejection of the true null hypothesis that characterises the Parks model.

Table 3.3: Nominal, asymptotic and bootstrapped type I error rates.

N	Test statistic	Nominal level	Asymptotic rejection rates	Bootstrapped rejection rates	
				Parametric	Nonparametric
	T=20				
5	g1	0.050	0.172	0.043	0.042
	g2	0.050	0.186	0.050	0.055
	g3	0.050	0.253	0.044	0.047
7	g1	0.050	0.195	0.039	0.039
	g2	0.050	0.235	0.047	0.047
	g3	0.050	0.325	0.052	0.051
10	g1	0.050	0.312	0.061	0.052
	g2	0.050	0.308	0.038	0.032
	g3	0.050	0.460	0.058	0.050
	T=11				
2	g1	0.050	0.175	0.036	0.037
	g2	0.050	0.184	0.046	0.040
	g3	0.050	0.308	0.051	0.047
5	g1	0.050	0.260	0.042	0.040
	g2	0.050	0.277	0.041	0.034
	g3	0.050	0.437	0.051	0.042
10	g1	0.050	0.407	0.030	0.020
	g2	0.050	0.471	0.039	0.025
	g3	0.050	0.644	0.055	0.041

Source: Author’s calculations.

Additionally, as the number of equations - or individuals - increases for a given value of the time period, the performance of the Parks model in producing accurate confidence interval systematically worsens. Such a result is also observed when the time period decreases but the number of equations is the same. These two observations combined indicate that the bias in the estimator standard error exhibits a negative relationship with the ratio of the time period dimension over the individual dimension of the data set (T/N)

The two last columns of Table 3.3 contain the rejection rates of the true null hypothesis with bootstrapped critical values using the Parks model. As was the case with the bootstrapped statistics, the rejection rates are close to each other and do not exhibit a particular pattern with respect to N or T. More interestingly, the values in both columns are very close to the nominal test level of 5 percent. The following second lesson is thus in order:

Lesson 2: ***Both parametric and non-parametric bootstrap techniques combined with the Parks model help successfully correct the size distortion of the statistical hypothesis test that characterises this model.***

3.6. Robustness diagnosis of findings.

In this section, we conduct the robustness diagnosis of the conclusions inspired by the test results according to which:

- the rejection rate of the true null hypothesis is higher with asymptotic critical values and roughly the same for parametric and non-parametric bootstrapped critical values; and
- both bootstrap techniques effectively eliminate the level distortion of the type-I error.

We do this robustness control by reproducing the bootstrap and Monte Carlo analyses of the last 2 sections using 2 new data sets[14]. We first present the new data sets and then the outcome of the control.

3.6.1. New data sets description.

The first data set is a subset of the data set used in Bruckner (2013) to study the effect of real per capita GDP growth on development aid in receiving countries. We have extracted

[14] We would like to make it clear that even though these data sets are drawn from previous research, our intention is not to compare our estimates with those obtained by authors of the papers using the original data sets; we just wanted some data for our own work.

from this original data set a balanced panel data set consisting of 44 countries and 25 time periods focussing on two key variables: the net official development aid received by countries and real per capita GDP growth. We then use multiple subsets of these data by including in the model different numbers of countries to allow the ratio of time to unit dimensions to vary. We use 5, 10, 15, 20, and 24 countries so that the range of the ratio of time to unit dimensions goes from 5 to 1.04.

The second data set is the one used in Biagi et al. (2012) to analyse the effect of tourism on crime in Italian provinces. This data consists of 95 provinces and 19 time periods. One time period will be lost due to the use of the GDP growth rate in the model as a control variable along with 5 other control variables. Here, as well, we use multiple values for the unit dimension (5, 10, 15 and 17) and keep the time period to 18 years. The ratio of the time and unit dimensions ranges from 3.6 to 1.06.

3.6.2. Analysis of replicated results.

The data sets described above are used to estimate the Parks model with SUR residuals. We then study the bootstrap techniques using Monte Carlo experiments as described and implemented in the previous two sections. We adapt the tests to accommodate the fact that there is just one explanatory variable for one of the two datasets. Accordingly, the following tests are carried out. For the first data set, that on growth and aid:

(i) the significance of the first slope for the first individual;

(ii) the difference of the first slope for the first two individuals; and

(iii) jointly, the difference of the intercepts for the first two individuals on the one hand, and that of the slopes for the first two cross-sections on the other hand.

For the other data set, the first two test specifications are the same as above while the last specification compares the first two slopes for the first and second equations rather than the intercept and the slope.

The restriction matrices R_1, R_2 and R_3 are easily adapted for the purpose of these tests. Likewise, we call the test statistics obtained for the above tests g1, g2, and g3 respectively.

We set the first focus on lesson 1 relative to the bootstrapped critical values. Table 3.4 contains the asymptotic and bootstrapped critical values of the three tests. We note that figures in this table conform to Lesson 1. Bootstrapped critical values are all well above their asymptotic counterparts. Besides, it is clear that of the 27 hypothesis tests carried out, no rejection appears with the non-parametric bootstrapped critical values; the parametric bootstrapped critical values allow us to reject the true null hypothesis only once while 10 rejections are recorded when asymptotic critical values are considered.

However, if the conformity of these results with Lesson 1 is reaffirmed, there is a major exception that needs to be pointed out. The proximity of the parametric and non-parametric bootstrapped critical values observed with the Grunfeld data does not hold here in a few cases. In most cases, the parametric and non-parametric bootstrapped critical values are close for given tests, but in a few cases, the non-parametric bootstrapped critical values are significantly larger than the parametric bootstrapped critical values. Furthermore, the gap between the two statistics is significantly larger for the data set on aid and growth when $N \geq 15$. This is not a general result, but it indicates a potential for the non-parametric bootstrap to lead to overconfidence in hypothesis test decisions.

Table 3.4: Critical values with the new data sets.

N	Test statistic		Asymptotic critical values	Bootstrapped critical values	
				Parametric	Nonparametric
	Aid and growth data (T = 25)				
5	g1 =	1.231	3.841	6.524	6.997
	g2 =	0.633	3.841	6.853	6.148
	g3 =	0.691	5.991	8.203	9.523
10	g1 =	1.083	3.841	11.171	11.115
	g2 =	1.459	3.841	11.000	11.943
	g3 =	1.519	5.991	13.211	15.174
15	g1 =	2.882	3.841	23.384	17.780
	g2 =	1.372	3.841	29.358	48.901
	g3 =	1.373	5.991	26.451	37.846
20	g1 =	22.712	3.841	86.706	70.612
	g2 =	11.089	3.841	115.379	251.708
	g3 =	12.992	5.991	75.240	190.361
24	g1 =	293.300	3.841	264.889	568.559
	g2 =	2.005	3.841	276.919	968.140
	g3 =	2.059	5.991	249.017	677.730
	Tourism and crime data (T = 18)				
5	g1 =	4.401	3.841	17.480	15.485
	g2 =	2.157	3.841	15.403	15.157
	g3 =	7.183	5.991	21.634	23.501
10	g1 =	3.704	3.841	32.103	27.348
	g2 =	1.519	3.841	26.035	19.365
	g3 =	7.789	5.991	41.810	35.690
15	g1 =	4.593	3.841	82.469	55.907
	g2 =	1.618	3.841	69.090	48.830
	g3 =	14.291	5.991	87.347	86.291
17	g1 =	1.476	3.841	45.083	38.762
	g2 =	0.387	3.841	46.905	38.460
	g3 =	19.729	5.991	88.408	81.123

Source: Author's calculations.

We now turn the focus to the Monte Carlo experiments' results reported in Table 3.5. We observe that the type I error rates reported in column 4 again confirm the over-rejection that characterises the Parks model when asymptotic critical values are used. We also note the confirmation that decreasing the ratio of the time to the unit dimensions of the time series cross-section data set increases the probability of rejecting the true null hypothesis under the asymptotic theory. More evidence of this assertion is found in Appendix 3.1, which summarizes statistics on the absolute deviations of the test sizes from the nominal level (5 percent). The average deviation, ideally expected to be zero, is actually at least 31 percent for any of the three tests, with the upper limit for each test above 65 percent. Appendix 3.2 investigates the role of N and T further by aggregating results separately over T and N, respectively. The results confirm that both data dimensions matter individually.

The two last columns of Table 3.5 contain the rejection rates of the null hypothesis with parametric (second last column) and non-parametric (last column) bootstrapped critical values. The interpretation of the statistics in these 2 columns leads to the confirmation of Lesson 2 with a clear nuance. On the one hand, it appears that the parametric bootstrap technique produces rejection rates that are comparable to the nominal level of 0.05 except in very few cases as observed with critical values. In that, we find that the parametric bootstrap technique suitably corrects the level distortion of hypothesis tests when combined with the Parks estimator.

On the other hand, it could be said of the non-parametric bootstrap technique that it is efficient in remediating the over-rejection of the null hypothesis characterizing the Parks model. Caution should be in order, though, as it shows overconfidence in an inconsistent way when the ratio of the time by unit dimensions falls. Further research is needed to identify the cause of this inconsistent overconfidence with the non-parametric bootstrap technique as we have no justification for it.

Table 3.5: Rejection rates with the new data sets.

N	Test statistic	Nominal level	Asymptotic rejection rates	Bootstrapped rejection rates	
				Parametric	Non-parametric
	Aid and growth data (T = 25)				
5	g1	0.05	0.139	0.043	0.040
	g2	0.05	0.150	0.066	0.062
	g3	0.05	0.127	0.045	0.015
10	g1	0.05	0.197	0.055	0.050
	g2	0.05	0.232	0.036	0.023
	g3	0.05	0.247	0.056	0.026
15	g1	0.05	0.355	0.030	0.033
	g2	0.05	0.369	0.030	0.007
	g3	0.05	0.367	0.048	0.013
20	g1	0.05	0.577	0.023	0.018
	g2	0.05	0.633	0.033	0.006
	g3	0.05	0.607	0.042	0.009
24	g1	0.05	0.705	0.027	0.008
	g2	0.05	0.774	0.035	0.009
	g3	0.05	0.750	0.043	0.005
	Tourism and crime data (T = 18)				
5	g1	0.05	0.305	0.045	0.047
	g2	0.05	0.289	0.048	0.042
	g3	0.05	0.471	0.076	0.080
10	g1	0.05	0.422	0.041	0.054
	g2	0.05	0.405	0.032	0.043
	g3	0.05	0.608	0.072	0.082
15	g1	0.05	0.647	0.050	0.070
	g2	0.05	0.655	0.061	0.073
	g3	0.05	0.807	0.059	0.085
17	g1	0.05	0.519	0.041	0.049
	g2	0.05	0.484	0.042	0.048
	g3	0.05	0.706	0.059	0.056

Source: Author's calculations.

Based on this empirical observation, we recommend favouring the parametric bootstrap result when one gets two significantly different results by applying simultaneously these two techniques. This recommendation is further supported by statistics in Appendix 3.1

showing that on average, the absolute deviation of test sizes from the nominal level is higher for the non-parametric bootstrap compared to the parametric bootstrap for any of the three hypotheses tests considered.

3.7. Feasibility of the bootstrap techniques.

One thing that may be seen as a limit to the implementation of the bootstrap techniques especially with large data sets is that they are computationally intensive. We examine the computation time requirements across three dimensions:

i. the number of independent restrictions;
ii. the size of the individual dimension; and
iii. the number of variables in the model.

The time period is held constant for this investigation. There are two alternatives with a fixed number of variables. First, we fix the number of individuals in the model and evaluate the cost of adding an extra restriction. Second, we fix the number of restrictions and examine the time cost of increasing the number of equations. The third alternative involves gradually increasing the number of variables and the number of independent restrictions. We thus study the effect of adding these extra variable and/or independent restrictions.

The data on tourism in Italy is used for this feasibility study. All the eight explanatory variables including the constant are used. When all eight variables are included in the model, we use ten different values for the cross-sectional units (N = 2, 4, 6, 8, 10, 13, 14, 15, 16 and 17) and implement the bootstrap techniques ten times for each of these values. We first test the significance of the first constant, and then we progressively add independent restrictions for the next coefficients up to the tenth. This covers all coefficients for the first individual plus the constant and the slope of the first explanatory variable for the second individual.

When variables are included progressively in the model, we implement the bootstrap techniques eight times, starting off with one variable plus the constant in the model and testing the significance of the first slope of the first equation. Then we add to this first test an independent test of the significance of the constant. Then the remaining variables are added to the model one by one followed by independent restrictions to test the significance of their respective slopes for the first equation. The execution times analysed in the next paragraphs are for both parametric and non-parametric bootstrap techniques modelled in a single serial code in SAS and executed on the supercomputer.

Table 3.6 contains the execution time of the SAS (IML) code for multiple combinations of independent restrictions and numbers of cross-section units when the number of variables in the model is fixed[15]. This data reveal a marked sensitivity of the execution time with respect to the two dimensions. The relationship between the execution time of the code and each dimension is further examined in the next paragraph.

The three last rows of Table 3.6 provide standard linear relationship parameters between the execution time of the code and the number of restrictions in the form of a simple regression of the execution time on the number of restrictions. These parameters suggest a very tight positive linear relationship between the two variables for different values of the cross-section units used. The R-squared values range between 0.85 and 1 for only 10 observations. Furthermore, the slope of the regression is positive and increases with the number of equations. The top panel of Appendix 3.3 graphically illustrates this relationship when the number of cross-sections is 17. We observe the positive trend with bumps that are explained by the fact that the supercomputer that allows us to run concurrently multiple instances of the code with different number of restrictions uses two partitions with different

[15] The Stata version of our SAS code will be used on a personal computer to further investigate the implement time requirement for both the parametric and nonparametric techniques developed in this Chapter.

performances. Panel b of Appendix 3.3 suggests that the time execution of the code increases exponentially with the number of cross-sectional units. The execution time cost of gradually including variables and restrictions is illustrated in the figure of Appendix 3.4. The number of cross-sections is fixed at 17. When the number of restrictions increases, the execution time rises exponentially.

The implication of these observations is that implementing the bootstrap techniques may take longer for models involving a large number of variables and many equations, with subsequent increase in the number of possible hypotheses that can be tested (significance of variables and linear combinations of coefficients).

Table 3.6: Distribution of execution time (in minutes) across the number of restrictions and cross-sections (N).

Independent Restrictions	N=17	N=16	N=15	N=14	N=13	N=10	N=8	N=6	N=4	N=2
1	5.17	3.30	2.00	1.65	1.33	0.65	0.35	0.18	0.07	0.03
2	13.95	6.72	4.03	3.45	2.68	1.30	0.70	0.33	0.13	0.05
3	18.90	9.83	6.00	4.95	4.63	1.93	1.18	0.50	0.20	0.05
4	25.80	13.25	13.12	6.60	6.77	2.60	1.40	0.65	0.28	0.08
5	40.80	16.48	10.05	8.25	8.28	3.25	1.73	0.82	0.32	0.10
6	48.58	19.78	12.03	9.90	10.38	3.88	2.10	0.98	0.38	0.10
7	96.32	23.15	14.27	11.55	11.60	4.60	2.92	1.32	0.45	0.12
8	68.12	26.68	16.00	13.42	13.20	5.17	2.78	1.30	0.52	0.13
9	110.50	29.80	18.02	14.85	14.92	5.88	3.13	1.47	0.57	0.15
10	83.18	32.90	19.97	16.55	13.33	6.48	3.48	1.63	0.62	0.18
Slope	11.17	3.30	1.91	1.65	1.53	0.65	0.35	0.16	0.06	0.02
Intercept	-10.32	0.02	1.05	0.03	0.28	0.00	0.04	0.01	0.02	0.01
R^2	0.85	1.00	0.93	1.00	0.96	1.00	0.98	0.99	1.00	0.97

Source: Author's calculations.

In today's information age, ways to counter this problem exist, which is rather good news. These ways include the availability of supercomputers, the performance improvements in personal computers in terms of processing power (multithreading) and advances in the capabilities of many statistical programming packages with improved programming features (internal parallelism). Our intention in presenting this feature is to bring it to the attention of researchers willing to gain from these techniques so they are aware of it and consequently adopt appropriate solutions they have available.

3.8. Conclusion.

In this study, we have used bootstrap techniques and Monte Carlo analysis to re-examine the performance of the Parks model using the accuracy of the estimator's confidence interval criterion. It has been an opportunity to reinforce what is already known about the performance of the Parks model using this performance criterion under the asymptotic theory. Our findings confirm that relying on the asymptotic theory to produce the estimator's confidence interval or to perform hypothesis tests with the Parks model yields wrong results due to a negative bias in the estimator's standard error. We further observe that this bias is negatively correlated with the ratio of the time to individual dimensions (T/N) of the TS-CS data set. The bias becomes severe when T/N is close to unity. This characteristic has discouraged many researchers from using the Parks model, despite its efficiency properties.

Most importantly, this study has provided an opportunity to find ways to effectively remedy the test level distortion associated with the Parks model. Our Monte Carlo experiments have shown that bootstrap techniques (both parametric and non-parametric) can be used with the Parks model to ensure accurate confidence intervals are built for estimators, and trustworthy hypothesis test decisions made. This result is important since it allows researchers to benefit from the Parks model's efficiency without worrying about its otherwise poor performance when applied to hypothesis testing.

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Appendices.

Appendix 3.1: Average absolute deviations of actual test sizes from the nominal level (0.05) by T/N ratio.

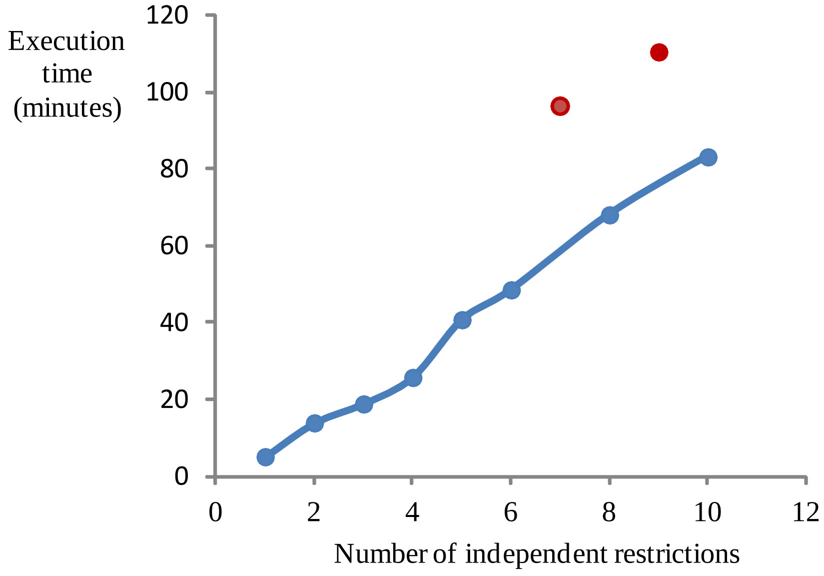
T/N	T	N	Test statistic = g1			Test statistic = g2			Test statistic = g3		
			Asymptotic	Parametric	Non-parametric	Asymptotic	Parametric	Non-parametric	Asymptotic	Parametric	Non-parametric
1.042	25	24	0.655	0.023	0.042	0.724	0.015	0.041	0.700	0.007	0.045
1.059	18	17	0.469	0.009	0.001	0.434	0.008	0.002	0.656	0.009	0.006
1.100	11	10	0.357	0.020	0.030	0.421	0.011	0.025	0.594	0.005	0.009
1.200	18	15	0.597	0.000	0.020	0.605	0.011	0.023	0.757	0.009	0.035
1.250	25	20	0.527	0.027	0.032	0.583	0.017	0.044	0.557	0.008	0.041
1.667	25	15	0.305	0.020	0.017	0.319	0.020	0.043	0.317	0.002	0.037
1.800	18	10	0.372	0.009	0.004	0.355	0.018	0.007	0.558	0.022	0.032
2.000	20	10	0.262	0.011	0.002	0.258	0.012	0.018	0.410	0.008	0.000
2.200	11	5	0.210	0.008	0.010	0.227	0.009	0.016	0.387	0.001	0.008
2.500	25	10	0.147	0.005	0.000	0.182	0.014	0.027	0.197	0.006	0.024
2.857	20	7	0.145	0.011	0.011	0.185	0.003	0.003	0.275	0.002	0.001
3.600	18	5	0.255	0.005	0.003	0.239	0.002	0.008	0.421	0.026	0.030
4.000	20	5	0.122	0.007	0.008	0.136	0.000	0.005	0.203	0.006	0.003
5.000	25	5	0.089	0.007	0.010	0.100	0.016	0.012	0.077	0.005	0.035
5.500	11	2	0.125	0.014	0.013	0.134	0.004	0.010	0.258	0.001	0.003
Observations			**15**	**15**	**15**	**15**	**15**	**15**	**15**	**15**	**15**
Mean			**0.309**	**0.012**	**0.014**	**0.327**	**0.011**	**0.019**	**0.424**	**0.008**	**0.021**
Minimum			**0.089**	**0.000**	**0.000**	**0.100**	**0.000**	**0.002**	**0.077**	**0.001**	**0.000**
Maximum			**0.655**	**0.027**	**0.042**	**0.724**	**0.020**	**0.044**	**0.757**	**0.026**	**0.045**

Source: Author's calculations.

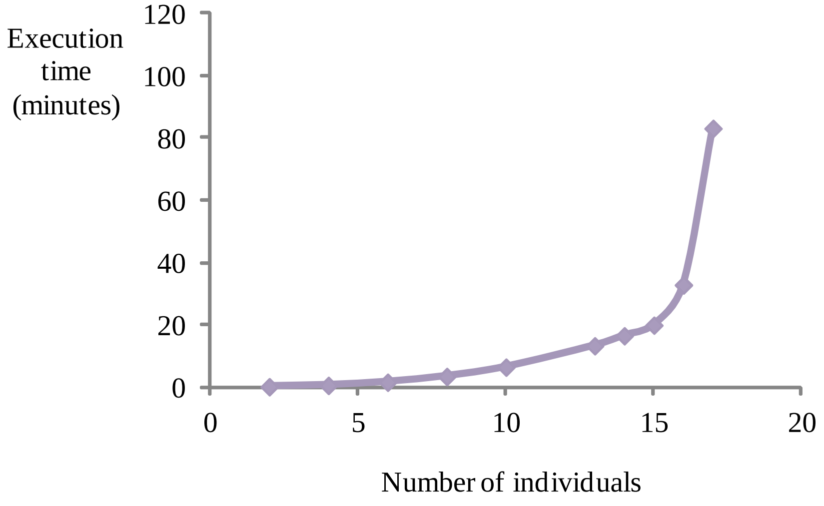
Appendix 3.2: Average absolute deviations of actual test sizes from the nominal level by data set.

Data set		Asymptotic			Parametric bootstrap			Non-parametric bootstrap		
		g1	**g1**	**g3**	**g1**	**g1**	**g3**	**g1**	**g1**	**g3**
	a) N Varies N									
Bruckner (2013)	5	0.089	0.100	0.077	0.007	0.016	0.005	0.010	0.012	0.035
	10	0.147	0.182	0.197	0.005	0.014	0.006	0.000	0.027	0.024
	15	0.305	0.319	0.317	0.020	0.020	0.002	0.017	0.043	0.037
	20	0.527	0.583	0.557	0.027	0.017	0.008	0.032	0.044	0.041
	24	0.655	0.724	0.700	0.023	0.015	0.007	0.042	0.041	0.045
Hill et al. (2008)	2	0.125	0.134	0.258	0.014	0.004	0.001	0.013	0.010	0.003
	5	0.166	0.182	0.295	0.008	0.005	0.004	0.009	0.011	0.006
	7	0.145	0.185	0.275	0.011	0.003	0.002	0.011	0.003	0.001
	10	0.310	0.340	0.502	0.016	0.012	0.007	0.016	0.022	0.005
Biagi et al. (2012)	5	0.255	0.239	0.421	0.005	0.002	0.026	0.003	0.008	0.030
	10	0.372	0.355	0.558	0.009	0.018	0.022	0.004	0.007	0.032
	15	0.597	0.605	0.757	0.000	0.011	0.009	0.020	0.023	0.035
	17	0.469	0.434	0.656	0.009	0.008	0.009	0.001	0.002	0.006
	b) T varies T									
Bruckner (2013)	25	0.345	0.382	0.370	0.016	0.016	0.006	0.020	0.033	0.036
Hill et al. (2008)	11	0.231	0.261	0.413	0.014	0.008	0.002	0.018	0.017	0.007
	20	0.176	0.193	0.296	0.010	0.005	0.005	0.007	0.009	0.001
Biagi et al. (2012)	18	0.423	0.408	0.598	0.006	0.010	0.017	0.007	0.010	0.026

Figures.



a. Time cost of additional restrictions when the number of cross-sections is 17



b. Time cost of additional cross-sections when testing 10 restrictions

Figure 3.1: Execution time costs for 7 regressors plus the constant.

