THE *PCSE* ESTIMATOR IS GOOD, JUST NOT AS GOOD AS YOU THINK

by

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Abstract

This paper investigates the properties of the PCSE estimator. The PCSE estimator is commonly used when working with time-series, cross-sectional (TSCS) data. In an influential paper, Beck and Katz (1995) (henceforth BK) demonstrated that FGLS produces coefficient standard errors that are severely underestimated. They report Monte Carlo experiments in which the PCSE estimator produces accurate standard error estimates at no, or little, loss in efficiency compared to FGLS. Our study further investigates the properties of the PCSE estimator. We first reproduce the main experimental results of BK using their Monte Carlo framework. We then show that the PCSE estimator does not perform as well when tested in data environments that better resemble "practical research situations." When (i) the explanatory variable(s) are characterized by substantial persistence, (ii) there is serial correlation in the errors, and (iii) the time span of the data series is relatively short, coverage rates for the PCSE estimator frequently fall between 80 and 90 percent. Further, we find many "practical research situations" where the PCSE estimator compares poorly with FGLS on efficiency grounds.

JEL Categories: C23, C15

Keywords: Panel data estimation, Monte Carlo analysis, FGLS, Parks, PCSE, finite sample

9 May 2010

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I. Introduction

Empirical studies frequently employ data consisting of repeated time-series observations on fixed, cross-sectional units. While providing a rich amount of information, time-series cross-sectional (TSCS) data are likely to be characterized by complex error structures. The application of OLS to data with nonspherical errors produces inefficient coefficient estimates, and the corresponding standard error estimates are biased. In contrast, GLS produces coefficient and standard error estimates that are efficient and unbiased, respectively, given certain assumptions. Two such assumptions are (i) the error covariance structure is correctly specified, and (ii) the elements of the error covariance matrix are known. Feasible GLS (FGLS) is used when the structure of the error covariance matrix is known, but its elements are not. The finite sample properties of FGLS are analytically indeterminate.

Beck and Katz (1995) (henceforth, BK) use Monte Carlo methods to study the performance of FGLS in a statistical environment characterized by (i) groupwise heteroscedasticity, (ii) first-order serial correlation, and (iii) contemporaneous cross-sectional correlation. They dub the corresponding FGLS estimator "Parks" (after Parks [1967]). BK report three major findings:

1. FGLS(Parks) produces dramatically inaccurate coefficient standard errors.
2. An alternative estimator, based on OLS but using "panel-corrected standard errors," (henceforth, PCSE) produces accurate coefficient standard errors.
3. The efficiency advantage of FGLS(Parks) over PCSE is at best slight, except in extreme cases of cross-sectional correlation, and then only when the number of time periods (*T*) is at least twice the number of cross-section units (*N*).

BK conclude that the PCSE estimator provides accurate standard error estimation with little loss in efficiency relative to FGLS(Parks), except in extreme cases of heteroscedasticity or cross-sectional correlation that are unlikely to be encountered in practice (Beck and Katz, 1995, page 645). BK has been very influential. A recent count identified over 900 Web of

Science citations.[1] The PCSE estimator is now included as a standard procedure in many statistical software packages, including STATA, GAUSS, RATS, and Shazam.

This paper provides Monte Carlo evidence refuting the claim that the PCSE estimator always provides accurate standard error estimation, and does so at little cost to efficiency in "practical research situations." The paper proceeds as follows. Section II describes the experimental data generating process and main performance measures employed by BK. Section III reports our successful attempts to replicate BK's main findings. Section IV discusses how we generalize BK's Monte Carlo methodology to better represent "practical research situations." Sections V and VI report the results of our attempts to replicate BK's TABLEs 4 and 5 using this more realistic testing environment. Section VII concludes.

II. Description of BK's Methodology

The experimental framework. BK build their Monte Carlo analysis around the following TSCS model:

$$\begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \vdots \\ \boldsymbol{y}_N \end{bmatrix} = \begin{bmatrix} 1 & \boldsymbol{Z}_1 \\ 1 & \boldsymbol{Z}_2 \\ \vdots & \vdots \\ 1 & \boldsymbol{Z}_N \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_N \end{bmatrix}, \text{ or } \quad \boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon};$$

where $\boldsymbol{y}_i$ and $\boldsymbol{Z}_i$ are $T \times 1$ vectors of observations on the dependent and independent variables for the i^{th} group, $i = 1,2,...,N$; $\boldsymbol{\beta}$ is a 2×1 vector of coefficients; $\boldsymbol{\varepsilon}_i$ is a $T \times 1$ vector of error terms; and $\boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \boldsymbol{\Omega}_{NT})$.

Following Parks (1967), they allow $\boldsymbol{\Omega}_{NT}$ to consist of (i) groupwise heteroscedasticity; (ii) common, first-order serial correlation;[2] and (iii) cross-sectional (spatial) correlation. Specifically,

[1] Cf. Web of Science, www.isinet.com/products/citation/wos, accessed May 2010.

[2] BK also allow study cases where the AR(1) parameters differ across groups. However, they assume a common AR(1) parameter in the work that we analyze here.

(2) $\boldsymbol{\Omega}_{NT} = \boldsymbol{\Sigma} \otimes \boldsymbol{\Pi}$,

where $\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{\varepsilon,11} & \sigma_{\varepsilon,12} & \cdots & \sigma_{\varepsilon,1N} \\ \sigma_{\varepsilon,21} & \sigma_{\varepsilon,22} & \cdots & \sigma_{\varepsilon,2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\varepsilon,N1} & \sigma_{\varepsilon,N2} & \cdots & \sigma_{\varepsilon,NN} \end{bmatrix}$, $\boldsymbol{\Pi} = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1 \end{bmatrix}$, and

$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + u_{it}$,

They proceed by selecting various combinations of N and T (the TSCS data are always assumed to be balanced); and specifying the values of ρ and $\sigma_{\varepsilon,ij}$, $i, j = 1,2,...,N$, in $\boldsymbol{\Omega}_{NT}$. BK set $\beta_0=\beta_1=10$ in all experiments, and simulate the values of the independent variable Z_{it} (more on this below), which is fixed in all experiments. Given $\boldsymbol{\Omega}_{NT}$, experimental observations are created in the usual manner. The simulated errors are added to a deterministic component, $\beta_0+\beta_1 Z_{it}, i = 1,2,...,N, t = 1,2,...,T$, to generate stochastic observations of y_{it} , where $y_{it}=\beta_0+\beta_1 Z_{it}+\varepsilon_{it}$. They perform 1000 replications for each experiment.

