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Is per capita real GDP stationary in China? Sequential panel selection method

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ABSTRACT

This paper investigates the time-series properties of per capita real GDP in China. The Sequential Panel Selection Method (SPSM) using the Panel KSS test with a Fourier function, a novel approach to panel unit testing, is applied to the data on 31 Chinese provinces over the period of 1979 to 2009. The SPSM classifies the whole panel into the group of stationary and non-stationary series, which identifies how many and which series are characterized by stationary processes. The results indicate that the per capita real GDP are non-stationary in all of these 31 regions in China, providing important policy implications.

1. Introduction

Since the seminal work of the Nelson and Plosser (1982), various studies have been devoted to investigating the potential non-stationarity of macroeconomic variables. Researchers have been especially interested in the time-series properties of real output levels. In this regard, Nelson and Plosser (1982) point out that whether real output levels should be modeled as a trend stationary or a difference stationary process has important implications vis-à-vis macroeconomic policy-making, modeling and testing, not to mention forecasting. Studies for this issue are of considerable concern to researchers conducting empirical studies and policy-makers alike. Numerous studies have found support of a unit root in real output levels, but critics have staunchly contended that the drawing of such a conclusion may be attributed to the lower power of the conventional unit root tests employed, when compared with near-unit-root but stationary alternatives. More than that, conventional unit root tests have reportedly failed to consider information across regions, thereby yielding less efficient estimations. It should not be, therefore, unexpected that these shortcomings have seriously been called into questions regarding many of the earlier findings based on a unit root in real output levels.

One feasible way to increase power of unit root test is, of course, to use panel data. Taylor and Sarno (1998), Breuer et al. (2001), Taylor (2003) and Taylor and Taylor (2004) show that methodological refinements of the Levin–Lin test fail to fully address the 'all-or-nothing' nature of the test. Because they are joint tests of the null hypothesis, they are not informative with regard to the number of series which are stationary processes, when the null hypothesis is rejected. Breuer et al. (2001) further claims that, by analogy with simple regression, it does not appear that each coefficient is nonzero when an *F*-statistic rejects the null that a vector of coefficients is equal to zero. Similarly, when the unit-root null hypothesis is rejected, it may be erroneous to conclude that all series in the panel are stationary. Perron (1989) argues that if there is a structural break, the power to reject a unit root decreases when the stationary alternative is true and the structural break is ignored. Meanwhile, neglect of the presence of structural changes in the data generating process sways the analysis toward accepting the null hypothesis of a unit root. It is well known that GDP might be affected by internal and external shocks generated by structural changes, which may be subject to considerable short-run variation. It is important to know whether or not the GDP has any tendency to settle down to a long-run equilibrium level. If GDP is found stationary by using unit root test with structural break(s), the effects of shocks, such as real and monetary shocks that cause deviations around a mean value or deterministic trend, are only temporary.

As the aforementioned, traditional unit root tests lose power if structural breaks are ignored in unit root testing. The general method to account for breaks is to approximate those using dummy variables. However, this approach has several undesirable consequences. First, recent developments in the econometrics literature highlight major drawbacks of commonly used unit root tests based on search procedures. When the break dates are unknown, it is useful to have information

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regarding the presence or absence of a change in order to investigate the potential presence of a unit root. These are not usually known and therefore need to be estimated. This in turn introduces an undesirable pre-selection bias (see Maddala and Kim, 1998). Second, current available tests account only for one to two breaks.[1] Nunes et al. (1997), Lee and Strazicich (2003) and Kim and Perron (2009), among others, demonstrate that such tests suffer from serious power and size distortions due to the asymmetric treatment of breaks under the null and alternative hypotheses. Third, the use of dummies suggests sharp and sudden changes in the trend or level. Consequently, the test may reject the unit root null when the noise component is integrated but the trend is changing, leading to spurious evidence in favor of broken trend stationarity. However, for low frequency data it is more likely that structural changes take the form of large swings which cannot be captured well using only dummies. Breaks should therefore be approximated as smooth and gradual processes (see Leybourne et al., 1998). These arguments motivate the use of a recently developed set of unit root and stationary tests that avoid this problem. Both Becker et al. (2004, 2006) and Enders and Lee (2011) develop tests which model any structural break of an unknown form as a smooth process via means of flexible Fourier transforms. Several authors, including Gallant (1981), Becker et al. (2004), Pascalau (2010) and Enders and Lee (2011), show that a Fourier approximation could often capture the behavior of an unknown function even if the function itself is not periodic. The authors argue that their testing framework requires only the specification of the proper frequency in the estimating equations. By reducing the number of estimated parameters, they ensure the tests have good size and power irrespective of the time or shape of the break.

