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Median-Unbiased Estimation in Panel Data: Methodology and Applications to the GDP Convergence and Purchasing Power Parity Hypotheses

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Abstract

This paper reviews the literature on the econometrics of median-unbiased estimation in panel data and provides methodological guidelines for its implementation. The method is then used to evaluate the well known GDP convergence and Purchasing Power Parity (PPP) hypotheses. In the first two examples, panel exactly median-unbiased estimates with yearly data show, respectively, fast conditional convergence rates of per capita income among the 48 USA contiguous states, and extremely slow convergence or non convergence of per capita GDP among the 32 Mexican states. In the third example, using monthly data for a sample of 14 developing countries, the results from panel exactly median-unbiased estimation show that the dynamics of real exchange rates is consistent with the PPP hypothesis, although this process is highly persistent.

Key words: Panel Median-Unbiased Estimation, Dynamic Panel Data Models, Least Squares Dummy Variables, Cross Sectional Dependence, GDP Convergence, Purchasing Power Parity.

JEL Classification: C33, C15, O40, F31.

Resumen

Este artículo revisa la literatura sobre estimación insesgada respecto a la mediana (median-unbiased) en modelos panel y desarrolla los lineamientos metodológicos para su implementación empírica. Como ilustración, este método es utilizado para evaluar las hipótesis de convergencia del ingreso y paridad del poder de compra (PPP). En los dos primeros ejemplos, los resultados del estimador panel exactamente insesgado respecto a la mediana (exactly median-unbiased) muestran, respectivamente, convergencia condicional relativamente rápida del ingreso por persona para los EE. UU. y convergencia muy lenta o ausencia de convergencia en el caso del PIB por persona de los estados de México. En el tercer ejemplo, utilizando el mismo estimador anterior se encuentra que la dinámica del tipo de cambio real de 14 países en desarrollo es consistente con la hipótesis PPP, aunque se trata de un proceso altamente persistente.

Palabras clave: estimación Median-Unbiased *en panel, modelos panel dinámicos, estimador de mínimos cuadrados con variables ficticias, dependencia de sección cruzada en panel, convergencia del PIB per cápita, paridad del poder de compra.*

Códigos de clasificación JEL: C33, C15, O40, F31.

Introduction

During the last decade and a half there have been considerable developments on median-unbiased Estimation for auto regressive processes (AR). This method provides unbiased point and confidence interval estimates for the AR parameter, thus offering useful information to characterize the persistence of a time series process, which is particularly important in cases where the evidence from unit root tests may not be conclusive (Andrews, 1993). As it is well known, the bias of the OLS estimator can be quite substantial particularly when the AR parameter is close to one and/or the sample size is relatively small, and can produce potentially misleading inferences.

There are a number of important economic questions such as convergence of per capita GDP, price convergence and purchasing power parity, where a correct measurement of the persistence of the process is crucial and where median-unbiased estimation can play an important role. Notwithstanding, this method is still not popular, perhaps because of its computational burden. In the panel data literature, the median-unbiased estimation method is even less known despite the fact that in several empirical applications the time dimension of the panel is relatively short.

The goal of this paper is to survey the literature on the econometrics of median-unbiased estimation in panel data and to provide methodological guidelines for its implementation. The method is then used to evaluate *(i)* the per capita Income or GDP convergence hypothesis in two different samples, namely, the USA and Mexican states, and *(ii)* the Purchasing Power Parity (PPP) hypothesis in a panel of 14 Developing countries.

The rest of the paper is organized as follows. Section 1 briefly surveys the literature on median unbiased estimation. Section 2 describes the method in detail and discusses some methodological issues for its implementation. The empirical applications are provided in section 3 and, finally, some conclusions and remarks are offered in last section.

1. Some Background

Orcutt and Winokur Jr. (1969) is probably the first paper that focuses on approximately mean-unbiased estimates of the AR parameter in stationary models, work that was motivated by the earlier findings by Hurwickz (1950), Marriot and Pope (1954) and Kendall (1954), who established the (mean) bias of the OLS estimator in AR models. Later, Le Breton and Pham (1989) calculated exact and asymptotic biases of the OLS estimator in stationary and non stationary $AR(1)$ processes.[1]

[1] Maddala and Kim (1998), p. 141.

The bias or more precisely the mean-bias of an estimator is simply defined as the difference between the unconditional expectation of the estimator and the true parameter value. Thus, if the expected value (mean) of the estimator is equal to the true parameter value then the estimator is said to be unbiased or more precisely mean-unbiased. The concept of median-unbiasedness, considers the median instead of the mean. If an estimator is normally distributed, there is no difference between the mean and median. However, in situations were the estimators have asymmetric distributions the concept of median-unbiasedness becomes more relevant as the median of the distribution is less sensitive to skewness and kurtosis problems. This is precisely the motivation for pursuing median-unbiased estimation as proposed by Andrews (1991, 1993) and Rudebusch (1992) who show the relevance and usefulness of this method to study the dynamics of time series where the bias of the OLS estimator can become a serious problem. Essentially the method consists of (i) estimating the AR parameter by OLS and (ii) correcting for the downward bias by matching the OLS estimate to the median of de distribution of the OLS estimator and finding its corresponding true or unbiased value, that is, the value of α that generates a process for which the median of the distribution of the OLS estimator is equal to the OLS estimate obtained from the actual data. Obtaining the OLS estimate is certainly a trivial task. However, obtaining the median-unbiased estimate requires computation of the distribution of the OLS estimator. More precisely, it is necessary compute the median as well as other relevant quantiles of that distribution. In practice this can be done (approximately) by Monte Carlo simulations, which will turn out to be a relatively easy task using actual storage and processing capacity of personal computers.

Andrews (1993) presents a comprehensive approach to median-unbiased estimation for first-order autoregressive-unit root models with independent and identically distributed normal errors.[2] The author considers models with no intercept, intercept only, and intercept and time trend, which are the well-known specifications used in the time series unit root testing literature. Generally, the AR parameter value is allowed to lie on the interval (-1, 1], which includes the unit root case. In addition to median-unbiased estimators and confidence intervals for the AR parameter, the corresponding impulse response function, the cumulative impulse response, and the half life of a unit shock can also be obtained with this method. The papers by Andrews and Chen (1992, 1994) and Rudebusch (1992) consider median-unbiased estimation in the context of $AR(p)$ processes.[3]

[2] Fuller (1995) develops an estimator that is median-unbiased in the unit root case and nearly unbiased elsewhere. This approach is summarized by Enders and Folk (1998). Essentially, the OLS estimate is adjusted upwards by an amount commensurate with the sample size and the proximity of the estimate to unity.

[3] A related approach is given in Stock (1991) who constructs unbiased asymptotic confidence intervals for the largest root in AR (p) processes when this root is close to one.

Indeed, the aforementioned work motivated several empirical applications. It is worthwhile to mention the papers by Kent and Cashing (2003), Cashin, McDermott, and Pattillo (2004), Cashin and McDermott (2003), Kim (2003), Murray and Papell (2002, 2005a) which were all applied in time series contexts. In most cases, the time series median-unbiased estimates imply slow convergence rates and confidence intervals consistent with shocks that have permanent effects.

Cermeño (1999) extended Andrews' (1993) approach to dynamic panel data models with fixed effects and homogeneous trends, showing that in typical macro panels the biases in the estimation of the AR parameter using the $LSDV$ estimator could be substantial even for relatively large T dimensions which may lead to erroneous conclusions if not taken into account. In particular, Cermeño's findings show that (conditional) convergence of per capita GDP is only supported in the cases of 48 USA states and 23 OECD countries but it does not hold in wider samples of countries.

Further, Phillips & Sul (2003) generalize this method to cases with cross-sectional dependence as well as full parameter heterogeneity. In addition to the original Panel Exactly Median-Unbiased estimator (PEMU), they propose the Panel Feasible Generalized Least Squares Median-Unbiased (PFGMU) for the case of cross-sectional dependence and the Panel Seemingly Unrelated Median Unbiased (SURMU) estimator for the case of complete coefficient heterogeneity of individual cross sections.

It is important to mention that the previous extensions of median-unbiased estimation to panel data have been made in the context of $AR(1)$ processes.[4] Its generalization to $AR(p)$ processes with heterogeneous dynamics and a general error covariance structure still remains to be done.

2. Median-Unbiased Estimation

In this section we offer a comprehensive summary on median-unbiased estimation in panel data, the main focus being to provide methodological guidelines for its implementation. In order to address the fundamental issues in some detail the time series approach is also included. As it will become apparent later, this approach will turn out to be a key component of the implementation of this method in panel data.

[4] Murray and Papell (2005b) extend Andrews (1993) and Andrews and Chen (1994) median unbiased estimators to study the PPP hypothesis in a panel of real exchange rates of 20 developed countries. Although this extension is innovative in various aspects, it still assumes homogeneous dynamics for all individual series in the panel.

