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Stationary bootstrapping for semiparametric panel unit root tests

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ABSTRACT

For panels of possible cross-sectional and serial dependency, stationary bootstrapping is applied to construct unit root tests that are valid regardless of the nuisance parameters of such dependency. The tests are semiparametric in that no model structure is imposed on the serial correlation and the cross-sectional correlation. The statistics are Wald tests and t-bar type tests based on the OLSE (ordinary least squares estimator). Residual-based and difference-based stationary bootstrapping are applied to obtain valid critical values of the tests. Both ordinary and recursive mean adjustments are considered. Large sample validity of the bootstrap tests is established for a large time series dimension. A Monte-Carlo simulation compares the proposed tests, yielding some promising tests, i.e., the t-bar type tests based on difference-based bootstrapping and recursive adjustment.

1. Introduction

Since Dickey and Fuller (1979), testing unit root has been a subject of on-going interest. During the last decade, the subject has been actively investigated in terms of bootstrapping methods and panel data sets.

Panel extensions of unit root tests were made by Levin et al. (2002), Im et al. (2003), and others for models with cross-sectionally independent errors. Efforts of constructing tests that are valid under cross-sectionally correlated errors were made by many authors. Phillips and Sul (2003) indicated that, unlike stationary cases, the generalized least squares (GLS) method, that is, the SUR method, does not resolve the nuisance-parameter dependency in the limiting null distributions of the usual tests such as GLS-based Wald tests and others. Phillips and Sul (2003), Moon and Perron (2004), and Bai and Ng (2004) used factor models for the cross-sectional dependency and developed nuisance-parameter-free tests by de-factoring. These tests are parametric in that parametric AR structures are imposed on serial correlation and factor models are imposed on cross-sectional correlation. Imposing no parametric models on cross-sectional correlation, Chang (2002) and Shin and Kang (2006) applied instrumental-variable estimation to obtain nuisance-parameter-free tests. Their tests are still parametric because AR structures are imposed on serial correlation.

As alternatives to parametric tests, semiparametric tests are worth developing because they are valid for a much wider class of models and are hence more robust than parametric tests. Instead of the adjustment methods of Phillips and Perron (1988) for univariate semiparametric unit root tests, we adopt a bootstrapping method. We want to retain the fully nonparametric feature requiring parametric models neither for serial correlation nor for cross-sectional correlation. For that purpose, the stationary bootstrapping method of Politis and Romano (1994) will be shown to be an appropriate method.

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Stationary bootstrapping methods have been widely used as powerful resampling techniques for approximating the sampling distribution of nonparametric estimators, see Lahiri (1999), Nordman (2009), Hwang and Shin (2011, 2012a,b), and many others. To implement semiparametric methods, stationary bootstrapping is more suitable than the AR-fitting-based sieve bootstrapping because the former requires no parametric models.

Bootstrapping methods were frequently used for unit root tests. Ferretti and Romo (1996) constructed bootstrap unit root tests for the AR(1) model using sieve bootstrapping for the centered residuals. Their results were extended to higher-order autoregressive models by Inoue and Kilian (2002). Park (2003) and Chang and Park (2003) considered a sieve bootstrap for ADF tests with the AR order increasing as the sample size increases. In addition to sieve bootstrap, Swensen (2003a) applied stationary bootstrap to centered differences for Phillips–Perron type unit root tests which are constructed from AR(1) fitting to the original observations. Paparoditis and Politis (2005) used residual-based stationary bootstrapping. They considered both ADF (Augmented Dickey–Fuller) tests and Phillips–Perron-type tests. Paparoditis and Politis (2005) studied sieve bootstrap for ADF tests. Parker et al. (2006) revisited stationary bootstrapping for Phillips–Perron-type unit root tests using differences as well as residuals. A comparative study of various bootstrap unit root tests was prepared by Palm et al. (2008). To construct panel unit root tests, Chang (2004) applied the sieve bootstrapping method of Park (2003) and Chang and Park (2003) to difference observation vectors. Her tests are parametric because the unit root tests are constructed using ADF (Augmented-Dickey–Fuller)-type regression. Palm et al. (2008) established first-order consistency of the moving block bootstrapping for the group mean test of Im et al. (2003) and the pooled unit root coefficient test of Levin et al. (2002). Their bootstrap tests are semiparametric in that unit roots are estimated by fitting AR(1) models. Shin and Hwang (2013) applied stationary bootstrapping for cointegration regression. Shin (in press) constructed stationary bootstrap tests for panel cointegration under cross-sectional dependence.

