

NONSTATIONARY PANELS, COINTEGRATION IN
PANELS AND DYNAMIC PANELS: A SURVEY

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ABSTRACT

This paper provides an overview of topics in nonstationary panels: panel unit root tests, panel cointegration tests, and estimation of panel cointegration models. In addition it surveys recent developments in dynamic panel data models.

I. INTRODUCTION

Two important areas in the econometrics of panel data that have received a lot of attention recently are dynamic panel data¹ and nonstationary panel time series models². This special issue focuses on these two topics. With the growing use of cross-country data over time to study purchasing power parity, growth convergence and international R&D spillovers, the focus of panel data econometrics has shifted towards studying the asymptotics of macro panels with large N (number of countries) and large T (length of the time series) rather than the usual asymptotics of micro panels with large N and small T . In fact, the limiting distributions of double indexed integrated processes had to be developed, see Phillips and Moon (1999a). The fact that T is allowed to increase to infinity in macro panel data, generated two strands of ideas. The first rejected the homogeneity of the regression parameters implicit in the use of a pooled regression model in favor of heterogeneous regressions, i.e., one for each country, see Pesaran and Smith (1995), Im, Pesaran and Shin (1997), Lee, Pesaran and Smith (1997), Pesaran, Shin and Smith (1999) and Pesaran and Zhao (1999) to mention a few. This literature critically relies on T being large to estimate each country's regression separately. Another strand of literature applied time series procedures to panels, worrying about nonstationarity, spurious regressions and cointegration. Adding the cross-section dimension to the time-series dimension offers an advantage in the testing for non-stationarity and cointegration. The hope of the econometrics of non-stationary panel data is to combine the best of both worlds: the method of dealing with non-stationary data from the time series and the increased data and power from the cross-section. The addition of the cross-section dimension, under certain assumptions, can act as repeated draws from the same distribution. Thus as the time and cross-section dimension increase panel test statistics and estimators can be derived which converge in distribution to normally

distributed random variables.

However, the use of such panel data methods are not without their critics, see Maddala, Wu and Liu (2000) who argue that panel data unit root tests do not rescue purchasing power parity (PPP). In fact, the results on PPP with panels are mixed depending on the group of countries studied, the period of study and the type of unit root test used. More damaging is the argument by Maddala et al. that for PPP, panel data tests are the wrong answer to the low power of unit root tests in single time series. After all, the null hypothesis of a single unit root is different from the null hypothesis of a panel unit root for the PPP hypothesis. Using the same line of criticism, Maddala (1999) argued that panel unit root tests did not help settle the question of growth convergence among countries. However, it was useful in spurring much needed research into dynamic panel data models. Also, Quah (1996) who argued that the basic issues of whether poor countries catch up with the rich can never be answered by the use of traditional panels. Instead, Quah suggested formulating and estimating models of income dynamics.

One can find numerous applications of time series methods applied to panels in recent years. Examples from the purchasing power parity literature include Bernard and Jones (1996), Jorion and Sweeney (1996), MacDonald (1996), Oh (1996), Wu (1996), Coakley and Fuertes (1997), Culver and Papell (1997), Papell (1997), O'Connell (1998), Choi (1999a), Andersson and Lyhagen (1999), and Canzoneri, Cumby and Diba (1999) to mention a few. On health care expenditures, see McCoskey and Selden (1998), and Gerdtam and Löthgren (1998). On growth and convergence, see Islam (1995), Evans and Karas (1996), Sala-i-Martin (1996), Lee, Pesaran and Smith (1997), and McCoskey and Kao (1999a). On international R&D spillovers, see Funk (1998) and Kao, Chiang and Chen (1999). On exchange rate models, see Groen and Kleibergen (1999), and Groen (1999). On savings and

investment models, see Coakely, Kulasi and Smith (1996) and Moon and Phillips (1998).

The first part of this paper surveys some of the developments in nonstationary panel models that have occurred since the middle of 1990s. Two other recent surveys on this subject include Phillips and Moon (1999b) on multi-indexed processes and Banerjee (1999) on panel unit roots and cointegration tests. We will pay attention to the following three topics: (1) panel unit root tests, (2) panel cointegration tests, and (3) estimation and inference in the panel cointegration models. The discussion of each topic will be illustrated by examples taken from the aforementioned list of references. Section 2 reviews panel unit root tests, while Section 3 discusses the panel spurious models. Section 4 considers the panel cointegration tests, while Section 5 discusses panel cointegration models. Section 6 reviews some recent developments in dynamic panels and Section 7 gives our conclusion.

A word on notation. We write the integral $\int_0^1 W(s)ds$ as $\int W$ when there is no ambiguity over limits. We define $\Omega^{1/2}$ to be any matrix such that $\Omega = (\Omega^{1/2})(\Omega^{1/2})'$, use \Rightarrow to denote weak convergence, \xrightarrow{p} to denote convergence in probability, $I(0)$ and $I(1)$ to signify a time series that is integrated of order zero and one, respectively, and $W_Z(r) = W(r) - \left[\int WZ' \right] \left[\int ZZ' \right]^{-1} Z(r)$ to denote an L_2 projection residual of $W(r)$ on $Z(r)$.

II. PANEL UNIT ROOTS TESTS

Testing for unit roots in time series studies is now common practice among applied researchers and has become an integral part of econometric courses. However, testing for unit roots in panels is recent, see Levin and Lin (1992), Im, Pesaran and Shin (1997), Harris and Tzavalis (1999), Maddala and Wu (1999), Choi (1999a), and Hadri (1999). Exceptions are Bharagava et al. (1982), Boumahdi and Thomas (1991), Breitung and Meyer (1994), and Quah (1994). Bharagava et al. proposed a test for random walk residuals in a dynamic model with fixed effects. They suggested a modified Durbin-Watson (DW) statistic based

on fixed effects residuals and two other test statistics based on differenced OLS residuals. In typical micro panels with $N \rightarrow \infty$, they recommended their modified DW statistic. Boumahdi and Thomas (1991) proposed a generalization of the Dickey-Fuller (DF) test for unit roots in panel data to assess the efficiency of the French capital market using 140 french stock prices over the period January 1973 to February 1986. Breitung and Meyer (1994) applied various modified DF test statistics to test for unit roots in a panel of contracted wages negotiated at the firm and industry level for Western Germany over the period 1972-1987. Quah (1994) suggested a test for unit root in a panel data model without fixed effects where both N and T go to infinity at the same rate such that N/T is constant. Levin and Lin (1992) generalized this model to allow for fixed effects, individual deterministic trends and heterogeneous serially correlated errors. They assumed that both N and T tend to infinity. However, T increases at a faster rate than N with $N/T \rightarrow 0$. Even though this literature grew from time series and panel data, the way in which N , the number of cross-section units, and T , the length of the time series, tend to infinity is crucial for determining asymptotic properties of estimators and tests proposed for nonstationary panels, see Phillips and Moon (1999a). Several approaches are possible including (i) sequential limits where one index, say N , is fixed and T is allowed to increase to infinity, giving an intermediate limit. Then by letting N tend to infinity subsequently, a sequential limit theory is obtained. Phillips and Moon (1999b) argued that these sequential limits are easy to derive and are helpful in extracting quick asymptotics. However, Phillips and Moon provided a simple example that illustrates how sequential limits can sometimes give misleading asymptotic results. (ii) A second approach, used by Quah(1994) and Levin and Lin (1992) is to allow the two indexes, N and T to pass to infinity along a specific diagonal path in the two dimensional array. This path can be determined by a monotonically increasing functional relation of the type

$T = T(N)$ which applies as the index $N \rightarrow \infty$. Phillips and Moon (1999b) showed that the limit theory obtained by this approach is dependent on the specific functional relation $T = T(N)$ and the assumed expansion path may not provide an appropriate approximation for a given (T, N) situation. (iii) A third approach is a joint limit theory allowing both N and T to pass to infinity simultaneously without placing specific diagonal path restrictions on the divergence. Some control over the relative rate of expansion may have to be exercised in order to get definitive results. Phillips and Moon argued that, in general, joint limit theory is more robust than either sequential limit or diagonal path limit. However, it is usually more difficult to derive and requires stronger conditions such as the existence of higher moments that will allow for uniformity in the convergence arguments. The multi-index asymptotic theory in Phillips and Moon (1999a,b) is applied to joint limits in which $T, N \rightarrow \infty$ and $(T/N) \rightarrow \infty$, i.e., to situations where the time series sample is large relative to the cross-section sample. However, the general approach given there is also applicable to situations in which $(T/N) \rightarrow 0$ although different limit results will generally obtain in that case.

A. Levin and Lin (1992) Tests

Consider the model

$$y_{it} = \rho_i y_{it-1} + z'_{it} \gamma + u_{it}, \quad i = 1, \dots, N; t = 1, \dots, T, \quad (1)$$

where z_{it} is the deterministic component and u_{it} is a stationary process. z_{it} could be zero, one, the fixed effects, μ_i , or fixed effect as well as a time trend, t . The Levin and Lin (LL) tests assume that u_{it} are *iid* $(0, \sigma_u^2)$ and $\rho_i = \rho$ for all i . LL are interested in testing the null hypothesis

$$H_0 : \rho = 1 \quad (2)$$

against the alternative hypothesis

$$H_a : \rho < 1.$$

Let $\hat{\rho}$ be the OLS estimator of ρ in (1) and define

$$\begin{aligned} z_t &= (z_{1t}, \dots, z_{Nt})', \\ h(t, s) &= z_t' \left(\sum_{t=1}^T z_t z_t' \right) z_s, \\ \tilde{u}_{it} &= u_{it} - \sum_{s=1}^T h(t, s) u_{is}, \end{aligned}$$

and

$$\tilde{y}_{it} = y_{it} - \sum_{s=1}^T h(t, s) y_{is}. \quad (3)$$

Then we have

$$\sqrt{NT}(\hat{\rho} - 1) = \frac{\frac{1}{\sqrt{N}} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \tilde{y}_{i,t-1} \tilde{u}_{it}}{\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T \tilde{y}_{i,t-1}^2}$$

and the corresponding t -statistic, under the null hypothesis is given by

$$t_\rho = \frac{(\hat{\rho} - 1) \sqrt{\sum_{i=1}^N \sum_{t=1}^T \tilde{y}_{i,t-1}^2}}{s_e},$$

where

$$s_e^2 = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \tilde{u}_{it}^2.$$