Recently, there is a growing consensus that macroeconomic variables exhibit nonlinearities and, consequently, conventional unit root tests, such as the Augmented Dickey Fuller (ADF) test, have low power in detecting mean reversion. To solve this problem, non-stationary tests based on a nonlinear framework must be applied. Ucar and Omay (2009) propose a nonlinear panel unit root test by combining the nonlinear framework in Kapetanios et al. (2003, KSS) with the panel unit root testing procedure of Im et al. (2003), which has been proved to be useful in testing the mean reversion of time-series data.

Our study applies Panel KSS test with a Fourier function, combining the Sequential Panel Selection Method (SPSM) procedure, to investigate the time-series properties of per capita real GDP for 31 regions in China over the period of 1979–2009. Empirical results indicate that the per capita real GDP is non-stationary in all of these 31 studied regions. These results have important policy implications for these 31 regions in China under study.

China provides an interesting arena to research for several reasons. First, China has made remarkable economic progress over the past two decades. China's average annual economic growth rate over the past two decades (1990–2010) is 9.818%. In 2010, per capita GDP in China and Taiwan were US$ 7,518 (PPP-adjusted). Second, China has become the world's first largest trading country with the foreign exchange reserves estimated at US$ 2.62 trillion at the end of 2010. Third, China started its open policy in the late 1970s, thus sufficient data are available for researchers to evaluate the effect of economic liberalization on economic phenomena.

There are several novelties of our study. First, to our best knowledge, this study is the first of this kind to utilize the panel KSS unit root test with a Fourier function through the SPSM procedure to investigate the time-series properties of per capita real GDP for 31 regions in China. This empirical study contributes to the field of empirical research by determining whether or not the unit root process is characteristic of the 31 regions' real output levels. Secondly, it is well-known that independence is not a realistic assumption because the real GDP of different regions may be contemporaneously correlated. To control for any cross-section dependence found among the data sets, we approximate the bootstrap distribution of the tests and this has not been done in the previous studies, which assume the individual variables are cross-section independent. O'Connell (1998) has, in fact, shown that the

Table 1
Summary statistics of real per capita GDP.

	Mean	Max.	Min.	Std. dev.	Skew.	Kurt.	J.-B.
Beijing	22115	58944	5529	16508	0.87	2.37	4.42
Tianjin	17357	52353	5052	13572	1.16	3.16	6.97**
Hebei	7181	20566	1628	5670	1.00	2.84	5.19*
Shanxi	6206	18006	1734	4713	1.24	3.39	8.17**
Inner Mongolia	7852	33702	1396	8043	1.79	5.45	24.32***
Liaoning	10655	29483	2919	7111	1.06	3.29	5.86**
Jilin	7243	22251	1698	5468	1.24	3.70	8.61***
Heilongjiang	7874	18780	2418	4900	0.83	2.53	3.83
Shanghai	27460	66086	10406	17733	0.81	2.30	4.04
Jiangsu	11650	37435	2073	10011	1.13	3.23	6.69**
Zhejiang	12747	37349	1698	11008	0.92	2.59	4.60*
Anhui	4731	13728	1089	3384	1.11	3.34	6.50**
Jiangxi	9494	28312	1221	7806	0.82	2.62	3.66
Fujian	4823	14503	1323	3601	1.16	3.36	7.11**
Shandong	9479	30031	1425	8223	1.13	3.17	6.63**
Henan	5480	17233	1086	4617	1.24	3.47	8.17**
Hubei	6193	18973	1667	4609	1.25	3.71	8.75***
Hunan	5453	17091	1396	4216	1.21	3.57	7.96**
Guangdong	11927	34442	1669	9592	0.90	2.70	4.27
Guangxi	4641	13424	1002	3506	1.05	3.18	5.78*
Hainan	6362	16109	1331	4098	0.64	2.51	2.40
Sichuan	5582	19176	1225	4599	1.26	3.92	9.31***
Chongqing	4829	14507	1177	3645	1.14	3.38	6.95**
Guizhou	2888	8625	830	1948	1.35	4.23	11.44***
Yunnan	4401	11327	1006	2937	0.76	2.64	3.16
Tibet	4778	12797	1645	3238	1.14	2.98	6.73**
Shaanxi	5273	18145	1310	4353	1.45	4.32	13.14***
Ganzu	4109	10769	1407	2699	1.12	3.14	6.51**
Qinghai	5588	16276	1669	3872	1.30	3.82	9.63***
Ningxia	5644	18220	1624	4230	1.38	4.20	11.70***
Xiangjing	6822	16685	1462	4673	0.79	2.46	3.59