Given observations on y_{it} and Z_{it}, and for a given replication r, BK calculate the FGLS(Parks) and PCSE estimators for $\hat{\boldsymbol{\beta}}$ and $Var(\hat{\boldsymbol{\beta}})$ using the following formulae:

(3) $\hat{\boldsymbol{\beta}}_{PARKS} = \left(\boldsymbol{X}'\boldsymbol{\Omega}^{-1}\boldsymbol{X}\right)^{-1} \boldsymbol{X}'\boldsymbol{\Omega}^{-1}\boldsymbol{y}$, $Var\left(\hat{\boldsymbol{\beta}}_{PARKS}\right) = \left(\boldsymbol{X}'\boldsymbol{\Omega}^{-1}\boldsymbol{X}\right)^{-1}$,

(4) $\hat{\boldsymbol{\beta}}_{PCSE} = \left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}}\right)^{-1} \tilde{\boldsymbol{X}}'\tilde{\boldsymbol{y}}$, $Var\left(\hat{\boldsymbol{\beta}}_{PCSE}\right) = \left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}}\right)^{-1} \left(\tilde{\boldsymbol{X}}'\boldsymbol{\Sigma}\tilde{\boldsymbol{X}}\right)\left(\tilde{\boldsymbol{X}}'\tilde{\boldsymbol{X}}\right)^{-1}$,

where $\tilde{\boldsymbol{X}}$ and $\tilde{\boldsymbol{y}}$ are the Prais-transformed observations of the explanatory and dependent variables, and $\boldsymbol{\Omega}$ and $\boldsymbol{\Sigma}$ are defined in Equation (2).

BK compare the (i) Parks and (ii) PCSE estimates of β_1 using two performance measures. The first performance measure quantifies the accuracy of the analytic formulae used to estimate coefficient standard errors. For each estimator (Parks and PCSE), BK calculate the following the "Overconfidence" measure:

(5) $$Overconfidence = 100 \cdot \frac{\sqrt{\sum_{r=1}^{1000}\left(\hat{\beta}^{(r)} - \bar{\hat{\beta}}\right)^2}}{\sqrt{\sum_{r=1}^{1000}\left(s.e.\left(\hat{\beta}^{(r)}\right)\right)^2}},$$

where $\bar{\hat{\beta}}$ is the mean of the 1000 estimates of $\hat{\beta}$. A value of 100 indicates that actual dispersion in the coefficient estimate equals the dispersion predicted by the estimate of the coefficient's standard error. Values greater than 100 indicate that the analytic formula underestimates the actual dispersion in coefficient estimates; hence, the standard error estimate is "overconfident."

The second performance measure, "Efficiency," measures the efficiency of PCSE relative to Parks and is defined by

$$Efficiency = 100 \cdot \frac{\sqrt{\sum_{r=1}^{1000}\left(\hat{\beta}_{Parks}^{(r)} - \beta_x\right)^2}}{\sqrt{\sum_{r=1}^{1000}\left(\hat{\beta}_{PCSE}^{(r)} - \beta_x\right)^2}}.$$

An "Efficiency" value less than 100 indicates that PCSE is less efficient than Parks.

III. Replication of BK's Results

<u>Replication of BK's TABLE 4</u>. TABLE 4 in BK (Beck and Katz, 1995, page 642) reports the results of Monte Carlo experiments that demonstrate the accuracy of the PCSE estimator in estimating coefficient standard errors. They conduct experiments where (i) $N=15$, (ii) $T=10,20,30,40$; (iii) there is no serial correlation, (iv) "Heteroscedasticity" takes values 0 and 0.3; and (v) "Contemporaneous Correlation" takes values 0, 0.25, and 0.50. In turn, the "Heteroscedasticity" and "Contemporaneous Correlation" values imply specific values for

the cross-sectional covariances, $\sigma_{\varepsilon,ij}$, $i=1,2,...,N,\ \ j=1,2,...,N,\ \ i \neq j$.[3] Observations of the independent variable, Z_{it}, are generated using the same distribution as the error terms.[4]

Column 4 of TABLE 1 reproduces BK's findings from their paper. Note that the PCSE estimator achieves "Overconfidence" values very close to 100. Column 5 reports the results of our efforts to replicate BK's findings. We obtain virtually identical results. Column 6 reports "Coverage Rates." These are the percent of replications (out of 1000) where the respective 95% confidence intervals include the population value of β_1. All of the coverage rates are close to 95. These findings provide support for BK's conclusion about the performance of their PCSE estimator:

> "Panel-corrected standard errors performed excellently in these experiments. They were always within 10% of the true variability, even under conditions of extremely high heteroscedasticity and contemporaneous correlation of the errors. In a typical research situation, we would expect PCSEs to be off by only a few percentage points" (page 641).

Replication of BK's TABLE 5. TABLE 5 in BK (Beck and Katz, 1995, page 642) reports the results of Monte Carlo experiments that demonstrate that the PCSE estimator generally performs as well as the Parks estimator on the grounds of efficiency, except when there is severe cross-sectional correlation. In these experiments, (i) $N=10,15,20$, (ii) $T=10,20,30,40$; (iii) there is no serial correlation, and (iv) "Contemporaneous Correlation" takes values *0*, *0.25*, *0.50*, and *0.75*.[5] Observations of the independent variable, Z_{it}, are

[3] Footnote 21 in BK discuss how they calculate "Heteroscedasticity." Our replication follows a very similar procedure and uses the same measure of "Heteroscedasticity." Once the groupwise variances are determined, the cross-sectional covariances are easily calculated from the given cross-sectional correlation value by $\sigma_{\varepsilon,ij} = (\textit{Cross-sectional correlation}) \times \sqrt{\sigma_{\varepsilon,ii}}\sqrt{\sigma_{\varepsilon,jj}}$.

[4] BK state that the "errors were then generated so that the variances and covariances of the errors were proportional to the variances and covariances of the independent variables" (page 641). We replicated their results using various proportionality factors and found that the results were invariant to the proportionality factor.