Assume that there exists a scaling matrix D_T and piecewise continuous function $Z(r)$ such that

$$D_T^{-1} z_{[Tr]} \rightarrow Z(r)$$

uniformly for $r \in [0, 1]$. For a fixed N , we have

$$\frac{1}{\sqrt{N}} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \tilde{y}_{i,t-1} \tilde{u}_{it} \Rightarrow \frac{1}{\sqrt{N}} \sum_{i=1}^N \int W_{iZ} dW_{iZ}$$

and

$$\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T \tilde{y}_{i,t-1}^2 \Rightarrow \frac{1}{N} \sum_{i=1}^N \int W_{iZ}^2,$$

as $T \rightarrow \infty$. Next we assume that $\int W_{iZ} dW_{iZ}$ and $\int W_{iZ}^2$ are independent across i and have finite second moments. Then it follows that

$$\begin{aligned} & \frac{1}{N} \sum_{i=1}^N \int W_{iZ}^2 \xrightarrow{p} E \left[\int W_{iZ}^2 \right] \\ & \frac{1}{\sqrt{N}} \sum_{i=1}^N \left(\int W_{iZ} dW_{iZ} - E \left[\int W_{iZ} dW_{iZ} \right] \right) \Rightarrow N \left(0, \text{Var} \left(\int W_{iZ} dW_{iZ} \right) \right) \end{aligned}$$

as $N \rightarrow \infty$ by a law of large numbers and the Lindeberg-Levy central limit theorem. The following moments are taken from Levin and Lin (1992):

z_{it}	$E \left[\int W_{iZ} dW_{iZ} \right]$	$\text{Var} \left[\int W_{iZ} dW_{iZ} \right]$	$E \left[\int W_{iZ}^2 \right]$	$\text{Var} \left[\int W_{iZ}^2 \right]$	
0	0	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{3}$	
1	0	$\frac{1}{3}$	$\frac{1}{2}$?	(4)
μ_i	$-\frac{1}{2}$	$\frac{1}{12}$	$\frac{1}{6}$	$\frac{1}{45}$	
(μ_i, t)	$-\frac{1}{2}$	$\frac{1}{60}$	$\frac{1}{15}$	$\frac{11}{6300}$	

Using (4), Levin and Lin (1992) obtain the following limiting distributions of $\sqrt{NT}(\hat{\rho} - 1)$

and t_ρ :

z_{it}	$\hat{\rho}$	t_ρ
0	$\sqrt{NT}(\hat{\rho} - 1) \Rightarrow N(0, 2)$	$t_\rho \Rightarrow N(0, 1)$
1	$\sqrt{NT}(\hat{\rho} - 1) \Rightarrow N(0, 2)$	$t_\rho \Rightarrow N(0, 1)$
μ_i	$\sqrt{NT}(\hat{\rho} - 1) + 3\sqrt{N} \Rightarrow N\left(0, \frac{51}{5}\right)$	$\sqrt{1.25}t_\rho + \sqrt{1.875N} \Rightarrow N(0, 1)$
$(\mu_i, t)'$	$\sqrt{N}(T(\hat{\rho} - 1) + 7.5) \Rightarrow N\left(0, \frac{2895}{112}\right)$	$\sqrt{\frac{448}{277}}(t_\rho + \sqrt{3.75N}) \Rightarrow N(0, 1)$

Sequential limit theory, i.e., $T \rightarrow \infty$ followed by $N \rightarrow \infty$, is used to derive the limiting

distributions in (5). In case u_{it} is stationary, the asymptotic distributions of $\hat{\rho}$ and t_ρ need to be modified due to the presence of serial correlation.

Harris and Tzavalis (1999) also derived unit root tests for (1) with $z_{it} = \{0\}, \{\mu_i\}$, or $\{(\mu_i, t)'\}$ when the time dimension of the panel, T , is fixed. This is the typical case for micro panel studies. The main results are:

$$\begin{array}{ll}
z_{it} & \hat{\rho} \\
0 & \sqrt{N}(\hat{\rho} - 1) \Rightarrow N\left(0, \frac{2}{T(T-1)}\right) \\
\mu_i & \sqrt{N}\left(\hat{\rho} - 1 + \frac{3}{T+1}\right) \Rightarrow N\left(0, \frac{3(17T^2 - 20T + 17)}{5(T-1)(T+1)^3}\right) \\
(\mu_i, t)' & \sqrt{N}\left(\hat{\rho} - 1 + \frac{15}{2(T+2)}\right) \Rightarrow N\left(0, \frac{15(193T^2 - 728T + 1147)}{112(T+2)^3(T-2)}\right)
\end{array}$$

Harris and Tzavalis (1999) also showed that the assumption that T tends to infinity at a faster rate than N as in LL rather than T fixed as in the case in micro panels, yields tests which are substantially undersized and have low power especially when T is small.

Recently, Frankel and Rose (1996), Oh (1996), and Lothian (1996) tested the PPP hypothesis using panel data. All of these articles use LL tests and some of them report evidence supporting the PPP hypothesis. O'Connell (1998), however, showed that the LL tests suffered from significant size distortion in the presence of correlation among contemporaneous cross-sectional error terms. O'Connell highlighted the importance of controlling for cross-sectional dependence when testing for a unit root in panels of real exchange rates. He showed that, controlling for cross-sectional dependence, no evidence against the null of a random walk can be found in panels of up to 64 real exchange rates.

Virtually all the existing nonstationary panel literature assume cross-sectional independence. It is true that the assumption of independence across i is rather strong, but it is needed in order to satisfy the requirement of the Lindeberg-Levy central limit theorem. Moreover, as pointed out by Quah (1994), modeling cross-sectional dependence is involved

because individual observations in a cross-section have no natural ordering. Driscoll and Kraay (1998) presented a simple extension of common nonparametric covariance matrix estimation techniques which yields standard errors that are robust to very general forms of spatial and temporal dependence as the time dimension becomes large. In a recent paper, Conley (1999) presented a spatial model of dependence among agents using a metric of economic distance that provides cross-sectional data with a structure similar to time-series data. Conley proposed a generalized method of moments (GMM) using such dependent data and a class of nonparametric covariance matrix estimators that allow for a general form of dependence characterized by economic distance.

B. Im, Pesaran and Shin (1997) Tests

The LL test is restrictive in the sense that it requires ρ to be homogeneous across i . As Maddala (1999) pointed out, the null may be fine for testing convergence in growth among countries, but the alternative restricts every country to converge at the same rate. Im, Pesaran and Shin (1997) (IPS) allow for a heterogeneous coefficient of y_{it-1} and proposed an alternative testing procedure based on averaging individual unit root test statistics. IPS suggested an average of the augmented DF (ADF) tests when u_{it} is serially correlated with different serial correlation properties across cross-sectional units, i.e., $u_{it} = \sum_{j=1}^{p_i} \varphi_{ij} u_{it-j} + \varepsilon_{it}$. Substituting this u_{it} in (1) we get:

$$y_{it} = \rho_i y_{it-1} + \sum_{j=1}^{p_i} \varphi_{ij} \Delta y_{it-j} + z'_{it} \gamma + \varepsilon_{it}. \quad (6)$$

The null hypothesis is

$$H_0 : \rho_i = 1$$

for all i and the alternative hypothesis is

$$H_a : \rho_i < 1$$

for at least one i . The IPS t -bar statistic is defined as the average of the individual ADF statistic as

$$\bar{t} = \frac{1}{N} \sum_{i=1}^N t_{\rho_i}, \quad (7)$$

where t_{ρ_i} is the individual t -statistic of testing $H_0 : \rho_i = 1$ in (6). It is known that for a fixed N

$$t_{\rho_i} \Rightarrow \frac{\int_0^1 W_{iZ} dW_{iZ}}{\left[\int_0^1 W_{iZ}^2 \right]^{1/2}} = t_{iT} \quad (8)$$

as $T \rightarrow \infty$. IPS assume that t_{iT} are *iid* and have finite mean and variance. Then

$$\frac{\sqrt{N} \left(\frac{1}{N} \sum_{i=1}^N t_{iT} - E[t_{iT} | \rho_i = 1] \right)}{\sqrt{Var[t_{iT} | \rho_i = 1]}} \Rightarrow N(0, 1) \quad (9)$$

as $N \rightarrow \infty$ by the Lindeberg-Levy central limit theorem. Hence

$$t_{IPS} = \frac{\sqrt{N} (\bar{t} - E[t_{iT} | \rho_i = 1])}{\sqrt{Var[t_{iT} | \rho_i = 1]}} \Rightarrow N(0, 1) \quad (10)$$

as $T \rightarrow \infty$ followed by $N \rightarrow \infty$ sequentially. The values of $E[t_{iT} | \rho_i = 1]$ and $Var[t_{iT} | \rho_i = 1]$ have been computed by IPS via simulations for different values of T and p_i 's.

In this volume, Breitung (2000) studies the local power of LL and IPS tests statistics against a sequence of local alternatives. Breitung finds that the LL and IPS tests suffer from a dramatic loss of power if individual specific trends are included. This is due to the bias correction that also removes the mean under the sequence of local alternatives. The simulation results indicate that the power of LL and IPS tests is very sensitive to the specification of the deterministic terms.

McCoskey and Selden (1998) applied the IPS test for testing unit root for per capita national health care expenditures (HE) and gross domestic product (GDP) for a panel of OECD countries. McCoskey and Selden rejected the null hypothesis that these two series contain unit roots. Gerdtham and Löthgren (1998) claimed that the stationarity found by

McCoskey and Selden are driven by the omission of time trends in their ADF regression in (6). Using the IPS test with a time trend, Gerdtham and Löthgren found that both HE and GDP are nonstationary. They concluded that HE and GDP are cointegrated around linear trends following the results of McCoskey and Kao (1999b).

C. Combining P-Values Tests

Let G_{iT_i} be a unit root test statistic for the i -th group in (1) and assume that as $T_i \rightarrow \infty$, $G_{iT_i} \Rightarrow G_i$. Let p_i be the p -value of a unit root test for cross-section i , i.e., $p_i = F(G_{iT_i})$, where $F(\cdot)$ is the distribution function of the random variable G_i . Maddala and Wu (1999) and Choi (1999a) proposed a Fisher type test

$$P = -2 \sum_{i=1}^N \ln p_i \tag{11}$$

which combines the p -values from unit root tests for each cross-section i to test for unit root in panel data. P is distributed as χ^2 with $2N$ degrees of freedom as $T_i \rightarrow \infty$ for all N . Maddala et al. (1999) argued that the IPS and Fisher tests relax the restrictive assumption of the LL test that ρ_i is the same under the alternative. Both the IPS and Fisher tests combine information based on individual unit root tests. However, the Fisher test has the advantage over the IPS test in that it does not require a balanced panel. Also, the Fisher test can use different lag lengths in the individual ADF regressions and can be applied to any other unit root tests. The disadvantage is that the p -values have to be derived by Monte Carlo simulations. Choi (1999a) echoes similar advantages of the Fisher test: (1) the cross-sectional dimension, N , can be either finite or infinite, (2) each group can have different types of nonstochastic and stochastic components, (3) the time series dimension, T , can be different for each i , and (4) the alternative hypothesis would allow some groups to have unit roots while others may not.