<u>Note:</u> Two points in the top panel fall far off the "perfect" linear relationship between the number of independent restrictions and the execution time (in minutes). This is due to the use of multiple processors with different performances to run the programmes for the different cases.

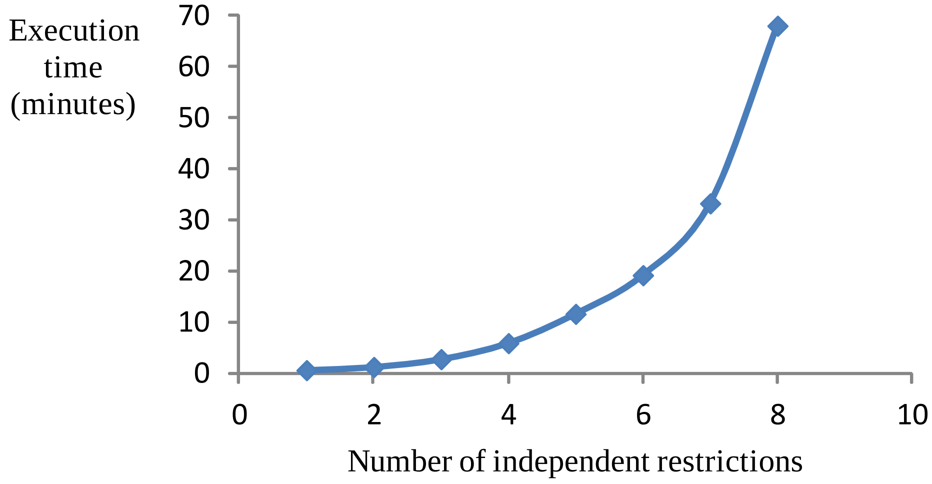


Figure 3.2: Execution time cost when gradually increasing regressors and restrictions (17 cross-sections included in the model).

Chapter 4 : Economic growth vs. human capital: links and drivers in Africa.

4.1. Introduction.

It seems obvious that the labour force is not homogeneous as workers differ greatly in abilities, skills and qualifications. In the same vein, even though unskilled jobs exist, there are many jobs requiring specific sets of skills at various levels, physical or intellectual. There are many ways people accumulate human capital. Formal schooling, on-the-job training, and health care services are all contributing activities to the human capital accumulation process. Migration is another means that determines an effective distribution of skilled labour force among organisations, regions, or countries.

Human capital accumulation entails explicit and implicit costs incurred by individuals, organisations and governments. Financial resources invested in human capital constitute explicit costs; while the time spent acquiring human capital accounts for implicit costs.[16] The rationale of incurring these costs is that skills invested in are expected to positively affect the workers output, thereby increasing the economic performance of the organisations they work for and that of society at large.

The recognition of the relationship between human capital and individual, business or collective economic performance is not recent. In the late 18th century, Adam Smith (1776) theorised in "The Wealth of Nations" that investing in skills and knowledge acquisition was a means to achieve labour efficiency. Furthermore, Smith compared a skilled worker's productivity to that of a new machine and argued that the cost of skills acquisition was expected to have future returns at least comparable to physical capital returns. It emerges from this view that skilled workers deserve higher earnings relative to unskilled workers in

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[16] According to Nordhaus and Tobin (1972) and Kendrick (1976), investment in human capital encompasses the cost of education and earnings forgone by students.

order to compensate their extra performance that is directly related to their personal skills.[17] Furthermore, at a country level where the total sum of individual workers' output constitutes the national output, increased human capital is expected to result in increased aggregate output.

Consequently, Smith's observation implies that, to be complete and accurate, economic analyses, especially growth models, need to include human capital as an output determinant in addition to physical capital and crude labour, where the latter two are traditional production factors following the neoclassical tradition[18]. That was not the case when, in the mid-20th century, early economic models emerged that left the human capital factor out of the picture. The immediate implication of this omission was that those models only explained a small portion of variations in the total output by variations in the physical capital and labour force factors, leaving a puzzle about the sources of the large unexplained portion of the output. [19]

This chapter sets the stage for the next by achieving two goals. The first goal is to review the connection between growth and human capital at both the conceptual and empirical levels. This exercise is intended to set forth the key reasons for which the introduction of the human capital concept in growth studies is made necessary, as well as fundamental challenges and limitations that are met in this attempt. The second goal is to examine whether Africa has sufficiently accumulated human capital in the last three decades

[17] Psacharopoulos (1995) defined this skills premium as "what a more educated individual earns (after taxes), above a control group of individuals with less education".

[18] A key assumption of Solow (1956)'s model of long term growth stipulated that output is produced with two inputs, (physical) capital and labour.

[19] For instance, Solow (1957) estimated that only 12.5 percent of increases in the US gross output per man hour over the period 1909-49 were attributable to increases in the (physical) capital; the technical progress explaining the remaining 87.5 percent.

to boost its growth. Africa is lagging behind the rest of the world in terms of socio-economic development due in part to a combination of factors including a low productive capacity, a lack of sound development planning, and adverse historical momentum and natural conditions. Slave trade and colonialism (Ojo, 2015, Mukhtar et al., 2013), endemic (malaria) or pandemic (HIV/AIDS) diseases (Over, 1992; Dixon et al., 2001, Bhattacharyya, 2009), and geography (Bloom et al., 1998) are cited causes of Africa's underdevelopment. Assessing its achievements in human capital accumulation is not only central in understanding the role played by this production factor in Africa's historical development process, but this could also serve the basis for forward looking policy recommendations.

In pursuit of the two goals mentioned above, the rest of this chapter is organised as follows. Section 2 reviews the development of human capital theory. Section 3 discusses the measurement of the human capital concept. Section 4 examines previous studies' findings and challenges. Africa's growth performance and human capital accumulation process are summarised in Section 5. Section 6 concludes the chapter.

4.2. The development of human capital theory.

Towards the early 1960s, a number of scholars turned back to the idea that investment in workers' skills and health is a major contributing factor to output changes. Pioneering research involving explicit economic assessment of such investment was led by Schultz (1961), Becker (1962), Denison (1962) and Mincer (1974). This was achieved by relaxing two assumptions, one allowing but a narrow view of capital restricted to physical capital, and the other claiming that labour is homogeneous (Mincer, 1981). Schultz (1961) identified five components of human capital investment - namely health services and facilities, on-the-job training, formal education, adults' education and migration - which, he believed, substantially accounted for the rise in individual workers' earnings and the aggregate output of the United

States in the post Second World War period. Becker (1962) developed a theory of investment in human capital that sought to provide evidence of the role of education in explaining the distribution of earnings across workers and along their lifetime. Mincer (1974) was the first to provide an empirical estimate of the effect of education on income at the individual level.

Since the revival of the human capital concept as a key to solve many economic puzzles, its development was carried out in three research strands: (i) the worker's return to human capital investment; (ii) the contribution of labour productivity in the performance of businesses, and (iii) the macro-economic relationship between human capital and growth at the regional, national or supranational levels. The two first strands fall in the microeconomic research field while the latter constitutes a building block of the macroeconomic analysis.

At the microeconomic level, households (firms) invest financial resources and time on their members (employees) for human capital accumulation, forgoing today's consumption or leisure (earnings), with the expectation for future private returns in the form of high earnings or improved productivity. Returns to human capital are believed to exceed these measurable benefits. Individuals utilise their skills in activities outside the job market - such as domestic activities - for which the concept of profit does not apply (Harmon, 2011).

There are also positive externalities to human capital that individuals and firms that invest financial resources or time in do not capture. Human capital has the potential to yield social returns enjoyable by the public at large as opposed to private returns reaped by more able and skilled individuals or firms investing in these skills. For instance, educated citizens with high prospect of earnings are likely to be a blessing for their neighbourhoods and their governments' fiscal administrations; while a worker trained by one firm may quit for another firm, carrying with him the knowledge acquired. For instance, Heckman (2011) noted that investing in early education for disadvantaged children under the age of 5 years reduces the achievement gap and the need for special education, and increases the likelihood of healthier lifestyles. Discussing the broad returns to education, Psacharopoulos (2006) distinguished market and non-market returns of education on the one hand, and private and social returns on the other.

This high potential for sizable spillovers and social returns represents an incentive for governments to invest in human capital, viewed here in a broad picture as a growth booster and a source of expansion for businesses and society's well-being. Other good reasons for allocating public resources to human capital accumulation are its crucial role in the prevention of the demographic explosion[20] and its positive contribution to the reduction of the poverty gap and inequalities through appropriate targeting of vulnerable groups[21]. Finally, the role of human capital in knowledge creation is an added motivation for governments to target continued and sustained prosperity by allocating public resources to its accumulation. These potential social or collective benefits of human capital are at the centre of public policy making in sectors producing human capital, which are primarily the education and health sectors.

For the purpose of our research, we are interested in the macro-economic strand of human capital theory. Both our review of the concept and our contribution to its evaluation that follow are primarily oriented toward this strand of interest. However, references to the micro-economic strand of education are rather frequent given the strong linkage between

[20] The opportunity cost of raising a child increases for educated women whose skills could be valued in the job market (see Schultz 1994).

[21] Heckman (2011) noted, for instance that investing in early education for disadvantaged children under the age of 5 years reduces the achievement gap and the need for education and the need for special education, and increases the likelihood of healthier lifestyles. Moreover, using a meta-analysis of the impact of education on income inequality, Abdullah, Doucouliagos and Manning (2015) found that education is an effective way of reducing income inequality by increasing the income share of the poor and reducing that of the rich. For Murphy and Topel (2016), a low number of high-skilled workers in a population exacerbates inequality.

individual and business performance on the one hand and the macroeconomic performance on the other hand.

4.3. The Measurement of human capital.

Though it is easy to understand the mechanism through which human capital enters economic analysis, this understanding does not make it easier to measure the concept, nor to find a single perfect variable to stand for the concept. As a result, researchers use a handful of variables related to education, health and migration to represent human capital in empirical studies. We discuss below commonly used human capital variables from the macroeconomic point of view by distinguishing between output and input variables in the education and health sectors.

4.3.1. Output variables.

The education output variables used in macroeconomics analyses are disproportionately subdivided between two subgroups: the most commonly used quantity variables, and the seldom used quality variables. The former category consists of stock variables on the one hand, and flow variables on the other. Stock variables capture the human capital factor incorporated in humans by the number of educated workforce, which is sometimes segmented according to different levels (primary, secondary, and tertiary) and types (technical vs. general, or subject based) of education. Average years of schooling and the literacy rate are also frequently used to proxy the stock of human capital. Flow variables capture the potential of additions to the stock of educated labour through enrolment rates at given education levels.

As for the quantity of education, various concepts are used as well. Some among those concepts refer to the achievement records of students measured by their performance in standard international tests designed to evaluate the comparative performance of education policies across countries.[22]

In the health sector, the output variables used for human capital include mortality rates (under-5, maternal, gross mortality), life expectancy, survival probabilities by age and gender groups, people's height or the incidence of specific diseases in the population such as malaria or AIDS/HIV.

4.3.2. Policy variables.

Human capital policy variables measure the resources committed by households, governments and businesses to the acquisition of human capital in the form of investment that is expected to yield future returns. The rationale behind the use of these variables is that a positive impact of sizable resources allocated for human capital accumulation will result from a significant boost in both the stock and quality of human capital. In this sense, resources invested in the education and health sectors are used to proxy human capital. Such resources are expressed in total amounts spent in the education and health sectors, or amount spent per student, or as a ratio of spending to total output. Non-financial resources such as health and education personnel (doctors and teachers), or the number of hours spent learning in classes in formal schooling are also key human capital policy indicators.

It is worth noting however that part of the private resources allocated to education and health are motivated by consumption rather than investment decisions, and ought not to be

[22] The International Association for the Evaluation of Educational Achievement (IEA) conducts worldwide the Trends in International Mathematics and Science Study (TIMSS) to measure students' knowledge in Mathematics and Science every 4 years since 1995. Another study, the Programme for International Student Assessment (PISA) is conducted every 3-year period since 2000 by the OECD in member and non-member states with the focus on the performance in Mathematics, Science and reading for 15-year-old pupils. Other quality variables of human capital relate to the distribution of education among the workforce.

counted as investment in human capital. This distinction is important in theory though its practical implementation is not straightforward. It is generally not possible to decompose total expenditures on human capital into its consumption and investment components.

4.3.3. Pros and cons of human capital variables.

The great merit of human capital variables is that they allow the empirical implementation of the theoretical concept they represent. They are observable counterparts of the abstract human capital concept and in this sense, they are useful in empirical research. Fundamentally, every single variable discussed above bears, to some extent, the content of human capital. Some human capital proxies are more representative of the concept than others, but none is perfect. An optimal mix of these proxies in a given research situation could help capture the impact of the human capital concept.

A combination of factors accounts for the limitations of and differences among the human capital proxies. While some are more direct determinants of output, others are distant determinants. Output variables in the education and health sectors are more directly related to productive activity compared with input variables. However, within the group of output indicators, differences exist. With respect to the health sector, morbidity rates are believed to better represent the human capital concept compared with mortality variables, but the latter are the most frequently used. And within the education sector, the quantity of education variables are the most commonly used relative to the quality variables despite the fact that the former are severely limited as output determinants, and for international comparisons of the contribution of education to the growth of output. These limitations have multiple sources, including the education contents or passing requirements that contribute to differences in the performances of national education systems.

Another problem with human capital variables is that they do not incorporate the concept of depreciation as is the case with the physical capital. The reality though is that human capital also depreciates due to the obsolescence of skills induced by the dynamic nature of the labour market, especially the demand side. The idleness that often occurs as a result of long term unemployment also contributes to the depreciation of the stock of human capital.

4.4. Empirical evaluation of human capital theory in macroeconomics.

It is noted that investigations into the relationship between human capital and growth does not produce robust findings as expected. We discuss this lack of robustness before turning to the claims made by researchers to justify the discrepancies in their findings.

4.4.1. Mixed empirical results.

The empirical literature about the association between human capital and macroeconomic performances across countries lacks consistency and consensus. Empirical results that deviate from the optimistic theoretical view of the value of human capital in macroeconomics are reported alongside those aligning with this view. That is, various contribution levels of human capital proxies to aggregate output, positive and negative, significant and non-significant have emerged from empirical studies estimating and assessing the robustness and consistency of the impact of human capital on economic growth. For Psacharopoulos (2004), there is no consistent evidence for high returns to investment in education in the macroeconomic literature, contrary to the microeconomic literature. Likewise, Hall and Jones (1999) contended that both human capital and physical capital contribute marginally to per capita growth. These views disagree with the belief held by the theorists of human capital regarding its macroeconomic contribution.

Reasons advanced to explain this lack of empirical validation of human capital theory are threefold. These are data quality concerns (nature of the proxy, measurement errors), econometric issues (model specification, estimation and diagnosis) and other reasons related to the preconditions under which the theory might hold. The first two of these sources of concern are intricately related in the same way as the quality of data sets and econometric models' performances are connected.

4.4.2. Data concerns.

The nature of the proxies of human capital used in empirical studies affects the magnitude, the significance and the robustness of the impact of human capital on growth. Aghion, Boustan, Hoxby and Vandenbussche (2009) argued that the fragile evidence of the relationship between education and growth contrasts with the enormous interest in this relationship. These authors explained this result by the use of inappropriate proxies (quantity of education), source of reverse causality and hence of biased estimates. Different human capital proxies produce different results and different conclusions. As we already mentioned earlier, the proximity of the respective proxies to productive activity partly dictates the level and the consistency of the resulting link with output growth.

For instance, Mankiw (1997) noted that years of schooling do not affect growth the same way for different levels of education (primary, secondary, tertiary). Equally, using the initial enrolment rates in a growth study, Chatterji (1997) found tertiary education to be more significant than secondary education when included together as explanatory variables. Furthermore, the author observed that omitting tertiary education lowers the quality of the model while omitting the secondary education does the opposite. The quality of education especially in science has positive and significant impact on growth that is less controversial relative to the result with the quantity of education. For instance, Murphy, Shleifer and Vishny (1991) found that countries with higher graduates in Engineering grow faster than those with higher graduates in Law. Likewise, Khan and Bashar (2015) contended that science and technology studies may be more growth enhancing than general arts studies. Other empirical studies also consistently suggest that educational inequality (standard deviation of schooling, low number of high-skilled workers) among the workforce has a negative impact on growth (Birdsall and Lodono, 1997; López et al., 1998; Castelló-Climent and Doménech, 2002; Sauer and Zagler, 2012; Murphy and Topel, 2016).[23]

Finally, errors in the raw data that enter different education proxies of human capital are reported to be significant sources of inconsistent estimates (see for instance Behrman and Rosenzweig, 1994; De La Fuente and Doménech, 2000; Wilson and Briscoe, 2004).

4.4.3. Econometric concerns.

There are three potential sources of inconsistency with estimates of the human capital contribution to output variations that are inherent in econometric modelling. These relate to model specification, the estimation technique and the sample size of the data used.

On the first above cited source of contradictory findings, (that is, specification), empirical studies differ in approaches. There are differences in data types (time series, cross-sectional data, and panel data) and variables included in the model that affect the results in different ways. Some human capital variables are prone to reverse causality with output growth to be explained, or to multicollinearity with other explanatory variables. For instance, studies including institutional variables are known to produce inconsistent and insignificant estimates of education variables due to the effect institutions have on the provision of education services (Bloom, Sachs, Collier and Udry, 1998). Moreover, education and health

[23] It is important to stress on the distribution among workers here, as Park (2006) shows that the regional dispersion of human capital has a positive and significant impact on growth.

are found to be correlated[24] so that including proxies for both in the same model affects the estimates.

Schultz (1999) used the effect of education on fertility to explain the inconsistency of estimates of female education in growth models including both variables. Mankiw (1995) observed that high growth countries have high enrolment rates and low rates of coups and revolutions – that is, more stable institutions – than low-growth countries. As well, a number of studies find significant estimates of the effect of the interaction between education and the inflow of foreign direct investment (see for example Borentzrein, De Gregorio and Lee, 1998 and Johnson, 2006)[25]. Hence, model specifications need to properly account for such associations among variables. The consequence of inappropriately modelling the interaction between two variables is treated in Balli and Sørensen (2013). Finally, the non-linearity of the contribution of human capital proxies to growth also potentially explains the inconsistency of empirical findings. Zhang and Zhuang (2011) for instance found an inverse U-shape relationship between the share of tertiary education enrolment and growth. Not all studies using tertiary enrolment to explain growth specify such a relationship.

Once variables are selected and the model specified, researchers have to choose among many alternative estimators, and this selection is far from being neutral towards the size, the sign and the significance of the estimates. The data sets and model specifications do not always satisfy the assumptions underlying all estimation techniques. Chapter 2 provides

[24] Arendt (2005) proved the positive effect of education on health using Danish data. Silles (2009) found that more schooling leads to better health using the data from the United Kingdom. Eide and Showalter (2011) conducted a literature review on the relationship between education and health which evidenced that higher levels of education are positively associated with longer life expectancy and better health throughout the lifespan.

[25] Empirical findings are contradictory about the effect of the interaction between FDI and education on growth. Some authors find insignificant or negative coefficients (examples are Olofsdotter, 1998, Carcovic and Levine 2005, Wijeweera, Villano and Dollery, 2010).

ample evidence of inefficiency and test level distortion in the presence of non-spherical errors for a sample of static panel data estimators.

Lastly, the sample size of the data modelled constitutes another source of disagreements among studies. Studies using large numbers of cross-sections make use of more data. However, such studies may suffer from biased estimates if the specifications adopted do not allow for the possibility of differentiating the contribution of human capital according to development levels of countries or regions. This is because the contribution of education to growth is shown to depend on the level of development[26].

4.4.4. Preconditions for a positive impact of human capital on growth.

That human capital has the potential to boost growth is a defensible idea, but it does not make it the panacea for growth. For Rogers (2003), it is the interaction of schooling with firm and economy level processes that matters, but not the former alone. In line with this argument, Pritchett (2000) named three sources of the lack of satisfactory contribution of education attainment to growth: these are poor governance, poor education quality and the rapidly diminishing marginal return of education.

Furthermore, it has been observed that investment in the health sector has the potential to crowd out investment in physical capital (see Gong, Li and Wang, 2012). Adequate investment policies might be needed to attract external investors in order to boost physical investment to its desired level.

4.5. Human capital and economic growth in Africa: recent trends.

This section reviews some key growth facts in Africa since the 1980s. Historical data

[26] See for instance Psacharopoulos (1994) for private and social returns estimates from the microeconomic perspective.

shows two contrasting growth patterns in Africa since the 1980s, partly influenced by changes in both physical capital accumulation and labour. Significant variations in human capital accumulation also occurred over this period. We discuss below the trends of growth and human capital on the one hand and their determinants on the other.

4.5.1. From growth tragedy to sustained growth.

Data available on a sample of 43 African countries from 1980 to 2014[27] indicate that Africa has been consistently growing since the mid-90s, after a long lasting period of economic recession (see Figure 4.1). From the 1980s to this turning point, most African economies lacked growth. Average per capita growth in the sample ranged from -2 percent (in 1992) to 1.5 percent (in 1988). Furthermore, for 15 years from 1980 to 1994, not only were there only four years of positive average per capita growth rates, but these rates were not statistically different from zero, as the lower bound of the 95 percent confidence interval of the average growth within the sample assumed negative values for the period. This description strikingly contrasts with the following 20 years. From 1995 to 2014, average per capita growth remained positive, ranging from 4 percent in 1996 to 0.5 percent in 2009, when the recent global financial crisis drove the world economy to its lowest growth in over three decades.

In a 2014 report, the Africa Progress Panel (APP) (APP 2014) identified five pillars on which the African economy has rested over the last decade. These include a mix of internal and external forces. Internal forces named by the panel are domestic demand and investment, and improved economic governance, whereas external engines are foreign capital flows,

[27] The data source is the World Bank Development Indicators. For each of the countries in the sample, there are no more than 3 missing data points over the indicated period.

strong commodity prices and trade with emerging markets. In addition, a four decade observation of the world economy structure by Memedovic and Iapadre (2009) reveal a deepening of specialization in Africa from 1995 in raw materials (mining and utilities, and then agriculture). Hikes in these resources in the late 1990s and early 2000s might have boosted Africa's economic progress. It is thus not surprising that this period coincides with the turning point of African growth. In support of this claim, Calamitsis, Basu and Ghura (1999) linked the Sub-Saharan Africa (SSA)'s recovery of the years 1995-97 to the region's improved performance in indicators such as the ratios of private investment and budget deficit to GDP, human capital development, external competitiveness, and exports volume growth.