Note: 1. The sample period is from 1979 to 2009.
2. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Table 2
Panel unit root tests—first generation panel unit root test.

Levin, Lin and Chu (2002)	t_ρ^*	$\hat{\rho}$	t_ρ^{*B}	t_ρ^{*C}	
	52.358	0.113***	52.294	52.291	
	(1.000)	(0.000)	(1.000)	(1.000)	
Im, Pesaran and Shin (2003)	t_bar_{NT}	$W_{t,bar}$	$Z_{t,bar}$	$t\_bar_{NT}^{DF}$	$Z_{t,bar}^{DF}$
	8.183	60.855	60.004	11.263	80.164
		(1.000)	(1.000)		(1.000)
Maddala and Wu (1999)	P_{MW}	Z_{MW}			
	0.792	−5.497			
	(1.000)	(1.000)			

Notes:
Levin, Lin and Chu (2002): t_p^* denotes the adjusted t-statistic computed with a Bartlett kernel function and a common lag truncation parameter given by $\overline{K} = 3.21T^{1/3}$ (Levin and Lin, 2002). Corresponding p-value is in parentheses. $\hat{\rho}$ is the pooled least squares estimator. Corresponding standard error is in parentheses. t_p^{*B} denotes the adjusted t-statistic computed with a Bartlett kernel function and individual bandwidth parameters (Newey and West, 1994). t_p^{*C} denotes the adjusted t-statistic computed with a Quadratic Spectral kernel function and individual bandwidth parameters. Finally, t_ρ^* denotes the adjusted t-statistic computed with a Bartlett kernel function and a common lag truncation parameter. Corresponding p-value is in parentheses. *** indicates significant at the 1% level.
Im, Pesaran and Shin (2003): $t\_bar_{NT}^{DF}$ (respectively t_bar_{NT}) denotes the mean of Dickey Fuller (respectively Augmented Dickey Fuller) individual statistics. $Z_{t,bar}^{DF}$ is the standardized $t\_bar_{NT}^{DF}$ statistic and associated p-values are in parentheses. $Z_{t,bar}$ is the standardized t_bar_{NT} statistic based on the moments of the Dickey Fuller distribution. $W_{t,bar}$ denotes the standardized t_bar_{NT} statistic based on simulated approximated moments (Im, Pesaran and Shin, 2003, Table 3). The corresponding p-values are in parenthesis.
Maddala and Wu (1999): P_{MW} denotes the Fisher's test statistic defined as $P_{MW} = -2\sum \log(p_i)$; where p_i are the p-values from ADF unit root tests for each cross-section. Under H_0; P_{MW} has χ^2 distribution with 2 N of freedom when T tends to infinity and N is fixed. Z_{MW} is the standardized statistic used for large N samples: under H0; Z_{MW} has a N (0, 1) distribution when T and N tend to infinity.

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[1] Bai and Perron (1998) and Carrion-i-Silverstre et al. (2005), among others, are the two studies allowing multiple structural breaks in their tests.