When N is large, Choi (1999a) proposed a Z test,

$$Z = \frac{\frac{1}{\sqrt{N}} \sum_{i=1}^N (-2 \ln p_i - 2)}{2} \quad (12)$$

since $E[-2 \ln p_i] = 2$ and $Var[-2 \ln p_i] = 4$. Assume that the p_i 's are *iid* and use the Lindeberg-Levy central limit theorem to get

$$Z \Rightarrow N(0, 1)$$

as $T_i \rightarrow \infty$ followed by $N \rightarrow \infty$.³

Choi (1999a) applied the Z test in (12) and the IPS test in (7) to panel data of real exchange rates and provided evidence in favor of the PPP hypothesis. Choi claimed that this is due to the improved finite sample power of the Fisher test. Maddala and Wu (1999) and Maddala et al. (1999) find that the Fisher test is superior to the IPS test, but they argue that these panel unit root tests still do not rescue the PPP hypothesis. When allowance is made for the deficiency in the panel data unit root tests and panel estimation methods, support for PPP turns out to be weak.

D. Residual Based LM Test

Hadri (1999) proposed a residual based Lagrange Multiplier (LM) test for the null that the time series for each i are stationary around a deterministic trend against the alternative of a unit root in panel data. Consider the following model

$$y_{it} = z'_{it} \gamma + r_{it} + \varepsilon_{it} \quad (13)$$

where z_{it} is the deterministic component, r_{it} is a random walk

$$r_{it} = r_{it-1} + u_{it}$$

$u_{it} \sim iid(0, \sigma_u^2)$ and ε_{it} is a stationary process. (13) can be written as

$$y_{it} = z'_{it} \gamma + e_{it} \quad (14)$$

where

$$e_{it} = \sum_{j=1}^t u_{ij} + \varepsilon_{it}.$$

Let \hat{e}_{it} be the residuals from the regression in (14) and $\hat{\sigma}_e^2$ be the estimate of the error variance. Also, let S_{it} be the partial sum process of the residuals,

$$S_{it} = \sum_{j=1}^t \hat{e}_{ij}.$$

Then the LM statistic is

$$LM = \frac{\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T S_{it}^2}{\hat{\sigma}_e^2}.$$

It can be shown that

$$LM \xrightarrow{p} E \left[\int W_{iZ}^2 \right]$$

as $T \rightarrow \infty$ followed by $N \rightarrow \infty$ provided $E \left[\int W_{iZ}^2 \right] < \infty$. Also,

$$\frac{\sqrt{N} (LM - E \left[\int W_{iZ}^2 \right])}{\sqrt{\text{Var} \left[\int W_{iZ}^2 \right]}} \Rightarrow N(0, 1)$$

as $T \rightarrow \infty$ followed by $N \rightarrow \infty$.

E. Finite Sample Properties of Unit Root Tests

Extensive simulations have been conducted to explore the finite sample performance of panel unit root tests, e.g., Karlsson and Löthgren (1999), Im et. al. (1997), Maddala and Wu (1999), and Choi (1999a). Choi (1999a) studied the small sample properties of IPS t -bar test in (7) and Fisher's test in (11). Choi's major findings are the following:

1. The empirical size of the IPS and the Fisher test are reasonably close to their nominal size 0.05 when N is small. But the Fisher test shows mild size distortions at $N = 100$, which is expected from the asymptotic theory. Overall, the IPS t -bar test has the most stable size.

2. In terms of the size-adjusted power, the Fisher test seems to be superior to the IPS t -bar test.
3. When a linear time trend is included in the model, the power of all tests decrease considerably.

III. SPURIOUS REGRESSION IN PANEL DATA

Entorf (1997) studied spurious fixed effects regressions when the true model involves independent random walks with and without drifts. Entorf found that for $T \rightarrow \infty$ and N finite, the nonsense regression phenomenon holds for spurious fixed effects models and inference based on t -values can be highly misleading. Kao (1999) and Phillips and Moon (1999a) derived the asymptotic distributions of the least squares dummy variable estimator and various conventional statistics from the spurious regression in panel data.

Consider a spurious regression model for all i using panel data:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + e_{it}, \quad (15)$$

where

$$x_{it} = x_{it-1} + \varepsilon_{it},$$

and e_{it} is $I(1)$. The OLS estimator of β is

$$\hat{\beta} = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{x}_{it} \tilde{x}'_{it} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{x}_{it} \tilde{y}_{it} \right], \quad (16)$$

where \tilde{y}_{it} is defined in (3) and

$$\tilde{x}_{it} = x_{it} - \sum_{s=1}^T h(t,s)x_{is}.$$

It is known that if a time-series regression for a given i is performed in model (15), the OLS estimator of β is spurious. It is easy to see that

$$\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T \tilde{x}_{it} \tilde{x}'_{it} \xrightarrow{p} E \left[\int W_{iZ} W'_{iZ} \right] \Omega_\varepsilon$$

and

$$\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T \tilde{x}_{it} \tilde{y}_{it} \xrightarrow{p} E \left[W_{iZ} W_{iZ}' \right] \Omega_{u\varepsilon}$$

as by a sequential limit theory, where

$$\begin{aligned} z_{it} &= E \left[\int W_{iZ} W_{iZ}' \right] \\ 0 &= \frac{1}{2} \\ 1 &= \frac{1}{2} \\ \mu_i &= \frac{1}{6} \mathbf{1}_k \\ (\mu_i, t) &= \frac{1}{15} \mathbf{1}_k \end{aligned}$$

Then we have

$$\widehat{\beta} \xrightarrow{p} \Omega_{\varepsilon}^{-1} \Omega_{\varepsilon u}. \quad (17)$$

(17) shows that the OLS estimator of β , $\widehat{\beta}$, is consistent for its true value, $\Omega_{\varepsilon}^{-1} \Omega_{\varepsilon u}$. This is due to the fact that the noise, e_{it} , is as strong as the signal, x_{it} , since both e_{it} and x_{it} are I(1). In the panel regression (15) with a large number of cross-sections, the strong noise of e_{it} is attenuated by pooling the data and a consistent estimate of β can be extracted. The asymptotics of the OLS estimator are very different from those of the spurious regression in pure time series. This has an important consequence for residual-based cointegration tests in panel data, because the null distribution of residual-based cointegration tests depends on the asymptotics of the OLS estimator. This point is explained further in the next section.

IV. PANEL COINTEGRATION TESTS

A. Kao Tests

Kao (1999) presented two types of cointegration tests in panel data, the DF and ADF types tests. The DF type tests from Kao can be calculated from the estimated residuals in (15) as:

$$\widehat{e}_{it} = \rho \widehat{e}_{it-1} + v_{it}, \quad (18)$$

where

$$\widehat{e}_{it} = \widetilde{y}_{it} - \widetilde{x}'_{it} \widehat{\beta}.$$

In order to test the null hypothesis of no cointegration, the null can be written as $H_0 : \rho = 1$.

The OLS estimate of ρ and the t -statistic are given as:

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

and

$$t_\rho = \frac{(\widehat{\rho}-1) \sqrt{\sum_{i=1}^N \sum_{t=2}^T \widehat{e}_{it-1}^2}}{s_e},$$

where $s_e^2 = \frac{1}{NT} \sum_{i=1}^N \sum_{t=2}^T (\widehat{e}_{it} - \widehat{\rho} \widehat{e}_{it-1})^2$. Kao proposed the following four DF type tests

by assuming $z_{it} = \{\mu_i\}$:

$$DF_\rho = \frac{\sqrt{NT}(\widehat{\rho} - 1) + 3\sqrt{N}}{\sqrt{10.2}},$$

$$DF_t = \sqrt{1.25} t_\rho + \sqrt{1.875N},$$

$$DF_\rho^* = \frac{\sqrt{NT}(\widehat{\rho} - 1) + \frac{3\sqrt{N}\widehat{\sigma}_u^2}{\widehat{\sigma}_{0v}}}{\sqrt{3 + \frac{36\widehat{\sigma}_u^4}{5\widehat{\sigma}_{0v}^4}}},$$

and

$$DF_t^* = \frac{t_\rho + \frac{\sqrt{6N}\widehat{\sigma}_u}{2\widehat{\sigma}_{0v}}}{\sqrt{\frac{\widehat{\sigma}_{0v}^2}{2\widehat{\sigma}_v^2} + \frac{3\widehat{\sigma}_u^2}{10\widehat{\sigma}_{0v}^2}}},$$

where $\widehat{\sigma}_v^2 = \widehat{\Sigma}_u - \widehat{\Sigma}_{u\varepsilon} \widehat{\Sigma}_\varepsilon^{-1}$ and $\widehat{\sigma}_{0v}^2 = \widehat{\Omega}_u - \widehat{\Omega}_{u\varepsilon} \widehat{\Omega}_\varepsilon^{-1}$. While DF_ρ and DF_t are based on the strong exogeneity of the regressors and errors, DF_ρ^* and DF_t^* are for the cointegration with

endogenous relationship between regressors and errors. For the *ADF* test, we can run the following regression:

$$\hat{e}_{it} = \rho \hat{e}_{it-1} + \sum_{j=1}^p \vartheta_j \Delta \hat{e}_{it-j} + v_{itp}. \quad (19)$$

With the null hypothesis of no cointegration, the ADF test statistics can be constructed as:

$$ADF = \frac{t_{ADF} + \frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{0v}}}{\sqrt{\frac{\hat{\sigma}_{0v}^2}{2\hat{\sigma}_v} + \frac{3\hat{\sigma}_v^2}{10\hat{\sigma}_{0v}}}}$$

where t_{ADF} is the t -statistic of ρ in (19). The asymptotic distributions of DF_ρ , DF_t , DF_ρ^* , DF_t^* , and ADF converge to a standard normal distribution $N(0, 1)$ by the sequential limit theory.

