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On Non Parametric Regression and Panel Unit Root Testing

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Abstract

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In this thesis, two different issues in econometrics are studied, the estimation of regression coefficients and the non-stationartiy analysis in a panel setting.

Regarding the first topic, we study a set of measure of location-based estimators (MLBEs) for the slope parameter in a linear regression model with a single stochastic regressor. The median-unbiased MLBEs are interesting as they can be robust to heavy-tailed and, hence, preferable to the ordinary least squares estimator (LSE) in such situations. Two cases, symmetric stable regression and contaminated normal regression, are considered as we investigate the statistical properties of the MLBEs. In addition, we illustrate how our results can be extended to include certain heteroscedastic regressions.

There are three papers concerning the second part. In the first paper, we propose a novel way to test the unit roots in the panel setting. The new tests are based on the observation that the trajectory of the cross sectional sample variance behaves differently for stationary than for non-stationary processes. Three different test statistics are proposed. The limiting distributions are derived and the small sample properties are studied by simulations. In the remaining papers, we focus on the studies of the block bootstrap panel unit root tests proposed by Palm, Smeekes and Urbain (2011) which aims at dealing with a rather general cross-sectional dependency structure. One paper studies the robustness of PSU tests by a comparison with two representative tests from the second generation panel unit root tests. In another paper, we generalized the block bootstrap panel unit root tests in the sense of considering the deterministic terms in the model. Two different methods to deal with the deterministic terms are proposed and the asymptotic validity of bootstrap tests under the main null hypothesis is theoretically checked. The small sample properties are studied by simulations.

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To my parents, wife and son

List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Liu, X., and Preve, D. (2012) Measure of location-based estimators in simple linear regression. Submitted.

II Liu,X. (2012) Panel unit root tests based on sample variance. Submitted.

III Liu, X., and Wei, J. (2014) On the robustness of the block bootstrap panel unit root test.

IV Liu, X., and Wei, J. (2014) Block bootstrap panel unit root tests with deterministic terms.

Contents

1. Introduction

1.1 The estimation of regression coefficients

Linear models are widely applied in statistics and econometrics. Suppose the observations are generated by a simple linear regression model

$$y_i = \alpha + \beta x_i + u_i, \tag{1.1}$$

then the question is how to estimate the regression coefficients? The first refereed classical solution must be the least squares estimator (LSE) created by Carl Friedrich Gauss. By minimizing the sum of squares of residuals, the LSE for β in (1.1) is

$$\hat{\beta}_{LS} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}, \tag{1.2}$$

There are other estimators of the slope coefficient, for example, the maximum likelihood estimator which is equivalent to LSE under the normality assumption. The LSE has a nice property provided by the Gauss-Markov theorem. If the explanatory variable is non-stochastic and the regression errors are uncorrelated random variables with zero mean and common finite variance, $\widehat{\beta}_{LS}$ is the most efficient among all linear unbiased estimators for β. In other words, the LSE has the smallest variance in the class of linear unbiased estimators if certain relatively restrictive conditions are satisfied. However, those conditions are quite strong and unrealistic in some empirical works. In financial econometrics, for example, researchers often work with the heavy tail distribution. (It will be discussed more in the next subsection). In this case, there will be some large values of the error term and the assumption that the error terms have finite variance may not be satisfied. Then the LSE is not the most efficient estimator anymore. To solve this problem, some estimation methods based on non-parametric or distribution free techniques have been invented, for example the Theil-Sen estimator, see Sen (1968).

1.2 Heavy tailed distribution and stable distribution

In probability theory, a heavy tailed distribution is a distribution whose tails are not exponentially bounded, i.e. the tails are heavier than the tails for the exponential distribution. A heavy tailed distribution provides a fundamental tool in the study of rare events. In the case for which the extreme values occur with relatively high probability, heavy tailed distributions can be applied to model those phenomena very well, for example in finance, economics, computer science and so on.

One class of the commonly used heavy tailed distributions is the family of stable distributions. Stable distributions are widely applied in financial modeling because they generalize the normal (Gaussian) distribution and allow heavy tails and skewness. The reason for the term *stable* is that they retain the shape (up to scale and shift) under addition: if X and $\{X_i\}_{i=1}^n$ are independent, identically distributed stable random variables, then for every n, $\sum_{i=1}^n X_i$ is equal to $c_nX + d_n$ in distribution for some constants $c_n > 0$ and d_n. The simplest example of a stable distribution is the normal distribution, where the sum of independent identically normally distributed random variables is still normal with the same mean and variance by some normalization.

Generally, the distribution of a stable random variable is described by four parameters, here denoted by a, b, c and d. The parameter a, the *index of stability*, is confined to the interval $(0,2]$. The *skewness parameter b* is confined to $[-1,1]$. The *scale parameter $c > 0$*, and the *location parameter d* can take on any real value. There exist a number of different parametrizations for symmetric stable distributions. In this thesis, we will use the $\mathscr{S}(a,b,c,d)$ parametrization in Definition 1.7 of Nolan (2012). This class may be defined by the characteristic function,

$$\varphi(t) = E\left(e^{itv}\right) = e^{-c^a|t|^a + idt}, \tag{1.3}$$

where t is a real number. A random variable v is $\mathscr{S}(a,0,c,d)$ distributed if its characteristic function is given by (1.3), while there is no general closed form expression for the density of a stable random variable. Beside the normal distribution, there are only two cases for which closed form expressions for the density of a stable distributed random variable exist. These are the Cauchy $\mathscr{S}(1,0,c,d)$ and the Levy $\mathscr{S}(1/2,1,c,d)$. For our study, the most useful properties are summarized as a Lemma in Paper I, and the reader is referred to Nolan (2012), Nolan (2013) and Zolotarev (1986) for details.