[5] BK do not explicitly state how they calculate the groupwise variances for their TABLE 5. We used a group-specific variance structure based on an actual TSCS dataset. Further details are given below.

simulated from a standard normal distribution, assuming the individual Z_{it} observations are independent of each other and the error terms.

The top panel of TABLE 2 reproduces BK's findings from their paper. Note that the PCSE estimator achieves "Efficiency" values greater than or equal to 100 when "Contemporaneous Correlation" is either 0 or 0.25. When Contemporaneous Correlation equals 0.50, the PCSE estimator is slightly less efficient than the Parks estimator. Only when Contemporaneous Correlation equals 0.75, a value unlikely to be encountered in actual practice according to BK (cf. page 642), is the PCSE estimator substantially less efficient than the Parks estimator, and then only when T is twice N.

The bottom panel of TABLE 2 reports the results of our efforts to replicate BK. Once again, we are able to replicate their results very closely. On the basis of findings such as these, BK conclude:

> "[PCSE] is, as expected, more efficient than Parks when the errors are uncorrelated (spherical). But even when the average correlation of the errors rises to .25, [PCSE] remains slightly more efficient than Parks. Parks becomes more efficient than [PCSE] when average contemporaneous correlations rise to .50, but this advantage is noticeable only when the number of time points is at least double the number of units. Even here, the efficiency advantage of Parks is under 20%. Only when the average contemporaneous correlation of the errors rises to .75 is the advantage of Parks marked, and then only when T is twice N" (page 642).[6]

IV. Generalizing the Methodology to "Practical Research Situations"

BK emphasize repeatedly that their Monte Carlo experiments attempt to replicate "practical research situations." While they do not define exactly what they mean by this, it no doubt includes setting values for the elements of $\boldsymbol{\Omega}_{NT}$ that are judged to be representative of values researchers are likely to encounter using real TSCS data sets.

[6] The original quote refers to OLS rather than PCSE. This is because PCSE can be thought of as applying OLS to the Prais-transformed variables (cf. Equation 4).

Rather than guessing at the values of ρ and $\sigma_{\varepsilon,ij}$, $i,j = 1,2,...,N$ that researchers are likely to encounter in "practical research situations," our study uses values estimated from real TSCS data sets. TABLE 3 identifies the twelve TSCS data sets used for our analyses. These represent a diverse number of empirical applications, from the relationship between taxes and the size of the government sector in studies of economic growth of both states and countries, to the relationship between the size of the trading partners and the amount of bilateral trade they undertake, to the effect of disasters on the economic growth of countries, to the determinants of revenues and number of patients for Taiwanese dentists.

To obtain representative values for $\boldsymbol{\Omega}_{NT}$, we regress the respective dependent variable on the corresponding independent variables listed in the table. In all cases, we include group fixed effects in the estimation of the residuals. In some cases we also include time fixed effects, which should diminish the size of the cross-sectional covariances (Roodman, 2006). The associated residuals are used to estimate the elements of $\boldsymbol{\Omega}_{NT}$, as would be done in conventional FGLS(Parks) estimation. These estimates are then used as the population values for the subsequent Monte Carlo analyses. Further details are given in the Appendix.

Using realistic values for the elements of $\boldsymbol{\Omega}_{NT}$ is important if one is serious about conducting experiments that are designed to represent "practical research situations." With respect to the elements of $\boldsymbol{\Omega}_{NT}$, the challenge in setting realistic values lies in the fact that there are $\left[\frac{N(N+1)}{2}+1\right]$ unique parameters in $\boldsymbol{\Omega}_{NT}$. For example, when $N = 20$, there are 211 elements in $\boldsymbol{\Omega}_{NT}$. Each must be given a population value for the Monte Carlo experiments. Unfortunately, theory offers little guidance as to which of these elements, or which relationships between elements, are most significant for the performance of the estimators in finite samples.

V. Further Replication of BK's TABLE 4

BK's TABLE 4 results demonstrated the accuracy of the PCSE estimator in estimating coefficient standard errors using a simulated explanatory variable and an error variance-covariance structure with no serial correlation. We continue to use the set of values for the elements of $\boldsymbol{\Omega}_{NT}$ that they used, but we now use an explanatory variable that is characterized by a high degree of persistence (i.e., the correlation between Z_t and Z_{t-1} is greater than 0.90). We then show the consequences of increasing serial correlation in the errors.

TABLE 4 reports the results of these additional experiments, where we focus on coverage rates for expository convenience. The numbers in the table represent averages across the experiments using the twelve data sets. Column 4 maintains the assumption of no serial correlation in the errors. A comparison with Column 6 of TABLE 1 shows that there is only a small effect of using an explanatory variable with a large degree of persistence when there is no serial correlation in the errors. However, as serial correlation in the errors increases (Columns 5 through 7), coverage rates decrease. The effect is exacerbated by T. When T is small ($T=10$) and serial correlation in the errors is severe ($\rho=0.9$), coverage rates fall to approximately 70 percent.

The preceding analysis employs the greatly simplified error structure used by BK. The next set of experiments investigates the effects of using error structures that are representative of actual TSCS data sets. For example, rather than imposing a constant cross-sectional correlation value for all pairs of groups, we allow the data to suggest plausible ranges of values. Following BK, we continue to focus on the $N=15$ case.

For each value of T, we have twelve data sets (except when $T=40$, because one of our data sets is less than 40 years long). Each of these data sets has its own unique error structure. We take representative values for these and use them as population values in the corresponding Monte Carlo experiments.

TABLE 5 summarizes the results of these experiments by T and ρ. The numbers in the table represent the average coverage rate for the experiments for a given T/ρ cell. For example, there were seven experiments where $T=10$ and the original TSCS data set was characterized by a ρ value less than 0.2. The average coverage rate for these experiments was 91.6 percent. Not all cells had entries. For example, none of the $T=10$ experiments had a value for ρ greater than 0.6. We see the same patterns here that we observed in TABLE 4 above. Coverage rates are generally decreasing in serial correlation, and inversely related to T. Results for individual TSCS data sets are reported in Appendix A.