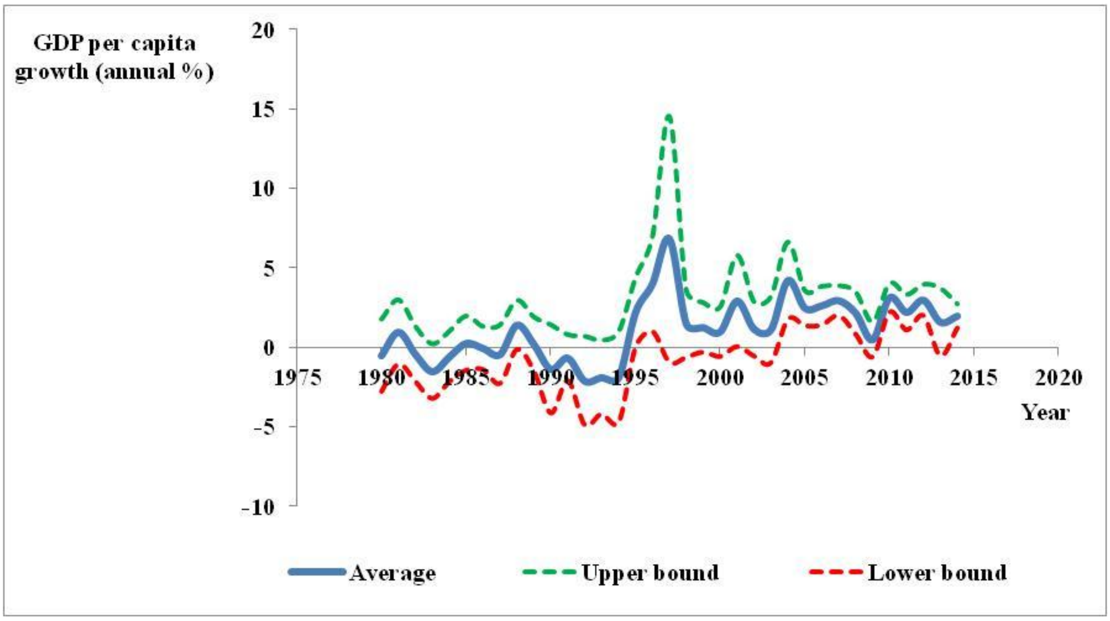

Figure 4.1: Average, upper and lower bounds GDP per capita growth (annual %) for 43 African countries. Data source: World Bank Group Development Indicators.

Another key feature of African growth as observed in this sample pertains to the volatility pattern over time and within the sample. Growth was exceptionally erratic and dispersed in the second half of the 1990s, jumping by over 4 percentage points in 1995 from nearly -2 percent and then sliding by over 5 percentage points 3 years later from the sample top growth performance (6.8 percent) since the 1980s. The largest within sample dispersion (measured by the standard deviation) occurred in 1997, but this was exceptional as African economies had rapidly converged thereafter, displaying narrower within sample dispersion figures from 2005.

4.5.2. Improved physical capital accumulation in Africa.

The trend of physical capital accumulation in Africa (Figure 4.2) generally follows that of the growth described above. In Sub-Saharan Africa, the share of gross fixed capital formation as a share of GDP had a downward trend in the 1980s and early 1990s. It reached its minimum (15.6 percent) in 1992. This share rose from 1993 to 2013, returning to its level of the mid-80s (about 20 percent), though below the peak it reached in 1981 (26 percent).

Net inflows of foreign direct investment as a share of GDP had an overall upward trend until the early 2000s before slowly sloping downward. In the period 1997-2013, the average share of FDI net inflow as a share of GDP increased by over 4 times - from 0.7 percent to 2.8 percent - in comparison with the period 1980-1996. In North Africa, the shrinking of the share of gross fixed capital formation (GFCF) took longer and it was not until 2002 that the trend reversed. Net inflow of foreign direct investment (FDI) temporarily shifted its share in GDP from 2005 to 2010 (6-year average of 3.74, over 3 times the average prior to this period since 1980 and over twice the average for the following 3 years).

A study by Mijiyawa (2015) of 53 African countries from 1970 to 2009 using 5-year average data finds that country size, political stability, trade openness, and the return to investment are major FDI drivers in Africa. Other FDI drivers found by earlier studies identified by Majiyawa (2015) in his review of literature include, but are not restricted to: the national market size, the natural resources endowment, the quality of institutions and that of the infrastructure, the availability of the educated labour force, and bilateral development assistance. According to Chen, Dollar and Tang (2016), the allocation of fast-growing Chinese FDI in Africa is determined by natural resources, market size, and the legal framework (protection of property rights and the rule of law).

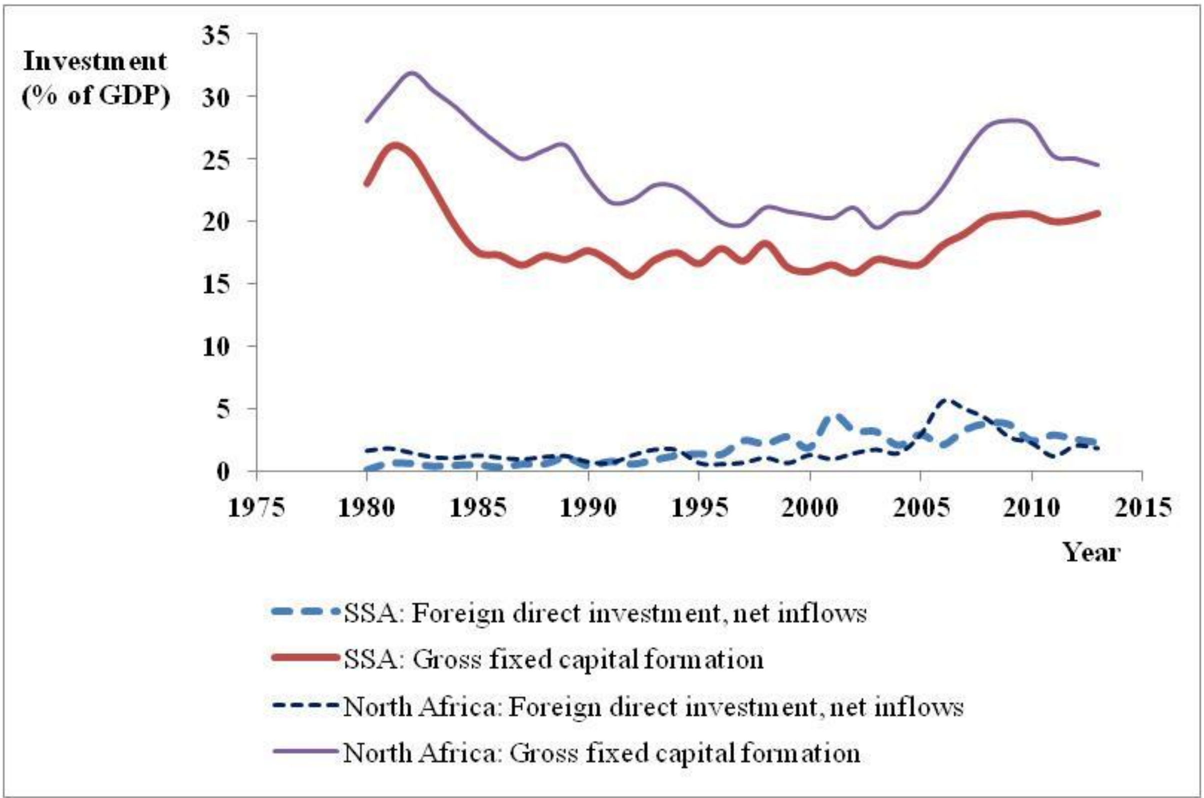

Figure 4.2: Gross fixed capital formation and net inflow of FDI as share of GDP for Sub-Saharan Africa and North Africa. Data source: The World Bank's World Development Indicators.

4.5.3. Africa's booming labour force.

One characteristic of Africa's population is its fast growth relative to most parts of the world. With respect to this aspect however, there exists a large gap between SSA on the one hand and North Africa on the other hand (see Table 4.1). The former has sustained high population growth rates, on average above 2.5 percent since the 70s. In the meantime, North Africa has enjoyed a different population dynamics. From the 70s to mid-80s, Algeria and

Libya populations grew on average faster than SSA, while the other countries population growth rates were lower. Thereafter, population growth rates in all northern countries have fallen significantly below the SSA average, with negative rates for Libya from 2012.

Table 4.1: Population growth and life expectancy at birth trends.

Country Name	1970	1980	1990	2000	2010	2014	Variation 2014 - 1970
	Population growth, (annual %)						
Sub-Saharan Africa	2.6	2.9	2.8	2.7	2.8	2.7	0.1
Algeria	2.8	3.0	2.6	1.3	1.8	1.9	-0.9
Egypt, Arab Rep.	2.2	2.4	2.4	1.8	2.0	2.2	0.0
Libya	4.3	3.9	2.4	1.7	0.9	-0.1	-4.4
Morocco	2.2	2.4	1.9	1.1	1.2	1.4	-0.8
Tunisia	1.9	2.7	2.4	1.0	1.0	1.0	-0.9
	Life expectancy at birth (years)						
Sub-Saharan Africa	44.3	48.2	49.9	50.3	56.3	58.6	14.3
Algeria	50.3	58.2	66.7	70.2	73.8	74.8	24.5
Egypt, Arab Rep.	52.1	58.3	64.5	68.6	70.3	71.1	19.0
Libya	56.1	64.3	68.6	70.6	71.7	71.7	15.6
Morocco	52.5	57.5	64.7	68.5	72.6	74.0	21.5
Tunisia	51.1	62.0	70.3	72.6	74.6	74.1	23.0

Source: The World Bank's World Development Indicators.

The gain in life expectancy at birth between 1970 and 2014 is 14.5 years in SSA, while the northern countries have gained further, from 15.6 years in Libya to 24.5 years in Algeria over the same period. This expansion in life expectancy at birth across Africa is due to "technological advances, the introduction of primary health care, increased literacy, access to safe water, sanitation and housing, and better understanding of social behaviour" (Macfarlane, Racelis and Muli-Musiime, 2000). Notwithstanding this significant absolute improvement in life expectancy, the African continent has the lowest life expectancy compared with the rest of the continents as a result of persistent, life-threatening natural and human circumstances such as civil conflicts, famine, and diseases (malaria, HIV/AIDS) (see for instance Kabir, 2008, or Austin and McKinney, 2012).

The average share of the working age population (15-64 years old) is above 50 percent in SSA and above 60 percent in North Africa. This potential labour force is exposed to high levels of both unemployment (8 percent on average in SSA and higher in North Africa) and underemployment.

4.5.4. Slow improvement in the quantity and quality of human capital.

The adult literacy rate indicator is often used by researchers to capture the effect of human capital on growth. African countries largely differ with respect to this variable. Table 4.2 summarises the literacy of adult female and male Africans. High performing countries and low performing countries on this indicator are featured by using the maximum and the minimum values recorded, the number of observations, and the years these extreme values are observed. We define the high performing countries as those with a respective minimum recorded literacy rate of at least 80 percent, and the low performing countries as those for which the respective maximum recorded values are below 30 percent for female literacy and 50 percent for male literacy.

It appears that for both genders, the adult literacy rate is increasing for high performing countries as well as for low performing countries. There are a few exceptions (Lesotho and Niger for female literacy and Angola for male literacy) where the maximum literacy rates are observed before the minimum rates, signalling a decrease in literacy.

Table 4.2: Adult literacy performances across Africa.

Country Name	Minimum	Maximum	Observations	Year minimum observed / Year maximum observed
Adult female literacy				
High performers				
Seychelles	85.5	95.8	5	1987/2015
Lesotho	85.0	92.0	3	2009/2000
Equatorial Guinea	81.6	92.9	3	2000/2015
South Africa	74.8	93.4	9	1980/2015
Mauritius	74.7	89.1	6	1990/2013
Namibia	74.0	90.6	5	1991/2015
Congo, Rep.	72.9	72.9	2	2011/2011
Zimbabwe	71.9	85.3	4	1982/2015
Botswana	71.3	89.2	4	1991/2015
Low performers				
Niger	8.9	15.1	4	2012/2005
Guinea	9.7	22.9	4	1996/2015
Mali	5.7	24.6	7	1976/2011
South Sudan	19.2	25.4	2	2008/2015
Benin	9.5	27.3	5	1979/2015
Burkina Faso	3.2	28.3	9	1975/2015
Adult male literacy				
High performers				
Equatorial Guinea	94.8	97.3	3	2000/2015
Congo, Rep.	86.4	86.4	2	2011/2011
Mauritius	85.1	94.7	6	1990/2012
Zimbabwe	84.2	88.9	4	1982/1992
Seychelles	82.9	94.8	5	1987/2015
Angola	82.0	82.9	3	2015/2001
Low performers				
South Sudan	34.8	38.6	2	2008/2015
Guinea	32.9	42.9	4	1996/2003
Niger	19.6	42.9	4	2001/2005
Mali	13.5	45.1	7	1976/2015
Burkina Faso	14.5	47.6	9	1975/2015
Chad	18.3	48.4	5	1993/2015
Benin	25.2	49.9	5	1979/2015

Source: The World Bank's World Development Indicators.

We also note that most high performing countries are from the English speaking group of African countries (former British colonies), while the low performing countries are from the French speaking countries (former French colonies). There are two complementary theories supporting the better literacy position of former British colonies. The first theory relates to colonial heritage (see for instance Benavot and Riddle 1988; Brown 2000, Lloyd, Kaufman & Hewett 2000), supplemented by that of missionary activities (Callego and Woodberry 2010, Frankema 2012).

Other researchers use skilled labour force by education level to proxy the stock of human capital. Here too, African countries perform very unevenly. Only limited data exist for 16 countries in Africa for the period 1988-2013 (Table 4.3). The general feature among these countries is that the labour force with primary education represents the highest share of total labour force, while the lowest share goes to the labour force with higher education. The few exceptions to this rule are Egypt, Nigeria and South Africa where the largest share goes to secondary education. Within education levels, shares also vary substantially among countries. For primary education, maximum shares range from nearly 70 percent in Uganda (in 1994) to as low as 10.4 percent in Egypt (in 2011) and in Niger (in 2001). South Africa has the highest maximum share of labour force with secondary education (above 74 percent in 2008) while Niger (0.5 percent in 2001), Chad (2 percent in 1993) and Rwanda (4.5 percent in 2012) have the lowest maximum shares of labour force with secondary education. Ghana has the largest maximum share of labour force with tertiary education (31 percent in 1992), while the lowest maximum shares are observed in Niger (0.4 percent in 2001) and in Chad (0.6 percent).

Table 4.3: Share of education labour force by education level (% of total labour force).

Country Name	Labour force with primary education				Labour force with secondary education				Labour force with tertiary education			
	Min.	Max.	Obs.	Year Min. observed / Year Max. observed	Min.	Max.	Obs.	Year Min. observed / Year Max. observed	Min.	Max.	Obs.	Year Min. observed / Year Max. observed
Algeria	50.4	52.9	2	2004/2011	20.6	21.5	2	2004/2011	10.0	15.2	2	2004/2011
Botswana	49.5	63.4	3	2010/1996	13.8	26.4	3	1996/2006	15.9	15.9	1	2010/2010
Chad	24.2	24.2	1	1993/1993	2.0	2.0	1	1993/1993	0.6	0.6	1	1993/1993
Egypt, Arab Rep.	4.5	10.4	6	2012/2011	36.5	38.0	6	2009/2012	16.9	19.7	6	2008/2012
Ethiopia	20.7	68.8	5	1999/2009	2.6	14.9	5	1999/2009	1.3	16.7	5	1999/2010
Ghana	21.3	48.0	2	1992/2010	17.4	17.4	1	2010/2010	2.5	31.0	2	2010/1992
Madagascar	41.4	56.0	3	2012/2005	12.1	33.3	3	2003/2012	3.4	5.2	3	2005/2012
Mauritius	42.4	65.4	6	2006/1995	26.0	45.8	6	1995/2006	2.5	11.2	6	1995/2007
Morocco	39.5	45.6	11	2006/1995	9.5	16.6	11	2005/1995	7.4	10.9	11	2002/1996
Namibia	23.6	60.4	5	2011/2004	19.9	53.9	5	2004/2010	4.7	8.6	5	1997/2010
Niger	10.4	10.4	1	2001/2001	0.5	0.5	1	2001/2001	0.4	0.4	1	2001/2001
Nigeria	20.9	20.9	1	1995/1995	40.2	40.2	1	1995/1995	27.3	27.3	1	1995/1995
Rwanda	53.8	66.7	2	1996/2012	3.4	4.5	2	1996/2012	0.3	2.7	2	1996/2012
South Africa	15.8	47.6	8	2008/2001	30.1	74.2	8	2009/2008	5.2	17.1	8	2008/2013
Tunisia	33.1	44.2	8	2011/1997	28.1	37.9	8	1994/2011	6.0	19.4	8	1994/2011
Uganda	49.4	69.6	3	1991/1994	3.5	13.1	3	1994/1991	0.4	2.4	3	1991/1994

Source: The World Bank's World Development Indicators.

Mortality rate is another indicator of human capital. Data on adult and under-5 mortality rates[28] (Table 4.4) indicate that SSA started with higher rates compared with any individual country in North Africa in 1960. Moreover, while some progress in cutting down high mortality is noted in SSA and North Africa, the latter did so with a superior performance relative to the former.

Table 4.4: Adult and under-5 mortality rate trends.

Country Name	1960	1970	1980	1990	2000	2010	2014
	Mortality rate, adult, male (per 1,000 male adults)						
Sub-Saharan Africa	491.2	444.4	402.2	395.3	424.7	354.9	328.2
Algeria	373.1	341.7	270.7	199.5	166.5	142.5	134.9
Egypt, Arab Rep.	286.7	267.2	247.7	230.8	216.8	198.3	189.3
Libya	418.5	311.6	237.1	190.2	168.4	170.1	173.4
Morocco	354.8	321.9	280.7	220.1	178.5	120.5	105.7
Tunisia	461.7	351.4	244.2	185.1	140.1	129.3	125.7
	Mortality rate, adult, female (per 1,000 female adults)						
Sub-Saharan Africa	431.5	384.2	341.0	334.1	383.8	315.4	284.7
Algeria	323.3	291.7	219.4	152.0	127.7	93.9	84.2
Egypt, Arab Rep.	183.9	167.5	154.7	143.7	135.0	122.2	113.0
Libya	368.4	249.3	176.8	139.1	120.2	100.7	98.6
Morocco	294.6	269.7	227.1	168.9	136.7	98.4	87.4
Tunisia	420.8	317.3	215.9	137.3	83.7	75.0	73.2
	Mortality rate, under-5 (per 1,000 live births)						
Sub-Saharan Africa	---	243.7	201.4	180.9	154.8	101.4	86.1
Algeria	246.3	241.7	148.1	46.8	39.7	27.3	25.6
Egypt, Arab Rep.	312.8	242.9	167.6	85.9	46.5	29	24.8
Libya	281.5	137.8	70.8	41.6	28.1	16.6	13.9
Morocco	239.4	188.7	133.8	80.1	50	33.1	28.6
Tunisia	---	180.6	95.7	57	31.7	17.4	14.6

Source: The World Bank's World Development Indicators.

[28] The WDI database provides the definitions of the adult mortality rate and the under-5 mortality rate. Adult mortality rate is the probability of dying between the ages of 15 and 60. Under-five mortality rate is the probability per 1,000 that a new-born baby will die before reaching age five, if subject to age-specific mortality rates of the specified year.

Egypt is the slowest North African country in reducing its mortality rate, yet it outperforms SSA. Its reduction in adult mortality (both female and male) between 1960 and 2014 is larger than the SSA's performance over the same period. Likewise, Morocco's reduction in under-5 mortality in 2014 compared with the 1960 is the lowest in North Africa (by 210.8 deaths for 1000 live births), but this figure is also above the average performance score for SSA.

Education and health are two of the three dimensions of the human development index statistic which is also indicative of the quality of human capital. Available statistics (Table 4.5) show that on average, the performance of Africa has moved from below the reference average (0.5) in 1990 to just above this average in 2014, with respective index values of 0.426 and 0.524. The percentage of countries performing below 0.5 has decreased from 70 percent to 49 percent in the reference period mentioned above.

Table 4.5: Human Development Index statistics for African countries.

Year	Number of countries			Average of indices		Average gap for those below 0.5
	Number of countries	with indices below 0.5	With indices below African average	Below 0.5	All	
1990	37	26	19	0.361	0.426	18.0
2000	47	33	29	0.380	0.449	17.9
2010	53	32	33	0.432	0.507	17.5
2011	53	32	33	0.437	0.512	17.1
2012	53	29	33	0.436	0.518	18.7
2013	53	26	33	0.432	0.521	20.6
2014	53	26	33	0.436	0.524	20.3

Source: UNDP's human development database.

Note: This indicator is not available for Somalia. That is the reason why there are only 53 countries from 2010.

However, the share of countries with indexes below the African average rose from 52 percent in 1990 to 60 percent in 2000 and remained constant thereafter through 2014. This mixed performance translates in a wider gap between the average performance of the group of countries with indexes below 0.5 and the African average index. The average index for underperformers was 17 to 18 percent below the continental performance from 1990 to 2012. This gap has exceeded 20 percent in 2013 and 2014, showing that African countries have been improving the quality of human capital by heterogeneous paces in favour of countries with relatively higher quality of human capital. In this group are Mauritius, Seychelles, Algeria, Libya and Tunisia, the African best performers in 2014 showing index measures above 0.7. Burundi, Chad, Eritrea, Central African Republic, and Niger were among the countries with lower indexes and appear at the bottom of the 2014 ranking with index measures not exceeding 0.4.

Finally, in addition to the contribution of the human capital embodied in domestically available labour force, the human capital of African immigrants across and outside the continent is a major source of growth in African countries. Immigration and growth in the sending countries are related via skills acquisition by returned immigrants and remittances that represent a substantial share of GDP in some countries. According to the World Bank and IMF estimates, the share of remittances to GDP reached double digits in five African countries in 2016: Liberia (29.6 %), Comoros (21.2 %), The Gambia (20.4 %), Lesotho (17.5 %), Senegal (13.5 %) and Cabo Verde (13.0 %)[29]. A positive effect of remittances on growth is expected through the investment and consumption boost from receiving countries, while a negative effect could arise from the appreciation of the real exchange rate, the decrease in labour supply by receiving households, or a lack of pressure for accountability in public policy making (see Ratha et al, 2011 for a review of the growth effect of remittances).

[29] Source: Migration and Development Brief 27.

4.5.5. Investment in human capital.

Investment in human capital consists of both public and private expenditures on education and health. Though part of these expenditures serves consumption rather than investment purposes, there is not a straightforward way to split them into their investment and consumption components. For this reason, we assume that the higher the cumulative investment, the higher the investment component and resulting human capital accumulation. One has to admit to the limitations of such an assumption as the allocation of public resources to education and health lacks further efficiency in Africa compared with other regions in the world (Gupta, Honjo and Verhoeven 1997). Isolating the specific case of higher education, the lack of adequacy between programmes and the local need of the job markets cause unemployment and brain drain, which represent a loss of resources invested in the graduates. A solution to this source of inefficiency of education investment is suggested by Bollag (2004) who argued that "often, part of precious higher education budgets might be better spent on shorter programs that train students for identified needs, rather than on traditional programs - often of four, five or six years duration - designed to prepare large numbers of students for white-collar government jobs that don't exist".

Moreover, while there might be a positive correlation between human capital investment and actual amounts spent, it is also true that countries have limited resources so that human capital investment could be considered low or high only relative to the size of the economy. This reality justifies the use of the relative importance given to measuring human capital investment by its share in GDP. Trends of this indicator for African economies are analysed below.

From 1970 to 2013, data available on education public expenditure as a share of GDP for 49 countries (of which 2 have one observation each) indicate that African governments have spent a minimum equivalent of 0.69 percent to 2.67 percent of GDP on education, and a maximum equivalent of 5.34 percent up to 44.33 percent (Figure 4.3).