1.3 Unit root tests

In time series econometrics, the non-stationary processes can be modeled by time trend models or unit root models. It is important to distinguish these two different non-stationary processes for many reasons both in terms of empirical analysis and from the technical point of view. From the empirical point of view, the unit root process has a special feature regarding the persistence of innovations which may have important implications for the formulation of economic models. More specifically, macroeconomists are interested in making an accurate judgment to see whether economic recessions have permanent consequences for the level of future GNP, or if only the temporary downturns with the lost output eventually made up during the recovery, Hamilton (1994). From the technical point of view, while, the presence of unit roots can result in spurious inference in regression analysis cf Granger and Newbold (1974). Simply speaking, if you repeat doing regression on two independent random walks 100 times, then, at the 5 percent level, you will probably get significant regression around 70 times. The most well known test for unit roots is the Dickey-Fuller test (DF test), see Dickey and Fuller (1979). Suppose the observations are generated by the AR(1) process

$$y_t = \rho y_{t-1} + u_t, \tag{1.4}$$

where $u_t \overset{iid}{\sim} N(0, \sigma^2)$, and $y_0 = 0$. The null hypothesis $H_0 : \rho = 1$ is tested against $H_1 : \rho < 1$. The test statistic is the LSE of ρ

$$\hat{\rho} = \frac{\sum_{t=1}^{T} y_{t-1} y_t}{\sum_{t=1}^{T} y_{t-1}^2}, \tag{1.5}$$

Under the null hypothesis, the LSE of ρ is super-consistent, i.e. $\hat{\rho}$ converges to 1 at a rate $1/T$. By proper normalizing, the asymptotic distribution of $\hat{\rho}$ is not normal but a non-standard distribution which can be expressed in terms of functional of Brownian motion.

$$T(\widehat{\rho} - 1) \xrightarrow{L} \frac{\frac{1}{2}\left\{W(1)^2 - 1\right\}}{\int_0^1 [W(r)]^2 dr} \tag{1.6}$$

where $W(r)$ is Brownian motion process. The unit root hypothesis is tested based on this limiting distribution which can be tabulated by Monte Carlo simulations. Dickey and Fuller (1979) and Said and Dickey (1984) considered the general serial correlation contained in the error terms and generalized it as the augmented Dickey-Fuller test (ADF test). Similarly, a semi-parametric test procedure which also considered the serial correlation was proposed by Phillips and Perron (1988). Additionally it is worth mentioning the test procedure proposed by Kwiatkowski, Phillips, Schmidt and Shin (1992), even though its null hypothesis is not unit root but stationarity. There are also some other unit root test procedures, for example the variance ratio test proposed by Lo and MacKinlay (1988). However, the most serious problem is that the power properties of all the existing tests are very poor especially when the sample size is small. Many researchers have endeavoured to improve the power properties, and one interesting effort is panel unit root tests.

1.4 Panel unit root tests

After the seminal work by Levin and Lin (1993), a number of authors have tried to improve the performance of unit root tests by adding the cross sectional dimension, i.e. the panel unit root test (see Breitung and Pasaran (2008) for an overall review). The first two most well known papers are Levin, Lin and Chu (2002) (LLC) and Im, Pesaran and Shin (2003) (IPS). They assume that time series $\{y_{i0},...,y_{iT}\}$ on the cross section units $i = 1,2,...,N$ are generated by a simple AR(1) process for each i, which can be expressed as simple Dickey-Fuller regressions

$$\Delta y_{it} = -\rho_i\mu_i + \rho_i y_{i,t-1} + \varepsilon_{it} \tag{1.7}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$. They further assume that the error terms ε_{it} are independent for all i and t. This crucial assumption can be seen as the main symbol of the first generation of panel unit root tests. The null hypothesis of interest is

$$H_0 : \rho_1 = ... = \rho_N = 0. \tag{1.8}$$

For the alternative hypothesis, LLC and IPS consider the following two hypotheses respectively:

$$H_{1a} : \rho_1 = ... = \rho_N \equiv \rho \text{ and } \rho < 0, \tag{1.9}$$

$$H_{1b} : \rho_1 < 0,...,\rho_{N_0} < 0, \text{ for some } N_0 \leq N. \tag{1.10}$$

Under H_{1a}, LLC assumed that the autoregressive parameter is identical for all cross section units. This is called the *homogeneous alternative*. Then the test statistic pools the observations across the different cross section units as

$$\tau_\rho = \frac{\sum_{i=1}^{N} \widehat{\sigma}_i^{-2} \Delta\mathbf{y}_i' \mathbf{M}_\tau \mathbf{y}_{i,-1}}{\sqrt{\sum_{i=1}^{N} \widehat{\sigma}_i^{-2} \left(\mathbf{y}_{i,-1}' \mathbf{M}_\tau \mathbf{y}_{i,-1}\right)}} \tag{1.11}$$

where $\Delta\mathbf{y}_i = (\Delta y_{i1},...,\Delta y_{iT})'$, $\mathbf{y}_{i,-1} = (y_{i0},...,y_{i,T-1})'$, $\mathbf{M}_\tau = \mathbf{I}_T - \tau_T\left(\tau_T'\tau_T\right)^{-1}\tau_T'$, τ_T is a $T \times 1$ vector of ones,