We conclude from these experiments that the PCSE estimator has difficulty estimating coefficient standard errors when there is substantial persistence in the explanatory variable(s) and the errors are serially correlated. Using parameters drawn from real TSCS data sets, we find coverage rates close to 85 percent for moderate values of serial correlation in the errors ($0.2 < \rho < 0.6$) when $T=10$, and for more severe serial correlation ($\rho > 0.6$) when $T=20$. While these coverage rates are considerably better than those produced by FGLS(Parks), they fall short of the performance suggested by the experiments reported in BK.

VI. Further Replication of BK's TABLE 5

The next set of experiments investigate the efficiency of the PCSE estimator relative to FGLS(Parks). As in the immediately preceding set of experiments, we again use error structures derived from "real" TSCS data sets. The results of these experiments are reported in TABLE 6.

As in TABLE 5, the numbers in the table represent averages over the respective experiments. For example, for $N=10$, $T=10$, there are a total of 10 experiments where the absolute value of the average cross-sectional correlation, ρ_{ij}, is between 0 and 0.25. For these experiments, the average efficiency of PCSE relative to FGLS(Parks) is 0.97. In other words, there is little efficiency loss to using PCSE versus FGLS(Parks). Note that some of the cells are empty, as no experiments fit the respective cell characteristics.

The major difference between these replications and those from TABLE 2 is that there are now substantial efficiency losses even when the cross-sectional correlations are substantially less than 0.75. For example, when *N=10, T=20,* and the average of the absolute value of the cross-sectional correlations lies between 0.25 and 0.50, the PCSE estimator is approximately 40 percent less efficient than FGLS(Parks). As *T* increases, the relative efficiency of the PCSE estimator diminishes further. Results for individual TSCS data sets are reported in Appendix B.

As indicated by the number of experiments represented in each cell, there are many "practical research situations" where the PCSE estimator performs substantially worse than the Parks estimator on the dimension of efficiency. While there are situations where the PCSE estimator can buy better estimation of coefficient standard errors at virtually no cost to efficiency – namely, when *T* is the same or very close to *N* – this result should not be generally expected. More generally, the researcher should expect a tradeoff between reliable coverage rates and efficiency.

VII. Conclusion

In their well-cited paper, Beck and Katz (1995) (henceforth BK) demonstrate that FGLS(Parks) greatly underestimates coefficient standard errors when applied to TSCS data in finite samples with complex error structures. They develop an alternative estimator, the PCSE estimator, that they claim provides accurate standard error estimation with no loss in efficiency relative to FGLS(Parks), except in extreme cases that are unlikely to be encountered in practice. In their words,

> "Monte Carlo evidence shows that panel-corrected standard errors perform extremely well, even in the presence of complicated panel error structures. The Monte Carlo evidence also shows that [PCSE]

> parameter estimates are themselves, at worst, not much inferior to the Parks parameter estimates. Thus the costs of the inaccurate Parks standard errors are in no sense paid for by the superiority of the Parks estimator of the model parameters" (page 635).

This study investigates these claims using a Monte Carlo framework identical to the one employed by BK.

We are able to reproduce BK's results when we use the same experimental parameters that they employ. However, when we use parameters that more closely resemble "practical research situations," we find that the PCSE estimator falls short of the claims made by BK. Specifically, when the explanatory variable(s) is characterized by substantial persistence, our experiments produce coverage rates of 85 percent (for 95 percent confidence intervals) in the presence of moderate serial correlation in the errors ($0.2 < \rho < 0.6$) when $T=10$; and for more severe serial correlation ($\rho > 0.6$) when $T=20$. While these coverage rates are substantially better than those produced by FGLS(Parks), researchers should be aware that the PCSE estimator will tend to underestimate standard errors, and over-reject hypotheses, when used in these situations.

In addition, we find many "practical research situations" where the PCSE estimator is substantially less efficient than FGLS(Parks). For example, when $N=10$, $T=20$, and the average of the absolute value of the cross-sectional correlations lies between 0.25 and 0.50, the PCSE estimator is approximately 40 percent less efficient than FGLS(Parks). As T increases, the relative efficiency of the PCSE estimator diminishes even further. As our analysis of individual data sets show, cross-sectional correlations in this range are quite common.

In conclusion, we emphasize that our analysis should in no way be taken as an endorsement of FGLS(Parks) for estimating coefficient standard errors. BK correctly demonstrate that FGLS(Parks) performs abysmally in many, if not most, "practical research situations." PCSE almost always provides improvement, often dramatic improvement, over

FGLS(Parks) when it comes to estimating standard errors. It's just that the PCSE estimator is not as accurate as claimed by BK.

Furthermore, the claim that PCSE provides a way of obtaining better performance on standard error estimation at no cost to efficiency is only generally true when the number of time periods is close to the number of groups (T is close to N). When $T > N$, it is quite common to find "practical research situations" where the PCSE estimator entails a substantial loss in efficiency.

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APPENDIX
Description of Procedure For Simulating TSCS Data Resembling Those Encountered In "Practical Research Situations"

Suppose we want to generate an artificial panel data set with N cross-sectional units and T time periods. We want this data to "look like" the kind of data likely to be encountered in actual research. We assume a DGP that consists of a linear model with a Parks-style (Parks, 1967) error structure:

(A1) $$\begin{bmatrix} \boldsymbol{y_1} \\ \boldsymbol{y_2} \\ \vdots \\ \boldsymbol{y_N} \end{bmatrix} = \begin{bmatrix} 1 & \boldsymbol{Z_1} \\ 1 & \boldsymbol{Z_2} \\ \vdots & \vdots \\ 1 & \boldsymbol{Z_N} \end{bmatrix} \boldsymbol{\beta} + \begin{bmatrix} \boldsymbol{\varepsilon_1} \\ \boldsymbol{\varepsilon_2} \\ \vdots \\ \boldsymbol{\varepsilon_N} \end{bmatrix}, \text{ or } \quad \boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon};$$

where $\boldsymbol{y_i}$ and $\boldsymbol{Z_i}$ are $T \times 1$ vectors of observations on the dependent and independent variables for the i^{th} group, $i = 1,2,...,N$; $\boldsymbol{\beta}$ is a 2×1 vector of coefficients; $\boldsymbol{\varepsilon}_i$ is a $T \times 1$ vector of error terms; and $\boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \boldsymbol{\Omega_{NT}})$.