2.1. Exactly Median-Unbiased Estimation

Consider the following latent-variable model for a time series:

$$y_t = d\beta + y_t^*, \qquad t = 0, \ldots T \tag{1}$$

Where d is a deterministic trend component that can take the values: $\{0, 1, (1, t)\}$, and β is a conformable vector of parameters which correspondingly can take the values: $\{0, \beta_0 . (\beta_0, \beta_1)'\}$. The coefficients β_0, β_1 are the intercept and trend respectively. Assume that the latent variable follows the $AR(1)$ process:

$$y_t^* = \alpha y_{t-1}^* + \varepsilon_t, t = 1, \ldots, T \tag{2}$$

Where the error terms (ε_t) are independent and identically distributed, denoted $\varepsilon_t \sim i.i.d(0, \sigma^2)$. The previous representation is quite convenient since if $|\alpha| < 1$, y_t becomes stationary around the deterministic trend $d\beta$. More precisely $(y_t - d\beta) = y_t^* \sim (0, \sigma^2 / (1 - \alpha^2))$, meaning that the deviation $(y_t - d\beta)$ is a stationary, zero mean, process. Also, as it can be seen in the following equations, the previous formulation nests the 3 cases considered in the unit root literature which are referred to as cases (or models) 1, 2 and 4.[5]

These are also known respectively as the cases with "no intercept and no trend", "intercept only" and "intercept and trend". For the stationary case, $|\alpha| < 1$, from (1) and (2) we can obtain the following models in terms of the observable variable:

$$\begin{aligned} y_t &= \alpha y_{t-1} + \varepsilon_t && \text{[case (1)]} \\ y_t &= \alpha y_{t-1} + \beta_0 (1 - \alpha) + \varepsilon_t && \text{[case (2)]} \\ y_t &= \alpha y_{t-1} + \beta_0 (1 - \alpha) + \beta_1 \alpha + \beta_1 (1 - \alpha) t + \varepsilon_t && \text{[case (4)]} \end{aligned} \tag{3}$$

The processes in (3) are stationary around 0, β_0 and $(\beta_0 + \beta_1 t)$ respectively. For the unit root (non-stationary) case, $\alpha = 1$, the previous models become:

$$\begin{aligned} y_t &= y_{t-1} + \varepsilon_t && \text{[case (1)]} \\ y_t &= y_{t-1} + \varepsilon_t && \text{[case (2)]} \\ y_t &= \beta_1 + y_{t-1} + \varepsilon_t && \text{[case (4)]} \end{aligned} \tag{4}$$

The first two processes in (4) are random walks without drifts while the third one is a random walk with drift parameter β_1. It is important to remark that (3) and (4) include, respectively, the corresponding processes under the alternative (stationarity) and null hypotheses (unit root), as considered, for

[5] See for example Hamilton (1994), pp. 487-502.

example, in Dickey and Fuller (1979).[6] For example, the third equation in (3) and (4) represent respectively the well known trend stationary and difference stationary processes, which are competing representations for trending processes such as GDP, prices or money stock.

Andrews (1993) shows that, under normality, the finite sample distribution of the OLS estimator of the parameter α in the previous $AR(1)$ models is a function of a quadratic form in standard normal variables. Therefore, under this assumption, it is possible to compute the median and other quantiles of the distribution of the OLS estimator of α, exactly, using Imohf's (1961) algorithm, implemented in the FORTRAN sub routines by Koerts and Abrahamse (1971). Specifically, given a model and a sample size $T+1$, the quantiles of the distribution of the OLS estimator of α are computed exactly for a grid of parameter values on the interval $(-1,1]$. Certainly, the same can be done by Monte Carlo simulations, although in this case the quantiles of the distribution will be approximate.[7] It is well known that the OLS estimator of the parameter α is downward biased which implies that the mean of its distribution is less than the true value of α. For example, when $\alpha=1$, the unit root case, and for $T+1=100$, the mean (which is equal to the median under normality) of the distribution of the OLS estimator of α is equal to 0.957 for model 2 (intercept only) and 0.911 for model 4 (intercept and trend).[8] Thus the median and mean biases of the OLS estimator are not negligible and can produce highly misleading results. In both cases we would conclude that the processes are stable with approximate convergence rates of 4 and 9% respectively, when in fact they are random walks. Therefore, the OLS estimator needs to be corrected for its bias and Andrews' approach performs this correction by eliminating the median bias. But before giving a definition of the median-unbiased estimator it is important to characterize the OLS estimator and its distribution. This is done in propositions 1 and 2 given below.

Proposition 1: Invariance of the distribution of the OLS estimator of α

In the previous $AR(1)$ models 2 and 4, the distribution of the OLS estimator of α is invariant to the specific values of the deterministic components (intercept and time trend). Also, this distribution does not depend on σ^2, the

[6] Strictly, the processes in (3) are non-linear in the parameters. Dickey and Fuller and the foregoing unit root literature consider the unrestricted linear versions of these models.

[7] This procedure is described in detail later in this paper.

[8] See Andrews (1993, p. 149). This result is well know in the unit root literature and implies that the distribution of the Dickey-Fuller *t*-test for unit root is leftward skewed. It is also known, more generally, that for a given model and sample size, the bias becomes larger the closer to one is the AR parameter and for a given AR parameter value the bias becomes larger the smaller is the sample size.

variance of the error term, and when $\alpha = 1$ it does not depend on y_0, the initial value of the process.

See Andrews (1993) for proofs. The first part of this proposition states that the distribution of the OLS estimator does not depend on the specific values of the intercept and time trend.

This result is well known in the time series literature. Intuitively, the inclusion of an intercept or an intercept and a time trend in the regression controls for the effect of these deterministic components (d). In fact, from partitioned regression theory, the OLS estimator of α in a model that includes the aforementioned deterministic components is equivalent to regressing $\tilde{y}_t$ on $\tilde{y}_{t-1}$, which are residuals from the regressions of y_t and y_{t-1} on d respectively. As it will become clear shortly, without this invariance property exactly median-unbiased estimation of the AR parameter would be impossible since it would require prior knowledge of the specific values of the deterministic components. The second part of Proposition 1, that the distribution of the OLS estimator of the parameter α is invariant to the specific values of σ^2, is less intuitive but given that essentially this estimator is obtained by regressing y_t on y_{t-1}, their variances cancel out.

Proposition 2: Existence of a monotonically increasing median function *of* $\hat{\alpha}_{OLS}$

For a given $AR(1)$ model and sample size, there exists a monotonically increasing relationship between α and the median of the distribution of the OLS estimator of this parameter.

Proposition 2 is fundamental for median-unbiased estimation since in the absence of a monotonically increasing median function, it would be impossible to map an actual OLS estimate to a unique (median-unbiased) value of the AR parameter α. Unfortunately, there is no formal proof available and the existence of such a relationship can only be shown by simulation. For the median and other relevant quantiles (.5th and .95th) there is overwhelming evidence supporting this proposition for models 2 and 4. However, Andrews (1993) points out that not every quantile exhibits this behavior in the case of model 1, particularly when T is relatively small and α takes on values near to one. In practice it is, therefore, advisable to check this relationship by simulation before proceeding.

Let $m_j = f_j(\alpha, T)$ denote the median function of the OLS estimator of α in model j and assume that Proposition 2 is satisfied. The median-unbiased estimator $(\hat{\alpha}_{MU})$ implies inverting the previous function in order to find the value of α for which the actual OLS estimate $(\hat{\alpha}_{OLS})$ corresponds exactly to the median. This is established in the following definition, stated along the lines of Andrews (1993).

Definition 1: Median-unbiased estimator of α

For a given $AR(1)$ model in (3) and for a given sample size T, the median-unbiased estimator of the parameter α $(\hat{\alpha}_{MU})$ is the value of the AR parameter for which the median of the distribution of the OLS estimator of this parameter equals the actual OLS estimate $(\hat{\alpha}_{OLS})$. Specifically, for a given $AR(1)$ model j, assume that $0<\alpha\leq 1$ and let m_j^{UR} denote the median of the distribution of the OLS estimator of α in the unit-root case, i.e. when $\alpha=1$. The median-unbiased estimator of the parameter α is defined as follows:

$$\hat{\alpha}_{MU}^{j}=\begin{cases} f_j^{-1}(\hat{\alpha}_{OLS}^{j}) & \text{if } \hat{\alpha}_{OLS}^{j}<m_j^{UR} \\ 1 & \text{if } \hat{\alpha}_{OLS}^{j}\geq m_j^{UR} \end{cases} \tag{5}$$

The previous definition can be symmetrically extended to the cases $-1<\alpha\leq 0$.[9] However, we focus here on positive values of the AR parameter for practical reasons. First, most economic phenomena do not seem to exhibit oscillatory dynamics, *i.e.* cases in which the AR parameter is negative. Secondly, several economic processes seem to be highly persistent, which is consistent with AR parameter values close to one. This will in fact be the case of the empirical applications considered in the next section.

According to Definition 1, the median-bias is subtracted from the OLS estimate thus providing an unbiased estimate. Actually, the median-bias is eliminated completely. For example, using the previous results for model 4, if the actual OLS estimate happens to be 0.911, the median-unbiased estimate will be equal to 1, which is precisely the value of the AR parameter for which the median of the distribution is equal to the actual OLS estimate (0.911). In this case the median-unbiased point estimate is equal to 1 which is consistent with the unit root hypothesis.

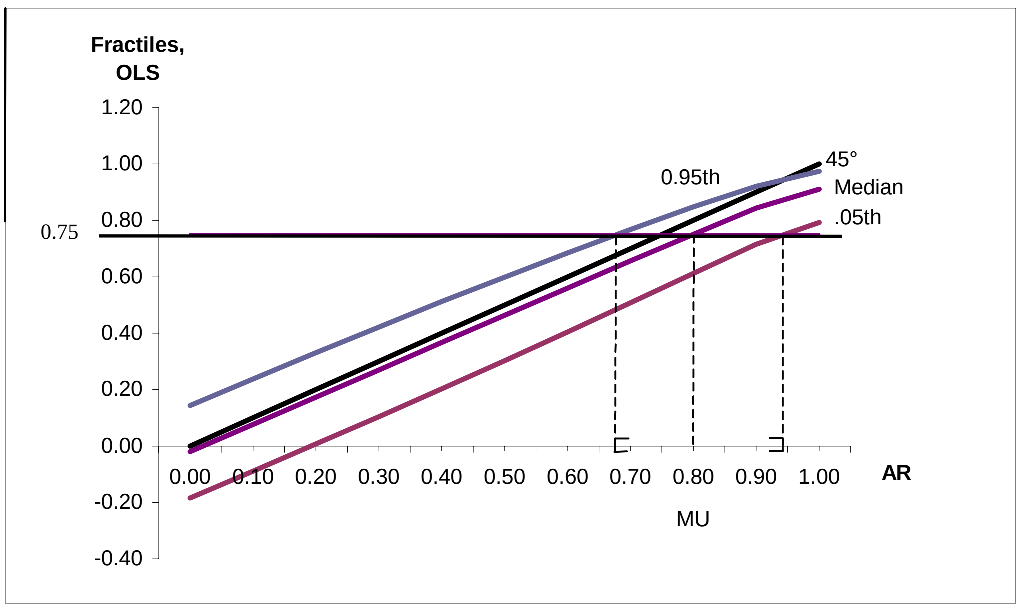
Implementing median-unbiased estimation requires computing the median of the distribution of the OLS estimator for each possible value of the AR parameter. More explicitly, for a given model and sample size we must obtain the median function which relates the AR parameter value with the median of the distribution of the OLS estimator of this parameter. We then use the median function to find the AR parameter value that corresponds to a given OLS estimate which is equated to the median. In practice, the median

[9] See Andrews (1993) for details.

function is a discrete set of pairs (α^j, m^j) and median-unbiased estimates are obtained by finding the median value that equals the OLS estimate computed using the actual sample $(m^j = \hat{\alpha}^j_{OLS})$ and locating its corresponding pair which will be the median-unbiased estimate $(\alpha^j = \hat{\alpha}^j_{MU})$. Given that $\hat{\alpha}^j_{OLS}$ will hardly coincide exactly with m^j, interpolation will be needed in most cases.