We apply stationary bootstrapping to panel unit root tests constructed by AR(1) fittings, which are performed by OLS. Our method is semiparametric in that only the AR(1) model is used regarding the unit root parameters and no parametric models are used for serial dependence and cross-sectional dependence. Wald tests and t-bar type tests are constructed and their limiting null distributions are derived, which depend on nuisance parameters arising from cross-sectional correlation and serial correlation.

The nuisance parameter problem is addressed by stationary bootstrapping. Stationary bootstrapping has an advantage of producing conditionally stationary bootstrap samples (Proposition 1 of Politis and Romano, 1994). This implies that the serial correlation structure of the original data is completely transferred to the bootstrap samples, which enables us to construct valid bootstrap critical values of the test statistics. Bootstrapping samples are generated using both differences and residuals.

The proposed bootstrap procedures are justified by showing that the limiting null conditional distributions of the bootstrap tests are the same as the limiting null distributions of the original tests for large time series dimension when the panel length dimension is fixed. Consistency of the bootstrap tests will also be established. For adjusting the mean functions, the ordinary adjustment of Dickey and Fuller (1979) and the recursive adjustment of Shin and So (2001) and So and Shin (1999) are used. A Monte-Carlo experiment compares finite sample performances of the proposed tests.

The remainder of the paper is organized as follows. In Section 2, test statistics as well as their limiting null distributions are provided. In Section 3, a stationary bootstrapping method is implemented. In Section 4, extensions to mean model and trend model are made. In Section 5, finite-sample performances of the proposed tests are investigated via a Monte-Carlo experiment. In Section 6, a concluding remark is given.

The following notation will be used. Let $\|a\| = \sqrt{\sum_{i=1}^{m} a_i^2}$ for $a = (a_1, \ldots, a_m)'$. Let $\xrightarrow{d^*}$, $\xrightarrow{p^*}$, P^*, E^* denote converge in distribution, converge in probability, probability, expectation, respectively, conditional on the realization of the sample.

2. Test statistics and limiting distributions

This section develops a limiting theory for several tests in a model without the mean and the trend term. Later, in Section 4, both the mean model and the trend model are discussed as well as several adjustment methods. Consider a dynamic panel model

$$\Delta y_{it} = \rho_i y_{i,t-1} + u_{it}, \tag{1}$$
$$\Delta y_{it} = y_{it} - y_{i,t-1}, \quad i = 1, \ldots, n,\ t = 2, \ldots, T,$$

where $\{y_{it},\ t = 0, 1, \ldots, T,\ i = 1, \ldots, n\}$ is the data set obtained from n-panel units over time $t = 0, 1, \ldots, T$. We are interested in testing the null hypothesis of unit roots

$$H_0 : \rho_1 = \cdots = \rho_n = 0$$

against the alternative hypothesis H_1: at least one of $\rho_i < 0$. We will derive the limiting null distributions of a Wald test and a t-bar type test on which our bootstrap tests are based. Even though the bootstrap tests based on the Wald test and the t-bar type test are consistent for large T under H_1 of at least one stationarity (see Theorem 4), the tests should not have high powers against stationarity in few units. We will develop bootstrap tests based on the Wald test and the t-bar test focusing on testing against stationarity in majority of units as in the usual panel unit root test literature. The bootstrapping method that will be developed in Section 3 can be easily modified to other tests such as the minimum t test of Chang and Song (2009)