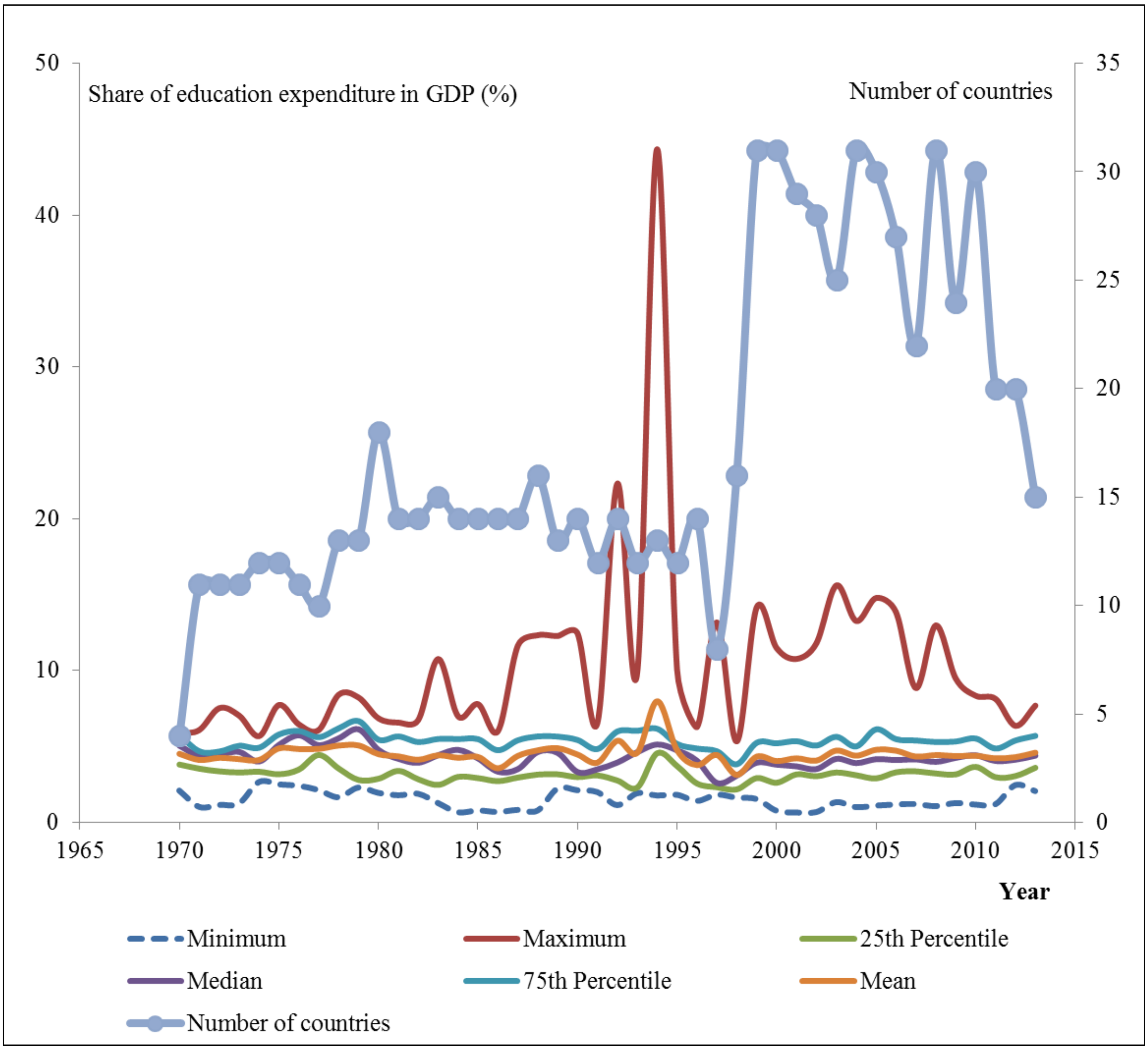

Figure 4.3: Basic statistics of shares of education expenditures in GDP across Africa. Data source: World Bank Group Development Indicators.

For 18 countries in this sample, the minimum was observed after the maximum suggesting weakening public efforts in allocating funding to the education sector in recent years. Education spending shares in GDP not exceeding 5 percent have been recorded for 17 countries, of which 11 never reported rates above 4 percent. Exceptional shares of government spending on education are reported for Zimbabwe (from 11.7 percent in 1987 to 44.3 percent in 1994[30]), Lesotho (from 1995 to 2008) and Botswana (from 2005) with rates including 2 digit figures.

Reported data indicate that the 25th percentile of education spending shares in GDP across Africa takes on values between 2.18 percent (1998) and 4.57 percent (1994). This range for the 75th percentile is 3.83 percent (1998) and 6.68 percent (1979). The median African country spends 2.61 percent (1997) and 6.14 percent (1979) of its GDP on education.

Unlike scarce statistics on education expenditures, those on health spending are rather abundantly recorded for 42 African countries[31] over the period from 1995 to 2014. Total health expenditure (public and private) as share of GDP averages around 6 percent for Sub-Saharan Africa with the private sector (between 3.1 and 4 percent of GDP) contributing more than the public sector. In North Africa, the public sector contribution to health expenditure exceeds that of the private sector only in Algeria and Tunisia (Table 4.6). Overall, in over 80 percent of countries, neither the public nor the private sectors ever allocated an equivalent of at least 5 percent of the gross domestic product to yearly health spending. From 2006 to 2013, the share in GDP of public spending on health was higher in Lesotho (between 5 percent and 9.5 percent respectively) than in any other Africa country. The highest ratios for the private sector go to Sierra Leone and Liberia. Countries with lowest expenditure shares in GDP are Cameroon, Nigeria and South Sudan for public expenditure; and South Sudan, Algeria and the Republic of Congo for private expenditure, with rates below 2 percent.

[30] The 44.3 percent of GDP spent in the education sector by the Government of Zimbabwe is an outlier at both the country and the continent levels despite what was known as the Zimbabwe “education miracle” following the country massive investment in education since its independence in 1980 (Mackenzie, 1998).

[31] There is no recorded data for Somalia, and South Sudan did not exist before 2011.

Table 4.6: Health expenditure as share of GDP in Africa.

Country/Region	1995/99	2000/04	2005/09	2010/14
		Public		
Sub-Saharan Africa	2.5	2.3	2.5	2.5
Algeria	2.5	2.8	2.8	4.5
Egypt, Arab Rep.	1.8	2.2	2.1	2.0
Libya	1.7	2.4	1.7	3.0
Morocco	1.1	1.4	1.8	2.1
Tunisia	2.9	2.9	3.1	4.1
		Private		
Sub-Saharan Africa	3.7	3.4	3.2	3.2
Algeria	1.0	0.9	1.2	1.7
Egypt, Arab Rep.	2.6	3.4	2.9	3.2
Libya	1.8	1.5	0.9	1.3
Morocco	2.6	3.5	3.6	3.9
Tunisia	2.6	2.5	2.7	3.0
		Total		
Sub-Saharan Africa	6.1	5.7	5.8	5.7
Algeria	3.5	3.6	4.0	6.2
Egypt, Arab Rep.	4.4	5.6	5.0	5.2
Libya	3.5	3.9	2.6	4.3
Morocco	3.7	4.9	5.4	6.0
Tunisia	5.5	5.4	5.7	7.0

Source: The World Bank’s World Development Indicators.

4.6. Conclusion.

This chapter sets the stage for the next by achieving three goals. It first summarises the development of the theoretical relationship between human capital and growth, including the measurement of the latter. Secondly, previous studies’ findings about this relationship are discussed. Lastly, the chapter analyses historical trends of growth and its human capital determinants in Africa.

With regard to the first goal, it appears that the recognition of the role played by human capital in the economic performance at the individual, business and national levels is not recent. However, the more formal application of this connection to theoretical and empirical analyses of the production level of growth was preceded by that of physical capital. This formal application, especially in the field of macroeconomics, faces a critical conceptual challenge of how to measure human capital and how the expected contribution should be modelled. Different approaches have been proposed, with their intrinsic merits and limitations. This challenge carries on to empirical findings about the macroeconomic impacts of human capital.

As for the second goal, empirical findings fall short in unequivocally meeting the expectations of a positive association between human capital and economic growth. There are conflicting results in the literature, some aligning with the conventional wisdom, others opposing a priori expectations by producing a negative relationship, while another group of investigations concludes an absence of any relationship. The nature of human capital proxies, the quality of the measurements, the models estimated, and the estimators chosen by researchers are all potential sources of conflicting results. The rationality of national economic policy making could also contribute in explaining the seemingly contradictory or unsatisfactory findings.

What we learn from pursuing the third goal is that African economies have experienced an upturn of their growth trends towards the mid-1990s. This economic recovery coincided with an upturn in physical capital investment after a long period of depressed economic activity. In the meantime, human capital factors have only slowly improved both qualitatively and qualitatively. In the next chapter, we propose to investigate the contribution of investment in human capital to growth in a sample of African countries using the lessons from previous chapters.

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Chapter 5 . Estimating the growth contribution of public spending on education and health in a sample of African countries.

5.1. Introduction.

This chapter applies lessons from the previous chapters to estimate the determinants of growth in Africa. We specifically focus on the contribution of human capital investment on per capita GDP growth in a sample of African countries. We justify the geographic scope of this study by the fact that more than any other region in the world, Africa needs to optimise the allocation of its resources in its pursuit of strong and sustained growth required to significantly cut its high poverty rate, durably improve the living standard of Africans, and reduce its development gap with the rest of the world.

Do governments across Africa have strong enough economic motivations to further allocate scarce public resources to the accumulation of human capital when poor households are unable to privately support the financial cost of such investment? This research provides an answer to this question by modelling and estimating the effects of education and health expenditures on per worker growth for a sample of 12 African countries over the period from 1999 to 2013. African economies are characterised by two key features in this period (according to the previous chapter). On the one hand, there is a relative stability of growth in contrast with previous years (1994-1998) of high volatility. On the other hand, we observe a progressive convergence of economies across the continent.

The study of the association of growth with human capital, especially with the allocation of public funds to its accumulation has been previously conducted by many researchers. However, findings are conflicting for purely African samples as well as those combining African countries with other countries around the world or those consisting of countries outside Africa. Among other reasons advanced to explain the conflicting results is the choice of econometric approach. In this respect, our research is innovative for at least two reasons. Firstly, using the results from chapter 2 in this thesis, we select the estimators that best suit our data characteristics. The cross-sectional and time dimensions of our data set belong to the range of dimensions of data sets used in that chapter, making this choice legitimate. Secondly, we compare the asymptotic theory based and the bootstrap theory based tests of significance of the estimates of the relationship between our human capital variables and the growth of real per capita GDP in Africa. This was discussed in chapter 3.

This chapter proceeds as follows. In Section 2 we review the empirical literature about the relationship between human capital and economic growth in Africa. Section 3 presents the model specification and the supporting theory discussion. Section 4 describes the data and addresses some econometric issues including model estimation techniques. Results of the model are reported in Section 5. They are analysed in light of econometric and data issues in Section 6 and towards drawing some policy recommendations in Section 7. Lastly, Section 8 concludes.

5.2. Contribution of human capital to growth in Africa: previous empirical findings.

This section is devoted to previous research aimed at investigating the growth effect of human capital in Africa. We provide a summary of empirical findings along with further details about selected individual studies in Tables 5.1 and 5.2.

5.2.1. An overview of empirical findings.

The empirical literature on African economies contains investigations into the association between GDP growth and human capital through its education and health components. Attempts to link the growth of output and measures of human capital are found in studies including samples of African countries with others from different parts of the world (see for instance, Romer, Mankiw and Weil, 1992; Collins and Bosworth, 1996; Gyimah-

Brempong and Wilson, 2004). Other studies focussed on samples of African countries (examples are, O'Connel and Ndulu, 2000; Ndulu and O'Connel, 2003; Oketch, 2006; Bloom, Canning and Chan, 2006; Danquah, Ouattara and Speight, 2010), on specific sub-regions of Africa (see for example Sacerdoti, Brunschwig and Tang, 1998) or on single African countries (Oluwatoyin, 2011; Burger and Teal, 2015).

Overall, empirical investigations into the contribution of human capital to output growth have produced mixed results for Africa, as is the case with other countries or samples of countries outside Africa. Some studies find that the relationship is insignificant (Ndjikam, Binam and Tachi, 2006) while others conclude that there is a significant and positive association (Anyanwu, 2014). Yet other studies report a significant and negative correlation between growth and human capital (Eggoh, Houeninvo and Sossou, 2015). More interestingly, conflicting results may appear within single studies[32] or with the same human capital proxy variable and the same sample in different studies using different methods[33].

As we discussed in the previous chapter, differences in findings may be related to a combination of data, econometric or policy concerns. Schultz (1999) argued that the quality of aggregate education and health data is problematic in Africa more than in any other part of the world. However, data quality has significantly improved for a few African countries making recent studies potentially more robust than previous ones. In addition, the high unemployment rates across Africa combined with the continent's economic environment

[32] Oluwatoyin (2011) estimated an error correction model with Nigerian data and found that: (i) the government expenditure on education and tertiary education enrolment rates are both positively and significantly associated with GDP growth; and (ii) government investment on health, primary education enrolment and secondary education enrolment rates are insignificant in explaining variations in GDP.

[33] Contrasting with Oluwatoyin (2011), Yakubu and Akanegbu (2011) use Granger Causality analysis and found that the government expenditure on education does not Granger cause GDP growth. They found similar result for the recurrent expenditure on education.

which is less conducive to innovation (lack of adequate funding and research structures) constitute negative factors in Africa's ability to reap a higher aggregate return from its educated and skilled active population.

The sources of inconsistencies with the estimated economic impact of human capital have served as the basis of an acute criticism and doubt about the validity of reported results and their usefulness for policy making purposes. Psacharopoulos (1994) reported the highest private and social returns to investment in education for the Sub-Saharan Africa (SSA) region compared with returns in other regions of the globe. However, Bennell (1996) later found the results about the SSA to be flawed and useless for policy decisions[34]. Schultz (1999) also made similar comments about empirical findings relating human capital proxies and growth in Africa, noting that "generalisations as to returns to education and health for the African region as a whole are at a minimum premature, if they will ever be warranted".

We present below a number of empirical results about the correlation between growth and human capital, distinguishing between regression and growth accounting studies.

5.2.2. Regression studies.

Mankiw, Romer and Weil (1992) estimated the growth contribution of human capital in a regression model and included in their sample African countries.[35] Their human capital proxy[36] was positively and significantly associated with GDP growth. Glewwe, Maiga and

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[34] Bennell (1996) pointed to the data and the methodologies used for individual countries to arrive at this conclusion. For the author, such results provide a strong case for investment in education in Africa that could be done at the expense of other sectors. But it is unlikely to be realistic due to limited wage employment and the predominance of agriculture sector in African countries.

[35] The sample comprised 121 countries of which 42 were African countries.

[36] This proxy was an approximation of the percentage of the working age population that is in secondary school. It was obtained by multiplying the ratio of the eligible population (12 to 17 years) enrolled in secondary school

Zheng (2007) replicated the results of this study only for the sample of African countries included in Mankiw et al. (1992) and found that the effect of human capital was half its initial value though it remained significant. The authors suggested that the original study coefficient was above the true effect of education on growth in Africa due to the low quality of education in African countries. Likewise, Anyanwu (2014) reported a positive and statistically significant coefficient (at the 10 percent confidence level) for enrolment at secondary education in a growth study of 53 countries from 1996 to 2009 using various panel data estimators. These positive and significant contributions using secondary enrolment conflict with an insignificant result reported for a sample of African countries by Savvides (1997), also using statistics on secondary enrolment. Though the quality of institutions was controlled for with potential implications for the significance of the education variable, the author rather pointed to the quality of the data to justify the inconsistent result.

Studying a sample of 103 countries over the period 1960 – 2000, Bloom, Canning and Chan (2006) predicted a substantial gain in output growth over the medium term for African countries as a result of an additional year to the stock of tertiary education. The gain in output growth for the next year estimated at 0.63 percentage point would be followed by an additional 3 percentage points five years later. Alvi (2013) used the average years of schooling and life expectancy among other variables with recent panel data from 37 developed and developing countries (Egypt, South Africa and Tunisia are included). These human capital proxies had positive signs and were significant with OLS and fixed effects estimators. However, the education variable ceases to be significant with the random effects estimation technique.

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by the fraction of the working population that is of school age (15 to 19 years).

Table 5.1: Effects of human capital variables in empirical findings with African data.

Publication reference	Dependent variable	Human capital variable	Results
Burger and Teal (2015)	Industry output.	Worker schooling years, worker schooling years squared.	The output per worker increases with the average level of education, but at a decreasing rate. The result is significant at conventional rates for all the estimation methods.
Eggoh, Houeninvo and Sossou (2015)	Growth rate of real GDP per capita.	Public spending on health (% of GDP) and on education (% of GDP); life expectancy at birth, survival at age 60 (% of cohort); secondary and primary school enrolment ratios.	Public expenditures on education and health have a negative impact on economic growth whereas their interaction is positively and significantly associated with the GDP growth at 5 to 10 percent. Human capital stock indicators have positive effects whose significances depend on the control variables included in the cross-section specification. In the panel data specification, the signs are maintained, but the coefficients are insignificant.
Kwendo and Muturi (2015)	Real gross domestic product.	Government expenditure on health.	The human capital variable coefficient is positive and significant at the 10 per cent level.
Anyanwu (2014)	Real GDP growth rate.	Secondary education enrolment ratio.	All estimation methods produce positive and significant coefficients (at 5 to 10 percent levels) for the human capital variable.
Amadi, Amadi and Nyenke (2013)	Real GDP.	Public spending on education, public spending on health.	Human capital variables have positive signs; the health variable is significant at the 10 per cent level; the education variable is insignificant.
Oluwatoyin (2011)	Gross domestic product.	Government expenditure on education and on health, primary, secondary and tertiary education enrolments.	The second lag of the government expenditure on education and the first lag of tertiary enrolment rate have positive and significant coefficients at the one percent level. The coefficients of Government expenditure on health and the primary enrolment ratio are negative but not significant. The coefficient of the secondary enrolment ratio is positive but not significant.

Table 5.1 (continued).

Publication reference	Dependent variable	Human capital variable	Results
Danquah, Ouattara, and Speight (2010)	Total factor productivity growth.	Total human capital stock (average years of schooling) and its interaction with the variable distance to frontier.	Total human capital has a positive and significant effect (at levels up to 10 percent) on the total factor productivity.
	Total factor productivity growth.	Primary, secondary, tertiary education attainment ratios and their interactions with the variable distance to frontier.	None of the human capital variables is significant at the 5 percent level. Coefficient signs are mostly negative for primary and secondary education levels. Coefficients for the tertiary education ratio and its interaction with the distance to frontier have positive signs and a few times significant at the 10 percent level.
Suliman and Mollick (2009)	Foreign direct investment, net inflows (% of GDP).	Literacy rate.	There is a positive and significant association (mostly at the 1 % confidence level) between FDI and the human capital variable.
Hassan and Ahmed (2008)	Per capita GDP growth.	Average years of schooling, literacy rate, primary enrolment ratio, secondary enrolment ratio, and life expectancy at birth times years of schooling (these are included one at a time with other control variables).	All five measures of human capital are significantly (at the 5 or 10 percent levels) and positively related with per capita income growth.

Table 5.1 (continued).

Publication reference	Dependent variable	Human capital variable	Results
Glewwe, Maiga and Zheng (2007)	Log of GDP per worker (as in Mankiw, Romer and Weil (1992)).	Education investment (as in Mankiw, Romer and Weil (1992)).	The coefficient of the human capital variable is positive for both samples. It is significant for the French colonies (0.414) at the one percent level and insignificant for the English colonies (0.328) at conventional levels.
	Growth rate of real per capita GDP.	Male years of secondary schooling, log of total fertility rate.	The coefficient of the human capital variable is negative (-0.0082) and not significant at conventional levels. The coefficient of the total fertility rate is not reported (the focus of the paper was on education).
Ndjikam, Binam and Tachi (2006)	Log of per capita growth rate of GDP.	Log of gross secondary school enrolment.	The human capital variable coefficient is negative and non-significant. Its interaction with trade openness (included together in the same equation) has a negative coefficient which is significant at 5 percent in the cross-section specification and insignificant in the fixed effects specification. The two other interactions are included separately in the cross-section and fixed effects estimations (without the human capital variable); their coefficients are positive but insignificant at conventional levels.
Oketch (2006)	Real per capita GDP growth rate.	Investment in basic and advanced education (% of GDP).	The estimated effect of the human capital variable is 5.22 and is significant at the 5 percent level.
Gyimah-Brempong and Wilson (2004)	Real per capita GDP growth rate.	Government health spending (% of GDP), Stock of Education (Barro and Lee, 1996).	The health human capital has a significant positive but decreasing effect on growth. The direct effect of the stock of education on per capita growth depends on the estimation method: it is positive and significant for the dynamic panel data estimation and negative and insignificant for the fixed effects.

Table 5 .1 (continued).

Publication reference	Dependent variable	Human capital variable	Results
Sacerdoti, Brunschwig and Tang (1998)	Growth rate of output per worker.	Average years of schooling, growth rate of wage-weighted years of schooling, initial human capital.	The coefficient of growth rate of years of schooling is negative and insignificant with the common intercept specification or with the initial GDP added in the model. The growth rate of the wage weighted years of schooling is positive but only significant without country fixed effects. The coefficient of the initial human capital is positive, but not significant.
Savvides (1995)	Real per capita GDP growth rate.	Initial secondary school enrolment.	Effects estimates are non-significant and range from -0.077 to 0.03 depending on variables included.
McMahon (1987)	Per capita GDP growth.	First lag of investment in primary and secondary education (% of GDP); first and second lags of investment in tertiary education (% of GDP).	The effect of the first lag of the ratio of investment on primary and secondary education to GDP is positive. It is significant only without the second lag of tertiary education investment ratio. The first lag of tertiary education investment ratio has a negative and insignificant coefficient while the second lag ha a positive coefficient and significant (at 5 percent).

<u>Source:</u> Author's compilation.

Sachs and Warner (1997) estimated a cross-country growth model including 32 African countries and other non-African countries for the period 1965-1990[37]. They found that the growth contribution of life expectancy at birth was greater at lower values. Interpreting this result, the authors noted that the underperformance of Africa on this human capital proxy was due to a combination of policy and natural factors;[38] implying that improvements in the provision and quality of health services by African countries would

[37] Different sample sizes and specifications have been used, with the number of countries varying from 74 to 79.

[38] The authors specifically named low income levels, poor health institutions, and endemic infectious diseases.

result in higher growth outcomes. Bhattacharyya (2009) investigated causes of Africa's under-development and suggested that malaria matters the most.

5.2.3. Growth accounting studies.

A growth accounting analysis by Loko and Diouf (2009) revealed that human capital has contributed one percentage point to growth in the Maghreb countries in the period 1970-2005. This performance was double the contribution of physical capital and compensated for the negative contribution of total factor productivity during this period. Furthermore, according to the same study, the only period during which growth was driven by physical capital accumulation was during the 1970s. From the 1980s until 2005, human capital was the key driver of long term growth.

Another growth accounting exercise for 19 SSA countries by Fosu (2012) highlighted the importance of human capital for growth, especially in the 1980s and 1990s when physical capital had a negative estimated contribution to growth. Over the full period 1960 - 2000, human capital contributed on average to overall growth with 0.25 percentage points against 0.36 percentage points' contribution for the physical capital.

Table 5.2: Sample, control variables and estimation methods used in empirical studies of human capital contribution to growth with African data.

Publication reference	Sample	Control variables	Method
Burger and Teal (2015)	9 South African industries; 36 unevenly spaced observations per industry between 1995 and 2011.	Log of capital stock and log of employment.	Pooled OLS, FE, 2-way FE, RE, FD, Mean group, Correlated mean group, Augmented mean group, OLS (cross section).
Eggoh, Houeninvo and Sossou (2015)	49 African countries, observed from 1996 to 2010.	Initial GDP, Inflation rate, Government expenditure to GDP, 2-way trade to GDP, Government expenditure minus health and education expenditure, investment ratio, net inflows of FDI to GDP, quasi-money to GDP.	Cross-section (OLS); Dynamic Panel data (GMM).
Kwendo and Muturi (2015)	5 East Africa countries; yearly data from 1995 to 2010.	Government expenditure on agriculture, Government expenditure on consumption, Government expenditure on Defence.	OLS (fixed and random effects).
Anyanwu (2014)	53 African countries; data are average over 3-year non-overlapping periods from 1996 to 2010.	GDP ratios of Domestic investment, Government consumption expenditure, ODA, FDI, 2-way trade and external debt, initial real per capita GDP, inflation rate, Polity2, Government effectiveness, urban population, credit to private sector, agricultural material price index, metal price index, oil price index, industrial material price index.	Pooled OLS, FGLS; IV-2SLS, GMM.

Table 5.2 (continued).