Let

(A2) $$\boldsymbol{\Omega_{NT}} = \boldsymbol{\Sigma} \otimes \boldsymbol{\Pi},$$

where $$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{\varepsilon,11} & \sigma_{\varepsilon,12} & \cdots & \sigma_{\varepsilon,1N} \\ \sigma_{\varepsilon,21} & \sigma_{\varepsilon,22} & \cdots & \sigma_{\varepsilon,2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\varepsilon,N1} & \sigma_{\varepsilon,N2} & \cdots & \sigma_{\varepsilon,NN} \end{bmatrix}, \quad \boldsymbol{\Pi} = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \rho^2 & \rho & 1 & \cdots & \rho^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1 \end{bmatrix}, \quad \text{and}$$

$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + u_{it}$. We want to set values for the elements of $\boldsymbol{\Omega_{NT}}$, ρ and $\sigma_{\varepsilon,ij}$, $i, j = 1,2,...,N$, that are representative of "real" TSCS data sets.

The starting point is an actual TSCS data set consisting of a large number of individual units and a long time series. For expositional purposes, let us assume that the data are balanced and that we have 40 years of observations stretching from *1960-1999*. We select N units from this TSCS data set. Next, we choose the T-year period, *1960* to (*1960+T-1*).

We then estimate a regression model that includes one or more independent variable(s) plus fixed effects. A typical regression specification would look like the following:

(A3) $$Y_{it} = \sum_{j=1}^{N} \alpha_j D_{it}^{j} + \alpha_{N+1} X_{it} + error\ term_{it},$$

where *i=1,2, ... ,N; t=1960,1961,...,1960+T-1;* and D^j is a group dummy variable that takes the value 1 for group *j*. The residuals from this estimated equation are used to estimate ρ and the $\sigma_{\varepsilon,ij}$ s in the usual manner, as if one were computing a conventional FGLS estimator.

Denote the associated estimates from this sample as $\hat{\rho}$ and $\hat{\boldsymbol{\Sigma}} = \begin{bmatrix} \hat{\sigma}_{\varepsilon,11} & \hat{\sigma}_{\varepsilon,12} & \cdots & \hat{\sigma}_{\varepsilon,1N} \\ \hat{\sigma}_{\varepsilon,21} & \hat{\sigma}_{\varepsilon,22} & \cdots & \hat{\sigma}_{\varepsilon,2N} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\sigma}_{\varepsilon,N1} & \hat{\sigma}_{\varepsilon,N2} & \cdots & \hat{\sigma}_{\varepsilon,NN} \end{bmatrix}$.

We repeat this process for every possible, T-contiguous year sample contained within the 40 years of data from 1960-1999 [i.e., *1960-(1960+T-1)*, *1961-(1961+T-1)*, *1962-(1962+T-1)*, …, *(1999-T+1)-1999*]. This produces a total of *40–T+1* estimates of ρ and $\boldsymbol{\Sigma}$, one for each T-contiguous year sample. We then average these to obtain "grand means" $\overline{\rho}$ and $\overline{\boldsymbol{\Sigma}}$. Our "representative" $NT \times NT$ error structure, $\boldsymbol{\Omega}_{NT}$, is then constructed as follows:

(A4) $$\boldsymbol{\Omega}_{NT} = \overline{\boldsymbol{\Sigma}} \otimes \overline{\boldsymbol{\Pi}},$$

where $\overline{\boldsymbol{\Sigma}} = \begin{bmatrix} \overline{\sigma}_{\varepsilon,11} & \overline{\sigma}_{\varepsilon,12} & \cdots & \overline{\sigma}_{\varepsilon,1N} \\ \overline{\sigma}_{\varepsilon,21} & \overline{\sigma}_{\varepsilon,22} & \cdots & \overline{\sigma}_{\varepsilon,2N} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{\sigma}_{\varepsilon,N1} & \overline{\sigma}_{\varepsilon,N2} & \cdots & \overline{\sigma}_{\varepsilon,NN} \end{bmatrix}$, and $\overline{\boldsymbol{\Pi}} = \begin{bmatrix} 1 & \overline{\rho} & \overline{\rho}^{2} & \cdots & \overline{\rho}^{T-1} \\ \overline{\rho} & 1 & \overline{\rho} & \cdots & \overline{\rho}^{T-2} \\ \overline{\rho}^{2} & \overline{\rho} & 1 & \cdots & \overline{\rho}^{T-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \overline{\rho}^{T-1} & \overline{\rho}^{T-2} & \overline{\rho}^{T-3} & \cdots & 1 \end{bmatrix}$.

This becomes the population error covariance matrix used for the associated Monte Carlo experiment.

Note that every element of $\boldsymbol{\Omega}_{NT}$ is based on error covariance matrices estimated from actual panel data. In this sense, $\boldsymbol{\Omega}_{NT}$ can be said to be "representative" of the kinds of error structures one might encounter in "practical research situations."

This same procedure can be modified in a straightforward manner to conduct Monte Carlo experiments for alternative *N* and *T* values from the same TSCS data set. In turn, the same general procedure can be following using other TSCS data sets. Further, alternative error structures can be constructed by including two-way fixed effects. This has the twin advantages of reducing cross-sectional dependence and increasing R^2.

TABLE 1
Replication of TABLE 4 in Beck and Katz (1995)

PARAMETER SETTINGS			***BK***	***REPLICATION***	
T ***(1)***	***Heteroscedasticity*** ***(2)***	***Contemporaneous Correlation*** ***(3)***	***Overconfidence*** ***(4)***	***Overconfidence*** ***(5)***	***Coverage Rate*** ***(6)***
10	0	0	102	103	93.5
10	0	0.25	105	106	91.1
10	0.3	0	102	103	93
10	0.3	0.25	105	105	91.3
20	0	0	96	101	94.7
20	0.3	0	96	99	94.2
20	0.3	0.5	103	98	94.2
30	0	0	101	100	94.7
30	0	0.5	107	98	94.4
30	0.3	0.5	106	99	94.2
40	0	0	104	104	94.2
40	0	0.5	105	102	94
40	0.3	0	102	102	93.7
40	0.3	0.5	104	101	93.7
10	0	0	102	103	93.5

NOTE: "Overconfidence" is defined in Equation (5) in the text. Column (4) reproduces BK's results from their TABLE 4 (Beck and Katz, 1995, page 642). Column (6) reports the results of our efforts to replicate their findings. "Coverage Rate" reports the percent of 95% confidence intervals (out of 1000 replications) that contained the true population parameter in the respective experiment.