$$\widehat{\sigma}_i^2 = \frac{\Delta\mathbf{y}_i'\mathbf{M}_i\Delta\mathbf{y}_i}{T-2}, \tag{1.12}$$

where $\mathbf{M}_i = \mathbf{I}_T - \mathbf{X}_i\left(\mathbf{X}_i'\mathbf{X}_i\right)^{-1}\mathbf{X}_i'$, and $\mathbf{X}_i = (\tau_T, \mathbf{y}_{i,-1})$. Under H_{1b}, IPS assumed that N_0 of the N $(0 < N_0 \leq N)$ panel units are stationary with individual specific autoregressive coefficients. This is referred to as the *heterogeneous alternatives*. For the construction of the test statistic, IPS suggests the mean of the individual specific t-statistics

$$\overline{\tau} = \frac{1}{N}\sum_{i=1}^{N}\tau_i \tag{1.13}$$

where τ_i is the Dickey-Fuller t-statistic of cross section unit i. In addition to improving the performance of unit root tests, there also are some other benefits by adding panel units. For example, people can do a set of unit root tests simultaneously. Another advantage is that the asymptomatic normality can be achieved again in most cases.

1.5 Panel unit root tests with cross-sectional dependence

Along with achieving the benefits of adding panel units, it also gives us some troubles. For example, a proper limit theory has to take into account the relationship between the increasing number of time periods and cross section units. Phillips and Moon (1999) subdivide the asymptotic behaviour into three kinds, sequential limit, diagonal limit and joint limit. They argued that the sequential limiting distribution is easy to achieve, but it does not necessarily imply the joint limiting distribution. A simple method of deriving the joint limiting distribution was provided. A more serious problem, however, is the assumption of independence of panel units. O'Connell (1998) showed that the good size and power properties will be violated if the convenient but unrealistic assumption of cross sectional independence is excluded. To overcome this problem, the so called second generation panel unit root tests have emerged. Some studies considered introducing cross-sectional dependence by augmenting the covariance matrix as an arbitrary positive definite matrix from a simple positive definite diagonal matrix. Under this assumption, some panel unit root tests are proposed, for example, introducing the non-linear instrumental variable in Chang (2002), applying the sieve bootstrap method in Chang (2004), a robust t test in Breitung and Das (2005), and so on.

Another more popular way is to model the cross-sectional dependence by a factor structure. Assume that the observations can be modeled by Equation (1.7), but the assumption of the independence of cross section units is relaxed and instead the error term can be written as

$$\varepsilon_t = \Gamma \mathbf{f}_t + \xi_t \tag{1.14}$$

where $\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{Nt})'$, $\mathbf{f}_t$ is an $m \times 1$ vector of serially uncorrelated unobserved common factors, and $\xi_t = (\xi_{1t}, ..., \xi_{Nt})'$ is an $N \times 1$ vector of serially uncorrelated errors with mean zero and a positive definite covariance matrix Ω_ξ, and Γ is an $N \times m$ matrix of factor loadings defined by $\Gamma = (\gamma_1, ..., \gamma_N)'$. Without loss of generality the covariance matrix of $\mathbf{f}_t$ is set to $\mathbf{I}_m$, and it is assumed that $\mathbf{f}_t$ and ξ_t are independently distributed. Intuitively, the cross-sectional dependence is specified by the factor structure, and all the drawbacks due to the cross-sectional dependence are gathered in the nuisance parameters, factor loadings. Then different methods are proposed to remove the nuisance parameters. Moon and Perron (2004) applied a modified version of the principal component approach to estimate the matrix of factor loadings and get the de-factored panel data by projecting the panel data into the space orthogonal to the factor loadings, then they performed a pooled DF test; Pesaran (2007) considers the single factor case and proxies the common factor by the cross-sectional averages. Another more influential approach is the so called PANIC procedure [1], proposed by Bai and Ng (2004). They consider a more general situation by allowing the non-stationarity to enter not only the idiosyncratic

[1]PANIC: Panel Analysis of Nonstationarity in Idiosyncratic and Common components

errors but also the common factors. Under this special framework, one could expect to overcome the difficulty that panel unit root tests may be severely biased if the panel units are cross-cointegrated, see Banerjee, Marcellino and Osbat (2005). As argued in Bai and Ng (2010), Moon and Perron (2004) and Pesaran (2007) all can be seen as a special case of the PANIC model under the homogeneous setting. Two asymptotic independent tests for unit roots in dynamic factors and uncorrelated errors are created. For the dynamic factors, if only one dynamic factor exists, the pooled DF test can be applied; If the number of dynamic factors is larger than 1, they apply the common trend tests and Johansen's cointegration methodology, see Johansen (1995), to the dynamic factors.