Interval estimation is performed analogously, applying the previous concepts to the appropriate quantiles. That is, for quantiles other than the median, we can use Definition 1 after replacing the median function by the appropriate function for the p_{th} quantile. Thus, the interval limits will be given by the AR parameter values for which the OLS estimate equals the corresponding interval quantiles. For 90% confidence intervals, the .05th and .95th quantiles are used. Figure 1 below illustrates the previous ideas. The horizontal axis represents different values of α over the interval $[0,1]$ while the vertical axis represents the 0.95th, 0.5th (median) and 0.05th quantiles of the distribution of the OLS estimator of this parameter.[10]

FIGURE 1: POINT AND INTERVAL MEDIAN-UNBIASED ESTIMATION



Two important points are worth noting. First, the relationship between the quantiles of the distribution and the value of α seems to be monotonically increasing, supporting Proposition 2. Second, the fact that the OLS estimator is downward median-biased can be seen by observing that the median

[10] Values from Table III, for $T+1=100$ from Andrews (1993, p.151) are used here and they correspond to the model that includes an intercept plus a linear time trend.

function lies below the 45 degree line. Finally, the closer to one is α the higher is the median bias of the OLS estimator.[11]

Median-unbiased estimation proceeds as follows. The value of the OLS estimate (uncorrected) which is assumed to be exactly equal to 0.751 (vertical axis) is mapped to its median-unbiased estimate using the median function, which gives a value of exactly 0.8 on the horizontal axis.

Therefore, the median-unbiased estimate will equal 0.8. The 90% confidence interval is found by mapping the same OLS estimate to the 0.95th and 0.05th quantiles respectively. This gives approximately the interval $[0.7, 0.93]$.[12]

2.2. Approximately Median-Unbiased Estimation

Andrews and Chen (1994) extend Andrews (1993) median-unbiased estimation method to $AR(p)$ models. However, in this case the method will only be approximate since it relies on simulation rather than exact computation of the quantiles of the distribution of the OLS estimator and also because the unknown nuisance parameters must be estimated using an iterative algorithm.

Consider the following latent variable model with an intercept and time trend: [13]

$$y_t = \beta_0 + \beta_1 t + y_t^*, \text{for} \qquad t = -p+1, \ldots T \tag{6}$$

Where the latent variable follows the $AR(p)$ process:

$$y_t^* = \phi_1 y_{t-1}^* + \phi_2 y_{t-2}^* + \ldots + \phi_p y_{t-p}^* + \varepsilon_t, \qquad \text{for} \qquad t = 1, \ldots T \tag{7}$$

The error process is assumed $i.i.d(0, \sigma^2)$. The previous process can equivalently be expressed as:

$$y_t^* = \alpha y_{t-1}^* + \psi_1 \Delta y_{t-1}^* + \ldots + \psi_{p-1} \Delta y_{t-p+1}^* + \varepsilon_t, \quad \text{for} \qquad t = 1, \ldots T \tag{8}$$

Andrews and Chen assume that y_t^* is stationary whenever $\alpha \in (-1,1)$ while Δy_t^* is stationary when $\alpha = 1$. This is equivalent to assuming that only the largest root of the characteristic polynomial in (7) can be equal to one. From (6) and (8) we can obtain:

$$y_t = \delta_0 + \delta_1 t + \alpha y_{t-1} + \psi_1 \Delta y_{t-1} + \ldots + \psi_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{9}$$

Where $\delta_0 = \beta_0(1-\alpha) + \beta_1(\alpha - \psi_1 - \ldots - \psi_{t-p+1})$ and $\delta_1 = \beta_1(1-\alpha)$. The invariance properties of the distribution of OLS estimator of α in model (9) can be summarized in the following proposition.

[11] Obviously, the smaller the sample sizes the larger with be the downward biases.

[12] For simplicity we have taken the closest values to 0.751 given in Andrews Tables. These are 0.746 for the .05th quantile and 0.768 for the 95th quantile. More precise values can be found either by interpolation or by computing these quantiles over a finer grid around 0.65 and 0.95.

[13] We focus here on case 4 only (model with intercept and time trend). A similar approach applies to cases 1 and 2.

Proposition 3: Invariance of the distribution of the OLS estimator of the parameter α

The distribution of OLS estimator of α $(\hat{\alpha}_{OLS})$ in model (9) depends on $(\alpha, \psi_1, \ldots, \psi_{p-1})$. It does not depend on β_0, β_1 or σ^2 and in the case $\alpha = 1$ it does not depend on the initial value y^*_{t-p+1}.

Proofs can be found in Andrews and Chen (1994, p.203). The previous proposition implies that Andrews (1993) exactly median-unbiased estimator cannot be applied in this context since $(\psi_1, \ldots, \psi_{p-1})$ are unknown. Andrews and Chen (1994) propose an iterative procedure to obtain approximately median-unbiased estimates. This is given in the following definition.

Definition 2: Approximately median-unbiased estimator

An approximately median-unbiased estimator of the parameter vector $(\alpha, \delta_0, \delta_1, \psi_1, \ldots, \psi_{p-1})$ in model (9), denoted by $(\hat{\alpha}, \hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots, \hat{\psi}_{p-1})_{AMU}$ can be determined using the following iterative algorithm:

Estimate model (9) by OLS to obtain $(\hat{\alpha}, \hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots, \hat{\psi}_{p-1})^{(1)}_{OLS}$, where the supra index (1) denotes the first iteration.

Treat $(\hat{\psi}_1, \ldots, \hat{\psi}_{p-1})^{(1)}_{OLS}$ as true parameter values and obtain the exactly median unbiased estimator $\hat{\alpha}^{(1)}_{MU}$.

Treat $\hat{\alpha}^{(1)}_{MU}$ as true parameter value and compute new values of $(\hat{\psi}_1, \ldots, \hat{\psi}_{p-1})$ from the OLS regression of $(y_t - \hat{\alpha}^{(1)}_{MU} y_{t-1})$ on $(1, t, \Delta y_{t-1}, \ldots, \Delta y_{t-p+1})$. Call them $(\hat{\psi}_1, \ldots, \hat{\psi}_{p-1})^{(2)}_{OLS}$. If $\hat{\alpha}^{(1)}_{MU} = 1$, exclude t from the regression, as implied by equation (9).

Treat the new values $(\hat{\psi}_1, \ldots, \hat{\psi}_{p-1})^{(2)}_{OLS}$ as given and compute again the exactly median unbiased estimator $\hat{\alpha}^{(2)}_{MU}$.

Repeat steps (iii) and (iv) until convergence or for a given number of iterations.

The Andrews-Chen algorithm will produce the following vector of estimates:

$$(\hat{\alpha}, \hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots, \hat{\psi}_{p-1})_{AMU} = \left\{\hat{\alpha}^{(J)}_{OLS}, \left(\hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots \hat{\psi}_{p-1}\right)^{(J+1)}_{OLS}\right\} \qquad (10)$$

Once convergence is achieved at iteration J, the approximately median-unbiased estimator of the AR parameter α, denoted $\hat{\alpha}_{AMU}$, will be equal to the OLS estimate found in step (iv). That is, $\hat{\alpha}_{AMU} = \hat{\alpha}^{(J)}_{OLS}$. Consequently, the approximately median-unbiased estimator of the remaining parameters will be obtained at iteration $(J+1)$ from the regression of $(y_t - \hat{\alpha}_{MU} y_{t-1})$ on $(1, t, \Delta y_{t-1}, \ldots, \Delta y_{t-p+1})$ in the case $\hat{\alpha}_{MU} < 1$, or from the regression of $(y_t - \hat{\alpha}_{MU} y_{t-1})$ on $(1, \Delta y_{t-1}, \ldots, \Delta y_{t-p+1})$ if $\hat{\alpha}_{MU} = 1$. These are denoted as $\left(\hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots, \hat{\psi}_{p-1}\right)_{OLS}^{(J+1)}$ in equation (10).

The only difficulty in the previous procedure is the computation of $\hat{\alpha}_{MU}^{(j)}$ in steps (ii) and (iv). In order to do this it is necessary to compute the median function which will be given by the set of pairs (α, m), where α is a given value on the interval $[-1,1]$, and m is the median of the distribution of $\hat{\alpha}_{OLS}$. This can be carried out through Monte Carlo simulations as follows:

Take the results of a given iteration $\left(\hat{\delta}_0, \hat{\delta}_1, \hat{\psi}_1, \ldots, \hat{\psi}_{p-1}\right)_{OLS}^{(j)}$ as well as the sample size and a given value of α as fixed and randomly generate a large number of $AR(p)$ processes (say 200,000) as described by equation (9). The error term can be obtained from a standard normal distribution, which implies assuming $\sigma^2 = 1$.

For each randomly generated sample estimate model (9) by OLS and store the value $\hat{\alpha}_{OLS}$ in some vector.

Compute the empirical distribution of $\hat{\alpha}_{OLS}$, particularly the median (m) and other relevant quantiles. This will give the pair (α, m) for the case of the median function.