TABLE 2
Replication of TABLE 5 in Beck and Katz (1995)

		CONTEMPORANEOUS CORRELATION OF THE ERRORS			
N	***T***	$\rho_{ij}=0$	$\rho_{ij}=0.25$	$\rho_{ij}=0.50$	$\rho_{ij}=0.75$
BK's Results:					
10	***10***	102	100	99	97
	20	109	101	88	72
	30	112	105	90	68
	40	109	101	87	66
15	***15***	101	100	99	98
	20	108	102	93	84
	30	111	101	88	72
	40	111	100	83	64
20	***20***	102	101	100	99
	25	107	102	97	90
	30	107	100	91	80
	40	112	104	92	76
Replication:					
10	***10***	102	100	98	96
	20	107	98	85	71
	30	109	101	86	67
	40	107	99	85	65
15	***15***	101	100	99	98
	20	107	99	90	83
	30	107	101	89	74
	40	111	99	83	65
20	***20***	101	100	99	98
	25	105	100	93	88
	30	109	101	93	83
	40	112	99	84	70

NOTE: The top panel reproduces BK's results from their TABLE 5 (Beck and Katz, 1995, page 642). The bottom panel reports the results of our efforts to replicate their findings.

TABLE 3
Description of Data Sets

Data Set	*Dependent Variable*	*Independent Variables*	*Source*
1	Log of real GDP	Ratio of government expenditures to GDP Country fixed effects	Penn World Table
2	Real GDP growth	Ratio of government expenditures to GDP Country fixed effects	Penn World Table
3	Log of real state PCPI	Tax Burden State fixed effects	Reed (2008)
4	Real state PCPI growth	Tax Burden State fixed effects	Reed (2008)
5	Log of real GDP	Ratio of government expenditures to GDP Country fixed effects Time fixed effects	Penn World Table
6	Real GDP growth	Ratio of government expenditures to GDP Country fixed effects Time fixed effects	Penn World Table
7	Log of real, state PCPI	Tax Burden State fixed effects Time fixed effects	Reed (2008)

Data Set	***Dependent Variable***	***Independent Variables***	***Source***
8	Real state PCP growth	Tax Burden State fixed effects Time fixed effects	Reed (2008)
9	Log of the value of real bilateral trade	Log product of real GDP Trade pair fixed effects	Rose (2004)
10	GDP growth rate	Measure of disaster magnitude Country fixed effects	Noy (2009)
11	Expenditure on dental services per day	Dentist-population ratio (Interpolated) Annual household income Dentist fixed effects	Jones and Lee (2004)
12	Number of dental visits per day	Dentist-population ratio (Interpolated) Annual household income Dentist fixed effects	Jones and Lee (2004)

TABLE 4
Replication of BK's TABLE 4 with Serially Correlated Independent Variable and Errors

EXPERIMENTAL PARAMETERS			*SERIAL CORRELATION OF ERRORS*				
T **(1)**	***Heteroscedasticity*** ***(2)***	***Contemporaneous Correlation*** ***(3)***	***ρ = 0*** ***(4)***	***ρ = 0.3*** ***(5)***	***ρ = 0.6*** ***(6)***	***ρ = 0.9*** ***(7)***	***Mean***
10	0	0	90.9	89.3	85.1	71.4	*84.2*
10	0	0.25	91.1	89.0	84.0	69.9	*83.5*
10	0.3	0	91.0	89.3	85.5	72.1	*84.5*
10	0.3	0.25	90.7	88.8	84.1	70.7	*83.6*
20	0	0	93.5	92.4	90.1	80.2	*89.1*
20	0.3	0	93.5	92.6	90.7	81.2	*89.5*
20	0.3	0.5	92.9	91.4	88.3	78.0	*87.7*
30	0	0	93.3	92.7	91.3	85.2	*90.6*
30	0	0.5	93.4	93.0	91.2	84.3	*90.5*
30	0.3	0.5	93.1	92.6	91.0	84.8	*90.4*
40	0	0	94.1	93.9	93.1	90.6	*92.9*
40	0	0.5	94.2	93.6	91.7	88.6	*92.0*
40	0.3	0	94.4	94.2	93.2	90.7	*93.1*
40	0.3	0.5	94.4	93.4	91.9	89.0	*92.2*
		Mean	*92.9*	*91.9*	*89.4*	*81.2*	*88.8*

NOTE: The primary difference between the experiments underlying this table and those underlying TABLE 1 above is that both the independent variable and the error term are allowed to have serial correlation. Details are provided in the text.

TABLE 5
Replication of BK's TABLE 4 with a Serially Correlated Independent Variable and Error Structures from "Real" TSCS Data Sets

T	***SERIAL CORRELATION OF ERRORS***		
	$0 < \rho < 0.2$	***$0.2 < \rho < 0.6$***	***$0.6 < \rho$***
10	91.6 (7)	84.7 (5)	n.a.
20	92.7 (6)	93.0 (1)	85.8 (5)
30	94.0 (4)	93.4 (3)	87.5 (5)
40	94.3 (3)	93.2 (3)	92.2 (5)

NOTE: The top number in each cell is the average coverage rate for the experiments satisfying the respective parameters (T,ρ) for that cell. The value in parentheses reports the number of real TSCS data sets (see TABLE 3) underlying the results for that cell. As there are twelve TSCS data sets, there are twelve experiments for each *T,* except for $T=40$, because one of the data sets is less than 40 years in length. The primary difference between the experiments underlying this table and those underlying TABLE 4 is that the error variance-covariance matrix, including the serial correlation of the errors, is representative of those from real TSCS data sets. Details are provided in the text.