B. Residual Based LM Test

McCoskey and Kao (1998) derived a residual-based test for the null of cointegration rather than the null of no cointegration in panels. This test is an extension of the LM test and the locally best invariant (LBI) test for an MA unit root in the time series literature, see Harris and Inder (1994) and Shin (1994). Under the null, the asymptotics no longer depend on the asymptotic properties of the estimating spurious regression, rather the asymptotics of the estimation of a cointegrated relationship are needed. For models which allow the cointegrating vector to change across the cross-sectional observations, the asymptotics depend merely on the time series results as each cross-section is estimated independently. For models with common slopes, the estimation is done jointly and therefore the asymptotic theory is based on the joint estimation of a cointegrated relationship in panel data.

For the residual based test of the null of cointegration, it is necessary to use an efficient estimation technique of cointegrated variables. In the time series literature a variety of

methods have been shown to be efficient asymptotically. These include the fully modified (FM) estimator of Phillips and Hansen (1990) and the dynamic least squares (DOLS) estimator as proposed by Saikkonen (1991) and Stock and Watson (1993). For panel data, Kao and Chiang (2000) showed that both the FM and DOLS methods can produce estimators which are asymptotically normally distributed with zero means.

The model presented allows for varying slopes and intercepts:

$$y_{it} = \alpha_i + x'_{it}\beta_i + e_{it}, \quad (20)$$

$$x_{it} = x_{it-1} + \varepsilon_{it} \quad (21)$$

$$e_{it} = \gamma_{it} + u_{it}, \quad (22)$$

and

$$\gamma_{it} = \gamma_{it-1} + \theta u_{it},$$

where u_{it} are *i.i.d* $(0, \sigma_u^2)$. The null of hypothesis of cointegration is equivalent to $\theta = 0$.

The test statistic proposed by McCoskey and Kao (1998) is defined as follows:

$$LM = \frac{\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T S_{it}^2}{\hat{\sigma}_e^2}, \quad (23)$$

where S_{it} is partial sum process of the residuals,

$$S_{it} = \sum_{j=1}^t \hat{e}_{ij}$$

and $\hat{\sigma}_e^2$ is defined in McCoskey and Kao. The asymptotic result for the test is:

$$\sqrt{N}(LM - \mu_v) \Rightarrow N(0, \sigma_v^2). \quad (24)$$

The moments, μ_v and σ_v^2 , can be found through Monte Carlo simulation. The limiting distribution of LM is then free of nuisance parameters and robust to heteroskedasticity.

Urban economists have long sought to explain the relationship between urbanization levels and output. McCoskey and Kao (1999a) revisited this question and test the long run stability of a production function including urbanization using non-stationary panel data techniques. McCoskey and Kao applied the IPS test and LM in (23) and showed that a long run relationship between urbanization, output per worker and capital per worker cannot be rejected for the sample of thirty developing countries or the sample of twenty-two developed countries over the period 1965-1989. They do find, however, that the sign and magnitude of the impact of urbanization varies considerably across the countries. These results offer new insights and potential for dynamic urban models rather than the simple cross-section approach.

C. Pedroni Tests

Pedroni (1997a) also proposed several tests for the null hypothesis of cointegration in a panel data model that allows for considerable heterogeneity. His tests can be classified into two categories. The first set is similar to the tests discussed above, and involve averaging test statistics for cointegration in the time series across cross-sections. The second set group the statistics such that instead of averaging across statistics, the averaging is done in pieces so that the limiting distributions are based on limits of piecewise numerator and denominator terms.

The first set of statistics as discussed includes a form of the average of the Phillips and Ouliaris (1990) statistic:

$$\tilde{Z}_\rho = \sum_{i=1}^N \frac{\sum_{t=1}^T (\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i)}{(\sum_{t=1}^T \hat{e}_{it-1}^2)}, \quad (25)$$

where \hat{e}_{it} is estimated from (15), and $\hat{\lambda}_i = \frac{1}{2} (\hat{\sigma}_i^2 - \hat{s}_i^2)$, for which $\hat{\sigma}_i^2$ and \hat{s}_i^2 are individual long-run and contemporaneous variances respectively of the residual \hat{e}_{it} . For his second

set of statistics, Pedroni defines four panel variance ratio statistics. Let $\hat{\Omega}_i$ be a consistent estimate of Ω_i , the long-run variance-covariance matrix. Define \hat{L}_i to be the lower triangular Cholesky composition of $\hat{\Omega}_i$ such that in the scalar case $\hat{L}_{22i} = \hat{\sigma}_\varepsilon$ and $\hat{L}_{11i} = \hat{\sigma}_u^2 - \frac{\hat{\sigma}_{u\varepsilon}^2}{\hat{\sigma}_\varepsilon^2}$ is the long-run conditional variance. In this survey we consider only one of these statistics:

$$Z_{t_{\hat{\rho}_{NT}}} = \frac{\sum_{i=1}^N \sum_{t=2}^T \hat{L}_{11i}^{-2} (\hat{e}_{it-1} \Delta \hat{e}_{it} - \hat{\lambda}_i)}{\sqrt{\tilde{\sigma}_{NT}^2 (\sum_{i=1}^N \sum_{t=2}^T \hat{L}_{11i}^{-2} \hat{e}_{it-1}^2)}} , \quad (26)$$

where

$$\tilde{\sigma}_{NT} = \frac{1}{N} \sum_{i=1}^N \frac{\hat{\sigma}_i^2}{\hat{L}_{11i}^2}.$$

It should be noted that Pedroni bases his test on the average of the numerator and denominator terms respectively, rather than the average for the statistic as a whole. Using results on convergence of functionals of Brownian motion, Pedroni finds the following result:

$$Z_{t_{\hat{\rho}_{NT}}} + 1.73\sqrt{N} \Rightarrow N(0, 0.93).$$

Note that this distribution applies to the model including an intercept and not including a time trend. Asymptotic results for other model specifications can be found in Pedroni (1997a). The intuition on these tests with varying slopes is not straightforward. The convergence in distribution is based on individual convergence of the numerator and denominator terms. What is the intuition of rejection of the null hypothesis? Using the average of the overall test statistic allows more ease in interpretation: rejection of the null hypothesis means that enough of the individual cross-sections have statistics “far away” from the means predicted by theory were they to be generated under the null.

Pedroni (1999) derived asymptotic distributions and critical values for several residual based tests of the null of no cointegration in panels where there are multiple regressors. The model includes regressions with individual specific fixed effects and time trends. Considerable heterogeneity is allowed across individual members of the panel with regards to the

associated cointegrating vectors and the dynamics of the underlying error process. Pedroni (1997b) showed that for test of the null of no cointegration, the appropriate weighting matrix of a GLS based estimator must be constructed using the long run conditional covariance matrix between individual members of the panel in order to eliminate nuisance parameters associated with member specific dynamics. Pedroni (1997b) found that the violation of cross sectional independence does not appear to play a significant role for the conclusions in favor of weak long run PPP provided that one also includes common time dummies in the regression. Pedroni (2000) also demonstrated how it is possible to construct a test that can be employed whether or not members of a panel with heterogeneous short run dynamics converge to a single common steady state.

D. Likelihood-Based Cointegration Test

Larsson, Lyhagen, and Löthgren (1998) presented a likelihood-based (LR) panel test of cointegrating rank in heterogeneous panel models based on the average of the individual rank trace statistics developed by Johansen (1995). The proposed LR-bar statistic is very similar to the IPS t -bar statistic in (7) - (10). In Monte Carlo simulation, Larsson et al. investigated the small sample properties of the standardized LR-bar statistic. They found that the proposed test requires a large time series dimension. Even if the panel has a large cross sectional dimension, the size of the test will be severely distorted.

Groen and Kleibergen (1999) proposed a likelihood-based framework for cointegrating analysis in panels of a fixed number of vector error correction models. Maximum likelihood estimators of the cointegrating vectors are constructed using iterated generalized method of moments (GMM) estimators. Using these estimators Groen and Kleibergen construct likelihood ratio statistics, $LR(\Pi_B|\Pi_A)$, to test for a common cointegration rank across the individual vector error correction models, both with heterogeneous and homogeneous coin-

tegrating vectors. Interestingly, the limiting distribution of $LR(\Pi_B|\Pi_A)$ is invariant to the covariance matrix of the error terms which implies that $LR(\Pi_B|\Pi_A)$ is robust with respect to the choices of covariance matrix. Let us define the $LR_s(r|k)$ as the summation of the N individual trace statistics

$$LR_s(r|k) = \sum_{i=1}^N LR_i(r|k) \quad (27)$$

where $LR_i(r|k)$ is the i -th Johansen's likelihood ratio statistic, so that

$$LR_i(r|k) \Rightarrow tr \left(\int dB_{k-r,i} B'_{k-r,i} \left[\int dB_{k-r,i} B'_{k-r,i} \right] \int dB_{k-r,i} B'_{k-r,i} \right)$$

as $T \rightarrow \infty$. Now for a fixed N , it is clear that

$$\begin{aligned} LR_s(r|k) &= \sum_{i=1}^N LR_i(r|k) \\ &\Rightarrow \sum_{i=1}^N tr \left(\int dB_{k-r,i} B'_{k-r,i} \left[\int dB_{k-r,i} B'_{k-r,i} \right] \int dB_{k-r,i} B'_{k-r,i} \right) \end{aligned} \quad (28)$$

as $T \rightarrow \infty$ by a continuous mapping theorem. It follows that $LR_s(r|k)$ is asymptotically equivalent to $LR(\Pi_B|\Pi_A)$ when N is fixed and T is large. This means that nothing is lost by assuming that the covariance matrix has zero non-diagonal covariances as far as the asymptotics are concerned for the proposed test statistics in this paper. More importantly, the tests based on the cross-independence like (27) will perform just as well (asymptotically) as the tests based on the cross-dependence such as $LR(\Pi_B|\Pi_A)$. Groen and Kleibergen verified that the likelihood-based cointegration tests proposed by Larsson et al. in (27) are robust with respect to the cross-dependence in panel data. The (asymptotic) equivalence of $LR_s(r|k)$ and $LR(\Pi_B|\Pi_A)$ found in Groen and Kleibergen has profound implications to econometricians and applied economists, e.g., there exists tests/estimators based on the cross-independence which are equivalent to tests/estimators based on the cross-dependence

in nonstationary panel time series. Define $\overline{LR}(r|k)$ be the average of $LR_i(r|k)$:

$$\overline{LR}(r|k) = \frac{1}{N} LR_s(r|k) = \frac{1}{N} \sum_{i=1}^N LR_i(r|k).$$