Repeating the previous procedure for a relevant grid of values of α will produce the desired median function. The median-unbiased estimate can then be obtained as shown in Definition 2. That is, by matching the OLS estimate from regression (9), based on actual data, to the closest median value and its corresponding pair, which is the median-unbiased estimate of the AR parameter.

2.3. Panel Exactly Median-Unbiased Estimation

Exactly median-unbiased estimation can be extended to panel data. The simplest case is considered by Cermeño (1999). This is a straightforward extension of Andrews (1993) to panel data with homogeneous dynamics and *i.i.d.* disturbances. Further, Phillips and Sul (2003) formulate a more general approach and consider a wider variety of models and estimators including parameter heterogeneity and cross-sectional correlation.

Consider the following panel model with a latent variable:

$$y_{it} = \mu_i + \lambda_t + y_{it}^*, \; i = 1, \ldots, N \text{ and } t = 0, \ldots, T \tag{11}$$

Where the index i refers to individuals or cross-sections such as firms or countries, and t indexes time periods. Thus, the panel is made up of $(T+1)$

observations for each of the N individuals or cross-sections. In the panel data literature, μ_i and λ_t are referred to as individual and time specific effects respectively and can be treated as fixed or random. In this paper, they are treated as fixed parameters. The latent variable follows the $AR(1)$ process:

$$y_{it}^* = \alpha y_{t-1}^* + \varepsilon_{it}\ , i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{12}$$

The error term (ε_{it}) is assumed to be independent and identically distributed both across time and individuals, denoted $\varepsilon_{it} \sim i.i.d(0,\sigma^2)$. This assumption implies homoskedastic, non autocorrelated as well as cross sectionally independent errors.[14] Explicitly:

$$\begin{aligned} &E(\varepsilon_{it}, \varepsilon_{js}) = \sigma^2 \text{ for } i = j, t = s \\ &E(\varepsilon_{it}, \varepsilon_{js}) = 0 \text{ for } i = j, t \neq s \\ &E(\varepsilon_{it}, \varepsilon_{js}) = 0 \text{ for } i \neq j, t = s \end{aligned} \tag{13}$$

Certainly, this assumption can be quite strong in a panel context and caution should be exercised in practice. We will turn back to this point later in this section.

From (11) and (12) we can obtain the following panel model in terms of the observable variable:

$$y_{it} = \mu_i^0 + \lambda_t^0 + \alpha y_{it-1} + \varepsilon_{it}\ ,\ i = 1,\ldots,N \text{ and } t = 0,\ldots,T \tag{14}$$

Where $\mu_i^0 = \mu_i(1-\alpha)$ and $\lambda_t^0 = \lambda_t - \alpha\lambda_{t-1}$. In panel regression, α can be estimated by OLS either after including individual specific and time specific dummy variables in the regression or by performing the so called Within transformation which is based on partitioned regression.

In both cases, the OLS estimator yields the same result and is generally known as the Least Squares Dummy Variable ($LSDV$) estimator.[15] The invariance of the $LSDV$ estimator of α in model (14) is established in the following proposition:

Proposition 4: Invariance of the distribution of the $LSDV$ estimator of α

Under the assumption that $\varepsilon_{it} \sim i.i.d(0,\sigma^2)$, the distribution of the $LSDV$ estimator of α $(\hat{\alpha}_{LSDV})$ in model (14) is invariant to the specific values of μ_i, λ_t, σ^2 and when $\alpha = 1$ it does not depend on the initial values y_{i0}. This invariance property also holds for the cases (i) $\mu_i \neq 0, \lambda = 0$, (ii) $\mu_i \neq 0, \lambda = 0$ and (iii) $\mu_i \neq 0, \lambda_t = \beta t$.

[14] The possibility of non contemporaneous cross correlation is ruled out elsewhere in the panel data literature and is ruled out here as well.

[15] See Baltagi (2003) or Hsiao (2002) for details on these panel data estimators.

Cermeño (1999) offers simulation evidence that supports this proposition. Phillips and Sul (2003) also show the monotonicity of the median function for the cases (i) $\mu_i = 0, \lambda = 0$, (ii) $\mu_i \neq 0, \lambda = 0$ and (iii) $\mu_i \neq 0, \lambda_t = \beta t$ and for sample sizes $N \geq 5$ and $T + 1 \geq 20$.

The invariance property of the $LSDV$ estimator in (14) can intuitively be seen by considering that the within transformation wipes out the individual and time specific effects. Therefore, the estimator $\hat{\alpha}_{LSDV}$ and its distribution are independent of these effects. The previous papers also show by simulation that, the median and other relevant quantiles are strictly increasing functions of α , condition that is required for implementation of median-unbiased estimation. The following definition is a straightforward extension of Definition 1 to the panel data case under the previous assumptions.

Definition 3: Panel exactly median-unbiased estimator of α

Let $m = f(\alpha, N, T)$ denote the median function of the $LSDV$ estimator of α ($0 < \alpha \leq 1$) for a given sample size (N, T) in model (14) and let m^{UR} denote the median of the distribution of the $LSDV$ estimator of α when $\alpha = 1$. The panel exactly median-unbiased estimator of α is defined as follows:

$$\hat{\alpha}_{MU}^{j} = \begin{cases} f^{-1}(\hat{\alpha}_{LSDV}) & \text{if } \hat{\alpha}_{LSDV} < m^{UR} \\ 1 & \text{if } \hat{\alpha}_{LSDV} \geq m^{UR} \end{cases} \tag{15}$$

Andrews (1993) was able to compute the quantiles of the distribution of the OLS estimator of the parameter α exactly for the time series case. For the panel data case this can be done approximately using Monte Carlo simulations as follows:

Take μ_i, λ_t as well as a sample size (T, N) and a given value of α as fixed and randomly generate a large number of $AR(1)$ processes as described by equation (14). The error term can be drawn from a standard normal distribution $(\sigma^2 = 1)$, assumption that is immaterial given the invariance property in Proposition 4.

For each randomly generated sample, estimate model (14) using the $LSDV$ estimator and store the value $\hat{\alpha}_{LSDV}$ in some vector.

Compute the empirical distribution of $\hat{\alpha}_{LSDV}$ particularly the median (m) and other relevant quantiles. This will give the pair (α, m) for the case of the median function.

The median function can be obtained by repeating the previous procedure for a relevant grid of values of α . Once the median function is obtained, the median-unbiased estimator can then be computed as shown in Definition 4. That is, by matching the $LSDV$ estimate from regression (14), based on actual data, to the closest median value (m) and finding its corresponding pair (α) which will be the panel exactly median-unbiased estimate of the AR parameter.

As we mentioned before, the assumption of $i.i.d.$ errors may not be appropriate in the panel case. Two possible avenues can be followed to deal with this potential problem: (i) model explicitly any departures from this assumption, and (ii) check the robustness of the median-unbiased estimator obtained under the $i.i.d.$ assumption when in fact this assumption is violated. Cermeño (1999) followed the last approach, showing that for autocorrelation, heteroskedasticity as well as cross-sectional correlation patterns of magnitudes similar to those found in the actual data, the PEMU estimator is quite robust and re-estimation of quantiles considering the previous problems leads to essentially the same conclusions. Phillips and Sul (2003) focus on the first avenue and develop a more general framework that explicitly considers cross-sectional correlation as well as heterogeneous AR parameter values. This is described in the following two sections.

2.4. Panel Feasible Generalized Median-Unbiased Estimation

Consider now that the error term in (12) is not independent among cross sections. In this case, the expectation in the third line of (13) is different from zero, that is

$$E(\varepsilon_{it}, \varepsilon_{js}) = \sigma_{ij} \neq 0 \text{ for } i \neq j, t = s \tag{16}$$

Assume for the moment that for all $t = s$ the covariance matrix of the vector of disturbances $[\varepsilon_{1t}, \varepsilon_{2t}, \dots \varepsilon_{Nt}]^{\tau}$ is known and is given by the NxN matrix $\mathbf{V}$. The supra index τ denotes the transposition operator.

Let $\boldsymbol{\varepsilon}$ be a vector of dimension TN that stacks the N individual vectors of residuals, each of dimension T. It is well known that the covariance matrix of $\boldsymbol{\varepsilon}$ can be expressed as

$$Cov(\boldsymbol{\varepsilon}) = E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}^{\tau}) = \boldsymbol{\Omega} = (\mathbf{V} \otimes \mathbf{I}_T) \tag{17}$$

Where $\otimes$ denotes the Kronecker product. From GLS theory it is also well known that

$$E(\boldsymbol{\varepsilon}\boldsymbol{\Omega}^{-1}\boldsymbol{\varepsilon}') = \mathbf{I}_{NT} \tag{18}$$

This implies that for a given matrix $\mathbf{V}$ we can perform the well known GLS transformation on (14) and compute the GLS estimator of the parameters. Also, with a consistent estimate of $\mathbf{V}$ the feasible GLS estimator can be obtained. For a given $\mathbf{V}$ it is possible to compute the median function for the GLS estimator and correct for the bias using median-unbiased estimation. For large T and small N panels, computation of the $FGLS$ estimator based upon a general covariance structure given by $\mathbf{V}$ follows straightforwardly.

However, for small T and large N or large T and large N panels the $FGLS$ estimator does not exist.