TABLE 6
Replication of BK's TABLE 5 with
Error Structures from "Real" TSCS Data Sets

		CONTEMPORANEOUS CORRELATION OF THE ERRORS			
N	***T***	***$0<\rho_{ij}<0.25$***	***$0.25<\rho_{ij}<0.50$***	***$0.50<\rho_{ij}<0.75$***	***$\rho_{ij}>0.75$***
10	***10***	n.a.	0.97 *(10)*	0.95 *(2)*	n.a
	20	1.00 *(3)*	0.61 *(7)*	0.59 *(1)*	0.53 *(1)*
	30	0.72 *(6)*	0.51 *(4)*	0.53 *(1)*	0.53 *(1)*
	40	0.61 *(5)*	0.41 *(4)*	0.54 *(1)*	0.43 *(1)*
15	***15***	1.01 *(2)*	0.96 *(8)*	0.97 *(2)*	n.a
	20	0.94 *(3)*	0.78 *(7)*	0.78 *(1)*	0.75 *(1)*
	30	0.77 *(5)*	0.57 *(5)*	0.62 *(1)*	0.52 *(1)*
	40	0.62 *(5)*	0.47 *(4)*	0.54 *(1)*	0.45 *(1)*
20	***20***	0.97 *(4)*	0.97 *(6)*	0.98 *(1)*	0.98 *(1)*
	25	0.87 *(5)*	0.81 *(5)*	0.81 *(1)*	0.79 *(1)*
	30	0.81 *(5)*	0.70 *(5)*	0.71 *(1)*	0.67 *(1)*
	40	0.67 *(5)*	0.57 *(4)*	0.59 *(1)*	0.52 *(1)*

<u>NOTE</u>: The top number in each cell is the average "Efficiency" value for the experiments satisfying the respective parameters (T,ρ) for that cell. The value in parentheses reports the number of real TSCS data sets (see TABLE 3) underlying the results for that cell. As there are twelve TSCS data sets, there are twelve experiments for each row, except when $T=40$, because one of the data sets is less than 40 years in length. The primary difference between the experiments underlying this table and those underlying TABLE 2 is that the error variance-covariance matrix, including the cross-sectional correlation of the errors, is representative of those from real TSCS data sets. Details are provided in the text.

APPENDIX A
Results Underlying TABLE 4

Data Set	*T*	*Hetero.*	*CSCorr*	*Rho*	*Coverage Rate*
1	10	0.42	0.36	0.48	84.5
2	10	0.54	0.30	-0.05	92.1
3	10	0.26	0.61	0.38	81.9
4	10	0.29	0.58	0.02	89.7
5	10	0.53	0.34	0.48	86.5
6	10	0.53	0.30	-0.06	91.2
7	10	0.38	0.33	0.48	83.8
8	10	0.39	0.32	-0.04	91.4
9	10	0.37	0.32	0.39	86.6
10	10	0.50	0.29	0.11	92.7
11	10	0.36	0.28	-0.02	91.3
12	10	0.40	0.28	-0.02	93.0
1	20	0.40	0.34	0.71	85.0
2	20	0.48	0.26	0.00	92.7
3	20	0.20	0.78	0.62	81.4
4	20	0.26	0.66	0.15	91.5
5	20	0.51	0.30	0.73	85.2
6	20	0.49	0.25	-0.02	93.4
7	20	0.34	0.30	0.71	88.5
8	20	0.35	0.29	0.02	94.1
9	20	0.38	0.30	0.66	89.0
10	20	0.48	0.23	0.23	93.0
11	20	0.33	0.22	0.12	92.9
12	20	0.35	0.22	0.11	91.8
1	30	0.40	0.32	0.81	87.6
2	30	0.49	0.22	0.03	94.0
3	30	0.20	0.78	0.75	87.1
4	30	0.26	0.65	0.19	93.2

Data Set	*T*	*Hetero.*	*CSCorr*	*Rho*	*Coverage Rate*
5	30	0.50	0.29	0.82	88.3
6	30	0.48	0.22	0.01	95.1
7	30	0.34	0.28	0.81	86.4
8	30	0.34	0.25	0.04	93.7
9	30	0.38	0.32	0.75	88.3
10	30	0.46	0.21	0.23	94.7
11	30	0.32	0.21	0.23	92.5
12	30	0.31	0.21	0.21	92.9
1	40	0.40	0.31	0.86	92.7
2	40	0.50	0.20	0.02	94.6
3	40	0.21	0.77	0.82	92.4
4	40	0.25	0.63	0.21	94.0
5	40	0.48	0.28	0.86	93.1
6	40	0.49	0.21	-0.01	93.5
7	40	0.35	0.26	0.86	95.2
8	40	0.34	0.23	0.03	94.8
9	40	0.36	0.30	0.80	87.7
11	40	0.31	0.19	0.31	92.9
12	40	0.28	0.19	0.27	92.8

APPENDIX B
Results Underlying TABLE 5

Data Set	*N*	*T*	*Hetero.*	*CSCorr*	*Rho*	*RelEff*
1	10	10	0.37	0.39	0.47	0.94
2	10	10	0.50	0.30	-0.03	0.95
3	10	10	0.27	0.62	0.38	0.98
4	10	10	0.29	0.57	0.08	0.97
5	10	10	0.51	0.37	0.49	0.94
6	10	10	0.49	0.31	-0.04	0.92
7	10	10	0.34	0.34	0.50	0.94
8	10	10	0.34	0.31	0.09	0.94
9	10	10	0.37	0.31	0.34	0.99
10	10	10	0.46	0.28	0.11	0.99
11	10	10	0.33	0.28	-0.04	1.01
12	10	10	0.42	0.28	-0.05	1.01
1	10	20	0.36	0.37	0.71	0.76
2	10	20	0.47	0.26	0.03	0.78
3	10	20	0.19	0.79	0.62	0.74
4	10	20	0.26	0.66	0.23	0.81
5	10	20	0.50	0.35	0.75	0.58
6	10	20	0.46	0.27	0.01	0.52
7	10	20	0.34	0.30	0.73	0.59
8	10	20	0.31	0.27	0.19	0.53
9	10	20	0.40	0.30	0.62	0.80
10	10	20	0.45	0.21	0.20	0.92
11	10	20	0.29	0.23	0.08	1.05
12	10	20	0.39	0.22	0.04	1.03
1	10	30	0.36	0.36	0.80	0.66
2	10	30	0.45	0.24	0.06	0.73
3	10	30	0.20	0.80	0.74	0.52
4	10	30	0.26	0.65	0.27	0.57
5	10	30	0.49	0.34	0.83	0.42
6	10	30	0.45	0.25	0.04	0.36
7	10	30	0.34	0.28	0.82	0.44
8	10	30	0.31	0.24	0.22	0.38
9	10	30	0.40	0.31	0.72	0.69
10	10	30	0.45	0.20	0.15	0.97
11	10	30	0.28	0.20	0.16	0.98
12	10	30	0.34	0.20	0.11	0.95
1	10	40	0.36	0.36	0.86	0.59
2	10	40	0.46	0.22	0.06	0.68
3	10	40	0.21	0.77	0.82	0.43