It can be shown that

$$\frac{\overline{LR}(r|k) - E[\overline{LR}(r|k)]}{Var[\overline{LR}(r|k)]} \Rightarrow N(0, 1)$$

as $T \rightarrow \infty$ followed by $N \rightarrow \infty$ by a continuous mapping theorem and a central limit theorem provided $E[\overline{LR}(r|k)]$ and $Var[\overline{LR}(r|k)]$ are bounded. Define

$$\overline{LR}(\Pi_B|\Pi_A) = \frac{1}{N} LR(\Pi_B|\Pi_A). \quad (29)$$

For a fixed N , it is easy to show that

$$\begin{aligned} \overline{LR}(\Pi_B|\Pi_A) &= \frac{1}{N} LR(\Pi_B|\Pi_A) \\ &\Rightarrow \frac{1}{N} \sum_{i=1}^N tr \left(\int dB_{k-r,i} B'_{k-r,i} \left[\int dB_{k-r,i} B'_{k-r,i} \right] \int dB_{k-r,i} B'_{k-r,i} \right) \\ &= \frac{1}{N} \sum_{i=1}^N Z_{ki} \end{aligned}$$

where

$$Z_{ki} = tr \left(\int dB_{k-r,i} B'_{k-r,i} \left[\int dB_{k-r,i} B'_{k-r,i} \right] \int dB_{k-r,i} B'_{k-r,i} \right)$$

as $T \rightarrow \infty$. Then

$$\frac{\frac{1}{N} \sum_{i=1}^N Z_{ki} - E\left[\frac{1}{N} \sum_{i=1}^N Z_{ki}\right]}{Var\left[\frac{1}{N} \sum_{i=1}^N Z_{ki}\right]} \Rightarrow N(0, 1)$$

as $N \rightarrow \infty$ since $B_{k-r,i}$ and $B_{k-r,j}$ are independent for $i \neq j$. It implies that

$$\frac{\overline{LR}(\Pi_B|\Pi_A) - E[\overline{LR}(\Pi_B|\Pi_A)]}{Var[\overline{LR}(\Pi_B|\Pi_A)]} \Rightarrow N(0, 1)$$

as $T \rightarrow \infty$ followed by $N \rightarrow \infty$. The above discussion indicates that $\overline{LR}(r|k)$ and $\overline{LR}(\Pi_B|\Pi_A)$ are also equivalent when T and N are large.

Groen and Kleibergen (1999) applied $LR(\Pi_B|\Pi_A)$ to a data set of exchange rates and appropriate monetary fundamentals. They found strong evidence for the validity of the

monetary exchange rate model within a panel of vector correction models for three major European countries, whereas the results based on individual vector error correction models for each of these countries separately are less supportive.

E. Finite Sample Properties

McCoskey and Kao (1999b) conducted Monte Carlo experiments to compare the size and power of different residual based tests for cointegration in heterogeneous panel data: varying slopes and varying intercepts. Two of the tests are constructed under the null hypothesis of no cointegration. These tests are based on the average ADF test and Pedroni's pooled tests in (25) - (26). The third test is based on the null hypothesis of cointegration which is based on the McCoskey and Kao LM test in (23). Wu and Yin (1999) performed a similar comparison for panel tests in which they consider only tests for which the null hypothesis is that of no cointegration. Wu and Yin compared *ADF* statistics with maximum eigenvalue statistics in pooling information on means and *p*-values respectively. They found that the average *ADF* performs better with respect to power and their maximum eigenvalue based *p*-value performs better with regards to size.

The test of the null hypothesis was originally proposed in response to the low power of the tests of the null of no cointegration, especially in the time series case. Further, in cases where economic theory predicted a long run steady state relationship, it seemed that a test of the null of cointegration rather than the null of no cointegration would be appropriate. The results from the Monte Carlo study showed that the McCoskey and Kao LM test outperforms the other two tests.

Of the two reasons for the introduction of the test of the null hypothesis of cointegration, low power and attractiveness of the null, the introduction of the cross-section dimension of the panel solves one: all of the tests show decent power when used with panel data. For those

applications where the null of cointegration is more logical than the null of no cointegration, McCoskey and Kao (1999b), at a minimum, conclude that using the McCoskey and Kao LM test does not compromise the ability of the researcher in determining the underlying nature of the data.

Recently, Hall et al. (1999) proposed a new approach based on principal components analysis to test for the number of common stochastic trends driving the non-stationary series in a panel data set. The test is consistent even if there is a mixture of $I(0)$ and $I(1)$ series in the sample. This makes it unnecessary to pretest the panel for unit root. It also has the advantage of solving the problem of dimensionality encountered in large panel data sets.

V. ESTIMATION AND INFERENCE IN PANEL COINTEGRATION MODELS

This section discusses the issues that arise in estimation and inference of cointegrated panel regression models. The asymptotic properties of the estimators of the regression coefficients and the associated statistical tests are different from those of the time series cointegration regression models. Some of these differences have become apparent in recent works by Kao and Chiang (2000), Phillips and Moon (1999a) and Pedroni (1996). The panel cointegration models are directed at studying questions that surround long-run economic relationships typically encountered in macroeconomic and financial data. Such a long-run relationship is often predicted by economic theory and it is then of central interest to estimate the regression coefficients and test whether they satisfy theoretical restrictions. Kao and Chen (1995) showed that the OLS in panel cointegrated models is asymptotically normal but still asymptotically biased. Chen, McCoskey, and Kao (1999) investigated the finite sample properties of the OLS estimator, the t-statistic, the bias-corrected OLS estimator, and the bias-corrected t-statistic. They found that the bias-corrected OLS estimator does

not improve over the OLS estimator in general. The results of Chen et al. suggested that alternatives, such as the fully modified (FM) estimator or dynamic OLS (DOLS) estimator may be more promising in cointegrated panel regressions. Phillips and Moon (1999a) and Pedroni (1996) proposed a FM estimator, which can be seen as a generalization of Phillips and Hansen (1990). In this volume, Kao and Chiang (2000) propose an alternative approach based on a panel dynamic least squares (DOLS) estimator, which builds upon the work of Saikkonen (1991) and Stock and Watson (1993).

Next, we provide a brief discussion of the OLS estimation methods in a panel cointegrated model. Consider the following panel regression:

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + u_{it}, \quad (30)$$

where $\{y_{it}\}$ are 1×1 , β is a $k \times 1$ vector of the slope parameters, z_{it} is the deterministic component, and $\{u_{it}\}$ are the stationary disturbance terms. We assume that $\{x_{it}\}$ are $k \times 1$ integrated processes of order one for all i , where

$$x_{it} = x_{it-1} + \varepsilon_{it}.$$

Under these specifications, (30) describes a system of cointegrated regressions, i.e., y_{it} is cointegrated with x_{it} . The OLS estimator of β is

$$\hat{\beta}_{OLS} = \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{x}_{it} \tilde{x}'_{it} \right]^{-1} \left[\sum_{i=1}^N \sum_{t=1}^T \tilde{x}_{it} \tilde{y}_{it} \right]. \quad (31)$$

It is easy to show that

$$\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T \tilde{x}_{it} \tilde{x}'_{it} \xrightarrow{p} \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N E[\zeta_{2i}], \quad (32)$$

and

$$\frac{1}{N} \sum_{i=1}^N \frac{1}{T} \sum_{t=1}^T \tilde{x}_{it} \tilde{u}_{it} \Rightarrow \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N E[\zeta_{1i}] \quad (33)$$

using sequential limit theory, where

$$\begin{array}{lll}
z_{it} & E[\zeta_{1i}] & E[\zeta_{2i}] \\
0 & 0 & \frac{1}{2} \\
1 & 0 & 0 \\
\mu_i & -\frac{1}{2}\Omega_{\varepsilon ui} + \Delta_{\varepsilon ui} & \frac{1}{6}\Omega_{\varepsilon i} \\
(\mu_i, t) & -\frac{1}{2}\Omega_{\varepsilon ui} + \Delta_{\varepsilon ui} & \frac{1}{15}\Omega_{\varepsilon i}
\end{array}$$

and

$$\Omega_i = \begin{bmatrix} \Omega_{ui} & \Omega_{u\varepsilon i} \\ \Omega_{\varepsilon ui} & \Omega_{\varepsilon i} \end{bmatrix}$$

is the long-run covariance matrix of $(u_{it}, \varepsilon'_{it})'$, also $\Delta_i = \begin{bmatrix} \Delta_{ui} & \Delta_{u\varepsilon i} \\ \Delta_{\varepsilon ui} & \Delta_{\varepsilon i} \end{bmatrix}$ is the one-sided long-run covariance. For example, when $z_{it} = \{\mu_i\}$, we get

$$\sqrt{NT}(\hat{\beta}_{OLS} - \beta) - \sqrt{N}\delta_{NT} \Rightarrow N \left(0, 6\Omega_{\varepsilon}^{-1} \left(\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \Omega_{u,\varepsilon i} \Omega_{\varepsilon i} \right) \Omega_{\varepsilon}^{-1} \right),$$

where $\Omega_{\varepsilon} = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N \Omega_{\varepsilon i}$ and

$$\delta_{NT} = \left[\frac{1}{N} \sum_{i=1}^N \frac{1}{T^2} \sum_{t=1}^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right]^{-1} \frac{1}{N} \left[\sum_{i=1}^N \Omega_{\varepsilon i}^{1/2} \left(\int \widetilde{W}_i dW_i' \right) \Omega_{\varepsilon i}^{-1/2} \Omega_{\varepsilon ui} + \Delta_{\varepsilon ui} \right].$$

Kao and Chiang (2000) in this volume studied the limiting distributions for the FM, and DOLS estimators in a cointegrated regression and showed they are asymptotically normal. Phillips and Moon (1999a) and Pedroni (1996) also obtained similar results for the FM estimator. The reader is referred to the cited papers for further details. Kao and Chiang also investigated the finite sample properties of the OLS, FM, and DOLS estimators. They found that (i) the OLS estimator has a non-negligible bias in finite samples, (ii) the FM estimator does not improve over the OLS estimator in general, and (iii) the DOLS estimator may be more promising than OLS or FM estimators in estimating the cointegrated panel regressions.

Choi (1999b) extended Kao and Chiang (2000) to study asymptotic properties of OLS, Within and GLS estimators for an error component model. The error component model involves both stationary and nonstationary regressors. Choi's simulation results indicated that the feasible GLS estimator is more efficient than the Within estimator. Choi (1999c) studied instrumental variable estimation for an error component model with stationary and nearly nonstationary regressors.