Phillips and Sul (2003) consider a specific pattern of cross-sectional correlation by specifying an error term with a common time effect which can impact differently each cross section. This is,

$$u_{it} = \delta_i \theta_t + \varepsilon_{it} \tag{19}$$

Where $\delta_i (i = 1,2,\ldots,N)$ are parameters, $\theta_t \sim i.i.d.N(0,1)$ over t and $\varepsilon_{it} \sim i.i.d.N(0,\sigma_i^2)$ over t and $\varepsilon_{it}, \varepsilon_{js}, \theta_s$ are independent for all $i \neq j$ and for all s,t. In this setting, the covariance among cross sections is given by

$$E(u_{it} u_{jt}) = \delta_i \delta_j \tag{20}$$

The latent variable model now consists of the following two equations

$$y_{it} = \mu_i + \lambda_t + y_{it}^*, \; i = 1,\ldots,N \text{ and } t = 0,\ldots,T \tag{21}$$

$$y_{it}^* = \alpha y_{t-1}^* + u_{it}, \; i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{22}$$

As in the previous subsection, form (21) and (22) the following model can be obtained in terms of the observable variable y_{it}:

$$y_{it} = \mu_i^0 + \lambda_t^0 + \alpha y_{it-1} + u_{it}, \; i = 1,\ldots,N \text{ and } t = 0,\ldots,T \tag{23}$$

Where $\mu_i^0 = \mu_i(1-\alpha)$ and $\lambda_t^0 = \lambda_t - \alpha\lambda_{t-1}$. Assume that u_{it} is defined in equation (19). Consider the cases (i) $\mu_i = \lambda_t = 0$ (ii) $\mu_i \neq 0, \lambda_t = 0$ and (iii) $\mu_i \neq 0, \lambda_t \neq 0$ and assume that $\lambda_t = \beta t$. Under these assumptions, the distribution of the panel GLS estimator of α has a similar invariance property than the PEMU estimator. This is formulated in the following proposition.

Proposition 5: Invariance of the distribution of the panel GLS estimator of α

Under the previous assumptions, the distribution of the panel GLS estimator of α $(\hat{\alpha}_{PGLS})$ in model (23) depends only on α in all cases. When $\alpha = 1$, it does not depend on the initial values y_{i0} in cases (ii) and (iii).

See Phillips and Sul (2003). This invariance property is remarkable and the intuitive explanation is that we are regressing y_t on y_{t-1} and performing the GLS transformation only implies re-scaling both of them. Unfortunately, in practice the covariance matrix is unknown and must be estimated (this is the panel feasible GLS estimator) and in this case the previous invariance property will not hold in general. However, Phillips and Sul (2003) show that provided a consistent estimator of the covariance matrix is used, the previous invariance property will hold asymptotically and they propose the following iterative procedure to obtain this estimator.

Definition 4: Panel feasible GLS median-unbiased estimator of α
The panel feasible median-unbiased estimator of the parameter α in model (23) denoted $\hat{\alpha}_{PFGLSMU}$, can be determined from the following iterative algorithm:

Start by assuming cross-sectional independence and obtain the panel exactly median-unbiased estimator

Using the estimated residuals from (i) construct an estimate of the error covariance matrix $\hat{V}$, following Phillips and Sul (2002), section 4.2

Using $\hat{V}$ compute the panel feasible GLS

Obtain the panel feasible GLS median-unbiased using the median function of this estimator, not the panel exactly median-unbiased estimator

Repeat steps (ii) to (iii) but in step (ii) use updated residuals from (iv) until the panel feasible GLS median-unbiased estimator converges

As in the previous cases, computation of the median function for the panel feasible GLS estimator can be done by Monte Carlo simulations. These simulations are similar to the ones explained for the panel exactly median-unbiased estimator, with the only difference being that in this case the residuals in the data generation process have a contemporaneous covariance pattern given by $\hat{\mathbf{V}}$, which is the estimated covariance matrix of residuals.

2.5. Panel SUR Median-Unbiased Estimation

The previous models assume the same AR parameter for all cross sections in the panel. This assumption can be relaxed by considering the following latent variable model:

$$y_{it} = \mu_i + \lambda_t + y_{it}^*, \; i = 1,\ldots,N \text{ and } t = 0,\ldots,T \tag{24}$$

$$y_{it}^* = \alpha_i y_{t-1}^* + u_{it}, \; i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{25}$$

In this case the following model is obtained in terms of the observable variable:

$$y_{it} = \mu_i^0 + \lambda_{it}^0 + \alpha_i y_{it-1} + u_{it}, \; i = 1,\ldots,N \text{ and } t = 0,\ldots,T \tag{26}$$

Where $\mu_i^0 = \mu_i(1-\alpha_i)$ and $\lambda_t^0 = \lambda_t - \alpha_i \lambda_{t-1}$.

Phillips and Sul consider the cases with $\mu_i = \lambda_t = 0$ (model M1), $\mu_i \neq 0, \lambda_t = 0$ (model M2) and $\mu_i \neq 0, \lambda_t = \theta t$ (model M3), which are analogous to the models with no intercept and no time trend, intercept only and intercept and time trend, mentioned before. In addition, these authors allow for cross-sectional dependence of the form given in equation (19) and show that using this information can lead to substantial efficiency gains. The iterative procedure for median-unbiased estimation in this setting is outlined as follows.

Definition 5: Panel SUR median-unbiased estimator of α_i

The panel SUR median-unbiased estimator of the parameter α_i in model (26), denoted as $\hat{\alpha}_{iSURMU}$, can be determined iteratively as follows:

Assuming cross-sectional independence, obtain exactly median-unbiased estimates for each series $\hat{\alpha}_{iEMU}, i=1,\ldots,N$ and use the estimated residuals to construct an estimate of the error covariance matrix $\hat{V}$ as in Phillips and Sul (2003).

Using $\hat{V}$ compute conventional SUR estimates for the panel $\hat{\alpha}_{iSUR}$.

Obtain the panel SUR-MU estimates by matching each $\hat{\alpha}_{iSUR}$ to its corresponding median-unbiased estimate using the median function of the $\hat{\alpha}_{iSUR}$ estimator.

Repeat steps (i) to (iii) until the panel SURMU converges.

It is important to remark that in step (iii) we need to obtain the median-function of the $\hat{\alpha}_{iSUR}$ estimator. As before, this can be achieved by Monte Carlo simulations as follows:

For a given sample size and a parameter value $\alpha_i = \alpha, i=1,\ldots,N$ generate a large number of processes using errors with a covariance structure given by $\hat{\mathbf{V}}$ (obtained at step ii) at each point in time.

For each process, compute the $\hat{\alpha}_{iSUR}$ estimator and store it in some matrix.

Compute the empirical distribution of the stored $\hat{\alpha}_{iSUR}$ estimates, particularly the median as well as other relevant quantiles.

Repeat (i) to (iii) for a relevant grid of values for $\alpha_i = \alpha$ to obtain the pairs of values that will define the median function.

2.6. How far Panel Median-Unbiased Estimation has reached?

The median-unbiased estimation techniques have been extended to panel and proved to be useful tools for empirical analysis. The most important contribution from a theoretical and methodological point of view has probably been made by Phillips and Sul (2003), as they generalize the simplest panel exactly median-unbiased estimator (PEMU) to the case that considers coefficient heterogeneity as well as heteroskedastic and cross-correlated disturbances (PSURMU). However their approach is focused on $AR(1)$ dynamic process. On the other hand, as we have mentioned in the previous section, more recently Murray and Papell (2005b) apply Andrews and Chen (1994) approximately median-unbiased estimation, which deals with $AR(p)$ processes, to panel data but their application is limited to homogeneous dynamics for all individual time series in the panel. Clearly, a model with heterogeneous dynamics as well as heteroskedastic and cross-correlated disturbances in the panel will be a natural extension of the panel median-unbiased estimation literature.

More recently, Cermeño and Grier (2006) have addressed the modeling of conditional heteroskedasticity and cross-sectional correlation in panel data. These authors point out that despite it is well known that most macroeconomic and financial processes are conditionally heteroskedastic, the empirical panel data literature in these areas has practically ignored this fact. The literature on panel median-unbiased estimation is not an exception. Thus, considering a time varying covariance matrix of disturbances as well as suitable non linear models to capture this behavior might be worth overtaking in order to get more accurate characterizations of the dynamics of real phenomena.

3. Empirical Applications

In this section we present three empirical applications of panel median-unbiased estimation. The first two applications investigate the well known hypothesis of convergence in per capita GDP for the cases of the USA and Mexican states. The third empirical application, evaluates the PPP hypothesis using data on real exchange rates of 14 developing countries. In all cases focuses on determining if point median-unbiased estimates are consistent with stationary, mean reverting processes or not. It is important to remark that the results discussed in this section are preliminary and they are based on panel exactly median-unbiased estimation only. These results will certainly constitute benchmarks for implementing the complete set of median-unbiased estimators discussed in this paper under less restrictive assumptions. This is ongoing research.

3.1. Convergence among the USA states

In this application we explore, whether the dynamics of per capita income of the 48 contiguous USA states is consistent with conditional convergence. The following panel model is considered.

$$y_{it} = \mu_i + (1-\alpha)\beta t + \alpha y_{it-1} + \varepsilon_{it} \qquad (27)$$

This model is obtained from (11) and (12) under the assumption that $\lambda_t = \beta t$. It is also assumed that μ_i are different and statistically significant, which is consistent with existing empirical evidence. In the case $0 < \alpha < 1$ the per capita income process would be consistent with conditional convergence and will be characterized as a trend stationary process. In this case, state economies will grow at the same average rate. On the other hand, when $\alpha = 1$ the process will have a stochastic trend and therefore it will be non convergent. In this case, the per capita income of the different states will be growing at different rates.

Similarly than in unit root testing, we also want to evaluate the null hypothesis $H_0 : \alpha = 1$ (non convergence) against the alternative $H_1 : \alpha < 1$ (conditional convergence). Thus, in addition to point median-unbiased estimates, we obtain 90% interval unbiased estimates. If the upper bound of the 90% confidence interval lies below unity, the null hypothesis H_0 would be rejected (at the 10% significance level in this case) result that would agree with conditional convergence.

We use per capita income data for the 48 contiguous states during the period 1929 to 2005. The $LSDV$ estimate of α is equal to 0.8318. The corresponding panel exactly median-unbiased estimate is equal to 0.8587 and the lower and upper bounds of the 90% confidence interval are 0.8419 and 0.8756 respectively. See Table 1 (case N=48, T+1=77) for tabulated quantiles of the distribution of this estimator. Clearly, the point and interval median-unbiased estimates support the hypothesis of conditional convergence even if we considered broader confidence intervals. The implied speed of convergence is approximately 15.23% which is relatively high but actually it is not surprising given the high degree of factor mobility across the USA states. These results are in line with previous findings by Evans (1997) but certainly differ sharply from those based on cross-sectional regressions, such as the 2% convergence rate reported by Barro and Sala-i-Martin (1991, 1992).[16] Clearly, the fixed effects bias of the OLS estimator used in these studies produces highly misleading results.