Publication reference	Sample	Control variables	Method
Amadi, Amadi and Nyenke (2013)	One African country (Nigeria); yearly data from 1981 to 2010.	Public spending on transport and communication, public spending on roads and construction, public spending on other economic services (electricity and water supply).	OLS.
Oluwatoyin (2011)	One country (Nigeria); there is no indication about the time period.	None	Error correction model.
Danquah, Ouattara, and Speight (2010)	19 Sub-Saharan Africa countries; data are averaged over 5 year periods from 1960 to 2003.	Distance to frontier, log of population, openness, Government consumption to GDP ratio, inflation, M2 to GDP ratio, Polity.	Pooled OLS; IV-2SLS, GMM.
Danquah, Ouattara, and Speight (2010)	19 Sub-Saharan Africa countries; data are averaged over 5 year periods from 1960 to 2003.	Distance to frontier.	Pooled OLS; IV-2SLS, GMM.
Suliman and Mollick (2009)	29 African countries, observed from 1980 to 2003.	Real GDP, real GDP growth, openness, liquidity (M2), number of telephone lines per 1000 population, lag of FDI, Freedom House score.	Cross-section (OLS-Weighted); SUR.
Hassan and Ahmed (2008)	Yearly data on 39 African countries from 1975 to 2005.	Investment ratio, inflation, openness, domestic interest rate, population growth.	OLS.

Table 5.2 (continued).

Publication reference	Sample	Control variables	Method
Glewwe, Maiga and Zheng (2007)	11 English colonies and 17 French colonies in the Mankiw, Romer and Weil (1992) sample.	Log of population growth, log of capital investment.	OLS.
Glewwe, Maiga and Zheng (2007)	18 Sub-Saharan countries in Barro and Sala-i-Martin (2004).	Log of per capita GDP, male years of secondary schooling, 1/(life expectancy at age 1), Government consumption ratio, rule of law, democracy, democracy squared, openness ratio, change in terms of trade, investment ratio, inflation rate.	OLS.
Ndjikam, Binam and Tachi (2006)	27 Sub-Saharan Africa countries; annual data and 3-year average data from 1965 to 2000.	Log of per worker capital, log of labour, log of openness, log of terms of trade, log of financial depth, log of population, log of ratio of gross investment to GDP.	Cross-section (OLS), FE, and Seemingly Unrelated Regressions (SUR).
Oketch (2006)	47 African countries; data points are averaged over the following periods: 1960–1965, 1965–1970, 1970–1975, 1975–1980, 1980–1985, 1985–1990, 1990–1995, 1995–1998.	Gross private domestic investment in physical capital ratio, 5-year average growth in net labour force, 5-year average population growth rate.	Panel data, 2SLS.

Table 5.2 (continued).

Publication reference	Sample	Control variables	Method
Gyimah-Brempong and Wilson (2004)	21 Sub-Saharan Africa countries; data are in 4-year averages from 1975-1994.	Medical spending to GDP ratio, investment to GDP ratio, ratio of population under 15, ratio of population over 15, export growth, per capita GDP (1987 PPP), openness, political instability.	Panel data, GMM (Dynamic Panel Data and Fixed Effects estimations).
Sacerdoti, Brunschwig and Tang (1998)	8 West African countries; yearly data from 1970 to 1996.	Capital growth, initial GDP per worker.	OLS, SUR.
Savvides (1995)	28 African countries; varying data points are averaged over 7-year periods (1960-1966; 1967-1973, 1973-1980, 1981-1987).	Initial per capita GDP, investment to GDP ratio, growth rate of population, inflation, growth rate of trade, Government consumption ratio to GDP, ratio of quasi-liquid liabilities of the financial system, coefficient of variation of the real exchange rate index, index of political freedom.	Panel data; 2-way fixed effects.
McMahon (1987)	30 African countries; 5-year average data for 1965-1970, 1970-1975, 1975-1980, and 1980-1985 periods.	Labour force growth, investment ratio.	OLS, 2SLS.

Source: Author’s compilation.

5.3. Theory and specification.

Our model specification draws from Hoeffler (2002)'s augmented Solow model inspired by previous cross-sectional studies by Barro (1991), Levine and Renelt (1992) and Sala-i-Martin (1997a, 1997b). In a panel data setting, Hoeffler's specification relates the growth rate of real GDP per worker to the level of real GDP per worker at the beginning of each period and other variables of interest such as the investment rate or the population growth. Bond, Leblebicioglu and Schiantarelli (2010) suggest adding further variables, including human capital variables to the same model. They also specified a shorter version by including only the investment ratio to GDP.

Due to diminishing marginal returns of capital, the relationship between the growth of per worker GDP and the initial level of GDP is expected to be negative, reflecting the convergence property of this model. Bond, Leblebicioglu and Schiantarelli (2010) showed that this model implied heterogeneous steady-state growth paths. This is in line with the conditional convergence theory relating growth to the level of per worker output in steady-state. As such, conditional on the implementation of effective economic policies that determine the level of the long-term output per worker, countries with lower levels of initial output per worker expected to achieve growth performances superior to their counterparts with higher levels of initial per worker income. The low level of initial per worker income in this conditional convergence model ceases to be a sufficient condition for growth differences among countries in the unconditional neoclassical convergence model developed by Ramsey (1928), Solow (1956), and others.

Previous empirical studies of growth determinants including De Gregorio (1992) and Barro (1997) investigated the growth contribution of major policy variables. Macroeconomic aggregates such as the investment ratio, inflation, and trade openness are among the common policy variables used in empirical studies. Another category of policy variables affecting growth encompasses political conditions such as the rule of law or the governance system. Human capital variables such as education, life expectancy, and fertility are also key policy variables affecting growth through the level of long-run per worker GDP.

In this research we focus on the growth contribution of human capital investment in the education and health sectors. We augment the model proposed by Hoeffler (2002) and Leblebicioglu and Schiantarelli (2010) by including human capital variables and further control variables. Equation (5.1) below is therefore adopted as our baseline specification, in line with this chapter's pursued goal to investigate the growth contribution of human capital investment in a sample of African countries.

$$\Delta y_{it} = \beta_0 + \sum_{m=1}^{M} \beta_m HK_{m,it} + \sum_{q=1}^{Q} \gamma_q X_{q,it} + \varepsilon_{it}, \qquad (5.1)$$

Where:

- i and t refer to individual countries and time (year) respectively;
- m and q refer to human capital and non-human capital variables respectively;
- M and Q refer to the number of human capital and non-human capital variables respectively;
- Δy_{it} is the growth rate of per capita GDP;
- $HK_{m,it}$, $m = 1, ..., M$ are M human capital variables;
- $X_{q,it}$, $q = 1, ..., Q$ are Q non-human capital determinants of growth;
- β_0, β_m, $m = 1, ..., M$, and γ_q, $q = 1, ..., Q$ are the model coefficients;
- ε_{it} is the error term.

Our dependent variable is the growth rate of real GDP per worker. Human capital variables include:

- public spending on education as a share of GDP ;
- public spending on health as a share of GDP ; and
- private spending on health as a share of GDP ;

Control variables are:

- the first lag of real GDP per worker ;
- per worker capital growth ;
- merchandise trade as a share of GDP ;
- agricultural value added as a share of GDP ;
- foreign direct investment as a share of GDP ;
- the annual inflation rate ; and
- the average value of the Freedom House political rights and civil liberties scores.

Country fixed effects as well as country specific time trends[39] are also included.

An alternative specification derived from this baseline specification is also considered in order to investigate previous empirical findings suggesting a delayed growth effect of investment on education. For this purpose, we include three lags of the public education expenditure ratio to GDP.

5.4. Data description and econometric issues.

This section is dedicated to a description of (i) the data used in our analysis, and (ii) the econometric approach of this research.

[39] We choose the specific time trends over the common time trend after estimating both specifications in the baseline model formulation. The latter was not significant while the specific trends were jointly significant.

5.4.1. Data Description.

The data description is conducted in four steps. First, the data sources are described. We then explain the process by which we obtain the model variables from the raw data. The description of the sampling process follows. In the last step, we analyse the descriptive statistics of the model variables.

5.4.1.1. Data sources.

Our primary data source is the World Bank's World Development Indicators (WDI) database. The raw series of interest from this source are presented in Table 5.3, using their exact codes and labels. These are variables commonly used in empirical growth studies either directly or as inputs in proxy variables calculations. This claim is evidenced by the list of variables in columns 2 and 3 of Table 5.1 summarising the empirical findings about the growth contribution of human capital variables in samples of African countries, and in column 3 of Table 5.2 that lists the control variables used in those empirical studies.

Though our main data source is the WDI, some of the series have missing values that we have to fill with estimations. The series having missing values are government expenditure on education (% of GDP) and gross fixed capital formation (current 2010 US$). The government expenditure on education series has 21 missing values unequally distributed across 8 countries. The number of missing values per country varies from 1 to 4. We first fill 5 of the missing values with projected values on this series published on the University of Sherbrooke's website[40]. The remaining missing values for this variable are imputed using

[40] The database is available at:
http://perspective.usherbrooke.ca/bilan/servlet/BMTendanceStatPays?codeTheme=4&codeStat=SE.XPD.TOTL.GD.ZS&codePays=AFG&optionsPeriodes=Aucune&codeTheme2=4&codeStat2=SE.XPD.TOTL.GD.ZS&codePays2=AFG&optionsDetPeriodes=avecNomP

linear associations with other variables. Stata's multiple imputation functionality[41] is used for this purpose. The government education spending to GDP ratio is linearly related to the first lag of per worker GDP and the government health spending to GDP ratio. The gross fixed capital ratio is first used to proxy per worker capital growth as explained below, which inherits the missing values of the input variable. These missing values are imputed according to the same procedure by linearly relating the per worker capital growth variable to the first lag of per worker GDP, the ratio of government spending on health, trade openness, the ratio of net inflows of FDI to GDP, and the ratio of agricultural value added to GDP.

Table 5.3: List of raw series of interest.

Code	**Label**
NY.GDP.MKTP.KD	: GDP at market prices (constant 2010 US$)
SL.TLF.TOTL.IN	: Labour force, total
NE.GDI.FTOT.KD	: Gross fixed capital formation (constant 2010 US$)
SH.XPD.PRIV.ZS	: Health expenditure, private (% of GDP)
SH.XPD.PUBL.ZS	: Health expenditure, public (% of GDP)
TG.VAL.TOTL.GD.ZS	: Merchandise trade (% of GDP)
BX.KLT.DINV.WD.GD.ZS	: Foreign direct investment, net inflows (% of GDP)
NV.AGR.TOTL.ZS	: Agriculture, value added (% of GDP)
FP.CPI.TOTL.ZG	: Inflation, consumer prices (annual %)

Source: The World Bank's World Development Indicators.

Our other data source from which a single series is drawn is a compilation of the Freedom House political rights and civil liberties scores over the period 1972 to 2016 realised by Edgell in 2016[42]. The series taken from this source is the average value of the Freedom House political rights and civil liberties scores. We use this variable to proxy the political

[41] The command used it **mi impute regress** with the two options **by**(Countryid) and **add**(1).

[42] This compilation is available at: http://acrowinghen.com/data.

governance indicator.

5.4.1.2. Data treatment.

The dependent variable (the per worker growth rate of the real GDP) is calculated after taking the ratio of the GDP to the labour force series.

We compute the per worker capital series by first applying the capital accumulation formula in equation (5.3) assuming a constant depreciation rate at 6 % per annum.

$$K_t = (1-\delta)*K_{t-1} + I_t, \tag{5.3}$$

where K_t is capital at year t, K_{t-1} is capital at year t-1, I_t is investment (GFCF) at year t and δ is the depreciation rate. The initial value of capital in 1999 is calculated as the 10-year cumulated GFCF values from 1989 to 1998[43]. We then take the growth rate of the ratio of the capital to the labour force series and use it as an explanatory variable. The remainder explanatory variables are taken directly from the respective sources described above.

The reason why we opt for the shares of expenditures in GDP for both education and health investment is that the monetary value for the expenditure on education is not reported in our main data source. Such a variable exists for health, but we think it would be better to have the same concept for education and health in our model. There is a possibility to generate monetary values of these expenditures using the information on the expenditure ratios and GDP series. However, the series description of the WDI does not allow us to identify which GDP series to use for such a conversion. Additionally, the use of the ratios of public spending on education and health in empirical growth studies on Africa is common as shown in Table 5.1.

[43] This method of deriving the stock of physical capital is used to produce the United Nations Productivity Database for over 100 countries, including African countries (Isaksson, 2007). The author used 6 % as the baseline depreciation rate. He also used the 10-year sum of investment to estimate the initial stock of capital.

5.4.1.3. Sampling: temporal and geographic coverage.

The time period and the sample of countries selection is constrained by two series, namely the GFCF series and the government expenditure on education series. There has been a significant improvement in the reporting of the latter series starting in 1999 with records available for 33 African countries compared with only 19 countries in 1998 and even fewer records in preceding years. From 1999-2013, this series has continued to be reported for no less than 23 countries each year. That dictates the choice of the time period from 1999 to 2013.

For this period, the combination of the two variables allows us to determine the sample of countries to include in the study. We start off with all 54 African countries and use one or the other of the two problematic variables to drop countries for which at least five missing values are recorded over the specified period (1999-2013). This threshold is a result of concerns over the quality of the missing values imputations.[44]

At the end of this procedure, we are left with a sample of 12 countries[45] whose geographical distribution across the continent is provided in Map 5.1 below.

The sample size of 12 countries out of 54 in Africa seems small as other researchers were able to include more countries in their studies. However, they did so by using different methodologies - such as five-year overlapping averaging, or estimation of proxies requiring strong assumptions - to address the data problem. Our sampling strategy is motivated by a balance between the sample size and the reliance on the data source for data quality.

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[44] One of the estimation techniques we adopt is not designed to accommodate missing values. For this reason, we need to impute them. Given data limitations, imputing a large number of missing values would be costly in terms of the quality of the imputations.

[45] These are: Benin, Cameroon, Madagascar, Mali, Mauritania, Mauritius, Senegal, Sierra Leone, South Africa, Swaziland, Togo and Tunisia.

<u>Map 5.1:</u> Geographical distribution of the sampled coutries.

5.4.1.4. Descriptive statistics of the model variables.

The basic descriptive statistics of the data presented above are summarized in Table 5.4. The pooled averages of the series appear in the first column, their minimum and maximum values are reported in the next two columns, and standard deviation values in the fourth column. The last column gives the simple correlations between the respective variables and the growth rate of real GDP per worker, our dependent variable.

The average growth rate of real GDP per worker over the sample period is relatively low at just above 1 percent when compared with the average growth rate of per worker capital of nearly 3 percent, and an average annual inflation rate of 5 percent. Combined annual public spending on health and education is well below 10 percent of GDP, on average. Agriculture value added counts for over a fifth of GDP, a share large enough for fluctuations in the sector to have an effect on aggregate economic performance. With respect to the governance indicator, the average Freedom House score of 3.8 corresponds to the category "partly free".[46] However, data in Table 5.4 indicate that there is a substantial dispersion in all variables, indicating large fluctuations both within and across countries.

The last column of Table 5.4 contains the correlation between the dependent variable and each individual independent variable. All the independent variables are only weakly correlated with the dependent variable. In absolute value, the highest correlation figures are recorded for per worker capital growth and the private health spending series, while the weakest correlations are obtained with trade openness and the agriculture share in GDP series.

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[46] The Freedom House scores serve to rank countries as free, partly free or not free. Until 2003, these categories correspond to respective score ranges of 1.0 to 2.5, 3.0 to 5.5 and 5.5 to 7.0. Since 2003, score ranges for partly free and free categories changed to 3.0 to 5.0 and 5.5 to 7.0. https://en.wikipedia.org/wiki/Freedom_House.

Table 5.4: Descriptive statistics of the model variables.

Variable	Count	Average	Minimum	Maximum	Standard deviation	Coefficient of variation	Correlation with per worker real GDP growth
Per Worker real GDP growth (%)	180	1.3	-15.4	20.2	3.9	2.9	1
First lag of per capita GDP (2010 US$)	180	8.1	6.7	10.0	1.0	0.1	0.05
Per worker capital growth (%)	180	2.8	-12.4	35.8	6.4	2.3	0.29
Public education spending (% GDP)	180	4.2	1.3	8.7	1.5	0.3	-0.06
Private health spending (% GDP)	180	3.4	1.6	10.9	1.9	0.6	0.21
Public health spending (% GDP)	180	2.6	0.8	7.4	1.1	0.4	-0.06
Trade share in GDP	180	62.9	13.0	170.3	27.7	0.4	0.01
FDI share in GDP	180	3.7	-3.2	37.2	5.2	1.4	0.13
Agriculture share in GDP	180	22.9	2.3	62.0	14.8	0.6	0.03
Inflation rate (%)	180	4.8	-35.8	34.1	5.4	1.1	-0.07
Freedom	180	3.8	1.0	6.5	1.7	0.4	-0.18

Source: Author's calculations.

5.4.2. Econometric issues.

Two key econometric issues are addressed below: (i) the econometric techniques we employ to estimate our model, and (ii) the model output reporting.

5.4.2.1. Estimation techniques.

The baseline specification of the model is estimated using three different estimation procedures: (i) the Parks estimator, (ii) the FGLS estimator with serially correlated and heteroskedastic errors, and (iii) the Panel Corrected Standard Errors (PCSE) estimator. The choice of these three methods follows the findings from chapters 2 and 3.

The ratios of the time dimensions (15 and 12) to the cross-sectional dimension (12) of our data set are less than 1.5. The findings of chapter 2 suggest that estimator (ii) (FGLS with groupwise heteroskedasticity and AR(1) serial correlation) produces the most efficient estimates. Further, chapter 2 suggests that the PCSE estimator produces the most reliable hypothesis tests. To these we compare the Parks estimator with parametric bootstrap-based hypothesis tests, as the results from chapter 3 indicate that this would produce the most reliable hypothesis testing.

5.4.2.2. Evaluation of the p-value of bootstrap based tests.

One of the estimation techniques of this investigation combines the parametric bootstrap technique with the Parks estimator to conduct hypothesis tests. Its practice follows the steps discussed in chapter 3. However, given that the specification here differs from that of chapter 3, the formulae employed to compute the error parameters used for data simulation under the null hypothesis also differ from those presented previously. Another difference with the earlier discussion is that we are now interested in the Student's t-distribution to test single restrictions as opposed to the chi-square distribution used before, which is suitable for more general tests. Therefore, the steps required to implement the parametric bootstrap technique in the present study could be summarised as follows:

(i). run the full equation 5.2 using the Parks method with the data presented above and compute the test statistics, $\hat{t}$;

(ii). run the restricted model under the null hypothesis (setting the coefficient to be tested equal to zero);

(iii). apply the Parks-type error variance-covariance matrix using the residuals from the restricted model according to equation 2.4 ;

(iv). apply this variance-covariance matrix to standard normal errors randomly sampled with replacement to generate the simulation error term ;

(v). use the estimated coefficients from the restricted model in ii and the error term formed in (iv) in equation 5.2 to generate the dependent variable ;

(vi). run the full model using the simulated dependent variable, the explanatory variables used in step (i) and compute a bootstrapped test statistic, $\hat{t}_{boot}$;

(vii). repeat (iii) through (vi) a large number of times, 999 times in this study, to get a series of 999 bootstrapped $\hat{t}_{boot}$;

(viii). compute the two-sided p-value to base the test decision using the method suggested by Davison and Hinkley (1997, pp 269-281):

$$\text{p-value} = 2\min\left[\frac{\#(\hat{t}_{boot} \leq \hat{t}) + 1}{1000},\ \frac{\#(\hat{t}_{boot} \geq \hat{t}) + 1}{1000}\right].$$

An alternative to the p-values computed with the equation above would be rejection intervals for the test statistics. For two-sided tests, upper and lower bounds for bootstrapped critical values corresponding to selected margin error levels (we used 1%, 5% and 10% in this study) could be computed with the $\hat{t}_{boot}$ series obtained in step (vii) and used for test decisions. The null hypothesis would then be rejected at levels for which the test statistic computed in step (i) falls inside the constructed interval. In Appendix 5.1 we provide the output for the baseline model with bootstrapped p-values and critical values ranges to illustrate the equivalence between the two indices – both lead to the same decision for each coefficient at the 5 percent and 10 percent significance levels.

5.5. Results.

The baseline model results are reported in Table 5.5. The output for the Parks estimator with asymptotic based tests is indicative, thus not worth consideration since this estimator is neither efficient given data set characteristics (time and cross-sectional dimensions) nor does it produce accurate hypothesis tests.

As mentioned earlier, the point estimates of coefficients would be more efficient using the FGLS estimator with serially correlated and heteroskedastic errors (column 2). Moreover, relatively reliable hypothesis tests are expected with the PCSE estimator (column 1), while the Parks estimator with bootstrapped critical values (last column) is the most reliable in performing the hypothesis tests of significance of the estimated coefficients.

Hence, the results in Table 5.5 suggest that public education spending/GDP has a positive coefficient according to the FGLS estimator and the two other estimators as well. Both the PCSE and the Parks estimates are larger in size than the coefficient with FGLS. However, the two first methods are less precise in getting the coefficient's size than the latter. The bootstrap based test indicates that the growth contribution of this variable is not significant at conventional levels.

Table 5.5: Baseline model results.

Independent variables	PCSE		FGLS + serially correlated and heteroskedastic errors		Parks		Parks + Bootstrapping	
Log of real GDP per worker $_{t-1}$	-56.886 (0.000)	***	-45.101 (0.000)	***	-55.020 (0.000)	***	-55.020 (0.052)	**
Per worker capital growth	0.059 (0.665)		0.281 (0.001)	***	0.078 (0.002)	***	0.078 (0.666)	
Public education spending/GDP	0.675 (0.167)		0.055 (0.869)		0.418 (0.000)	***	0.418 (0.504)	
Public health spending/GDP	-1.400 (0.122)		-1.654 (0.003)	***	-1.168 (0.000)	***	-1.168 (0.376)	
Private health spending/GDP	0.339 (0.760)		-0.811 (0.134)		0.037 (0.796)		0.037 (0.992)	
Trade openness/GDP	0.080 (0.009)	***	-0.001 (0.950)		0.076 (0.000)	***	0.076 (0.044)	**
Agriculture value added/GDP	-0.395 (0.026)	**	-0.292 (0.007)	***	-0.389 (0.000)	***	-0.389 (0.162)	
FDI/GDP	-0.067 (0.457)		-0.047 (0.456)		-0.065 (0.000)	***	-0.065 (0.600)	
Inflation (annual %)	-0.018 (0.824)		-0.054 (0.321)		-0.029 (0.000)	***	-0.029 (0.734)	

Freedom House score	0.538		0.534		0.574	***	0.574	
	(0.404)		(0.204)		(0.000)		(0.504)	
Constant	431.567	***	347.954	***	418.403	***	418.403	**
	(0.000)		(0.000)		(0.000)		(0.026)	
Observations	180		180		180		180	
Number of countries	12		12		12		12	
Country fixed effects ($F_{joint\ significance}$)	56.140		65.200		655.400		---	
	(0.000)		(0.000)		(0.000)		---	
Specific country time trends ($F_{joint\ significance}$)	41.400		53.260		565.010		---	
	(0.000)		(0.000)		(0.000)		---	
Specific country time trends ($F_{equality}$)	38.510		44.860		383.330		---	
	(0.000)		(0.000)		(0.000)		---	

Notes: P-values are in parentheses. *, **, and *** indicate respectively significance at the 10 percent, 5 percent and 1 percent levels.

As for the public spending on health, the negative sign of the coefficient is found by all three estimators. The negative association of private expenditure on health is not common across the estimators as only the FGLS estimator with serially correlated and heteroskedastic errors produces a negative relationship between the two variables. The bootstrap based tests indicate that none of the health indicators are significant at levels up to 10 percent.

We now turn to the specification including lags of the spending on education whose results are contained in Table 5.6. We first note that according to the FGLS estimator with serially correlated and heteroskedastic errors, the growth effect of the third lag of the education variable is negative while the current value and the other lags are positively related to the real GDP growth per worker. With the other two estimators, the negative association appears at the first lag. Secondly, the public education spending series and its first three lags do not significantly explain the growth rate of real GDP per worker.

To sum up the findings under both specifications, we have failed to find evidence that public spending on education and health have any effect on per worker GDP growth. The only variables that matter for growth are the first lag of the real GDP per worker, trade openness, and the agriculture value added ratio. The significant relationship involving the logarithm of the first lag of the GDP per worker aligns with convergence theory while the others evidence the growth benefits of trade promoting policies and the necessity to modernise agricultural economies by increasing the shares of the manufacturing and services sectors.