Phillips and Moon (1999a) studied various regressions between two panel vectors that may or may not have cointegrating relations, and present a fundamental framework for studying sequential and joint limit theories in nonstationary panel data. In particular, Phillips and Moon studied regression limit theory of nonstationary panels when both N and T go to infinity. Their limit theory allows for both sequential limits, where $T \rightarrow \infty$ followed by $N \rightarrow \infty$ and joint limits, where $T, N \rightarrow \infty$ simultaneously. Phillips and Moon require that $N/T \rightarrow 0$, so that these results apply for moderate N and large T macro panel data and not large N and small T micro panel data. The panel models considered allow for four cases: (i) panel spurious regression, where there is no time series cointegration, (ii) heterogeneous panel cointegration, where each individual has its own specific cointegration relation, (iii) homogeneous panel cointegration where individuals have the same cointegration relation, and (iv) near-homogeneous panel cointegration, where individuals have slightly different cointegration relations determined by the value of a localizing parameter. Phillips and Moon (1999a) investigated these four models and developed panel asymptotics for regression coefficients and tests using both sequential and joint limit arguments. In all cases considered the pooled estimator is consistent and has a normal limiting distribution. In fact, for the spurious panel regression, Phillips and Moon (1999a) showed that under quite weak regularity conditions, the pooled least squares estimator of the slope coefficient β is

\sqrt{N} consistent for the long-run average relation parameter β and has a limiting normal distribution. Also, Moon and Phillips (1998a) showed that a limiting cross-section regression with time averaged data is also \sqrt{N} consistent for β and has a limiting normal distribution. This is different from the pure time series spurious regression where the limit of the OLS estimator of β is a nondegenerate random variate that is a functional of Brownian motions and is therefore not consistent for β . The idea in Phillips and Moon (1999a) is that independent cross-section data in the panel adds information and this leads to a stronger overall signal than the pure time series case. Pesaran and Smith (1995) studied limiting cross-section regressions with time averaged data and established consistency with restrictive assumptions on the heterogeneous panel model. This differs from Phillips and Moon (1999a) in that the former use an average of the cointegrating coefficients which is different from the long run average regression coefficient. This requires the existence of cointegrating time series relations, whereas the long run average regression coefficient β is defined irrespective of the existence of individual cointegrating relations and relies only on the long run average variance matrix of the panel. Phillips and Moon (1999a) also showed that for the homogeneous and near homogeneous cointegration cases, a consistent estimator of the long-run regression coefficient can be constructed which they call a pooled FM estimator. They showed that this estimator has faster convergence rate than the simple cross-section and time series estimators. See also Phillips and Moon (1999b) for a concise review. In fact, the latter paper also shows how to extend the above ideas to models with individual effects in the data generating process. For the panel spurious regression with individual specific deterministic trends, estimates of the trend coefficients are obtained in the first step and the detrended data is pooled and used in least squares regression to estimate β in the second step. Two different detrending procedures are used based on OLS and GLS regressions.

OLS detrending leads to an asymptotically more efficient estimator of the long run average coefficient β in pooled regression than GLS detrending. Phillips and Moon (1999b) explain that “the residuals after time series GLS detrending have more cross section variation than they do after OLS detrending and this produces great variation in the limit distribution of the pooled regression estimator of the long run average coefficient.”

Moon and Phillips (1999) investigate the asymptotic properties of the Gaussian MLE of the localizing parameter in local to unity dynamic panel regression models with deterministic and stochastic trends. Moon and Phillips find that for the homogeneous trend model, the Gaussian MLE of the common localizing parameter is \sqrt{N} consistent, while for the heterogeneous trends model, it is inconsistent. The latter inconsistency is due to the presence of an infinite number of incidental parameters (as $N \rightarrow \infty$) for the individual trends. Unlike the fixed effects dynamic panel data model where this inconsistency due to the incidental parameter problem disappears as $T \rightarrow \infty$, the inconsistency of the localizing parameter in the Moon and Phillips model persists even when both N and T go to infinity.

Pesaran, Shin, and Smith (1999) derived the asymptotics of a pooled mean group (PMG) estimator. The PMG estimation constrains the long-run coefficients to be identical, but allow the short run and adjustment coefficients as the error variances to differ across the cross-sectional dimension.

Recently, Binder, Hsiao and Pesaran (2000) considered estimation and inference in panel vector autoregressions (PVARs) with fixed effects when T is finite and N is large. A maximum likelihood estimator as well as unit root and cointegration tests are proposed based on a transformed likelihood function. This MLE is shown to be consistent and asymptotically normally distributed irrespective of the unit root and cointegrating properties of the PVAR model. The tests proposed are based on standard chi-square and normal distributed statis-

tics. Binder, et al. also show that the conventional GMM estimators based on standard orthogonality conditions break down if the underlying time series contain unit roots. Monte Carlo evidence is provided which favors MLE over GMM in small samples.

In this volume, Kauppi (2000) develops a new joint limit theory where the panel data may be cross sectionally heterogeneous in a general way. This limit theory builds upon the concepts of joint convergence in probability and in distribution for double indexed processes by Phillips and Moon (1999a) and develops new versions of the law of large numbers and the central limit theorem that apply in panels where the data may be cross sectionally heterogeneous in a fairly general way. Kauppi demonstrates how this joint limit theory can be applied to derive asymptotics for a panel regression where the regressors are generated by a local to unit root with heterogeneous localizing coefficients across cross-sections. Kauppi discusses issues that arise in the estimation and inference of panel cointegrated regressions with near integrated regressors. Kauppi shows that a bias corrected pooled OLS for a common cointegrating parameter has an asymptotic normal distribution centered on the true value irrespective of whether the regressor has near or exact unit root. However, if the regression model contains individual effects and/or deterministic trends, then Kauppi's bias corrected pooled OLS still produces asymptotic bias. Kauppi also shows that the panel FM estimator is subject to asymptotic bias regardless of how individual effects and/or deterministic trends are contained if the regressors are nearly rather than exactly integrated. This indicates that much care should be taken in interpreting empirical results achieved by the recent panel cointegration methods that assume exact unit roots when near unit roots are equally plausible.

Kao et al. (1999) apply the asymptotic theory of panel cointegration developed by Kao and Chiang (2000) to the Coe and Helpman (1995) international R&D spillover regression.

Using a sample of 21 OECD countries and Israel, they re-examine the effects of domestic and foreign R&D capital stocks on total factor productivity of these countries. They find that OLS with bias-correction, the fully modified (FM) and the dynamic OLS (DOLS) estimators produce different predictions about the impact of foreign R&D on total factor productivity (TFP) although all the estimators support the result that domestic R&D is related to TFP. Kao et al.'s empirical results indicate that the estimated coefficients in the Coe and Helpman's regressions are subject to estimation bias. Given the superiority of the DOLS over FM as suggested by Kao and Chiang (2000), Kao et al. leaned towards rejecting the Coe and Helpman hypothesis that international R&D spillovers are trade related.

Funk (1998) examined the relationship between trade patterns and international R&D spillovers among the OECD countries using the panel cointegration methods developed by Kao (1999), Kao and Chiang (2000), and Pesaran, Shin, and Smith (1999). Using randomly simulated bilateral trade patterns, Funk found that the choice of weights used in constructing foreign R&D stocks is informative of the avenue of spillover transmission when panel cointegration methods are employed. A re-examination of the relationship between import patterns and R&D spillovers found no evidence to link the patterns of R&D spillovers to the patterns of imports. Funk found strong evidence indicating that exporters receive substantial R&D spillovers from their customers.

V. DYNAMIC PANEL DATA MODELS

This section surveys recent developments in dynamic panel data models. The dynamic panel data regression is characterized by two sources of persistence over time. Autocorrelation due to the presence of a lagged dependent variable among the regressors and individual effects characterizing the heterogeneity among the individuals

$$y_{it} = \delta y_{i,t-1} + x'_{it}\beta + \mu_i + u_{it} \quad (34)$$

for $i = 1, 2, \dots, N$; and $t = 1, 2, \dots, T$. δ is a scalar, x_{it} is $k \times 1$, μ_i denotes the i -th individuals effect and u_{it} is the remainder disturbance. Basic introductions to this topic are found in Hsiao (1986), Baltagi (1995) and Matyas and Sevestre (1996). Applications using this model are too many to enumerate. These include employment equations, see Arellano and Bond (1991), liquor demand, see Baltagi and Griffin (1995), growth convergence, see Islam (1995) and Nerlove (1999), life cycle labor supply models, see Ziliak (1997), and demand for gasoline, see Baltagi and Griffin (1997) to mention a few.

It is well known that for typical micro-panels where there are a large number of firms or individuals (N) observed over a short period of time (T), the fixed effects (FE) estimator is biased and inconsistent (since T is fixed and $N \rightarrow \infty$), see Nickell (1981) and more recently Kiviet (1995, 1999). Monte Carlo results have shown that first order asymptotic properties do not necessarily yield correct inference in finite samples. Therefore, Kiviet (1995) examined higher order asymptotics which may approximate the actual finite sample properties more closely and lead to better inference. In fact, Kiviet (1995) considered the simple dynamic linear panel data model with serially uncorrelated disturbances and strongly exogenous regressors and derived an approximation for the bias of the FE estimator. When a consistent estimator of this bias is subtracted from the original FE estimator, a corrected FE estimator results. This corrected FE estimator performed well in simulations when compared with eight other consistent instrumental variable or GMM estimators.⁴

In macro-panels studying for example long run growth, the data covers a large number of countries N over a moderate size T . In this case, T is not very small relative to N . Hence, some researchers may still favor the FE estimator arguing that its bias may not

be large. Judson and Owen (1999) performed some Monte Carlo experiments for $N = 20$ or 100 and $T = 5, 10, 20$ and 30 and found that the bias in the FE can be sizeable, even when $T = 30$. The bias of the FE estimator increases with δ and decreases with T . But even for $T = 30$, this bias could be as much as 20% of the true value of the coefficient of interest. Judson and Owen (1999) recommend the corrected FE estimator proposed by Kiviet (1995) as the best choice, GMM being second best and for long panels, the computationally simpler Anderson and Hsiao (1982) estimator. This last estimator first differences the data to get rid of the individual effects and then uses lagged predetermined variables in levels as instruments.⁵ Arellano and Bond (1991) proposed GMM procedures that are more efficient than the Anderson and Hsiao (1982) estimator. Ahn and Schmidt (1995) derive additional nonlinear moment restrictions not exploited by the Arellano and Bond (1991) GMM estimator.⁶ Ahn and Schmidt (1995, 1997) also give a complete count of the set of orthogonality conditions corresponding to a variety of assumptions imposed on the disturbances and the initial conditions of the dynamic panel data model. While many of the moment conditions are nonlinear in the parameters, Ahn and Schmidt (1997) propose a linearized GMM estimator that is asymptotically as efficient as the nonlinear GMM estimator. They also provide simple moment tests of the validity of these nonlinear restrictions. In addition, they investigate the circumstances under which the optimal GMM estimator is equivalent to a linear instrumental variable estimator. They find that these circumstances are quite restrictive and go beyond uncorrelatedness and homoskedasticity of the errors. Ahn and Schmidt (1995) provide some evidence on the efficiency gains from the nonlinear moment conditions which provide support for their use in practice. By employing all these conditions, the resulting GMM estimator is asymptotically efficient and has the same asymptotic variance as the MLE under normality. In fact, Hahn (1997) showed that

GMM based on an increasing set of instruments as $N \rightarrow \infty$ would achieve the semiparametric efficiency bound.