1.6 Bootstrap method and bootstrap test

In order to introduce the main research subject of Paper III and IV, we will briefly discuss the main ideas of an important tool in statistical inference, the bootstrap method. Almost all of the problems of statistical inference can ultimately be reduced to the understanding of the sampling distribution. Let $\{X_i\}_{i=1}^n$ be a random sample with common distribution F and let $T_n = T_n(X_1, ..., X_n)$ as a statistic of interest. In order to control the uncertainty and draw a statistical inference, the sampling distribution of the statistic T_n is crucial. The main obstacle, however, is the unknown distribution function F. Even if the distribution function is known, it is still difficult to find the exact distribution for a given sample size because of the limitation of analytical abilities. For the latter case, the situation is not too bad since one could find the exact distribution using Monte Carlo simulations. More specifically, we can repeatedly generate the realizations of a random sample $\{X_i\}_{i=1}^n$ from the common distribution function F, and then calculate the statistic T_n for each sample and sequentially get the approximation of the distribution of statistic T_n. While, in the most tricky situation, if the distribution function is totally unknown, then it is impossible to generate the random sample from F. In classical statistical inference, the asymptotic approximation which only depends on some moment conditions is always the first alternative.

After the seminal work of Efron (1979), however, bootstrap methodology becomes another sword for statistical inference because of its success in many cases. In fact, it is more efficient than the asymptotic methods in some situations, since it converges faster to the exact distribution than the asymptotic approximation does. The basic idea is quite similar in finding the exact distribution by Monte Carlo simulations. Instead of generating a random sample from the distribution function F, the bootstrap method generates the random sample from the empirical distribution function F_n which is a discrete probability distribution that gives probability $1/n$ to each observed value $\{x_i\}_{i=1}^n$. In other words, a sample of size n from F_n is just equivalent to drawing a sample of size n with replacement from the collection $\{x_i\}_{i=1}^n$. Now, let us call the resampling methods depending on F and F_n as parametric and non-parametric bootstrap methods respectively. Since the parametric bootstrap depends on the distribution function F, one could expect a good approximation of the exact distribution for a given sample size as long as the replicates are large enough. For the non-parametric bootstrap, it highly depends on the observed values $\{x_i\}_{i=1}^n$. If we have a "perfect" sample from F, then a good performance of the bootstrap method can be anticipated. While, it is almost impossible to evaluate whether a sample is "perfect" or not, we could pin our hope on the large sample size again. We could expect that the distribution of T_n^* converges to the asymptotic distribution of T_n when n is large enough, and this is called the validity of the bootstrap method. Furthermore, under some conditions, we could also expect that the approximation of the exact distribution by the bootstrap distribution is better than the asymptotic distribution, and this is called the second order property. Beside the second order property, another attractiveness of the bootstrap happens when the asymptotic distribution is inapplicable due to the nuisance parameters which are difficultly addressed. This idea is essential in Paper III and IV.

As we said before, different statistical inferences, such as confidence intervals and hypothesis tests, can be implemented once we get the knowledge of the distribution of statistic. To illustrate the bootstrap test, suppose we are interested in doing hypothesis tests when the unknown θ belongs to parameter set Θ and $H_0 : \theta \in \Theta_0$ against $\theta \in \Theta_1$, and the test statistic is T_n. Then the basic steps of the bootstrap test can be listed as follows:

1. Calculate the test statistic by the observed values $\{x_i\}_{i=1}^n$, say $T_n(x) = T_n(x_1,...,x_n)$;
2. Generate the bootstrap sample, $\{x_i^*\}_{i=1}^n$, in the way which is mentioned above;
3. Calculate the test statistic by the bootstrap samples $\{x_i^*\}_{i=1}^n$, say $T_n^*(x) = T_n(x_1^*,...,x_n^*)$;
4. Repeat step (2)-(3) B times and obtain the bootstrap replicates, $T_{n,b}^*$ where $b = 1,2,...,B$
5. Get the critical value from the bootstrap replicates, and do the hypothesis test. Or do the hypothesis test by estimating the P-value by

$$P = B^{-1} \sum_{b=1}^{B} I_{\left\{T_{n,b}^*(x) < T_n(x)\right\}} \tag{1.15}$$

where I is the identity function.

1.7 Robust block bootstrap panel unit root tests

As discussed in Section 1.5, after the critique of the unrealistic assumption of cross-sectional independence, many studies have shifted their interest to the handling of cross-sectional dependence from the original purpose. Even though many models with complicated cross-sectional dependence have been proposed, the existing models still have many restrictions which are difficult to check by statistical tests. For example, Bai and Ng (2004) considered the relatively general model, however, dependence between the common factors and idiosyncratic errors is not allowed, and the independence between the idiosyncratic errors must be restricted if one wants to do a pooled test on the idiosyncratic errors. Furthermore, the cross-sectional dependence which is introduced by the dynamic dependence is seldom studied.

To consider a more general DGP with less restriction on the cross-sectional dependence leads to a dilemma between the issue of over parameterizations and the practicability of the test. For this dilemma, an expedient that applies the non-parametric block bootstrap algorithm provides a potential solution. Following this thinking, Palm, Smeekes and Urbain (2011) (PSU) generalized the residual based block bootstrap theory which is proposed by Paparoditis and Politis (2003) (PP) and designed for univariate time series into a panel setting. In such a way, the block bootstrap algorithm based panel unit root tests can be applied to the DGPs which contain a wild range of cross-sectional dependence, and many existing models which are applied in panel unit root test can be treated as a special case of PSU. They assume that y_t is generated as

$$y_t = \Lambda F_t + w_t \tag{1.16}$$

where the factor loadings, $\Lambda = (\lambda_1, ..., \lambda_d)'$, the common factors, $F_t = (F_{1,t}, ..., F_{d,t})'$ and the idiosyncratic error, $w_t = (w_{1,t}, ..., w_{N,t})'$. Let the factor and idiosyncratic components be generated by