Table 5.6: Output of the model specification with lags of the education public spending variable.

Independent variables	PCSE		OLS + serially correlated and heteroskedastic errors		Parks		Parks + Bootstrapping	
Log of real GDP per worker $_{t-1}$	-35.863	***	-25.682	***	-33.443	***	-33.443	**
	(0.000)		(0.000)		(0.000)		(0.054)	
Per worker capital growth	0.227	*	0.301	***	0.176	***	0.176	
	(0.039)		(0.001)		(0.000)		(0.424)	
public education spending/GDP	0.320		0.182		0.261	***	0.261	
	(0.475)		(0.663)		(0.000)		(0.694)	
Public education spending/GDP $_{t-1}$	-0.376		0.065		-0.423	***	-0.423	
	(0.381)		(0.874)		(0.000)		(0.536)	
Public education spending/GDP $_{t-2}$	0.061		-0.104		0.043		0.043	
	(0.894)		(0.801)		(0.473)		(0.942)	
Public education spending/GDP $_{t-3}$	0.044		0.005		0.141	**	0.141	
	(0.921)		(0.991)		(0.022)		(0.872)	
Public health spending/GDP	-2.182	**	-2.197	***	-1.742	***	-1.742	
	(0.013)		(0.002)		(0.000)		(0.616)	
Private health spending/GDP	1.381		0.508		1.074	***	1.074	
	(0.153)		(0.485)		(0.000)		(0.746)	
Trade openness/GDP	0.117	***	0.052	*	0.109	***	0.109	
	(0.003)		(0.098)		(0.000)		(0.322)	

Agriculture value added/GDP	-0.883	***	-0.593	***	-0.939	***	-0.939	**
	(0.000)		(0.000)		(0.000)		(0.044)	
FDI/GDP	-0.174	*	-0.132	*	-0.169	***	-0.169	
	(0.031)		(0.067)		(0.000)		(0.442)	
Inflation (annual %)	-0.091		-0.084		-0.093	***	-0.093	
	(0.161)		(0.142)		(0.000)		(0.752)	
Freedom House score	2.358	***	1.802	***	2.389	***	2.389	
	(0.000)		(0.001)		(0.000)		(0.244)	
Constant	284.821	***	205.782	**	267.973	***	267.973	
	(0.000)		(0.000)		(0.000)		(0.102)	
Observations	144		144		144		144	
Number of countries	12		12		12		12	
Country fixed effects ($F_{joint\ significance}$)	74.090		39.620		1591.410		---	
	(0.000)		(0.000)		(0.000)		---	
Specific country time trends ($F_{joint\ significance}$)	54.720		21.380		753.190		---	
	(0.000)		(0.011)		(0.000)		---	
Specific country time trends ($F_{equality}$)	48.920		17.490		740.620		---	
	(0.000)		(0.026)		(0.000)		---	

Notes: P-values are in parentheses. *, **, and *** indicate respectively significance at the 10 percent, 5 percent and 1 percent levels.

5.6. Understanding the findings: econometric and data issues.

There are technical reasons and economic reasons that could be called to explain our findings. We address the technical issues here and discuss the economic reasons in the next section. On the technical ground, it could be that the data available to us is not of good quality as discussed in the previous chapter. For instance, our data on education and health public spending do not account for discrepancies that may exist between the execution of budgetary provision figures we use in our study and the actual expenses incurred in the education sector due to corruption and other inefficiency sources that characterize government bureaucracies. Such gaps are far from negligible in many African countries. We may also think of the simple linear econometric specification of the models estimated that capture nonlinearity and reverse causality relationships nor the long term nature of investment in both education and health sectors as a possible cause of our finding of their insignificant growth effects. Using African data, McMahon (1987) found that primary and secondary investment in education has a significant positive growth effect after two and half to five years lag while it takes as long as 7 and half years for investment in tertiary education to have impact significantly growth positively. In this respect, our data do not separate public education spending for different education levels either.

Our results should therefore be taken with great caution as evidence for a robust and significant impact of health and education expenditures on growth was established in previous empirical studies on different samples and using different estimation methods.

5.7. Policy discussion.

In this section, we provide an economic interpretation of the empirical results presented in the previous section from a policy perspective. We treat separately the implications with respect to the responses of the growth rate of per capita real GDP to changes in resources allocated to the education sector on the one hand, and to changes in resources allocated to the health sector on the other hand.

5.7.1. The insignificant growth contribution of public education spending.

We have found that public expenditure on education is not a significant growth determinant. Yet, this result is not meant to base a definite claim of the insignificance of the relationship between growth and public resources allocated to the education sector for a number of reasons we discussed in the previous chapter. Indeed, previous studies with a similar conclusion exist alongside those leading to a more optimistic view in terms of growth return of public investment in education.

Both conclusions are defensible. Apart from data quality and other technical issues discussed in the previous section, the current result could be explained in the following way. Public spending in Africa tends to be oriented toward improving the quantity of education rather than enhancing the quality of education, while the latter feature of education is the most closely related to growth. Education programmes do not align with needs of the economies productive sectors, thus resulting in an ineffective and ill-equipped workforce on which businesses cannot rely to optimise their output. This leads to the puzzle of high unemployment rates among the scarce educated labour force in Africa. Moreover, this lack of education quality hinders innovation and limits the ability of economies to grow as a result of investing on education. In this respect, our result may imply that African economies would gain from public financing of education only on condition that policy makers target both qualitative and quantitative improvements in the provision of education services.

5.7.2. Health spending's insignificant effect on economic growth.

Another key result from the model is that public and private expenditure on health do not affect growth after controlling for the effect of a number of other variables. The mechanism of transmission of spending on health to economic performance provides an explanation of this lack of significant correlation between per worker output growth and health expenditure. It is suggested that the contribution to growth of expenditure in the health sector passes through the R&D component, which is significant in developed countries, but rather low to non-existent in developing countries.

This result also indirectly poses the problem of the effectiveness of the health care system which is much broader, encompassing the efficient use of resources and the quality of the services it delivers. With this line of reasoning, resources allocated to other aspects of health outside R&D follow the consumption rather than the productive investment logic.

Alternatively, we could invoke a performance deficiency of health systems in sampled countries, which would have failed to deliver the expected health output. The mechanism for this effect passes through a wastage or diversion of resources allocated to the production of health care services. The implication of this resources mismanagement is that improvements taking place in the health status of the average population including the average worker are not proportionate to the level of the investment made.

5.8. Conclusion.

In this chapter, we applied recommendations from previous chapters to study the growth effects of education and health expenditures (shares in GDP) as proxies for human capital in a sample of 12 African countries over the period from 1999-2013. Following these recommendations, we have chosen the PCSE, the FGLS with serially correlated and heteroskedastic errors, and the Parks estimator with bootstrap based hypothesis tests to investigate the growth contribution of the above human capital variables. Other variables known to affect output growth are controlled for, namely the growth of the per worker capital stock, the first lag of the real GDP per worker, inflation, governance, the share of agriculture in the GDP, and the ratio of net inflows of FDI to GDP.

The results of the model indicate that neither spending on education nor that on health significantly affect per worker growth. This finding could well be attributed to the econometric model specification or the data quality. However, other reasons directly related to the education and health sectors performances are not to be excluded.

The result with regards to education may well highlight the poor quality of education services that do not adequately equip learners with skills needed by businesses to boost their activities. Education policy and decision makers need to adopt a joint focus on education's quantity and quality when it comes to allocating public resources for the provision of education services.

The lack of growth effect of resources allocated to the health sector may also be explained internally in two ways: (i) spending in the health sector might boost the consumption of health care services rather than the investment through R&D in the sampled countries; or (ii) the health systems might not be efficient enough to convert the financial allocation into improvements in the workers' health that in turn would positively affect their contribution to growth.

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Appendices.

Appendix 5.1: Output of the baseline model with bootstrap p-values and critical values ranges.

Variables	Coefficients	t-statistic	p-value	Upper and Lower bounds of critical values			
				5%		10%	
				Lower	Upper	Lower	Upper
Log of GDP/worker, first lag	-55.020	-21.389	0.052	-22.1	19.9	-14.5	15.5
Per worker capital growth	0.078	3.150	0.666	-20.9	21.6	-16.0	15.9
Public education spending/GDP	0.418	4.526	0.504	-18.8	20.5	-15.5	14.3
Public health spending/GDP	-1.168	-6.563	0.376	-18.1	19.1	-14.4	13.2
Private health spending/GDP	0.037	0.258	0.992	-17.6	21.0	-13.7	15.9
Trade openness/GDP	0.076	16.327	0.044	-16.7	15.6	-11.8	11.6
agriculture value added/GDP	-0.389	-12.993	0.162	-20.4	21.4	-16.3	16.5
FDI/GDP	-0.065	-4.394	0.600	-21.4	16.3	-14.6	13.0
Inflation (annual %)	-0.029	-3.601	0.734	-25.4	23.6	-18.2	18.4
Freedom House score	0.574	5.423	0.504	-18.2	17.5	-13.2	13.6
Constant	418.403	21.667	0.026	-16.8	16.1	-13.8	11.9

Source: Author's calculations.

Chapter 6 : General Conclusion.

The general objective of this thesis research was to study the performance of panel data estimators with a view to advising other researchers on which estimator to choose for specific research settings. This broad objective was broken down into three specific objectives. The research was first concerned with a comparative performance study of linear, static panel data estimators assuming a general form of dependencies in the error term. Next, it proposed to develop guidelines that could be useful in choosing the most suitable estimator by future researchers among the ones readily available to many empirical researchers through standard econometric packages. The third and last specific objective was to provide an empirical application of these guidelines in a case study using real data to investigate a real policy question. Our policy application study sought to estimate the impact of human capital spending on economic growth in a sample of African countries.

Chapters 2 and 3 addressed the two first objectives. In the second chapter, the performances of 11 estimators were studied. These estimators are built into Stata or Eviews and are readily available to a large number of researchers using econometrics, even without having advanced knowledge of econometric properties of these estimators implied by their respective underlying assumptions. This investigation of the estimators' comparative performances was a replication of a previous study by RY who used Monte Carlo experiments to develop a set of practical rules that researchers could use for panel data estimator selection. However, the experimental design in RY's research was flawed. We adjusted their experimental design for that flaw and reassessed the worthiness of the original findings and provided a robustness control for our findings.

We found that the ratio of time (T) to the cross-sectional dimensions of panel data sets (N) is the only data set characteristic one needs to know to choose the most efficient estimator among the studied static panel data model estimators. The original research we replicated found that the degree of error heteroskedasticity also played a role in the efficiency based estimator selection, but our findings did not support this conclusion. These first findings are effective and robust to the error dependence parameters.

Another key result of the original research was related to the choice of the estimator that produces the most accurate confidence intervals for the model's estimated coefficients. The replication study also shed more light on this result by basing the estimator choice on more evident indices compared with RY. However, here our results were of limited practical significance since we, like RY, did not find that one estimator substantially dominated the others, and that all of the estimators had shortcomings in estimating confidence intervals across the full range of error parameters.

The bottom line of the two sets of key findings of the replication study is that there is no single estimator that is best for both the point estimator and the confidence interval construction. As it is not common for researchers to use one estimator for coefficient values and another for hypothesis tests (though there is nothing inconsistent with this procedure), this means that one would have to choose the efficiency of an estimator at the expense of a correct test decision or vice versa. This has led us to further investigate the Parks estimator - which was the most efficient of all the 11 estimators where applicable - in chapter 3 by basing tests on the bootstrap theory rather than on the asymptotic theory. The Parks estimator performed very poorly in estimating confidence intervals asymptotically. The bootstrap techniques have the virtue of producing better test sizes with pivotal statistics compared with the asymptotic theory based tests. We conducted extra Monte Carlo experiments to assess the extent to which this size improvement takes place with this particular estimator. We found that the bootstrap technique effectively removes the size distortion observed with the asymptotic theory tests, showing little deviations from the nominal size of 5 percent. The added value of chapter 3 was that it has made it possible to recommend a single panel data estimator with good performance on both efficiency and test decision grounds.

The findings of chapters 2 and 3 were used in chapter 5 to study the growth effect of education and health spending in a sample of 12 African countries observed from 1999 to 2013. Before getting to this application of the findings, we set the stage in chapter 4 by summarizing (i) the background information about the theoretical and empirical linkages between human capital and economic performance at the macroeconomic level, and (ii) historical growth and human capital trends in Africa. Human capital is commonly thought to be a key growth driver. However, there is no direct measure of human capital.

Many proxies in the education and health sectors have been used in studies that attempted to assess the economic value of human capital. Due to the use of these different proxies and other problems such as data quality or model misspecification, estimates of the impact of the human capital on growth in different empirical studies have not led to converging conclusions. Some estimates are significant while others are not. Some results indicate a positive association while others point to the opposite. Magnitudes of positive or negative estimates also vary greatly. It is in this context that we proposed to investigate the impact of education and health spending on the growth rate of per worker GDP, which is of great policy relevance.

With our sample of 12 African countries and 15 years of data from 1999 to 2013, we estimated the real per worker GDP growth contribution of health and education expenditures as measured by their shares of GDP. We used the FGLS estimator with first order serially correlated and heteroskedastic errors, the Parks (1967) estimator with bootstrap based hypothesis tests, and the Beck and Katz' (1995) panel corrected standard errors (PCSE) estimator. This set of estimators was motivated by the findings of chapters 2 and 3. According to chapters 2 and 3, given our data set dimensions the FGLS estimator should be the most efficient while the PCSE and Parks-bootstrapped estimators should be preferable for hypothesis testing.

The estimation results indicate that public investment in health and education does not significantly affect the growth rate of per worker real GDP. Policy implications of this result are that human capital investments in both education and health need to be invested more efficiently, or targeted in different ways, than they are currently being invested. This is a topic for future research.

Annexes.

Annex 1. SAS/IML codes for Chapter 2: Specification 1.

```
*** I. THIS PROGRAM EVALUATES OLS;


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
```

```
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);
b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];


***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
covb=(e`*e/(nt-2))*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;


end;
```

```
***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 1 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** II. THIS PROGRAM EVALUATES OLS (ROBUST);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
```

```
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;


** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];


***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
v=diag(e#e);
covb=nt/(nt-2)*inv(z`*z)*z`*v*z*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
       (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
```

```
mse_1[k]=(b_1[k]+1.0)**2;


end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 2 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** III. THIS PROGRAM EVALUATES OLS (CLUSTER-CROSS-SECTIONAL UNITS);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
```

```
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
ee=e*e`;
v=j(nt,nt,0);
do i=1 to n;
v[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=ee[((i-1)*t)+1:i*t,((i-
1)*t)+1:i*t];
end;
covb=((nt-1)/(nt-2))*(n/(n-1))*inv(z`*z)*z`*v*z*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
```

```
tcrit=tinv(0.975,(n-1));
if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;


end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 3 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** IV. THIS PROGRAM EVALUATES OLS (CLUSTER-TIME PERIODS);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
```

```
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
```

```
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
ystar=j(nt,1,0);
zstar=j(nt,2,0);
numberr = 0;
numberri=0;
do j=1 to t;
do i=1 to n;
   numberr = numberr +1;
   numberri= numberri + 1;
   if numberri > n then numberri = 1;
   ystar[numberr] = y[((numberri-1)*t)+j];
   zstar[numberr,] = z[((numberri-1)*t)+j,];
end;
end;
b=inv(zstar`*zstar)*zstar`*ystar;
mse_0[k]=(b[2]+1.0)**2;
estar=ystar-zstar*b;
eestar=estar*estar`;
vstar=j(nt,nt,0);
```

```
do i=1 to t;
vstar[((i-1)*n)+1:i*n,((i-1)*n)+1:i*n]=eestar[((i-1)*n)+1:i*n,((i-
1)*n)+1:i*n];
end;
covb=((nt-1)/(nt-2))*(t/(t-1))*inv(zstar`*zstar)*
zstar`*vstar*zstar*inv(zstar`*zstar);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(t-1)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
tcrit=tinv(0.975,(t-1));
if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 4 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
*** V. THIS PROGRAM EVALUATES FGLS (Groupwise Heteroscedasticity);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
```

```
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
```

```
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);
```

```
meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
estar=j(t,n,0);
do i=1 to n;
   estar[,i]=e[((i-1)*t)+1:i*t];
end;
sigma2e=j(n,n,0);
do i=1 to n;
   sigma2e[i,i]=estar[,i]`*estar[,i]/t;
end;
****CONSTRUCT COVARIANCE MATRIX V*****;
v=sigma2e@i(t);
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
bfgls=inv(z`*vinv*z)*z`*vinv*y;
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-1.0 - zcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
```

```
mse_1[k]=(b_1[k]+1.0)**2;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 5 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** VI. THIS PROGRAM EVALUATES FGLS (Groupwise Heteroscedasticity +
Autocorrelation);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
```

```
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
```

```
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;

if rhohat >= 1 then check1=check1+1;
if rhohat <= -1 then check2=check2+1;

if (rhohat < 1) & (rhohat > -1) then do;
*rhohat=0.6740;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma2u=j(n,n,0);
do i=1 to n;
   sigma2u[i,i]=eestar[,i]`*eestar[,i]/t;
end;
sigma2e=(1/(1-(rhohat**2)))*sigma2u;
****CONSTRUCT COVARIANCE MATRIX V*****;
omega=j(t,t,1);
do i=2 to t;
   do j=1 to (i-1);
      omega[i,j]=rhohat**(i-j);
   end;
end;
do i=1 to (t-1);
   do j=(i+1) to t;
      omega[i,j]=rhohat**(j-i);
   end;
end;
v=sigma2e@omega;
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
bfgls=inv(z`*vinv*z)*z`*vinv*y;
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
```

```
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-1.0 - zcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;

end;

if rhohat >= 1 then k=k-1;
if rhohat <= -1 then k=k-1;

end;
***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 6 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** VII. THIS PROGRAM EVALUATES FGLS (PARKS);
proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
```

```
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
```

```
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;
```

```
if rhohat >= 1 then check1=check1+1;
if rhohat <= -1 then check2=check2+1;

if (rhohat < 1) & (rhohat > -1) then do;
*rhohat=0.6740;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma2u=j(n,n,0);
do i=1 to n;
   do j=1 to n;
      sigma2u[i,j]=eestar[,i]`*eestar[,j]/t;
   end;
end;
sigma2e=(1/(1-(rhohat**2)))*sigma2u;
****CONSTRUCT COVARIANCE MATRIX V*****;
omega=j(t,t,1);
do i=2 to t;
   do j=1 to (i-1);
      omega[i,j]=rhohat**(i-j);
   end;
end;
do i=1 to (t-1);
   do j=(i+1) to t;
      omega[i,j]=rhohat**(j-i);
   end;
end;
v=sigma2e@omega;
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
bfgls=inv(z`*vinv*z)*z`*vinv*y;
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
```

```
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-1.0 - zcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;

end;

if rhohat >= 1 then k=k-1;
if rhohat <= -1 then k=k-1;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 5 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** VIII. THIS PROGRAM EVALUATES PCSE (PARKS);


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
```

```
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1 = 0;
check2 = 0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+1.0)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   if check > 1 then check1 = check1 + 1;
```

```
   if check > 1 then check = 1;
   if check < -1 then check2 = check2 + 1;
   if check < -1 then check = -1;
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;
*rhohat=0.6740;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma=(1/t)*eestar`*eestar;
vstar=sigma@i(t);
****CALCULATE PANEL-CORRECTED STANDARD ERRORS*****;
covb=inv(zstar`*zstar)*zstar`*vstar*zstar*inv(zstar`*zstar);
seb=sqrt(vecdiag(covb));
tratio=bstar/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bstar[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-1.0 - zcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+1.0;
mse_1[k]=(b_1[k]+1.0)**2;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
```

```
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 6 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** IX. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White cross-section);


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
```

```
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+1.0)**2;
e=y-z*b;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
sigma=j(n,n,0);
```

```
do i=1 to n;
   sigma[i,i]=ee[,i]`*ee[,i]/t;
end;
v=sigma@i(t);
rank=round(trace(ginv(v)*v));
if rank = nt then do;
   *v=omgbar;
   vinv=inv(v);
   b=inv(z`*vinv*z)*z`*vinv*y;
   estar=y-z*b;
   omegastar=estar*estar`;
   omega=j(nt,nt,0);
   number1=0;
   do j=1 to nt;
      number1=number1+1;
      do i=1 to n;
         if number1 > t then number1 = 1;
         omega[((i-1)*t)+number1,j]=omegastar[((i-1)*t)+number1,j];
      end;
   end;
   covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
   seb=sqrt(vecdiag(covb));
   tratio=b/seb;
   prt=2*(1-probt(abs(tratio),(nt-2)));
   b_1[k]=b[2];
   se_1[k]=sqrt(covb[2,2]);
   cint_1[k]=0;
   if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
   bias_1[k]=b_1[k]+1.0;
   mse_1[k]=(b_1[k]+1.0)**2;
end;

if rank < nt then do;
   k = k-1;
end;

end;



***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
```

```
cname={"Level" "SERatio" "Efficiency" };
print 'Procedure 9 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** X. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White period);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
```

```
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;



***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];


***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+1.0)**2;
e=y-z*b;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
```

```
sigma=j(n,n,0);
do i=1 to n;
   sigma[i,i]=ee[,i]`*ee[,i]/t;
end;
v=sigma@i(t);
rank=round(trace(ginv(v)*v));
if rank = nt then do;
   *v=omgbar;
   vinv=inv(v);
   b=inv(z`*vinv*z)*z`*vinv*y;
   estar=y-z*b;
   eestar=j(t,n,0);
      do i=1 to n;
         eestar[,i]=estar[((i-1)*t)+1:i*t];
      end;
   omega=j(nt,nt,0);
   do i=1 to n;
      omega[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=eestar[,i]*eestar[,i]`;
   end;
   covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
   seb=sqrt(vecdiag(covb));
   tratio=b/seb;
   prt=2*(1-probt(abs(tratio),(nt-2)));
   b_1[k]=b[2];
   se_1[k]=sqrt(covb[2,2]);
   cint_1[k]=0;
   if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
      (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
   bias_1[k]=b_1[k]+1.0;
   mse_1[k]=(b_1[k]+1.0)**2;
end;

if rank < nt then do;
   k = k-1;
end;

end;



***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
cname={"Level" "SERatio" "Efficiency" };
```

```
print 'Procedure 10 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** XI. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White diagonal);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
```

```
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+1.0*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
```

```
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(1.0*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+1.0)**2;
e=y-z*b;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
sigma=j(n,n,0);
do i=1 to n;
```

```
      sigma[i,i]=ee[,i]`*ee[,i]/t;
   end;
   v=sigma@i(t);
   rank=round(trace(ginv(v)*v));
   if rank = nt then do;
      *v=omgbar;
      vinv=inv(v);
      b=inv(z`*vinv*z)*z`*vinv*y;
      estar=y-z*b;
      eestar=estar*estar`;
      omega=j(nt,nt,0);
      do i=1 to nt;
         omega[i,i]=eestar[i,i];
      end;
      covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
      seb=sqrt(vecdiag(covb));
      tratio=b/seb;
      prt=2*(1-probt(abs(tratio),(nt-2)));
      b_1[k]=b[2];
      se_1[k]=sqrt(covb[2,2]);
      cint_1[k]=0;
      if (b_1[k] >= (-1.0 - tcrit*se_1[k])) &
         (b_1[k] <= (-1.0 + tcrit*se_1[k]))then cint_1[k]=1;
      bias_1[k]=b_1[k]+1.0;
      mse_1[k]=(b_1[k]+1.0)**2;
   end;

   if rank < nt then do;
      k = k-1;
   end;

   end;



   ***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
   meanb1[1]=b_1`*onesr/R;
   meanseb1[1]=se_1`*onesr/R;
   menbias1[1]=bias_1`*onesr/R;
   meanmse1[1]=mse_1`*onesr/R;
   meanmse0[1]=mse_0`*onesr/R;
   seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
   (meanb1[1]*onesr))/R));
   level1[1]=100*(cint_1`*onesr/R);
   efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);


   results=level1||seratio1||efishnc1;
   cname={"Level" "SERatio" "Efficiency" };
   print 'Procedure 11 Results';
   print n periods;
   print rhohatbar;
   print results[colname=cname];
   print number;
```

```
finish;
run program;
quit;

run;
```

```
*** XII. THIS PROGRAM CALCULATES THE PARAMETERS OF THE ERRORS;

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
   end;
zi=si||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
```

```
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;
```

```
***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1 = 0;
check2 = 0;


RHO = j(R,1,0);
CSCORR = j(R,1,0);
corrr = j(n,n,0);
HET = j(R,1,0);
HETRANGE = j(R,1,0);

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
```

```
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   if check > 1 then check1 = check1 + 1;
   if check > 1 then check = 1;
   if check < -1 then check2 = check2 + 1;
   if check < -1 then check = -1;
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;
RHO[k] = rhohat;
*rhohat=0.6740;

** I started Here;

*corr = ((1/periods)*(ee`*ee))/(1-rhohat**2);
corrr = CORR(ee);
do i=2 to n;
     do j=1 to (i-1);
     CSCORR[k]=CSCORR[k]+abs(corrr[i,j]);
     end;
end;
CSCORR[k] = (2/(n**2-n))*CSCORR[k];

start Qntl(q0, x00, p0);       /** definition 5 from UNIVARIATE doc
**/
   n0 = nrow(x00);               /** assume nonmissing data **/
   q0 = j(ncol(p0), ncol(x00));/** allocate space for return values
**/
   do j = 1 to ncol(x00);     /** for each column of x... **/
      y00 = x00[,j];
      call sort(y00,1);       /** sort the values **/
      do i = 1 to ncol(p0); /** for each quantile **/
         k = n0*p0[i];        /** find position in ordered data **/
         k1 = int(k);       /** find indices into ordered data **/
         k2 = k1 + 1;
         g = k - k1;
         if g>0 then
            q0[i,j] = y0[k2];/** return a data value **/
         else                /** average adjacent data **/
            q0[i,j] = (y00[k1]+y00[k2])/2;
      end;
  end;
  finish;

   x00 = sqrt(vecdiag((1/periods)*(ee`*ee)));
   p0 = {.25 .75};
   call qntl(q0,x00,p0);
   HET[k] = q0[2]/q0[1];
```

```
   HETRANGE[k] = q0[2]-q0[1];



end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
cscorrbar = j(1,1,0);
rhobar = j(1,1,0);
HETRANGECOEF = J(1,1,0);
cscorrbar = CSCORR`*onesr/R;
rhobar  = RHO`*onesr/R;
HETCOEF = HET`*onesr/R;
HETRANGECOEF = HETRANGE`*onesr/R;
nperiods = n||periods;
Parameters = nperiods||cscorrbar||rhobar||HETCOEF||HETRANGECOEF;
cname = {'N' 'T' 'CSCORR' 'RHOHATBAR' 'HETCOEF' 'HETRANGECOEF'};

print 'RGF1 AD DATA';
print Parameters[colname = cname];

finish;
run program;
quit;

run;
```