Hahn (1997) considers the asymptotic efficient estimation of the dynamic panel data model with sequential moment restrictions in an environment with i.i.d. observations. Hahn (1997) shows that the GMM estimator with an increasing set of instruments as the sample size grows attains the semiparametric efficiency bound of the model. Hahn (1997) explains how Fourier series or polynomials may be used as the set of instruments for efficient estimation. In a limited Monte Carlo comparison, Hahn finds that this estimator has similar finite sample properties as the Keane and Runkle (1992) and/or Schmidt, et. al. (1992) estimators when the latter estimators are efficient. In cases where the latter estimators are not efficient, the Hahn efficient estimator outperforms both estimators in finite samples.

Recently, Wansbeek and Bekker (1996) considered a simple dynamic panel data model with no exogenous regressors and disturbances u_{it} and random effects μ_i that are independent and normally distributed. They derived an expression for the optimal instrumental variable estimator, i.e., one with minimal asymptotic variance. A striking result is the difference in efficiency between the IV and ML estimators. They find that for regions of the autoregressive parameter δ which are likely in practice, ML is superior. The gap between IV (or GMM) and ML can be narrowed down by adding moment restrictions of the type considered by Ahn and Schmidt (1995). Hence, Wansbeek and Bekker (1996) find support for adding these nonlinear moment restrictions and warn against the loss in efficiency as compared with MLE by ignoring them.

Blundell and Bond (1998) revisit the importance of exploiting the initial condition in generating efficient estimators of the dynamic panel data model when T is small. They consider a simple autoregressive panel data model with no exogenous regressors

$$y_{it} = \delta y_{i,t-1} + \mu_i + u_{it} \quad (35)$$

with $E(\mu_i) = 0$; $E(u_{it}) = 0$; and $E(\mu_i u_{it}) = 0$ for $i = 1, 2, \dots, N$; $t = 1, 2, \dots, T$. Blundell and Bond (1998) focus on the case where $T=3$ and therefore there is only one orthogonality condition given by $E(y_{i1} \Delta u_{i3}) = 0$, so that δ is just-identified. In this case, the first stage IV regression is obtained by running Δy_{i2} on y_{i1} . Note that this regression can be obtained from (2) evaluated at $t = 2$ by subtracting y_{i1} from both sides of this equation, i.e.,

$$\Delta y_{i2} = (\delta - 1)y_{i,1} + \mu_i + u_{i2} \quad (36)$$

Since we expect $E(y_{i1} \mu_i) > 0$, $(\delta - 1)$ will be biased upwards with

$$plim(\hat{\delta} - 1) = (\delta - 1) \frac{c}{c + (\sigma_\mu^2 / \sigma_u^2)} \quad (37)$$

where $c = (1 - \delta)/(1 + \delta)$. The bias term effectively scales the estimated coefficient on the instrumental variable y_{i1} towards zero. They also find that the F-statistic of the first stage IV regression converges to χ_1^2 with noncentrality parameter

$$\tau = \frac{(\sigma_u^2 c)^2}{\sigma_\mu^2 + \sigma_u^2 c} \rightarrow 0 \text{ as } \delta \rightarrow 1 \quad (38)$$

As $\tau \rightarrow 0$, the instrumental variable estimator performs poorly. Hence, Blundell and Bond attribute the bias and the poor precision of the first difference GMM estimator due to the problem of weak instruments described in Nelson and Startz (1990) and Staiger and Stock (1997) and characterize this weak IV by its concentration parameter τ .

Next, Blundell and Bond (1998) show that an additional mild stationarity restriction on the initial conditions process allows the use of an extended system GMM estimator that uses lagged differences of y_{it} as instruments for equations in levels, in addition to lagged

levels of y_{it} as instruments for equations in first differences, see Arellano and Bover (1995). The system GMM estimator is shown to have dramatic efficiency gains over the basic first difference GMM as $\delta \rightarrow 1$ and $(\sigma_\mu^2/\sigma_u^2)$ increases. In fact, for $T = 4$ and $(\sigma_\mu^2/\sigma_u^2) = 1$, the asymptotic variance ratio of the first difference GMM estimator to this system GMM estimator is 1.75 for $\delta = 0$ and increases to 3.26 for $\delta = 0.5$ and 55.4 for $\delta = 0.9$. This clearly demonstrates that the levels restrictions suggested by Arellano and Bover (1995) remain informative in cases where first differenced instruments become weak. Things improve for first difference GMM as T increases. However, with short T and persistent series, the Blundell and Bond findings support the use of the extra moment conditions. These results are reviewed and corroborated in Blundell, Bond and Windmeijer (2000) in this volume, using Monte Carlo experiments as well as an empirical example. Hahn (1999) examines the role of the initial condition imposed by the Blundell and Bond (1998) estimator. This is done by numerically comparing the semiparametric information bounds for the case that incorporates the stationarity of the initial condition and the case that does not. Hahn (1999) finds that the efficiency gain can be substantial.

Ziliak (1997) asks the question whether the bias/efficiency trade-off for the GMM estimator considered by Tauchen (1986) for the time series case is still binding in panel data where the sample size is normally larger than 500. For time series data, Tauchen (1986) shows that even for $T = 50$ or 75 there is a bias/efficiency trade-off as the number of moment conditions increase. Therefore, Tauchen recommends the use of sub-optimal instruments in small samples. This result was also corroborated by Andersen and Sorensen (1996) who argue that GMM using too few moment conditions is just as bad as GMM using too many moment conditions. This problem becomes more pronounced with panel data since the number of moment conditions increase dramatically as the number of strictly exogenous

variables and the number of time series observations increase. Even though it is desirable from an asymptotic efficiency point of view to include as many moment conditions as possible, it may be infeasible or impractical to do so in many cases. For example, for $T = 10$ and five strictly exogenous regressors, this generates 500 moment conditions for GMM. Ziliak (1997) performs an extensive set of Monte Carlo experiments for a dynamic panel data model and finds that the same trade-off between bias and efficiency exists for GMM as the number of moment conditions increase, and that one is better off with sub-optimal instruments. In fact, Ziliak finds that GMM performs well with suboptimal instruments, but is not recommended for panel data applications when all the moments are exploited for estimation.⁷ Ziliak estimates a life cycle labor supply model under uncertainty based on 532 men observed over 10 years of data (1978-1987) from the panel study of income dynamics. The sample was restricted to continuously married, continuously working prime age men aged 22-51 in 1978. These men were paid an hourly wage or salaried and could not be piece-rate workers or self-employed. Ziliak finds that the downward bias of GMM is quite severe as the number of moment conditions expands, outweighing the gains in efficiency. Ziliak reports estimates of the intertemporal substitution elasticity which is the focal point of interest in the labor supply literature. This measures the intertemporal changes in hours of work due to an anticipated change in the real wage. For GMM, this estimate changes from .519 to .093 when the number of moment conditions used in GMM are increased from 9 to 212. The standard error of this estimate drops from .36 to .07. Ziliak attributes this bias to the correlation between the sample moments used in estimation and the estimated weight matrix. Interestingly, Ziliak finds that the forward filter 2SLS estimator proposed by Keane and Runkle (1992) performs best in terms of the bias/efficiency trade-off and is recommended. Forward filtering eliminates all forms of serial correlation while still maintaining

orthogonality with the initial instrument set. Schmidt, Ahn and Wyhowski (1992) argued that filtering is irrelevant if one exploits all sample moments during estimation. However, in practice, the number of moment conditions increases with the number of time periods T and the number of regressors K and can become computationally intractable. In fact for $T = 15$ and $K = 10$, the number of moment conditions for Schmidt, et al. (1992) is $T(T - 1)K/2$ which is 1040 restrictions, highlighting the computational burden of this approach. In addition, Ziliak argues that the overidentifying restrictions are less likely to be satisfied possibly due to the weak correlation between the instruments and the endogenous regressors.⁸ In this case, the forward filter 2SLS estimator is desirable yielding less bias than GMM and sizeable gains in efficiency. In fact, for the life cycle labor example, the forward filter 2SLS estimate of the intertemporal substitution elasticity was .135 for 9 moment conditions compared to .296 for 212 moment conditions. The standard error of these estimates dropped from .32 to .09.

The practical problem of not being able to use more moment conditions as well as the statistical problem of the trade-off between small sample bias and efficiency prompted Ahn and Schmidt (1999a) to pose the following questions: “Under what conditions can we use a smaller set of moment conditions without incurring any loss of asymptotic efficiency? In other words, under what conditions are some moment conditions redundant in the sense that utilizing them does not improve efficiency?” These questions were first dealt with by Im, Ahn, Schmidt and Wooldridge (1999) who considered panel data models with strictly exogenous explanatory variables. They argued that, for example, with ten strictly exogenous time-varying variables and six time periods, the moment conditions available for the random effects (RE) model is 360 and this reduces to 300 moment conditions for the FE model. GMM utilizing all these moment conditions leads to an efficient estimator. How-

ever, these moment conditions exceed what the simple RE and FE estimators use. Im et al. (1999) provide the assumptions under which this efficient GMM estimator reduces to the simpler FE or RE estimator. In other words, Im et al. (1999) show the redundancy of the moment conditions that these simple estimators do not use. Ahn and Schmidt (1999a) provide a more systematic method by which redundant instruments can be found and generalize this result to models with time-varying individual effects. However, both papers deal only with strictly exogenous regressors. In a related paper, Ahn and Schmidt (1999b) consider the cases of strictly and weakly exogenous regressors. They show that the GMM estimator takes the form of an instrumental variables estimator if the assumption of no conditional heteroskedasticity (NCH) holds. Under this assumption, the efficiency of standard estimators can often be established showing that the moment conditions not utilized by these estimators are redundant. However, Ahn and Schmidt (1999b) conclude that the NCH assumption necessarily fails if the full set of moment conditions for the dynamic panel data model are used. In this case, there is clearly a need to find modified versions of GMM, with reduced set of moment conditions that lead to estimates with reasonable finite sample properties.