$$\begin{aligned} F_t &= \Phi F_{t-1} + f_t \\ w_t &= \Theta w_{t-1} + v_t \end{aligned}$$

where $\Phi = diag(\phi_1, ..., \phi_d)$ and $\Theta = diag(\theta_1, ..., \theta_N)$. v_t and f_t are generated by

$$\begin{pmatrix} v_t \\ f_t \end{pmatrix} = \psi(L)\varepsilon_t = \begin{bmatrix} \psi_{11}(L) & \psi_{12}(L) \\ \psi_{21}(L) & \psi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{v,t} \\ \varepsilon_{f,t} \end{bmatrix} \tag{1.17}$$

where the lag polynomial $\psi(z) = \sum_{j=0}^{\infty} \psi_j z^j$ and $\psi_0 = I$. The coefficients of the lag polynomial satisfy some regular conditions. ε_t are i.i.d. with $E\varepsilon_t = 0$, $E\varepsilon_t\varepsilon_t' = \Sigma$ and $E|\varepsilon_t|^{2+\varepsilon} < \infty$ for some $\varepsilon > 0$. This DGP is more general than the existing models in many ways, for example, normally they assumed that the common factors and idiosyncratic errors are independent. However, it is not the case in PSU, and more importantly, almost all studies assume that the matrix of the coefficients of the lag polynomial, ψ_{11}, are diagonal so that the cross-sectional dependence which is caused by dynamic dependence is wiped, however, this is also not the case in PSU.

Retaining the original purpose of panel unit root tests, PSU considers the simple null hypothesis that each cross section unit contains a unit root, and this null hypothesis can be implied by different combinations of non-stationarity of common factors and idiosyncratic errors. To understand the main ideas behind their tests, an important issue must be clarified. The following auxiliary regression is introduced when they construct the test statistics.

$$\Delta y_{it} = \rho_i y_{i,t-1} + e_{it} \tag{1.18}$$

Note that there are no ρ_i in the DGP, however, according to the null hypothesis and following the spirit of LLC and IPS, two test statistics can be constructed by the pooled OLS estimation of ρ_i and the average of OLS of ρ_i from each i respectively. Say τ_p and τ_{gm}. Their asymptotic results indicate that two test statistics converge to some limiting distributions for fixed N. Since too many nuisance parameters are present in the limiting distribution, there is no doubt that it can not applied for statistical inference. While the non-parametric tool, the block bootstrap algorithm can be applied to mimic the exact distribution of those two statistics. By the theoretical justification of PSU, the block bootstrap based panel unit root tests are asymptotically valid, and the simulation studies indicate that their tests have robustness against a wide range of cross-sectional dependence when comparing with LLC and IPS.

2. Summary of the papers

2.1 Paper I: Measure of location based estimators in simple linear regression.

We consider certain measure of location-based estimators (MLBEs) for the slope parameter in a linear regression model with a single stochastic regressor. The median-unbiased MLBEs are interesting as they can be robust to heavy-tailed samples. As we have discussed, the classical LSE is very sensitive to large values of the error term. We also introduced the idea that the estimators which are robust to heavy tail error distributions can be obtained using non-parametric or distribution free techniques. In this paper, we study the robust MLBEs for the slope parameter in a regression model and investigate their finite-sample and asymptotic properties in a parametric setting.

We consider any estimator $\hat{\beta}$ for β that can be decomposed into $\hat{\beta} = \beta + \text{med}\{z_1, z_2, \ldots, z_k\}$, where the z_i are i.i.d. continuous random variables with zero median and k is odd. For an example of an MLBE, consider the incomplete pairwise-slope estimator for β based on a sample of size n

$$\begin{aligned} \hat{\beta}_{PS} &= \text{med}\left\{\frac{y_2 - y_1}{x_2 - x_1}, \frac{y_4 - y_3}{x_4 - x_3}, \ldots, \frac{y_{2k} - y_{2k-1}}{x_{2k} - x_{2k-1}}\right\} \\ &= \beta + \text{med}\{z_1, z_2, \ldots, z_k\}, \end{aligned} \tag{2.1}$$

where

$$z_i = \frac{u_{2i} - u_{2i-1}}{x_{2i} - x_{2i-1}},$$

and $\text{med}\{z_1, z_2, \ldots, z_k\}$ is the sample median of $z_1, z_2, \ldots, z_k$. If the z_i are i.i.d. continuous random variables, standard results for order statistics show that the *exact* distribution of $\hat{\beta}_{PS} - \beta$ when k is odd can be expressed in terms of the incomplete beta function

$$\begin{aligned} G(z;k) &= \left[F_z(z)\right]^{r+1} \sum_{s=0}^{r} \binom{r+s}{r} \left[1 - F_z(z)\right]^s \\ &= \frac{\Gamma(k+1)}{\Gamma(r+1)\Gamma(r+1)} \int_0^{F_z(z)} t^r (1-t)^r dt, \end{aligned} \tag{2.2}$$

where $\Gamma(\cdot)$ is the gamma function, $F_z(\cdot)$ is the cdf of the z_i and $k = 2r+1$. Another example of a MLBE that we consider is

$$\hat{\beta}_{UF} = \text{med}\left\{\frac{y_1 - \mu_y}{x_1 - \mu_x}, \frac{y_2 - \mu_y}{x_2 - \mu_x}, \ldots, \frac{y_n - \mu_y}{x_n - \mu_x}\right\}, \tag{2.3}$$