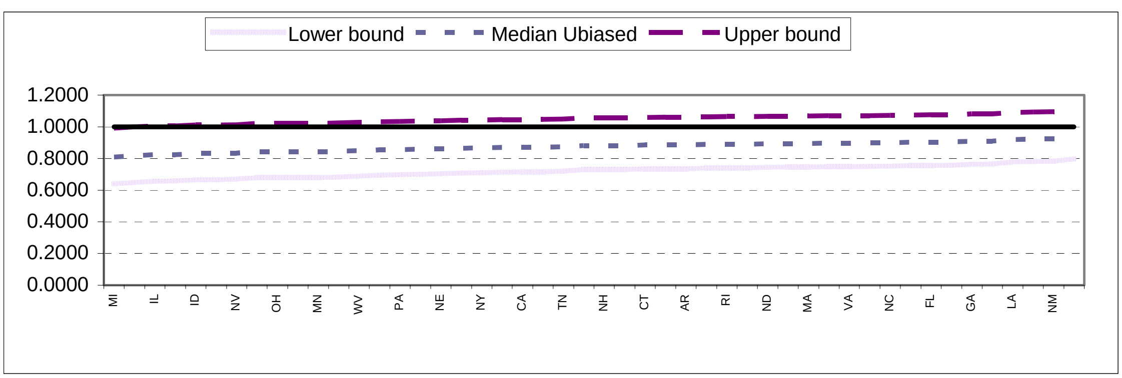
In order to have a better picture of the degree of heterogeneity in the previous panel, we have obtained median-unbiased estimates for each state separately, following Andrews (1993).

16 Evans (1997) shows that the conventional cross-section regression approach produces inconsistent estimates of convergence rates given its inability to control for all cross economy heterogeneity. Using Stock (1991) approach, Evans finds an average converge rate of 15.5% for the 48 U.S. contiguous sates.

It should be pointed out, though, that given the relatively short time span, biases are expected to be higher than in the panel data case. For the same reason, unbiased confidence intervals are much wider in the time series case.[17] A few facts should be remarked. First, the median-unbiased point estimates are relatively homogeneous and concentrate on the interval (0.81, 0.94) with an average value of 0.87 and a standard deviation of 0.03. Roughly, the previous average median unbiased estimate of the AR parameter implies a convergence rate of 13.9 %. Secondly, the median-unbiased point estimates are consistent with the conditional convergence hypothesis for all states. This is a remarkable result since the point estimates indicate that all series are in fact trend stationary, which it is consistent with the panel results and the problem of having stationary and non stationary series within the panel is not present here. As expected, the time series unbiased 90% confidence intervals are consistent with the unit root hypothesis in all but two individual series, supporting the non convergence hypothesis.[18] This result simply confirms that with a relatively small number of time series observations it is impossible to distinguish unit root from near to unit root dynamics. Figure 2 plots the time series median-unbiased estimates and corresponding 90% confidence intervals.

Overall, both the panel data and time series median-unbiased estimates are consistent with conditional convergence hypothesis and indicate convergence rates of 15.2 and 13.9% respectively.

FIGURE 2: MEDIAN-UNBIASED ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE USA STATES



[17] Compare corresponding panels of Table 1 (panel data) and Table 2 (time series).
[18] Table 3 shows median unbiased and 90% confidence intervals for each USA state.

3.2. Convergence among the Mexican states

The previous convergence hypothesis can also be evaluated in the case of the Mexican states.

This avenue of research is particularly relevant given the availability of a newly constructed yearly GDP data base for the 32 Mexican states over the period 1940 to 2004 by German-Soto (2005).[19] As it was pointed out in Cermeño (2001), the extremely limited time span of available time series of the GDP for the Mexican states, has made it difficult to test convergence hypotheses in the past, forcing most researchers to assume a priori some form of convergence, usually absolute convergence. In fact, this author attempts to distinguish between absolute and conditional convergence finding no support for absolute convergence.

Notwithstanding, as Garrido (2007) points out, the available information used in all previous studies about convergence in Mexico is seriously limited both in terms of time span and reliability. The present application attempts to contribute to the convergence debate by applying median-unbiased estimation to the newly available yearly data base.

For the case of the Mexican states, the $LSDV$ estimate is equal to 0.94. However, after the correction for the median bias we obtain a median-unbiased point estimate of 0.9844, which certainly indicates a trend stationary although highly persistent, near to unit root, process. See Table 1 (case N=32, T+1=65) for tabulated fractiles of the distribution of the $LSDV$ estimator for this case. Roughly, the implied convergence rate in the case of Mexico is 1.57 per year with a corresponding half-life of 44.1 years. Differently than in the USA case, the 90% confidence interval ranges between 0.97 and 1.00, thus including the possibility of non convergence.

It is important to remark that even if no form of convergence is supported when taking all 32 states it is still possible to find some convergence clusters or "clubs" at the regional level or by pairs of states. Precisely, Garrido (2007), using a time series approach, finds some evidence in favor of absolute and conditional convergence among pairs of states in Mexico, although he also remarks that in no case the previous results are favored in more than 50% of the pairs.

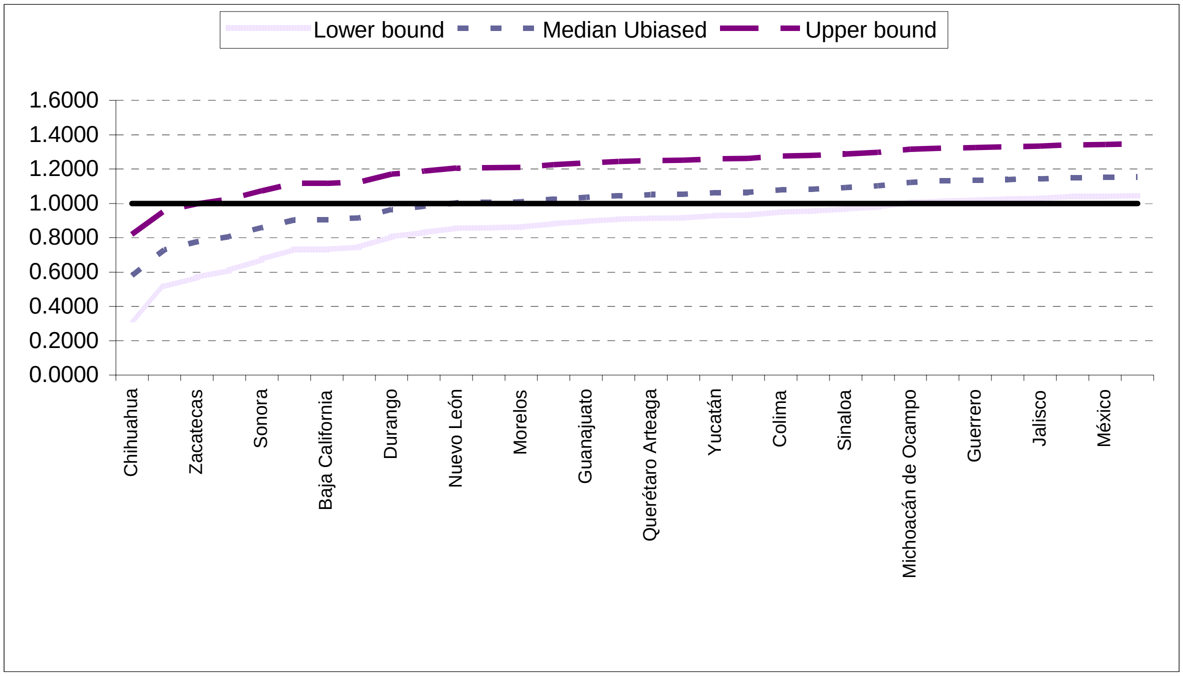
As expected, the time series median-unbiased estimates are consistent with difference stationary processes.[20] Differently than in the USA states case, where all individual median-unbiased estimates lie below unity, in the Mexican case only in 10 cases (out of 32) the point median unbiased estimates are consistent with conditional convergence. Also, all but one unbiased 90% confidence intervals do not reject the maintained null hypothesis of non convergence. See Figure 3 for a plot of these results. To give a numerical idea, the time series median-unbiased estimates are in the range (0.60, 1.15),

[19] See Garrido (2007) for details on how this data base was constructed.

[20] See Table 4 for a complete list of individual median unbiased estimates and the corresponding plot.

with an average of 1.00, and standard deviation of 0.14. Thus, the average median-unbiased estimate of individual states does not support the conditional convergence hypothesis, pointing to a situation where economies are growing at different rates.

FIGURE 3: MEDIAN-UNBIASED ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE MEXICAN STATES



Overall, both the interval panel estimates and the time series point estimates are consistent with the non convergence hypothesis in the case of the Mexican states. Using the point panel median-unbiased estimates only we can argue in favor of conditional convergence although with a remarkably slow convergence rate.

3.3. The PPP hypothesis in 14 Developing Countries.

This application attempts to evaluate the well known purchasing power parity hypothesis (PPP). Consider the following model:

$$e_{it} = p_{it} - p^{*}_{it} + u_{it} \qquad (28)$$

Where e_{it} is the logarithm of the nominal exchange rate in country i and p_{it}, p^{*}_{it} are the price levels in the domestic and foreign country (USA in this case) respectively (also in logarithms).