Annex 2. SAS/IML codes for Chapter 2: Specification 2.

```
*** I. THIS PROGRAM EVALUATES OLS;


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
```

```
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);
b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
xo = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
covb=(e`*e/(nt-2))*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;
```

```
end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 1 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** II. THIS PROGRAM EVALUATES OLS (ROBUST);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;


***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
```

```
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
```

```
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
xo = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
v=diag(e#e);
covb=nt/(nt-2)*inv(z`*z)*z`*v*z*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
```

```
se_1[k]=sqrt(covb[2,2]);
if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;


end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 2 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** III. THIS PROGRAM EVALUATES OLS (CLUSTER-CROSS-SECTIONAL UNITS);


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;


***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
```

```
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
```

```
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
ee=e*e`;
v=j(nt,nt,0);
do i=1 to n;
v[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=ee[((i-1)*t)+1:i*t,((i-
1)*t)+1:i*t];
end;
```

```
covb=((nt-1)/(nt-2))*(n/(n-1))*inv(z`*z)*z`*v*z*inv(z`*z);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
tcrit=tinv(0.975,(n-1));
if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;


end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 3 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** IV. THIS PROGRAM EVALUATES OLS (CLUSTER-TIME PERIODS);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
ystar=j(nt,1,0);
zstar=j(nt,2,0);
numberr = 0;
numberri=0;
do j=1 to t;
do i=1 to n;
   numberr = numberr +1;
   numberri= numberri + 1;
   if numberri > n then numberri = 1;
   ystar[numberr] = y[((numberri-1)*t)+j];
   zstar[numberr,] = z[((numberri-1)*t)+j,];
end;
end;
b=inv(zstar`*zstar)*zstar`*ystar;
mse_0[k]=(b[2]+0.01)**2;
```

```
estar=ystar-zstar*b;
eestar=estar*estar`;
vstar=j(nt,nt,0);
do i=1 to t;
vstar[((i-1)*n)+1:i*n,((i-1)*n)+1:i*n]=eestar[((i-1)*n)+1:i*n,((i-
1)*n)+1:i*n];
end;
covb=((nt-1)/(nt-2))*(t/(t-1))*inv(zstar`*zstar)*
zstar`*vstar*zstar*inv(zstar`*zstar);
seb=sqrt(vecdiag(covb));
tratio=b/seb;
prt=2*(1-probt(abs(tratio),(t-1)));
b_1[k]=b[2];
se_1[k]=sqrt(covb[2,2]);
tcrit=tinv(0.975,(t-1));
if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 4 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;
run;
```

```
*** V. THIS PROGRAM EVALUATES FGLS (Groupwise Heteroscedasticity);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0=j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
estar=j(t,n,0);
do i=1 to n;
   estar[,i]=e[((i-1)*t)+1:i*t];
end;
sigma2e=j(n,n,0);
do i=1 to n;
   sigma2e[i,i]=estar[,i]`*estar[,i]/t;
end;
```

```
****CONSTRUCT COVARIANCE MATRIX V*****;
v=sigma2e@i(t);
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
bfgls=inv(z`*vinv*z)*z`*vinv*y;
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-0.01 - zcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 5 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;
run;
```

```
*** VI. THIS PROGRAM EVALUATES FGLS (Groupwise Heteroscedasticity +
Autocorrelation);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
```

```
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
```

```
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
```

```
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;

if rhohat >= 1 then check1=check1+1;
if rhohat <= -1 then check2=check2+1;

if (rhohat < 1) & (rhohat > -1) then do;
*rhohat=0.6725;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma2u=j(n,n,0);
do i=1 to n;
   sigma2u[i,i]=eestar[,i]`*eestar[,i]/t;
end;
sigma2e=(1/(1-(rhohat**2)))*sigma2u;
****CONSTRUCT COVARIANCE MATRIX V*****;
omega=j(t,t,1);
do i=2 to t;
   do j=1 to (i-1);
      omega[i,j]=rhohat**(i-j);
   end;
end;
do i=1 to (t-1);
   do j=(i+1) to t;
      omega[i,j]=rhohat**(j-i);
   end;
end;
v=sigma2e@omega;
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
```

```
bfgls=inv(z`*vinv*z)*z`*vinv*y;
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-0.01 - zcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;

end;

if rhohat >= 1 then k=k-1;
if rhohat <= -1 then k=k-1;

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 6 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** VII. THIS PROGRAM EVALUATES FGLS (PARKS);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));

****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;

***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;

***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));
onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1=0;
check2=0;

** This section selects a random slice of the independent variable
to be used for simulations;
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
```

```
   check=(rhatnum/rhatden);
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;

if rhohat >= 1 then check1=check1+1;
if rhohat <= -1 then check2=check2+1;

if (rhohat < 1) & (rhohat > -1) then do;
*rhohat=0.6725;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma2u=j(n,n,0);
do i=1 to n;
   do j=1 to n;
      sigma2u[i,j]=eestar[,i]`*eestar[,j]/t;
   end;
end;
sigma2e=(1/(1-(rhohat**2)))*sigma2u;
****CONSTRUCT COVARIANCE MATRIX V*****;
omega=j(t,t,1);
do i=2 to t;
   do j=1 to (i-1);
      omega[i,j]=rhohat**(i-j);
   end;
end;
do i=1 to (t-1);
   do j=(i+1) to t;
      omega[i,j]=rhohat**(j-i);
   end;
end;
v=sigma2e@omega;
vinv=inv(v);
****CALCULATE FGLS ESTIMATES*****;
bfgls=inv(z`*vinv*z)*z`*vinv*y;
```

```
covb=inv(z`*vinv*z);
seb=sqrt(vecdiag(covb));
tratio=bfgls/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bfgls[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-0.01 - zcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;

end;

if rhohat >= 1 then k=k-1;
if rhohat <= -1 then k=k-1;
end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);

results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 7 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** VIII. THIS PROGRAM EVALUATES PCSE (PARKS);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
```

```
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
```

```
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1 = 0;
check2 = 0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
```

```
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   if check > 1 then check1 = check1 + 1;
   if check > 1 then check = 1;
   if check < -1 then check2 = check2 + 1;
   if check < -1 then check = -1;
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;
*rhohat=0.6725;
***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
pstar=j(nt,nt,0);
pstari=j(t,t,0);
pstari[1,1]=sqrt(1-(rhohat**2));
do i=2 to t;
   pstari[i,(i-1)]=-rhohat;
   pstari[i,i]=1;
end;
do i=1 to n;
   pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
end;
***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
SECTIONAL COVARIANCES**;
zstar=pstar*z;
ystar=pstar*y;
bstar=inv(zstar`*zstar)*zstar`*ystar;
estar=ystar-(zstar*bstar);
eestar=j(t,n,0);
do i=1 to n;
   eestar[,i]=estar[((i-1)*t)+1:i*t];
end;
sigma=(1/t)*eestar`*eestar;
vstar=sigma@i(t);
****CALCULATE PANEL-CORRECTED STANDARD ERRORS*****;
covb=inv(zstar`*zstar)*zstar`*vstar*zstar*inv(zstar`*zstar);
seb=sqrt(vecdiag(covb));
tratio=bstar/seb;
prt=2*(1-probt(abs(tratio),(nt-2)));
b_1[k]=bstar[2];
se_1[k]=sqrt(covb[2,2]);
zcrit=probit(0.975);
if (b_1[k] >= (-0.01 - zcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + zcrit*se_1[k]))then cint_1[k]=1;
bias_1[k]=b_1[k]+0.01;
mse_1[k]=(b_1[k]+0.01)**2;


end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
```

```
meanmse0[1]=mse_0`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
*rname={PCSE};
cname={"Level" "SERatio" "Efficiency"};
print 'Procedure 8 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number check1 check2;

finish;
run program;
quit;

run;
```

```
*** IX. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White cross-section);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;



***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;


n = 5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
```

```
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
```

```
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+0.01)**2;
e=y-z*b;
```

```
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
sigma=j(n,n,0);
do i=1 to n;
   sigma[i,i]=ee[,i]`*ee[,i]/t;
end;
v=sigma@i(t);
rank=round(trace(ginv(v)*v));
if rank = nt then do;
   *v=omgbar;
   vinv=inv(v);
   b=inv(z`*vinv*z)*z`*vinv*y;
   estar=y-z*b;
   omegastar=estar*estar`;
   omega=j(nt,nt,0);
   number1=0;
   do j=1 to nt;
      number1=number1+1;
      do i=1 to n;
         if number1 > t then number1 = 1;
         omega[((i-1)*t)+number1,j]=omegastar[((i-1)*t)+number1,j];
      end;
   end;
   covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
   seb=sqrt(vecdiag(covb));
   tratio=b/seb;
   prt=2*(1-probt(abs(tratio),(nt-2)));
   b_1[k]=b[2];
   se_1[k]=sqrt(covb[2,2]);
   cint_1[k]=0;
   if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
   bias_1[k]=b_1[k]+0.01;
   mse_1[k]=(b_1[k]+0.01)**2;
end;

if rank < nt then do;
   k = k-1;
end;

end;



***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
```

```
level1[1]=100*(cint_1`*onesr/R);
efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
cname={"Level" "SERatio" "Efficiency" };
print 'Procedure 9 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;


finish;
run program;
quit;

run;
```

```
*** X. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White period);

proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;


***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;



***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
```

```
Q=root(vbar);
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+0.01)**2;
e=y-z*b;
ee=j(t,n,0);
do i=1 to n;
```

```
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
sigma=j(n,n,0);
do i=1 to n;
   sigma[i,i]=ee[,i]`*ee[,i]/t;
end;
v=sigma@i(t);
rank=round(trace(ginv(v)*v));
if rank = nt then do;
   *v=omgbar;
   vinv=inv(v);
   b=inv(z`*vinv*z)*z`*vinv*y;
   estar=y-z*b;
   eestar=j(t,n,0);
      do i=1 to n;
         eestar[,i]=estar[((i-1)*t)+1:i*t];
      end;
   omega=j(nt,nt,0);
   do i=1 to n;
      omega[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=eestar[,i]*eestar[,i]`;
   end;
   covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
   seb=sqrt(vecdiag(covb));
   tratio=b/seb;
   prt=2*(1-probt(abs(tratio),(nt-2)));
   b_1[k]=b[2];
   se_1[k]=sqrt(covb[2,2]);
   cint_1[k]=0;
   if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
   bias_1[k]=b_1[k]+0.01;
   mse_1[k]=(b_1[k]+0.01)**2;
end;

if rank < nt then do;
   k = k-1;
end;

end;



***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);
```

```
results=level1||seratio1||efishnc1;
cname={"Level" "SERatio" "Efficiency" };
print 'Procedure 10 Results';
print n periods;
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** XI. THIS PROGRAM EVALUATES GLS (Weights=Cross-Section weights,
Covariance=White diagonal);


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;

***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
```

```
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_0=j(R,1,0);
mse_0=j(R,1,0);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
efishnc1=j(1,1,0);

number=0;

** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
b_0[k]=b[2];
mse_0[k]=(b_0[k]+0.01)**2;
e=y-z*b;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
```

```
end;
sigma=j(n,n,0);
do i=1 to n;
   sigma[i,i]=ee[,i]`*ee[,i]/t;
end;
v=sigma@i(t);
rank=round(trace(ginv(v)*v));
if rank = nt then do;
   *v=omgbar;
   vinv=inv(v);
   b=inv(z`*vinv*z)*z`*vinv*y;
   estar=y-z*b;
   eestar=estar*estar`;
   omega=j(nt,nt,0);
   do i=1 to nt;
      omega[i,i]=eestar[i,i];
   end;
   covb=inv(z`*vinv*z)*z`*vinv*omega*vinv*z*inv(z`*vinv*z);
   seb=sqrt(vecdiag(covb));
   tratio=b/seb;
   prt=2*(1-probt(abs(tratio),(nt-2)));
   b_1[k]=b[2];
   se_1[k]=sqrt(covb[2,2]);
   cint_1[k]=0;
   if (b_1[k] >= (-0.01 - tcrit*se_1[k])) &
      (b_1[k] <= (-0.01 + tcrit*se_1[k]))then cint_1[k]=1;
   bias_1[k]=b_1[k]+0.01;
   mse_1[k]=(b_1[k]+0.01)**2;
end;

if rank < nt then do;
   k = k-1;
end;

end;



***THIS SECTION CALCULATES AND PRINT OVERALL RESULTS;
meanb1[1]=b_1`*onesr/R;
meanseb1[1]=se_1`*onesr/R;
menbias1[1]=bias_1`*onesr/R;
meanmse1[1]=mse_1`*onesr/R;
meanmse0[1]=mse_0`*onesr/R;
seratio1[1]=100*(meanseb1[1]/sqrt((b_1-(meanb1[1]*onesr))`*(b_1-
(meanb1[1]*onesr))/R));
level1[1]=100*(cint_1`*onesr/R);
efishnc1[1]=100*sqrt(meanmse1)/sqrt(meanmse0);


results=level1||seratio1||efishnc1;
cname={"Level" "SERatio" "Efficiency" };
print 'Procedure 11 Results';
print n periods;
```

```
print rhohatbar;
print results[colname=cname];
print number;

finish;
run program;
quit;

run;
```

```
*** XII. THIS PROGRAM CALCULATES THE PARAMETERS OF THE ERRORS;


proc iml;
start program;
use data.ccl;
read all var {rgdp} into y;
read all var {ges} into x;
read all var ('c1':'c77') into s;
read all var ('t1':'t40') into t;


***THIS SECTION CREATES THE OMEGA MATRIX AND;
***INITIALIZES THE MONTE CARLO PARAMETERS;
n=5;
periods=10;
t=periods;
nt=n*periods;
yi=j(nt,1,0);
xi=j(nt,1,0);
si=j(nt,n,0);
yearsi=j(nt,(periods-1),0);
omega=j(nt,nt,0);
ones=j(nt,1,1);
r2=0;
yy=j(nt,1,0);
xx=j(nt,1,0);
phitotal=j(n,n,0);
rhohattotal=0;
yy=0;
xx=0;
r2=0;
do k=1 to (40-periods+1);
   do j=1 to n;
      yi[1+(j-1)*periods:j*periods]=y[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      xi[1+(j-1)*periods:j*periods]=x[k+(j-1)*40:k+(periods-1)+(j-
1)*40];
      si[1+(j-1)*periods:j*periods,]=s[k+(j-1)*40:k+(periods-1)+(j-
1)*40,1:n];
      yearsi[1+(j-1)*periods:j*periods,1:(periods-1)]=years[k+(j-
1)*40:k+(periods-1)+(j-1)*40,k+1:k+(periods-1)];
   end;
zi=si||yearsi||xi;
ei=yi-zi*inv(zi`*zi)*zi`*yi;
a=i(nt)-(1/nt)*ones*ones`;
r2i=1-((ei`*ei)/(yi`*a*yi));
eols1=j(n*(periods-1),1,0);
eols2=j(n*(periods-1),1,0);
pp=j(periods,periods,0);
bols=inv(zi`*zi)*zi`*yi;
do i=1 to n;
   eols1[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(2+((i-
1)*periods)):i*periods];
```

```
   eols2[1+((i-1)*(periods-1)):(i*(periods-1))]=ei[(1+(i-
1)*periods):((i*periods)-1)];
end;
***NOTE THAT I AM USING A DIFFERENT FORMULA;
***THE GREENE FORMULA;
***TO CALCULATE RHOHAT;
rhohati=(eols1`*eols2)/(ei`*ei);
*rhohat=0;
pp[1,1]=sqrt(1-(rhohati**2));
do i=2 to periods;
pp[i,i]=1;
pp[i,i-1]=-rhohati;
end;
p=i(n)@pp;
bstep2=inv(zi`*p`*p*zi)*zi`*p`*p*yi;
estep2=p*yi-(p*zi*bstep2);
ee=j(periods,n,0);
do i=1 to n;
   ee[,i]=estep2[1+(i-1)*periods:i*periods];
end;
phii=(ee`*ee)/periods;
*sigmai=phi/(1-(rhohati**2));


****THIS SECTION IS USED TO CALCULATE MEAN OMEGA;
****AND Y AND X VALUES OVER ALL SUBSAMPLES;
phitotal=phitotal+phii;
rhohattotal=rhohattotal+rhohati;
yy=yy+yi;
xx=xx+xi;
r2=r2+r2i;
end;

phibar=phitotal/(40-periods+1);
rhohatbar=rhohattotal/(40-periods+1);
omegabar=j(periods,periods,0);
do i=1 to periods;
   do j=1 to periods;
      omegabar[i,j]=rhohatbar**(abs(i-j));
   end;
end;
sigmabar=phibar/(1-(rhohatbar**2));
vbar=sigmabar@omegabar;


***R2BAR MEASURES THE AVERAGE R2 IN THE FIRST STAGE;
***OF THE DATA GENERATING PROCESS;
yy=yy/(40-periods+1);
xx=xx/(40-periods+1);
r2=r2/(40-periods+1);
ybar=yy`*ones/nt;
xbar=xx`*ones/nt;
b00=ybar+0.01*xbar;
Q=root(vbar);
```

```
tcrit=tinv(0.975,nt-2);
z=ones||xx;
seed=11011;
R=1000;


***THIS SECTION CREATES THE "EMPTY VECTORS" THAT THE;
***SUBSEQUENT MONTE CARLO WORK WILL "FILL";
tcrit=tinv(0.975,(nt-2));

onesr=j(R,1,1);

b_1=j(R,1,0);
se_1=j(R,1,0);
cint_1=j(R,1,0);
mse_0=j(R,1,0);
mse_1=j(R,1,0);
bias_1=j(R,1,0);

meanb1=j(1,1,0);
meanseb1=j(1,1,0);
menbias1=j(1,1,0);
meanmse0=j(1,1,0);
meanmse1=j(1,1,0);
seratio1=j(1,1,0);
level1=j(1,1,0);
number=0;
check1 = 0;
check2 = 0;


RHO = j(R,1,0);
CSCORR = j(R,1,0);
corrr = j(n,n,0);
HET = j(R,1,0);
HETRANGE = j(R,1,0);


** This section selects a random slice of the independent variable
to be used for simulations
x0 = j(nt,1,0);
Max = nrow(x)-nt+1;
i0 = ceil(Max*UNIFORM(seed));
x0 = x[i0:i0+nt-1];

***THIS SECTION CONDUCTS THE REPLICATIONS;
do k=1 to R;
number=number+1;
u=normal(j(nt,1,seed+1000*number));
epsilon=Q`*u;
*epsilon=u;
y=(b00*ones)-(0.01*x0)+epsilon;
z=ones||x0;
b=inv(z`*z)*z`*y;
```

```
mse_0[k]=(b[2]+0.01)**2;
e=y-z*b;
*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
   ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
   rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
   rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
   check=(rhatnum/rhatden);
   if check > 1 then check1 = check1 + 1;
   if check > 1 then check = 1;
   if check < -1 then check2 = check2 + 1;
   if check < -1 then check = -1;
   rhohati=rhohati+check;
end;
rhohat=rhohati/n;
RHO[k] = rhohat;
*rhohat=0.6740;

** I started Here;

*corr = ((1/periods)*(ee`*ee))/(1-rhohat**2);
corrr = CORR(ee);
do i=2 to n;
     do j=1 to (i-1);
     CSCORR[k]=CSCORR[k]+abs(corrr[i,j]);
     end;
end;
CSCORR[k] = (2/(n**2-n))*CSCORR[k];

start Qntl(q0, x00, p0);       /** definition 5 from UNIVARIATE doc
**/
   n0 = nrow(x00);              /** assume nonmissing data **/
   q0 = j(ncol(p0), ncol(x00));/** allocate space for return values
**/
   do j = 1 to ncol(x00);     /** for each column of x... **/
      y00 = x00[,j];
      call sort(y00,1);       /** sort the values **/
      do i = 1 to ncol(p0); /** for each quantile **/
         k = n0*p0[i];        /** find position in ordered data **/
         k1 = int(k);       /** find indices into ordered data **/
         k2 = k1 + 1;
         g = k - k1;
         if g>0 then
            q0[i,j] = y0[k2];/** return a data value **/
         else               /** average adjacent data **/
            q0[i,j] = (y00[k1]+y00[k2])/2;
      end;
  end;
  finish;
```

```
    x00 = sqrt(vecdiag((1/periods)*(ee`*ee)));
    p0 = {.25 .75};
    call qntl(q0,x00,p0);
    HET[k] = q0[2]/q0[1];
    HETRANGE[k] = q0[2]-q0[1];

end;

***THIS SECTION CALCULATES AND PRINTS RESULTS;
cscorrbar = j(1,1,0);
rhobar = j(1,1,0);
HETRANGECOEF = J(1,1,0);
cscorrbar = CSCORR`*onesr/R;
rhobar  = RHO`*onesr/R;
HETCOEF = HET`*onesr/R;
HETRANGECOEF = HETRANGE`*onesr/R;
nperiods = n||periods;
Parameters = nperiods||cscorrbar||rhobar||HETCOEF||HETRANGECOEF;
cname = {'N' 'T' 'CSCORR' 'RHOHATBAR' 'HETCOEF' 'HETRANGECOEF'};

print 'RGF2 AD DATA';
print Parameters[colname = cname];

finish;
run program;
quit;

run;
```