where μ_y and μ_x are location parameters of the y_i and x_i, respectively. We will sometimes refer to this estimator as unfeasible as it requires both μ_y and μ_x to be known, which for most cases will not be realistic (cf. the $b(\alpha)$ estimators of Blattberg and Sargent, 1971). Then, in view of Equation (2.2), it is readily shown that the median of $\hat{\beta} - \beta$ is zero also. Hence, $\hat{\beta}$ is a median-unbiased estimator for β. If, in addition, the density of the z_i is symmetric about zero, then so is that of $\hat{\beta} - \beta$. This tells us that the distribution of $\hat{\beta}$ is centered about the unknown parameter β. Furthermore, if the median of z_i is unique (in general, the median may be an interval instead of a single number), then the sample median is a consistent estimator for the population median (e.g. Jiang, 2010, p. 5) and $\hat{\beta}$ converges in probability to β as k tends to infinity.

About the heavy tail behavior, we apply a symmetric stable distribution or a normal mixture to describe it such that the problems can be parameterized. More specifically, we focus on the case where the explanatory variable, which is assumed to be stochastic, follows a symmetric stable distribution and the error is either symmetric stable, with the same index of stability as the explanatory variable, or a normal mixture. In addition, we also consider a conditionally heteroscedastic specification. Then for the different models, we establish different conditions under which Equation (2.1) and Equation (2.3) are consistent, median-unbiased estimators with exact distribution that can be expressed in terms of Equation (2.2), and with exact densities that are symmetric about β.

2.2 Paper II: Panel unit root tests based on the sample variance.

Since unit root tests have poor power properties especially for small sample sizes, many researchers consider borrowing the strength from cross section units to improve the power performance. However, no matter the first generation or the second generation panel unit root test, almost all of them are small modifications of Dickey-Fuller tests. Thus, in this paper, we propose a set of tests for the unit root in an entirely different way when the cross-sectional dimension is considered.

Compared to the standard statistical methods, there is a special and tricky situation in time series econometrics. That is we can not observe the realization of one process several times repeatedly. It implies that we can not directly study the properties of expectation and variance of economic variables at any given time point. However this impossible issue becomes "feasible" in a panel setting, since one economic variable can be repeatedly observed from different regions or countries. Assuming the economic variable has similar properties among all cross section units, then the properties of expectation and variance at each time point can be applied. On the other hand, it is well known that the first-order autoregressive process is weakly stationary for a suitable choice

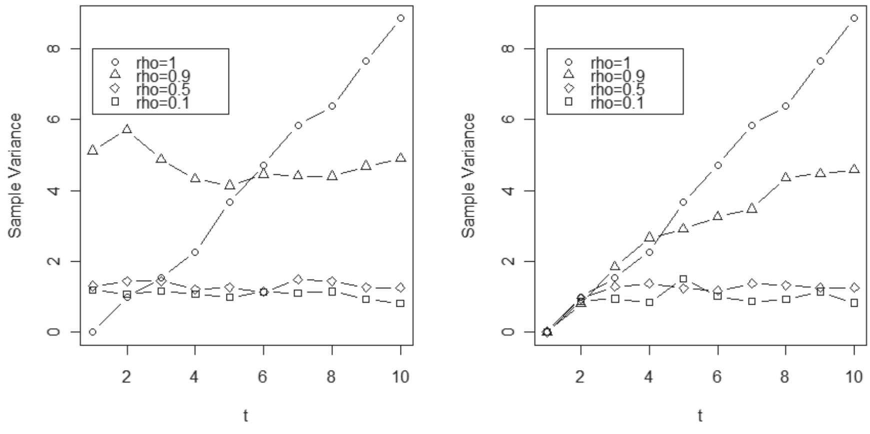

Figure 2.1. Indicating graph of sample variances at each time points of simulated panel data. Repeatedly generate simple $AR(1)$ process with standard Gaussian innovations, then calculate the sample variance for each fixed time points and draw the time series graphs for each cases. Left panel: The proper distribution of the initial values are given. Right panel: The initial values are fixed as 0

of the distribution of its initial value, provided that the autoregressive coefficient is less than one in absolute value. Thus, the basic idea of our tests is that the trajectory of the cross sectional sample variance behaves differently for stationary than for non-stationary processes. Figure 2.1 gives an illustration. Given this idea, we construct the framework of our method as follows: For simplicity, consider the DGP

$$y_{it} = \rho_i y_{it-1} + \varepsilon_{it} \tag{2.4}$$

where $i = 1, ..., N$ and $t = 1, ..., T$. Assume that ε_{it} are independent standard Gaussian noise, i.e. $\varepsilon_{it} \sim \mathcal{N}(0, \sigma^2)$, and the initial values are fixed as 0, i.e. $y_{i0} = 0$ for all i. Consider the null hypothesis

$$H_0 : \rho_1 = ... = \rho_N = 1 \tag{2.5}$$

and the alternative hypothesis

$$H_{1a} : \rho_1 = ... = \rho_N \equiv \rho \text{ and } |\rho| < 1 \tag{2.6}$$

or

$$H_{1b} : |\rho_i| < 1 \tag{2.7}$$

for all i. The cross sectional sample variance at time t is

$$S_t^2 = \frac{1}{N}\sum_{i=1}^{N}(y_{it} - \bar{y}_t)^2 = \frac{1}{N}\sum_{i=1}^{N} y_{it}^2 - \bar{y}_t^2. \tag{2.8}$$