Data Set	*N*	*T*	*Hetero.*	*CSCorr*	*Rho*	*RelEff*
4	10	40	0.25	0.61	0.29	0.49
5	10	40	0.48	0.32	0.88	0.30
6	10	40	0.44	0.24	0.05	0.28
7	10	40	0.34	0.27	0.86	0.28
8	10	40	0.30	0.22	0.16	0.28
9	10	40	0.39	0.30	0.78	0.64
11	10	40	0.26	0.20	0.24	0.96
12	10	40	0.29	0.20	0.20	0.92
1	15	15	0.41	0.35	0.62	0.97
2	15	15	0.50	0.27	-0.01	0.95
3	15	15	0.22	0.70	0.53	0.97
4	15	15	0.26	0.65	0.10	0.97
5	15	15	0.52	0.31	0.64	0.96
6	15	15	0.50	0.27	-0.03	0.95
7	15	15	0.35	0.31	0.62	0.96
8	15	15	0.35	0.30	0.00	0.95
9	15	15	0.38	0.31	0.56	0.96
10	15	15	0.50	0.25	0.19	0.96
11	15	15	0.33	0.24	0.06	0.98
12	15	15	0.37	0.24	0.06	1.03
1	15	20	0.40	0.34	0.71	0.87
2	15	20	0.48	0.26	0.00	0.82
3	15	20	0.20	0.78	0.62	0.87
4	15	20	0.26	0.66	0.15	0.94
5	15	20	0.51	0.30	0.73	0.78
6	15	20	0.49	0.25	-0.02	0.74
7	15	20	0.34	0.30	0.71	0.78
8	15	20	0.35	0.29	0.02	0.75
9	15	20	0.38	0.30	0.66	0.84
10	15	20	0.48	0.23	0.23	0.86
11	15	20	0.33	0.22	0.12	0.94
12	15	20	0.35	0.22	0.11	1.01
1	15	30	0.40	0.32	0.81	0.74
2	15	30	0.49	0.22	0.03	0.67
3	15	30	0.20	0.78	0.75	0.61
4	15	30	0.26	0.65	0.19	0.61
5	15	30	0.50	0.29	0.82	0.58
6	15	30	0.48	0.22	0.01	0.52
7	15	30	0.34	0.28	0.81	0.57
8	15	30	0.34	0.25	0.04	0.53
9	15	30	0.38	0.32	0.75	0.67
10	15	30	0.46	0.21	0.23	0.86

Data Set	*N*	*T*	*Hetero.*	*CSCorr*	*Rho*	*RelEff*
11	15	30	0.32	0.21	0.23	0.86
12	15	30	0.31	0.21	0.21	0.96
1	15	40	0.40	0.31	0.86	0.64
2	15	40	0.50	0.20	0.02	0.57
3	15	40	0.21	0.77	0.82	0.46
4	15	40	0.25	0.63	0.21	0.49
5	15	40	0.48	0.28	0.86	0.43
6	15	40	0.49	0.21	-0.01	0.39
7	15	40	0.35	0.26	0.86	0.41
8	15	40	0.34	0.23	0.03	0.40
9	15	40	0.36	0.30	0.80	0.61
11	15	40	0.31	0.19	0.31	0.83
12	15	40	0.28	0.19	0.27	0.92
1	20	20	0.43	0.35	0.72	0.97
2	20	20	0.55	0.25	0.04	0.96
3	20	20	0.20	0.77	0.63	0.91
4	20	20	0.26	0.65	0.19	0.96
5	20	20	0.62	0.30	0.72	0.97
6	20	20	0.53	0.25	0.02	0.96
7	20	20	0.36	0.32	0.71	0.97
8	20	20	0.38	0.29	0.12	0.97
9	20	20	0.37	0.31	0.68	0.97
10	20	20	0.50	0.24	0.15	0.97
11	20	20	0.36	0.23	0.10	0.96
12	20	20	0.36	0.23	0.10	0.98
1	20	25	0.44	0.35	0.78	0.87
2	20	25	0.56	0.24	0.05	0.81
3	20	25	0.19	0.79	0.70	0.80
4	20	25	0.26	0.65	0.21	0.79
5	20	25	0.62	0.28	0.78	0.82
6	20	25	0.54	0.23	0.02	0.79
7	20	25	0.36	0.31	0.77	0.83
8	20	25	0.37	0.28	0.14	0.79
9	20	25	0.37	0.31	0.74	0.86
10	20	25	0.49	0.22	0.17	0.87
11	20	25	0.36	0.22	0.16	0.90
12	20	25	0.35	0.22	0.15	0.95
1	20	30	0.43	0.34	0.81	0.80
2	20	30	0.56	0.22	0.06	0.73
3	20	30	0.20	0.78	0.75	0.73
4	20	30	0.25	0.64	0.23	0.68
5	20	30	0.60	0.28	0.81	0.71

Data Set	*N*	*T*	*Hetero.*	*CSCorr*	*Rho*	*RelEff*
6	20	30	0.53	0.22	0.03	0.67
7	20	30	0.36	0.30	0.81	0.71
8	20	30	0.37	0.27	0.15	0.68
9	20	30	0.36	0.31	0.78	0.78
10	20	30	0.48	0.21	0.17	0.82
11	20	30	0.36	0.21	0.20	0.87
12	20	30	0.34	0.21	0.20	0.93
1	20	40	0.44	0.33	0.86	0.66
2	20	40	0.54	0.20	0.05	0.67
3	20	40	0.21	0.78	0.82	0.56
4	20	40	0.25	0.62	0.25	0.55
5	20	40	0.58	0.27	0.87	0.55
6	20	40	0.52	0.20	0.03	0.51
7	20	40	0.36	0.27	0.86	0.52
8	20	40	0.36	0.24	0.12	0.51
9	20	40	0.35	0.30	0.83	0.71
11	20	40	0.35	0.20	0.28	0.83
12	20	40	0.32	0.20	0.27	0.85