Crepon, Kramarz and Trognon (1997) argue that for the dynamic panel data model, when one considers a set of orthogonal conditions, the parameters can be divided into parameters of interest (like δ) and nuisance parameters (like the second order terms in the autoregressive error component model). They show that the elimination of such nuisance parameters using their empirical counterparts does not entail an efficiency loss when only the parameters of interest are estimated. In fact, Sevestre and Trognon in chapter 6 of Matyas and Sevestre (1996) argue that if one is only interested in δ , then one can reduce the number of orthogonality restrictions without loss in efficiency as far as δ is concerned.

However, the estimates of the other nuisance parameters are not generally as efficient as those obtained from the full set of orthogonality conditions.

The Alonso-Borrego and Arellano (1999) paper is also motivated by the finite sample bias in panel data instrumental variable estimators when the instruments are weak. The dynamic panel model generates many overidentifying restrictions even for moderate values of T . Also, the number of instruments increases with T , but the quality of these instruments is often poor because they tend to be only weakly correlated with first differenced endogenous variables that appear in the equation. Limited information maximum likelihood (LIML) is strongly preferred to 2SLS if the number of instruments gets large as the sample size tends to infinity. Hillier (1990) showed that the alternative normalization rules adopted by LIML and 2SLS are at the root of their different sampling behavior. Hillier (1990) also showed that a symmetrically normalized 2SLS estimator has properties similar to those of LIML. Following Hillier (1990), Alonso-Borrego and Arellano (1999) derive a symmetrically normalized GMM (SNM) and compare it with ordinary GMM and LIML analogues by means of simulations. Monte Carlo and empirical results show that GMM can exhibit large biases when the instruments are poor, while LIML and SNM remain unbiased. However, LIML and SNM always had a larger interquartile range than GMM. For $T = 4$, $N = 100$, $\sigma_\mu^2 = 0.2$ and $\sigma_\nu^2 = 1$, the bias for $\delta = 0.5$ was 6.9% for GMM, 1.7% for SNM and 1.7% for LIML. This bias increases to 17.8% for GMM, 3.7% for SNM and 4.1% for LIML for $\delta = 0.8$.

Alvarez and Arellano (1997) studied the asymptotic properties of FE, one-step GMM and non-robust LIML for a first-order autoregressive model when both N and T tend to infinity with $(N/T) \rightarrow c$ for $0 \leq c < 2$. For $T < N$, GMM bias is always smaller than FE and LIML bias is smaller than the other two. In fixed T framework, GMM and LIML

are asymptotically equivalent, but as T increases, LIML has a smaller asymptotic bias than GMM. These results provide some theoretical support for LIML over GMM.⁹

Wansbeek and Knaap (1999) consider a simple dynamic panel data model with a time trend and heterogeneous coefficients on the lagged dependent variable and the time trend, i.e.,

$$y_{it} = \delta_i y_{i,t-1} + \xi_i t + \mu_i + u_{it} \quad (39)$$

This model results from Islam's (1995) version of Solow's model on growth convergence among countries. Wansbeek and Knaap (1999) show that double differencing gets rid of the individual country effects (μ_i) on the first round of differencing and the heterogeneous coefficient on the time trend (ξ_i) on the second round of differencing. Modified OLS, IV and GMM methods are adapted to this model and LIML is suggested as a viable alternative to GMM to guard against the small sample bias of GMM. Macroeconomic data are subject to measurement error and Wansbeek and Knaap (1999) show how these estimators can be modified to account for measurement error that is white noise. For example, GMM is modified so that it discards the orthogonality conditions that rely on the absence of measurement error.

Jimenez-Martin (1998) performs Monte Carlo experiments to study the performance of the Holtz-Eakin (1988) test for the presence of individual heterogeneity effects in dynamic small T unbalanced panel data models. The design of the experiment includes both endogenous and time-invariant regressors in addition to the lagged dependent variable. The test behaves correctly for a moderate autoregressive coefficient. However, when this coefficient approaches unity, the presence of an additional regressor sharply affects the power and the size of the test. The power of this test is higher when the variance of the specific effects

increases (they are easier to detect), when the sample size increases, when the data set is balanced (for a given number of cross-section units) and when the regressors are strictly exogenous.

A. Heterogeneous Dynamic Panel Data Models

The fundamental assumption underlying pooled homogeneous parameter models has been called into question. Robertson and Symons (1992) warned about the bias from pooled estimators when the estimated model is dynamic and homogeneous when in fact the true model is static and heterogeneous. Pesaran and Smith (1995) argued in favor of dynamic heterogeneous models when N and T are large. In this case, pooled homogeneous estimators are inconsistent whereas an average estimator of heterogeneous parameters can lead to consistent estimates as N and T tend to infinity. Maddala, Srivastava and Li (1994) argued that shrinkage estimators are superior to either heterogeneous or homogeneous parameter estimates especially for prediction purposes. In fact, Maddala, Trost, Li and Joutz (1997) considered the problem of estimating short run and long run elasticities of residential demand for electricity and natural gas for each of 49 states over the period 1970-1990.¹⁰ They conclude that individual heterogeneous state estimates were hard to interpret and had the wrong signs. Pooled data regressions were not valid because the hypothesis of homogeneity of the coefficients was rejected. They recommend shrinkage estimators if one is interested in obtaining elasticity estimates for each state since these give more reliable results.

Baltagi and Griffin (1997) compare short run and long run estimates as well as forecasts for pooled homogeneous, individual heterogeneous and shrinkage estimators of a dynamic demand model for gasoline across 18 OECD countries over the period 1960-1990. Based on one, five and ten year forecasts and plausibility of the short run and long run elasticity estimates, the results are in favor of pooling. Similar results were obtained for a dynamic

model for cigarette demand across 46 states over the period 1963-1992, see Baltagi, Griffin and Xiong (2000).

In chapter 8 of Matyas and Sevestre (1996), Pesaran, Smith and Im investigated the small sample properties of various estimators of the long-run coefficients for a dynamic heterogeneous panel data model using Monte Carlo experiments. Their findings indicate that the mean group estimator performs reasonably well for large T . However, when T is small, the mean group estimator could be seriously biased, particularly when N is large relative to T . Pesaran and Zhao (1999) examine the effectiveness of alternative bias-correction procedures in reducing the small sample bias of these estimators using Monte Carlo experiments. An interesting finding is that when the coefficient of the lagged dependent variable is greater than or equal to 0.8, none of the bias correction procedures seem to work.

Hsiao, Pesaran and Tahmiscioglu (1999) suggest a Bayesian approach for estimating the mean parameters of a dynamic heterogeneous panel data model. The coefficients are assumed to be normally distributed across cross-sectional units and the Bayes estimator is implemented using Markov Chain Monte Carlo methods. Hsiao, et al. argue that Bayesian methods can be a viable alternative in the estimation of mean coefficients in dynamic panel data models even when the initial observations are treated as fixed constants. They establish the asymptotic equivalence of this Bayes estimator and the mean group estimator proposed by Pesaran and Smith (1995). The asymptotics are carried out for both N and $T \rightarrow \infty$ with $\sqrt{N}/T \rightarrow 0$. Monte Carlo experiments show that this Bayes estimator has better sampling properties than other estimators for both small and moderate size T . Hsiao, et al. also caution against the use of the mean group estimator unless T is sufficiently large relative to N . The bias in the mean coefficient of the lagged dependent variable appears to be serious when T is small and the true value of this coefficient is larger than 0.6. Hsiao, et al. apply

their methods to estimate the q-investment model using a panel of 273 US firms over the period 1972-1993.

VI. CONCLUSION

This survey gives a brief overview of some of the main results in the econometrics non-stationary panels as well as recent developments in dynamic panels. There has been an immense amount of research in this area recently with the demand for empirical studies exceeding the supply of econometric theory developed for these models. As this survey indicates, several issues have been resolved but a lot remains to be done.

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NOTES

1. A collection of dynamic panel data routines can be found in: <http://www.cemfi.es/~arellano/#dpd>.
2. Chiang and Kao (2000) have recently put together a fairly comprehensive set of subroutines, NPT 1.0, for studying non-stationary panel data. NPT 1.0 can be downloaded from <http://web.syr.edu/~cdkao>.
3. Testing for cointegration in panel data by combining p -values tests is a straightforward extension of the testing procedures in this Section. For cointegration tests, the relevant model is equation (15). We let G_{iT_i} be a test for the null of no-cointegration and apply the same tests and asymptotic theory in this Section.
4. Kiviet(1999) extends this derivation to the case of weakly exogenous variables and examines to what degree this order of approximation is determined by the initial conditions of the dynamic panel model.
5. Arellano(1989) found that using lagged differences of predetermined variables as instruments is not recommended since it has a singularity point and very large variances over a significant range of the parameter values.
6. See also Arellano and Bover(1995), chapter 8 of Baltagi (1995) and chapters 6 and 7 of Matyas and Sevestre (1996) for more details.

7. For a Hausman and Taylor (1981) type model, Metcalf (1996) shows that using less instruments may lead to a more powerful Hausman specification test. Asymptotically, more instruments lead to more efficient estimators. However, the asymptotic bias of the less efficient estimator will also be greater as the null hypothesis of no correlation is violated. Metcalf argues that if the bias increases at the same rate as the variance (as the null is violated) for the less efficient estimator, then the power of the Hausman test will increase. This is due to the fact that the test statistic is linear in variance but quadratic in bias.
8. See the growing literature on weak instruments by Nelson and Startz (1990), Bekker (1994), Angrist and Kreuger (1995), Bound, Jaeger and Baker (1995) and Staiger and Stock (1997) to mention a few.
9. An alternative one-step method that achieves the same asymptotic efficiency as robust GMM or LIML estimators is the maximum empirical likelihood estimation method, see Imbens (1997). This maximizes a multinomial pseudo-likelihood function subject to the orthogonality restrictions. These are invariant to normalization because they are maximum likelihood estimators.
10. Maddala, et. al. (1997) also provide a unified treatment of classical, Bayes and empirical Bayes procedures for estimating this model.

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