First, it is natural to consider the variation of the variance at each time point to distinguish the unit root process from the stationary process. The test statistic is

$$\psi = \frac{\sqrt{\sum_{t=1}^{T}\left(S_t^2 - \overline{S^2}\right)^2 / T}}{\overline{S^2}} \tag{2.9}$$

Secondly, we consider fitting a straight line to go through each circle point in the right panel of Figure 2.1. For the unit root case, those points can be fit by the straight line very well, however, it is not so in the stationary case. Then we use the R^2 and F statistics to measure the goodness of fit, thereby they can be applied to do hypothesis tests on unit roots. Consider the auxiliary model

$$S_t^2 = \beta_0 + \beta_1 t + u_t \tag{2.10}$$

and the test statistics

$$\psi_{R^2} = \frac{\widehat{\beta}_1^2 \sum_{t=1}^{T} (t - \bar{t})^2}{\sum_{t=1}^{T}\left(S_t^2 - \overline{S^2}\right)^2} \tag{2.11}$$

and

$$\psi_F = \frac{\widehat{\beta}_1^2 \sum_{t=1}^{T} (t - \bar{t})^2}{\sum_{t=1}^{T}\left(S_t^2 - \widehat{S_t^2}\right)^2 / (T-2)}. \tag{2.12}$$

The statistic ψ_{R^2} should be close to 1 under the null hypothesis, and close to 0 for the stationary case. Similarly, under the null hypothesis, the statistic ψ_F should be larger than in the case when the processes are stationary. Furthermore, our test statistics all have an interesting property which can be illustrated by simulation, that is, the distribution of the test statistics is robust to a particular covariance structure of the cross section units. The particular covariance structure is the so called "equal correlation" i.e. the covariance matrix can be formulated as

$$\Sigma = \begin{pmatrix} 1 & \tau & \cdots & \tau \\ \tau & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \tau \\ \tau & \cdots & \tau & 1 \end{pmatrix} \tag{2.13}$$

About the asymptotic results, we show that the sequential limiting distributions of ψ and ψ_{R^2} are normal. For the asymptotic distribution of ψ_F, we find a non-standard limiting distribution which can be described in terms of functionals of a Gaussian process.

2.3 Paper III: On the robustness of the block panel unit root test

Although many panel unit root tests which consider the model with rather complicated cross-sectional dependence structure have been proposed in the literature, the existing models still have many restrictions which are difficult to confirm by statistical tests or economic theory. In order to fill those gaps, PSU developed block bootstrap based panel unit root tests which can be applied under a more general assumption of the cross-sectional dependence. In such a way, most of the existing models can be treated as special cases of PSU.

The asymptotic validity of block bootstrap panel unit root tests has been rigorously proved in PSU. However, the small sample properties have not been fully investigated. More specifically, they only compared their tests with two panel unit root tests from the first generation, and the DGPs of their simulations do not fully display the generality as made by their assumptions, for example, they only considered the case in which common factors and idiosyncratic errors are not dependent neither in the sense of wide range of plausible dynamic dependencies nor the contemporaneous dependence. Moreover, there are some other detailed issues which are not concerned as well. For example, they did not consider the case in which the common factors are $I(0)$ and idiosyncratic errors are $I(1)$ and the multi-factors case is also not included. Thus in this study, we do a further investigation on the small sample properties of the PSU by comparison with two other panel unit root tests from the second generation and under a more general and complicated DGP. Specifically, the PSU test will be applied on the data which are generated by the model considered in Bai and Ng (2004) and Chang (2004) to investigate the small sample performance under some relatively restrictive assumptions. Meanwhile, PSU tests and those two referred tests will also be applied to the data which is generated by the PSU's DGP with more general cross-sectional dependence to exactly see the robustness of PSU. Those issues are also studied in this paper. Based on our simulation results, we have the following main conclusions:

1. Under the specific DGPs of Chang (2004) and Bai and Ng (2004), the PSU test, especially τ_{gm} has generally as good size and power properties as Chang and BN tests, except in the case when negative moving average coefficients are present. In the case with negative moving average coefficients, both τ_p and τ_{gm} have extreme size distortions.
2. Under the DGP of PSU with general cross-sectional dependence structure, the PSU test exhibits robustness with good size and power properties when the idiosyncratic error and common factor part have the same integrated order, and better than the other two methods.
3. About the case in which the common factor and idiosyncratic error have a different integrated order, the PSU test is oversized. This problem is more severe in the case where common factors contain unit roots.

4. In general, the group mean test τ_{gm} is more robust than the pooled test τ_p. In both the DGP of Chang (2004) and Bai and Ng (2004), when the ARMA coefficients are randomly chosen from $U[-0.8, 0.8]$, τ_p exhibits severe size distortion.