The disturbance term u_{it} can be viewed as a temporary deviation from parity. One popular test of the PPP hypothesis is made by evaluating whether there is cointegration among e, p, p^*, with cointegration vector equal to $(1,-1,1)$. Essentially, given that the previous variables are integrated to order one, denoted $I(1)$, if they are in fact cointegrated, the deviations u must be a zero mean stationary process. In this case, the deviations from the PPP will only be temporary. An alternative approach is to consider, instead, the real exchange rate defined as $q_{it} = e_{it} - p_{it} + p^*_{it}$ and to evaluate if this process is stationary. That is, to evaluate whether the real exchange rate is a mean reverting process or not. Sometimes this approach is referred to as restricted cointegration, since in this case the restriction that the coefficients are equal to $(1,-1,1)$ is imposed a priori. This approach is suitable for median-unbiased estimation and will be used here. In order to test the PPP hypothesis consider the model:

$$q_{it} = \mu_i(1-\alpha) + \alpha q_{it-1} + \varepsilon_{it} \tag{29}$$

This model corresponds to case 2 mentioned in the previous section and allows for individual fixed effects under the alternative hypothesis that the PPP holds $H_1 : \alpha < 1$. The null hypothesis is $H_0 : \alpha = 1$, in which case the PPP hypothesis will not hold. For this application, we use monthly data on real effective exchange rates for 14 developing countries over the period July, 1978 to September, 2003.[21]

In the present case the $LSDV$ estimate (uncorrected) is equal to 0.9769. The corresponding median-unbiased estimate of this parameter is equal to 0.9853 and the unbiased 90% confidence interval has bounds of 0.9791 and 0.9919. See the estimated quantiles of the distribution of this estimator in Table 1 (case N=14, T+1=303).

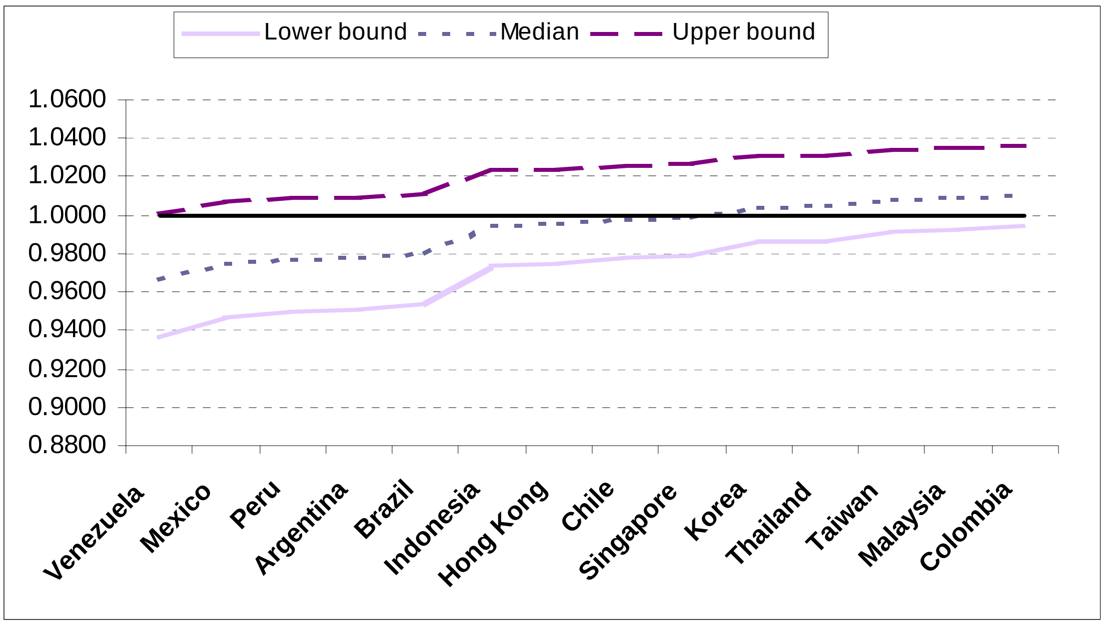
Certainly, both the point and interval unbiased estimates are consistent with the PPP hypothesis, although they indicate that the real exchange rate process is highly persistent and convergence towards steady state parity levels happens at the slow rate of 1.48%. This rate of convergence implies a half life estimated time of 46.8 months, about 4 years.

The evidence from time series estimates indicates that 5 out of the 14 developing countries do exhibit non mean reverting real exchange rate processes (See Table 5). Figure 4 illustrates median-unbiased estimates and 90% confidence intervals for this sample of countries. For the other 9 countries the processes are stationary although in 2 cases the point median-unbiased estimates indicate that real exchange rates do follow near to unit root dynamics. In terms of unbiased 90% confidence intervals, in all cases the PPP hypothesis is not supported, despite the relatively large time span of the

[21] The author acknowledges Kevin Grier and Robin Grier for generously providing this data base.

series. Overall, the panel evidence points to stationary but extremely persistent real exchange rate processes which is consistent with the mix of unit root and stationary but near to unit root processes found by examining individual time series.

FIGURE 4: MEDIAN-UNBIASED ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE RER IN 14 DEVELOPING COUNTRIES



These findings are in line with other results found in the empirical literature on the dynamics of real exchange rates that also show either non-reverting or extremely slow mean reverting processes, as documented for example in Murray and Papell (2002, 2005a).

Conclusions

In the last decade we have seen important developments on panel median-unbiased estimation, from the simplest case of panel exactly median-unbiased estimation to the more general case of panel SUR median-unbiased estimation, which allows for parameter heterogeneity as well as heteroskedastic and cross-sectionally correlated disturbances. Yet, these developments can still be taken further, for example by considering higher order AR processes. In addition, given that several dynamic processes, particularly in macroeconomics and finance might be subject to volatility clustering, it seems necessary to model explicitly a time varying covariance matrix.

The paper provides three empirical applications that use both the panel as well as the time series exactly median-unbiased estimator. Roughly speaking, the results obtained in the first two examples are consistent with conditional convergence of per capita income among the USA states and with non convergence or extremely slow conditional convergence of per capita GDP among the Mexican states. In the third example, the panel median-unbiased estimates are consistent with the PPP hypothesis in a sample of 14 developing countries, although the real exchange processes are extremely persistent and, hence, they exhibit quite slow convergence rates. In all previous applications, it remains to see how robust are these results when considering other panel median-unbiased estimators under less restrictive assumptions.

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TABLE 1: FRACTILES OF THE LSDV ESTIMATOR IN A DYNAMIC PANEL DATA MODEL WITH FIXED EFFECTS

LSDV	N=14, T+1=303			N=32, T+1=65			N=48, T+1=77		
	0.05	0.50	0.95	0.05	0.5	0.95	0.05	0.5	0.95
0.7500	0.7261	0.7445	0.7605	0.6928	0.7199	0.7453	0.7052	0.7253	0.7438
0.7600	0.7369	0.7532	0.7699	0.7030	0.7298	0.7548	0.7156	0.7351	0.7534
0.7700	0.7475	0.7639	0.7792	0.7132	0.7397	0.7638	0.7253	0.7449	0.7632
0.7800	0.7570	0.7735	0.7892	0.7228	0.7491	0.7738	0.7355	0.7546	0.7727
0.7900	0.7677	0.7839	0.7991	0.7332	0.7588	0.7825	0.7451	0.7645	0.7822
0.8000	0.7775	0.7937	0.8086	0.7431	0.7685	0.7922	0.7557	0.7741	0.7918
0.8100	0.7879	0.8037	0.8180	0.7533	0.7785	0.8012	0.7656	0.7840	0.8011
0.8200	0.7982	0.8133	0.8274	0.7628	0.7879	0.8107	0.7757	0.7937	0.8106
0.8300	0.8088	0.8237	0.8374	0.7735	0.7979	0.8202	0.7857	0.8034	0.8201
0.8400	0.8190	0.8341	0.8478	0.7833	0.8072	0.8288	0.7958	0.8133	0.8293
0.8500	0.8292	0.8433	0.8568	0.7936	0.8171	0.8383	0.8059	0.8229	0.8387
0.8600	0.8398	0.8539	0.8667	0.8030	0.8266	0.8477	0.8161	0.8327	0.8480
0.8700	0.8497	0.8632	0.8761	0.8130	0.8361	0.8563	0.8262	0.8425	0.8576
0.8800	0.8600	0.8733	0.8856	0.8231	0.8456	0.8656	0.8361	0.8518	0.8667
0.8900	0.8709	0.8833	0.8947	0.8335	0.8553	0.8748	0.8460	0.8616	0.8760
0.9000	0.8812	0.8934	0.9041	0.8433	0.8646	0.8838	0.8560	0.8713	0.8853
0.9100	0.8911	0.9031	0.9134	0.8533	0.8740	0.8926	0.8656	0.8806	0.8940
0.9200	0.9014	0.9132	0.9238	0.8629	0.8834	0.9015	0.8757	0.8901	0.9032
0.9300	0.9123	0.9231	0.9324	0.8727	0.8925	0.9099	0.8856	0.8996	0.9119
0.9400	0.9230	0.9330	0.9416	0.8824	0.9018	0.9186	0.8952	0.9088	0.9210
0.9500	0.9336	0.9431	0.9513	0.8920	0.9107	0.9269	0.9049	0.9180	0.9297
0.9600	0.9442	0.9532	0.9604	0.9013	0.9194	0.9349	0.9140	0.9269	0.9381
0.9700	0.9546	0.9626	0.9692	0.9105	0.9280	0.9431	0.9234	0.9356	0.9464
0.9800	0.9655	0.9721	0.9783	0.9191	0.9361	0.9506	0.9322	0.9440	0.9543
0.9900	0.9747	0.9814	0.9863	0.9279	0.9441	0.9579	0.9408	0.9521	0.9619
1.0000	0.9841	0.9897	0.9939	0.9358	0.9516	0.9647	0.9492	0.9597	0.9689

Fractiles were tabulated using Monte Carlo simulations with 20,000 replications

(a) model includes fixed effects in the stationary case and becomes a random walk without drift when $\alpha = 1$

(b) model includes fixed effects and a linear time trend in the stationary case and individual specific drifts when $\alpha = 1$.