Annex 3. SAS/IML code for chapter 3 (Grunfeld data, T= 20).

```
***THIS PROGRAM EVALUATES FGLS (PARKS);
libname PARKSSUR '/hpc/home/Parks_SUR';

proc iml;
start program;
use PARKSSUR.grunfeld;
read all var {inv} into y1;
read all var {v,k} into x1;

T = 20;
n = 5;


nT = n*T;
reps = 1000;
nboots = 999;
M0 = 1;
y = j(nT,1,0);
y = y1[1:nT];
Ones = j(10*T,1,1);
x2 = Ones||x1;
X= j(nT,ncol(x2)*n,0);
R = j(1,ncol(x2)*n,0);
R[2] = 1;

R2 = j(1,ncol(x2)*n,0);
R2[2] = 1;
R2[5] = -1;


R3 = j(2,ncol(x2)*n,0);
R3[1,2] = 1;
R3[1,5] = -1;
R3[2,3] = 1;
R3[2,6] = -1;

seed = 1002;

** IMPLEMENT SUR;

X = j(nT,ncol(x2)*n,0);
do i = 1 to n;
   X[(1+(i-1)*T):i*T,(ncol(x2)*(i-1)+1):ncol(x2)*i] = x2[(M0-
1)*T+(1+(i-1)*T):(M0-1)*T+i*T,];
end;

start ParksSur(rhohatsur, Test, sigmahat, H, A, P, bparks,
vcovbparks, T, y, X);
        n = nrow(X)/T;
        nT = n*T;

        ** OLS Residuals;

        eols = y-X*solve(X`*X,X`*y);
```

```
ee = j(T,n,0);
do i = 1 to n;
        ee[,i] = eols[1+(i-1)*T:i*T];
end;
sigmahatsur = (1/T)*(ee`*ee);

start MyInv1(InvM, M);
        D0 = sqrt(diag(M));
        R0 = ginv(D0)*M*ginv(D0);
        InvM = ginv(D0)*ginv(R0)*ginv(D0);
finish MyInv1;

run MyInv1(invsigmahatsur, sigmahatsur);
invomegahatsur = invsigmahatsur@I(T);

start MyInv2(InvM, M);
        call SVD(Ustar, qstar, Vstar, M);
        InvM = Vstar*ginv(diag(qstar))*Ustar;
finish MyInv2;

v = X`*invomegahatsur*X;
run MyInv1(invv, v);
bsur = invv*(X`*invomegahatsur*y);
esur = y - X*bsur;

*** COMPUTE PARKS ESTIMATOR USING THE SUR RESIDUALS;
eesur = j(T,n,0);
do i = 1 to n;
        eesur[,i] = esur[1+(i-1)*T:i*T];
end;
rhohatsur = j(n,n,0);
rhohati = j(n,1,0);
do i = 1 to n;
        eesur1 = eesur[2:T,i];
        eesur2 = eesur[1:T-1,i];
        rhohatsur[i,i] = eesur1`*eesur2/(eesur2`*eesur2);
end;

*** find P0;

P0 = j(nT,nT,0);

** I leave zeros at for the first observation. I will cut
 those below and upgrade this matrix later to P;

do i  = 1 to n;
        do j = 2 to T;
                P0[(i-1)*T + j,(i-1)*T + j] = 1;
                P0[(i-1)*T + j,(i-1)*T + j-1] = -
                 rhohatsur[i,i];
        end;
end;

*** Transform y and x using P0;
```

```
y_trans = P0*y;
x_trans = P0*X;
yreduced = j(nT-n,1,0);
xreduced = j(nT-n,ncol(X),0);
do i = 1 to n;
 yreduced[1+(i-1)*(T-1):i*(T-1)] = y_trans[2+(i-1)*T:i*T];
 xreduced[1+(i-1)*(T-1):i*(T-1),] = x_trans[2+(i-1)*T:i*T,];
end;

/* reduce transfoormed Y and X by deleting the first values
 for each equation then run an OLS model and compute
 sigmahat */;

breduced = solve(xreduced`*xreduced, xreduced`*yreduced);
ereduced = yreduced - xreduced*breduced;
eereduced = j(T-1,n,0);
do i = 1 to n;
        eereduced[,i] = ereduced[1+(i-1)*(T-1):i*(T-1)];
end;
sigmahat = (1/(T-1))*eereduced`*eereduced;

*** compute V0;

V0 = j(n,n,0);
do i = 1 to n;
        do j = 1 to n;
          V0[i,j] = sigmahat[i,j]/(1 -
          rhohatsur[i,i]*rhohatsur[j,j]);
        end;
end;

**** Compute A;

H = root(sigmahat, "NoError");
B = root(V0, "NoError");
        Test = 1;
if any(B = .) then Test = 0;
if any(H = .) then Test = 0;
if Test > 0 then do;
         detB = det(B/B[:]);
         if detB = 0 then Test = 0;
         if Test = 1 then do;
        *run MyInv2(Bi, B`);
              Bi = inv(B`);
        A = H`*Bi;

        *** Construct P by completing P0;

        P = P0;
        do i = 1 to n;
                do k = 1 to i;
                        P[1+(i-1)*T, 1+(k-1)*T] = A[i,k];
                end;
```

```
                end;

                *** Use P to transform Y and X;

                Ystar = P*y;
                Xstar = P*X;

                *** Use transformed Y and X to compute Parks
                  estimator and coefficient standard errors;

                run MyInv1(invsigmahat, sigmahat);
                v1 = Xstar`*(invsigmahat@i(T))*Xstar;
                run MyInv1(invv1, v1);
                bparks = invv1*(Xstar`*(invsigmahat@i(T))*Ystar);
                vcovbparks = invv1;
            end;
     end;
finish ParksSur;

** run the Parks model and compute the empirical test statistics;

run ParksSur(rhohatsur, Test, sigmahat, H, A, P, bparks, vcovbparks,
T, y, X);

g1 = (R*bparks)`*inv(R*vcovbparks*R`)*(R*bparks);
g2 = (R2*bparks)`*inv(R2*vcovbparks*R2`)*(R2*bparks);
g3 = (R3*bparks)`*inv(R3*vcovbparks*R3`)*(R3*bparks);


** Get transformed data to be used in the DGP under the null
hypothesis for all three different tests;

bparksres = bparks;
bparksres[2] = 0;

start delcol(X,i);
     return(x[,setdif(1:ncol(x),i)]);
finish delcol;
Xres = delcol(X,2);


bparksres2 = bparks;
bparksres2[2] = bparks[5];
Xres2 = delcol(X,5);
Xres2[,2] = X[,2] + X[,5];



bparksres3 = bparks;
bparksres3[2] = bparks[5];
bparksres3[3] = bparks[6];
Xres3 = delcol(X,{5 6});
Xres3[,2] = X[,2] + X[,5];
Xres3[,3] = X[,3] + X[,6];
```

```
*** THE BOOTSTRAP STARTS HERE;
Testres = 0;
do until (Testres = 1);
      Testrank = 0;
      do until (Testrank = 3);
         v = normal(j(n,T,seed));
         e = H`*v;
         u = j(n, T, 0);
         run MyInv2(InvA, A);
         u[,1] = InvA*e[,1];
         do i = 2 to T;
                 u[,i] = rhohatsur*u[,i-1] + e[,i];
         end;
         ysim1 = X*bparksres + shape(u,nT, 1);
         ysim2 = X*bparksres2 + shape(u,nT,1);
         ysim3 = X*bparksres3 + shape(u,nT,1);


         asympt_crit_value1 = 3.841455338;
         asympt_crit_value2 = 3.841455338;
         asympt_crit_value3 = 5.991464547;

         run ParksSur(rhohatr, Testr, sigmahatr, Hr, Ar, Pr, bparksr,
             vcovbparksr, T, ysim1, Xres);
                 *A_boot = Ar;
                 *H_boot = Hr;
                 *rhohat_boot = rhohatr;
         run ParksSur(rhohatr2, Testr2, sigmahatr2, Hr2, Ar2, Pr2,
                      bparksr2, vcovbparksr2, T, ysim2, Xres2);
         run ParksSur(rhohatr3, Testr3, sigmahatr3, Hr3, Ar3, Pr3,
             bparksr3, vcovbparksr3, T, ysim3, Xres3);
            rank1 = round(trace(ginv(Ar)*Ar));
            rank2 = round(trace(ginv(Ar2)*Ar2));
            rank3 = round(trace(ginv(Ar3)*Ar3));
            if rank1 = ncol(Ar) then Testrank = Testrank+1;
            if rank2 = ncol(Ar2) then Testrank = Testrank+1;
            if rank3 = ncol(Ar3) then Testrank = Testrank+1;
       end;
      Testres = min(Testr, Testr2, Testr3);
  end;

start Statistic(bootcrit, bootcrit_np, n, nboots, R, T, ysim, X,
bparksres, asympt_crit_value, Xres, Ar, Hr, rhohatr, bparksr, seed);

         nT = n*T;
         gboot = j(nboots,1,0);
         gboot_np = j(nboots,1,0);

         do boot = 1 to nboots;

                 *** parametric bootstrap;

                 vp_boot = normal(j(n,T,seed));
```

```
  ep_boot = Hr`*vp_boot;
  up_boot = j(n,T,0);
        InvAr = ginv(Ar);
  *run MyInv2(InvAr, Ar);
  up_boot[,1] = InvAr*ep_boot[,1];
  do i = 2 to T;
      up_boot[,i] = rhohatr*up_boot[,i-1] +
      ep_boot[,i];
  end;

  yboot = Xres*bparksr + shape(up_boot,nT,1);
  run ParksSur(rhohatbu, Testboot, sigmahatbu, Hbu,
      Abu, Pbu, bparksbu, vcovbparksbu, T, yboot, X);
  if Testboot = 1 then do;
          run MyInv1(Invbu, R*vcovbparksbu*R`);
          gbu = (R*bparksbu)`*Invbu*(R*bparksbu);
          gboot[boot] = gbu;
  end;

*** non parametric bootstrap;

 *** transforming the correlated residuals to
independent residuals;
  e_original = ysim - Xres*bparksr;
  ee_original = shape(e_original, n, T);
  v_original = j(n,T,0);
  v_original[,1] = Ar*ee_original[,1];
  do i = 2 to T;
     v_original[,i] = ee_original[,i] -
      rhohatr*ee_original[,i-1];
  end;

  InvHr = ginv(Hr);
        *run MyInv2(InvHr, Hr);
  u_original =InvHr*v_original;

*resampling the independent residuals and inducing
back the initial structure;

  u_sample = j(n,T,0);
  do i = 1 to T;
          i0 = ceil(T*UNIFORM(i*seed));
          u_sample[,i] = u_original[,i0];
  end;

   enp_boot = Hr`*u_sample;
  unp_boot = j(n,T,0);
  unp_boot[,1] = InvAr*enp_boot[,1];
  do i = 2 to T;
    unp_boot[,i] = rhohatr*unp_boot[,i-1] +
                   enp_boot[,i];
  end;

  yboot_np = Xres*bparksr+ shape(unp_boot, nT,1);
```

```
                run ParksSur(rhohatbu_np, Testboot_np,
                  sigmahatbu_np, Hbu_np, Abu_np, Pbu_np,
                  bparksbu_np,vcovbparksbu_np, T, yboot_np, X);
                if Testboot_np = 1 then do;
                   run MyInv1(Invbu_np, R*vcovbparksbu_np*R`);
                   gbu_np=(R*bparksbu_np)`*Invbu_np*(R*bparksbu_np);
                   gboot_np[boot] = gbu_np;
                end;
                if Testboot = 0 then boot = max(1, boot-1);
                if Testboot_np = 0 then boot = max(1, boot-1);
        end;
        percentile = .95;
        call qntl(bootcrit, gboot, percentile, 3);
        call qntl(bootcrit_np, gboot_np, percentile, 3);

finish Statistic;

run Statistic(bootcrit1, bootcrit_np1, n, nboots, R, T, ysim1, X,
bparksres, asympt_crit_value1, Xres,
                                Ar, Hr, rhohatr, bparksr, seed);
run Statistic(bootcrit2, bootcrit_np2, n, nboots, R2, T, ysim2, X,
bparksres2, asympt_crit_value2, Xres2,
                                Ar2, Hr2, rhohatr2, bparksr2, seed);
run Statistic(bootcrit3, bootcrit_np3, n, nboots, R3, T, ysim3, X,
bparksres3, asympt_crit_value3, Xres3,
                                Ar3, Hr3, rhohatr3, bparksr3, seed);
Stat_crit_values = j(3,4,0);
Statistics = g1||g2||g3;
asympt_crit =
asympt_crit_value1||asympt_crit_value2||asympt_crit_value3;
boot_crit = bootcrit1||bootcrit2||bootcrit3;
boot_crit_np = bootcrit_np1||bootcrit_np2||bootcrit_np3;
Stat_crit_values[,1] = Statistics`;
Stat_crit_values[,2] = asympt_crit`;
Stat_crit_values[,3] = boot_crit`;
Stat_crit_values [,4] = boot_crit_np`;
statrownames = { "g1" "g2" "g3" };
statcolnames = { "Statistic" "Asymptotic" "Bootstrap"
"NP_Bootstrap"};


*** THE MC-SIMULATION STARTS HERE;

start MCsimulation(RRboot, RRboot_np, RRasympt, n, reps, nboots, R,
     T, rhohatsur, H, A, X, bparksres, bparksr, asympt_crit_value,
     Xres, seed);

        gboot = j(nboots,1,0);
        p_asym = j(reps, 1,0);
        p_boot = j(reps,1,0);
        p_boot_np = j(reps,1,0);
        nT = n*T;
```

```
        do k = 1 to reps;
                v = normal(j(n,T,seed));
                e = H`*v;
                u = j(n, T, 0);
                      InvA = ginv(A);
                      *run MyInv2(InvA, A);
                u[,1] = InvA*e[,1];
                do i = 2 to T;
                        u[,i] = rhohatsur*u[,i-1] + e[,i];
                end;
                ysim = X*bparksres + shape(u,nT, 1);
                run ParksSur(rhohatsim, Testsim, sigmahatsim, Hsim,
                   Asim, Psim, bparkssim, vcovbparksim, T, ysim, X);
                if Testsim = 1 then do;
                  run MyInv1(Invbsim, R*vcovbparksim*R`);
                  g_sim = (R*bparkssim)`*Invbsim*(R*bparkssim);
                  run ParksSur(rhohatr, Testsimr, sigmahatr, Hr, Ar,
                      Pr, bparksr, vcovbparksr, T, ysim, Xres);
                               *A_boot = Ar;
                               *H_boot = Hr;
                               *rhohat_boot = rhohatr;
                  if Testsimr = 1 then do;
                   if k = 1 then bparksrestricted = bparksr;
                   run Statistic(bootstrap_crit_value,
                     bootstrap_crit_value_np, n, nboots, R, T,ysim,
                     X, bparksres, asympt_crit_value, Xres, Ar, Hr,
                     rhohatr, bparksr, seed);

                   if g_sim > asympt_crit_value then p_asym[k] = 1;
                   if g_sim > bootstrap_crit_value then p_boot[k]=1;
                   if g_sim > bootstrap_crit_value_np then
                     p_boot_np[k]=1;
                 end;
                 if Testsimr = 0 then k = max(1, k-1);
               end;
              if Testsim = 0 then k = max(1, k-1);
           end;

        RRboot = p_boot[:,];
        RRboot_np = p_boot_np[:,];
        RRasympt = p_asym[:,];

finish MCsimulation;

run MCsimulation(RRboot1, RRboot_np1, RRasympt1, n, reps, nboots, R,
T, rhohatsur, H, A, X, bparksres, bparksr, asympt_crit_value1, Xres,
seed);
run MCsimulation(RRboot2, RRboot_np2, RRasympt2, n, reps, nboots,
R2, T, rhohatsur, H, A, X, bparksres2, bparksr2, asympt_crit_value2,
Xres2, seed);
run MCsimulation(RRboot3, RRboot_np3, RRasympt3, n, reps, nboots,
R3, T, rhohatsur, H, A, X, bparksres3, bparksr3,
asympt_crit_value3, Xres3, seed);
RRate = j(3,3,0);
```

```
RRate[1,] = RRboot1||RRboot_np1||RRasympt1;
RRate[2,] = RRboot2||RRboot_np2||RRasympt2;
RRate[3,] = RRboot3||RRboot_np3||RRasympt3;
statistics = {"g1" "g2" "g3"};
columns = {"Bootstrap" "NP_Bootstrap" "Asymptotic"};
print Stat_crit_values[rownames = statrownames colnames =
statcolnames];
print RRate[rownames = statistics colnames = columns];

finish;
run program;
quit;

run;
```

Annex 4. SAS/IML code for chapter 5 (Parks+ Bootstrap).

```
/******************************************************
THIS CODE RUNS A GROWTH MODEL USING THE PARKS ESTIMATOR WITH
DATA ON A SAMPLE OF AFRICAN COUNTRIES
******************************************************/
proc iml;
start program;
use PROD.Africa;
read all var {PwGDPgr} into y;
read all var {Year} into Year;
read all var {Country} into Country;
read all var {GDP, PWCapitalgrmi, PubEducationmi, PubHealth, PrivHealth,
Trade, Agriculture, FDI, Inflation, Freedom} into z0;

n = 12;
t = 15;
seed = 1002;
nboots = 999;
nt = n*t;
ones = j(nt,1,1);

start delcol(X,i);
     return(x[,setdif(1:ncol(x),i)]);
finish delcol;

IDummy1 = i(n)@j(t,1,1);
IDummy = delcol(IDummy1, {1});

TDummy = j(n,1,1)@i(t);
TDummy = delcol(TDummy, 1);

* common time trend;
CTT = 1:nt;

* Specific time trends;
TT = 1:T;
STTrend = TT`;
IDummyYear =i(n)@ STTrend;

*Right hand side variables;
z1 = ones||z0||CTT`||IDummy;
k1 = 2 + ncol(z0);

z2 = ones||z0||IDummy||IDummyYear;
k2 = k1-1;

start PARKS(v, bfgls, Tstats, RejectNull, z, y, n, t);

      start MyInv1(InvM, M);
          D0 = sqrt(diag(M));
          R0 = ginv(D0)*M*ginv(D0);
          InvM = ginv(D0)*ginv(R0)*ginv(D0);
      finish MyInv1;

      nt = n*t;



      *run MyInv1(invz, z`*z);
```

```
invz = inv(z`*z);

b=invz*z`*y;
e=y-z*b;

*****USE OLS RESIDUALS TO CALCULATE COMMON AUTOCORRELATION
PARAMETER*********;
ee=j(t,n,0);
do i=1 to n;
	ee[,i]=e[((i-1)*t)+1:i*t];
end;
rhohati=0;
do i=1 to n;
	rhatnum=ee[2:t,i]`*ee[1:(t-1),i];
	rhatden=ee[1:(t-1),i]`*ee[1:(t-1),i];
	check=(rhatnum/rhatden);
	rhohati=rhohati+check;
end;
rhohat=rhohati/n;
if (rhohat < 1) & (rhohat > -1) then do;

	***CONSTRUCT THE TRANSFORMATION MATRIX PSTAR*****;
	pstar=j(nt,nt,0);
	pstari=j(t,t,0);
	pstari[1,1]=sqrt(1-(rhohat**2));
	do i=2 to t;
		pstari[i,(i-1)]=-rhohat;
		pstari[i,i]=1;
	end;
	do i=1 to n;
		pstar[((i-1)*t)+1:i*t,((i-1)*t)+1:i*t]=pstari;
	end;

	***USE RESIDUALS FROM TRANSFORMED EQUATION TO CALCULATE CROSS-
	SECTIONAL COVARIANCES**;
	zstar=pstar*z;
	ystar=pstar*y;

	*run MyInv1(invzstar, zstar`*zstar);
	invzstar =  inv(zstar`*zstar);
	bstar=invzstar*zstar`*ystar;
	estar=ystar-(zstar*bstar);
	eestar=j(t,n,0);
	do i=1 to n;
		eestar[,i]=estar[((i-1)*t)+1:i*t];
	end;
	sigma2u=j(n,n,0);
	do i=1 to n;
		do j=1 to n;
			sigma2u[i,j]=eestar[,i]`*eestar[,j]/t;
		end;
	end;
	sigma2e=(1/(1-(rhohat**2)))*sigma2u;
	****CONSTRUCT COVARIANCE MATRIX V*****;
	omega=j(t,t,1);


	do i=2 to t;
		do j=1 to (i-1);
```

```
                    omega[i,j]=rhohat**(i-j);
                end;
            end;
            do i=1 to (t-1);
                do j=(i+1) to t;
                    omega[i,j]=rhohat**(j-i);
                end;
            end;
            v=sigma2e@omega;
            vinv=inv(v);
            *run MyInv1(vinv, v);

            ****CALCULATE FGLS ESTIMATES*****;
            *run MyInv1(inv, z`*vinv*z);
            inv =inv(z`*vinv*z);
            bfgls=inv*z`*vinv*y;
            covb=inv;
            seb=sqrt(vecdiag(covb));
            tratio=bfgls/seb;
            prt=2*(1-probt(abs(tratio),(nt-2)));
            RejectNull = j(ncol(z),1,0);
            TStats  = j(ncol(z),1,0);
            do k = 1 to ncol(z);
                se=sqrt(covb[k,k]);
                zcrit=probit(0.975);
                stat = (bfgls[k])/se;
                Tstats[k] = stat;
                if abs(stat)>=zcrit then RejectNull[k] = 1;
            end;
        end;
finish PARKS;

run PARKS(v1, bfgls1, Tstats1, RejectNull1, z1, y, n, t);
run PARKS(v2, bfgls2, Tstats2, RejectNull2, z2, y, n, t);

*** parametric bootstrap of the test statistic starts here;
start Statistic(g, pval_p, bootcritvect, n, nboots, t, z, bfgls, Tstats, v,
         k, seed);
        nt = n*t;
        gboot = j(nboots,1,0);
        gboot_np = j(nboots,1,0);
        pval_p = j(k,1,0);
        bootcritvect = j(k,4,0);
        g = j(k,1,0);

        start delcol(x,i);
            return(x[,setdif(1:ncol(x),i)]);
        finish delcol;

        do j = 1 to k;
            g[j] = Tstats[j];
            bfglsres = bfgls;
            bfglsres[j] = 0;
            zres = delcol(z,j);
            e = normal(j(nt,1,seed));
            Q = sqrt(max(v))*root(v/max(v), "NoError");
            epsilon = Q`*e;
            ysim = z*bfglsres + epsilon;
            run PARKS(vr, bfglsr, Tstatsr, RejectNullr, zres, ysim, n, t);
```

```
            Qr = sqrt(max(vr))*root(vr/max(vr), "NoError");

            do boot = 1 to nboots;
                  e = normal(j(nt,1,seed));
                  epsilon = Qr`*e;
                  yboot = zres*bfglsr + epsilon;
                  run PARKS(vu, bfglsu, Tstatsu, RejectNullu, z, yboot, n,
                         t);
                  gboot[boot] = Tstatsu[j];
            end;

            pval_p[j] = 2*(1/(nboots+1))*(nboots*(min(mean(gboot>g[j]),
                  mean(gboot<g[j]))+ mean(gboot=g[j]))+1);

            percentile1 = .025;
            percentile2 = .05;

            call qntl(bootcritL1, gboot, percentile1, 3);
            call qntl(bootcritU1, gboot, (1-percentile1), 3);
            bootcritvect[j, 1] = bootcritL1;
            bootcritvect[j, 2] = bootcritU1;

            call qntl(bootcritL2, gboot, percentile2, 3);
            call qntl(bootcritU2, gboot, (1-percentile2), 3);
            bootcritvect[j, 3] = bootcritL2;
            bootcritvect[j, 4] = bootcritU2;
      end;

finish Statistic;


*run Statistic(g1, pval_p1, bootcritvect1, n, nboots, t, z1, bfgls1,
Tstats1, v1, k1, seed);
run Statistic(g2, pval_p2, bootcritvect2, n, nboots, t, z2, bfgls2,
Tstats2, v2, k2, seed);

*print bfgls1 Tstats1 pval_p1 bootcritvect1;
print bfgls2 Tstats2 pval_p2 bootcritvect2;

finish;
run program;
quit;

run;
```