2.4 Paper IV: Block bootstrap panel unit root tests with deterministic terms

Based on the block bootstrap method, PSU proposed panel unit root tests which are robust against a wide range of cross-sectional dependence. However several open problems are left and one of the most important issues is the handling of deterministic terms, especially for empirical studies. Thus, we aim to generalize the block bootstrap panel unit root tests in the sense of considering deterministic terms in the model in this paper. Let $x_t = (x_{1,t}, ..., x_{N,t})$ for $t = 1, ..., T$ be generated by

$$x_t = d_t^m + y_t, \tag{2.14}$$

where $d_t^m = \left(d_{1,t}^m, ..., d_{N,t}^m\right)'$ for $m = 0, 1, 2$ is the deterministic part. For each i, $d_{i,t}^m = \beta_i^{m\prime} z_t^m$, where

$$z_t^m = \begin{cases} 0 & \text{if } m = 0 \\ 1 & \text{if } m = \mu \\ (1,t)' & \text{if } m = \tau \end{cases} \text{ and } \beta_i^m = \begin{cases} 0 & \text{if } m = 0 \\ \beta_{1i} & \text{if } m = \mu \\ (\beta_{1i}, \beta_{2i})' & \text{if } m = \tau. \end{cases} \tag{2.15}$$

Then d_t^m can be expressed as $d_t^m = \beta^m z_t^m$ where $\beta^m = (\beta_1^m, ..., \beta_N^m)'$. For future reference, we also partition β^τ in another way and define $\beta^\tau = (\beta_{1\cdot}, \beta_{2\cdot})$ where $\beta_{j\cdot} = \left(\beta_{j1}, ..., \beta_{jN}\right)'$ and $j = 1, 2$. y_t is the stochastic part and follows the same model as in PSU, see Section 1.7.

We propose two different strategies to deal with the deterministic terms. One is to modify the test statistics by adding the deterministic terms into the auxiliary Dickey-Fuller regression and adjust the bootstrap algorithm regarding the model specification. More specifically, instead of applying the auxiliary regression (1.18), we consider the following auxiliary regressions given the model specification. For model μ,

$$\Delta x_{it} = \alpha + \rho_i x_{i,t-1} + e_{it}. \tag{2.16}$$

For model τ,

$$\Delta x_{it} = \alpha + \beta t + \rho_i x_{i,t-1} + e_{it}. \tag{2.17}$$

Then the test statistics are constructed by the corresponding pooled OLS estimation of ρ_i and average of the OLS estimation of ρ_i from each i. Besides the modification of the test statistics, we modify the bootstrap algorithm by generalizing the residual based block bootstrap theory proposed by PP. The second strategy is applying a certain detrending method on the observations and then performing the block bootstrap panel unit root tests on the detrended residuals, i.e. a two stage method. More specifically, we apply the same test statistics but modify the bootstrap algorithm based on the suggestions which are proposed by Smeekes (2009). The modifications of the bootstrap algorithm mainly concern the detrending step, and can be summarized as the following: (i) the data must be detrended not only for the construction of the independent bootstrap residuals but also for calculating the test statistics based on bootstrap samples; (ii) the detrending procedures for calculating the test statistics based on the original sample and bootstrap sample must be identical; (iii) the detrending procedure for constructing the bootstrap residuals can be different from another two, however some conditions of the convergence rate must be satisfied. About the selection of detrending methods, full sample OLS detrending, GLS detrending and recursive detrending are considered in this paper, however, we only provide justification of asymptotic consistency for OLS detrending under the main null hypothesis.

The simulation results show that all tests have acceptable size properties. The tests which are based on detrending methods have better power than the tests which are based on the conventional methods. Furthermore the tests based on the GLS detrending method have the best power among all detrending methods. About the difference between pooled and group mean statistics, even though group mean statistics have better power than pooled in general, we still recommend pooled statistics because of the unexpected results of size of group mean statistics in some cases. At last, we provide an application which illustrates the use of the tests.

3. Further research

About the first paper, we only create the results for the simple linear regression. Besides generalizing it into the multivariate case, other potential further research is to apply those results to the unit root test. The main problems could be concentrated on how to deal with the dependency structure.

About the second paper, we only considered the simplest case. Next, there are several substantial directions to generalize this idea. First, we will consider including deterministic terms which are not identical for all cross section units. So far, we only consider the simple AR(1) process without drift term for each cross section unit. Despite the lack of realism in an empirical study, it is still worth mentioning that the properties of cross section sample variances at each time point will not be affected by the drift terms if we assume that the drift terms are identical through all cross section units. More generally, we consider the model as

$$y_{it} = D_t + \rho y_{i,t-1} + \varepsilon_{it} \tag{3.1}$$

where D_t denotes the deterministic terms. Thus the cross section sample variance at each time is invariant with D_t, no matter how complicated it is. However, if we consider AR(1) processes with non-identical deterministic terms, then the distribution of the test statistic will depend on the variation of the coefficients of deterministic terms. Therefore, we will consider an AR(1) process with non-identical drift terms first.

Second, we will consider more general stochastic processes, for example with non-normal innovations and serial correlations. Third, even though our methods have robustness to a particular covariance structure, they still should be called first generation panel unit root tests. Thus how to deal with cross section dependence in this framework could be an interesting problem. For this point, we try to handle the cross-sectional dependence under the single factor assumption in other research. Furthermore, in most cases, we only create the asymptotic results in a sense of sequential limits. It is still worth finding the joint limiting distribution.

Regarding the third paper, there are two further problems which are worth studying. First, the study indicates that all tests have more or less size distortion when the coefficient of moving average is negative for all cross-section units. This problem is well studied in the univariate unit root test, for example, Ng and Perron (2001), however, there is no study on this problem in a panel setting. So far, it is still difficult to give a proper solution, but we can see that choosing the number of lag terms by some better criteria is the most important step. Second, for the pooled tests which are based on PANIC residuals, the assumption of independence of idiosyncratic errors is always necessary. However, we could relax this assumption by applying some other test which is free of the dependence, e.g. the robust t test by Breitung and Das (2005), to the PANIC residuals. We proceed with this idea in future research.

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