TABLE 2: FRACTILES OF THE OLS ESTIMATOR IN A TIME SERIES AR (1) MODEL

OLS	T+1=303 [a]			T+1=65 [b]			T+1=77 [b]		
	0.05	0.50	0.95	0.05	0.5	0.95	0.05	0.5	0.95
0.7500	0.6695	0.7410	0.7992	0.4844	0.6764	0.8080	0.5191	0.6893	0.8106
0.7600	0.6805	0.7516	0.8081	0.4935	0.6860	0.8171	0.5253	0.6988	0.8164
0.7700	0.6916	0.7616	0.8174	0.5061	0.6943	0.8254	0.5363	0.7075	0.8238
0.7800	0.7033	0.7708	0.8255	0.5147	0.7029	0.8302	0.5479	0.7169	0.8345
0.7900	0.7149	0.7814	0.8343	0.5238	0.7118	0.8401	0.5597	0.7261	0.8402
0.8000	0.7249	0.7910	0.8430	0.5337	0.7223	0.8457	0.5647	0.7344	0.8469
0.8100	0.7373	0.8011	0.8522	0.5447	0.7295	0.8534	0.5812	0.7437	0.8552
0.8200	0.7482	0.8110	0.8606	0.5538	0.7402	0.8601	0.5882	0.7529	0.8621
0.8300	0.7585	0.8205	0.8686	0.5600	0.7484	0.8687	0.6014	0.7632	0.8681
0.8400	0.7678	0.8303	0.8775	0.5701	0.7574	0.8743	0.6073	0.7716	0.8771
0.8500	0.7819	0.8407	0.8857	0.5823	0.7663	0.8794	0.6179	0.7797	0.8836
0.8600	0.7921	0.8503	0.8939	0.5910	0.7728	0.8884	0.6304	0.7895	0.8904
0.8700	0.8033	0.8607	0.9026	0.6000	0.7829	0.8965	0.6382	0.7977	0.8971
0.8800	0.8136	0.8709	0.9109	0.6096	0.7912	0.9009	0.6480	0.8060	0.9044
0.8900	0.8256	0.8801	0.9188	0.6219	0.8001	0.9081	0.6566	0.8153	0.9119
0.9000	0.8377	0.8901	0.9271	0.6270	0.8063	0.9129	0.6690	0.8232	0.9161
0.9100	0.8490	0.9000	0.9357	0.6358	0.8137	0.9188	0.6779	0.8327	0.9241
0.9200	0.8604	0.9101	0.9430	0.6462	0.8228	0.9254	0.6883	0.8397	0.9292
0.9300	0.8718	0.9203	0.9514	0.6526	0.8291	0.9307	0.6938	0.8481	0.9360
0.9400	0.8837	0.9300	0.9587	0.6628	0.8375	0.9373	0.7008	0.8543	0.9406
0.9500	0.8953	0.9395	0.9662	0.6678	0.8432	0.9419	0.7086	0.8621	0.9469
0.9600	0.9069	0.9496	0.9734	0.6729	0.8490	0.9484	0.7174	0.8691	0.9519
0.9700	0.9198	0.9590	0.9807	0.6756	0.8537	0.9512	0.7234	0.8738	0.9565
0.9800	0.9311	0.9687	0.9873	0.6841	0.8578	0.9535	0.7276	0.8786	0.9612
0.9900	0.9436	0.9777	0.9937	0.6826	0.8611	0.9587	0.7303	0.8822	0.9630
1.0000	0.9538	0.9857	0.9995	0.6860	0.8612	0.9589	0.7319	0.8824	0.9647

Fractiles were tabulated using Monte Carlo simulations with 20,000 replications

(a) model includes an intercept in the stationary case and becomes a random walk without drift when $\alpha = 1$

(b) the model is trend stationary under the alternative and a random walk with drift under the null.

TABLE 3: MEDIAN-UNBIASED POINT ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE 48 USA STATES

State	OLS	Unbiased Estimates			State	OLS	Unbiased Estimates		
		Lower	Median	Upper			Lower	Median	Upper
MI	0.7443	0.6387	0.8096	0.9919	NH	0.8030	0.7298	0.8815	1.0565
IA	0.7508	0.6488	0.8176	0.9991	WA	0.8033	0.7303	0.8819	1.0569
IL	0.7558	0.6566	0.8237	1.0045	CT	0.8054	0.7336	0.8845	1.0592
DE	0.7564	0.6575	0.8245	1.0052	AL	0.8061	0.7347	0.8854	1.0600
ID	0.7617	0.6658	0.8310	1.0111	AR	0.8065	0.7352	0.8858	1.0604
VT	0.7620	0.6663	0.8313	1.0114	NJ	0.8093	0.7396	0.8893	1.0635
NV	0.7639	0.6691	0.8336	1.0135	RI	0.8096	0.7401	0.8897	1.0638
WI	0.7698	0.6783	0.8408	1.0200	ME	0.8097	0.7402	0.8898	1.0639
OH	0.7701	0.6787	0.8412	1.0203	ND	0.8124	0.7443	0.8930	1.0669
MS	0.7708	0.6799	0.8421	1.0211	MD	0.8129	0.7451	0.8936	1.0674
MN	0.7710	0.6801	0.8423	1.0213	MA	0.8133	0.7457	0.8941	1.0678
SC	0.7733	0.6838	0.8452	1.0239	WY	0.8148	0.7481	0.8960	1.0695
WV	0.7769	0.6893	0.8495	1.0278	VA	0.8151	0.7486	0.8964	1.0699
IN	0.7804	0.6948	0.8539	1.0317	MT	0.8162	0.7503	0.8978	1.0711
PA	0.7832	0.6991	0.8573	1.0347	NC	0.8173	0.7520	0.8991	1.0723
CO	0.7843	0.7008	0.8587	1.0360	OR	0.8196	0.7555	0.9018	1.0748
NE	0.7859	0.7033	0.8606	1.0377	FL	0.8201	0.7564	0.9026	1.0754
KY	0.7890	0.7080	0.8644	1.0411	OK	0.8210	0.7578	0.9037	1.0764
NY	0.7901	0.7098	0.8657	1.0423	GA	0.8251	0.7640	0.9086	1.0808
UT	0.7931	0.7144	0.8694	1.0456	KS	0.8260	0.7655	0.9097	1.0819
CA	0.7938	0.7155	0.8703	1.0464	LA	0.8345	0.7786	0.9201	1.0912
MO	0.7941	0.7160	0.8707	1.0467	TX	0.8354	0.7801	0.9213	1.0923
TN	0.7966	0.7198	0.8737	1.0495	NM	0.8371	0.7828	0.9234	1.0942
AZ	0.8030	0.7298	0.8816	1.0566	SC	0.8471	0.7982	0.9356	1.1051

TABLE 4: MEDIAN-UNBIASED ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE 32 MEXICAN STATES

State	OLS	Unbiased Estimates		
		Lower bound	Median	Upper bound
Chihuahua	0.5505	0.3242	0.5791	0.8176
Coahuila de Zaragoza	0.6678	0.5125	0.7293	0.9553
Zacatecas	0.7037	0.5701	0.7753	0.9975
Baja California Sur	0.7275	0.6083	0.8058	1.0254
Sonora	0.7681	0.6735	0.8579	1.0731
San Luis Potosí	0.8043	0.7317	0.9043	1.1157
Baja California	0.8050	0.7328	0.9052	1.1165
Distrito Federal	0.8125	0.7447	0.9147	1.1252
Durango	0.8510	0.8065	0.9641	1.1704
Quintana Roo	0.8655	0.8298	0.9826	1.1875
Nuevo León	0.8819	0.8562	1.0037	1.2067
Veracruz de Ignacio de la Llave	0.8828	0.8577	1.0049	1.2078
Morelos	0.8853	0.8617	1.0081	1.2107
Aguascalientes	0.8978	0.8817	1.0241	1.2254
Guanajuato	0.9069	0.8963	1.0357	1.2360
Tamaulipas	0.9140	0.9078	1.0449	1.2445
Querétaro Arteaga	0.9182	0.9144	1.0502	1.2493
Puebla	0.9194	0.9164	1.0518	1.2508
Yucatán	0.9274	0.9292	1.0619	1.2601
Hidalgo	0.9290	0.9318	1.0640	1.2620
Colima	0.9400	0.9494	1.0781	1.2749
Campeche	0.9436	0.9552	1.0827	1.2791
Sinaloa	0.9515	0.9679	1.0928	1.2884
Oaxaca	0.9587	0.9795	1.1021	1.2969
Michoacán de Ocampo	0.9746	1.0049	1.1224	1.3155
Nayarit	0.9801	1.0138	1.1294	1.3220
Guerrero	0.9836	1.0194	1.1340	1.3261
Tlaxcala	0.9867	1.0244	1.1380	1.3298
Jalisco	0.9895	1.0289	1.1415	1.3331
Tabasco	0.9970	1.0410	1.1512	1.3419
México	0.9973	1.0415	1.1516	1.3423
Chiapas	0.9993	1.0446	1.1541	1.3446

TABLE 5: MEDIAN-UNBIASED ESTIMATES AND 90% CONFIDENCE INTERVALS FOR THE RER PROCESS IN 14 DEVELOPING COUNTRIES

Country	OLS	Unbiased Estimates		
		Lower bound	Median	Upper bound
Venezuela	0.9547	0.9359	0.9661	1.0002
Mexico	0.9626	0.9463	0.9742	1.0068
Peru	0.9652	0.9497	0.9768	1.0089
Argentina	0.9657	0.9505	0.9774	1.0094
Brazil	0.9684	0.9541	0.9802	1.0116
Indonesia	0.9826	0.9735	0.9949	1.0235
Hong Kong	0.9832	0.9743	0.9955	1.0239
Chile	0.9855	0.9775	0.9979	1.0259
Singapore	0.9863	0.9786	0.9987	1.0266
Korea	0.9916	0.9860	1.0042	1.0309
Thailand	0.9920	0.9866	1.0046	1.0313
Taiwan	0.9951	0.9910	1.0079	1.0339
Malaysia	0.9961	0.9924	1.0089	1.0347
Colombia	0.9973	0.9941	1.0101	1.0357

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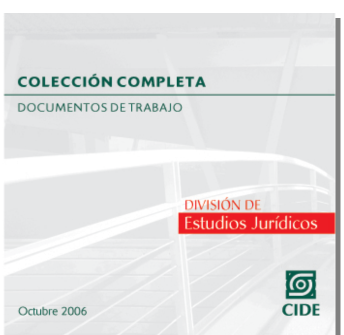

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