A Note on Empirical Performance of PANIC

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Abstract

This paper analyses empirical performance of PANIC, a procedure developed by Bai and Ng (2002) for unit root testing in presence of contemporaneous cross-section correlation based on factor representation of the panel data set. The procedure is applied to 5 different panels of typical dimensions in macroeconomic analysis. The major finding is that in presence of excessively volatile series the three proposed information criteria for detemining the number of factors give very inconclusive results. Consequently, valid inference on the order of integration is seriously questioned.

Povzetek

V tem članku je empirično testiran PANIC, procedura za testiranje prisotnosti korena enote v panelnih podatkih ob prisotnosti sočasne presečne korelacije, ki sta jo razvila Bai in Ng (2002) in temelji na faktorski dekompoziciji podatkov. Procedura je aplicirana na 5 različnih panelov z dimenzijami, ki so običajne pri makroekonomski analizi. Ključna ugotovite članka je, da ob prisotnosti zelo volatilnih serij v panelu, trije predlagani informacijski kriteriji za določanje števila faktorjev dajejo zelo različne rezultate. Posledično postane zanesljivost zaključkov o redu integriranosti spremenljivk zelo vprašljiva.

JEL codes:

Keywords: panel unit root testing, factor representation

Ključne besede: panelno testiranje korena enote, faktorska analiza

1 Introduction

PANIC - a "Panel Analysis of Non-Stationarity in Idiosyncratic and Common Components" is a procedure developed by Jushan Bai and Serena Ng (2002) that uses a factor structure of large dimensional panels to develope a new approach to univariate and panel unit-root testing. Besides providing theoretical proofs for their main conclusions in the paper, Bai and Ng provide also some Monte-Carlo evidence on favorable size and power properties of PANIC testing procedure.

The aim of this paper is to evaluate the performance of PANIC on some additional examples of typical macro panel data: OECD data on real effective exchange rates for 29 countries, OECD data on inflation rates for 32 countries, and a set of 29 industry-level price indexes for Slovenia. Results show that, in spite of the appealing theoretical properties of PANIC, the reliability of its empirical performance depends on the presence of excessively volatile series in the estimation of the factors. Different authors have proposed two different approaches to handling outliers: standardization and elimination of outliers. Here I do not attempt to compare the outcomes under the two strategies, the focus is rather on the issue of difficulties that series with relatively high volatility, that is not uncommon in applied macro analysis, bring into empirical applications of PANIC. This might imply that a particular factor structure of data that PANIC assumes cannot be empirically supported in a number of real data examples. The usefulness of PANIC as a uniform approach to univariate and panel unit root testing is decreased accordingly.

2 The Mechanics of PANIC

The main idea of PANIC is to exploit the factor structure of panel data to devise panel unit root tests, and also univariate counterparts, with favorable size and power properties. The power deficiencies of univariate unit root test in finite time series are well documented. The goal of panel unit root test was to increase the power of unit root tests by pooling observations across cross sections. However, pooling is valid only if the assumption of no cross-section correlation among units is satisfied. Banerjee at al. (2001) show how panel unit root test become oversized when this assumption is violated.

A factor structure of the data exploits the contemporaneous correlation between cross-section units to split the process into two parts: a common and idiosyncratic component. In particular, Bai and Ng consider the following static factor model:

$$X_{it} = D_{it} + \lambda_i^{'} F_t + e_{it}. \tag{1}$$

D_{it} is a polynomial trend function (a constant and a linear trend), F_t is a $r \times 1$ vector of common factors, and λ_i is the corresponding vector of factor loadings. The error term e_{it} is assumed to be largely idiosyncratic, while $\lambda_i^{'} F_t$ represent the common components of the process whose dimension is considerably smaller than N. Weak correlation between e_{it} and e_{jt}, $\forall j \neq i$, is allowed, which qualifies this model as an approximate static factor model.

The pooling of idiosyncratic components e_{it} , in order to investigate their integration properties, is valid. Individual unit root test on small number of common features (factors) then gives a combined evidence on the order of integration of the whole process X_{it}. The common components and the idiosyncratic components (ICs) are allowed to be integrated of different orders. If this is the case for an individual series X_{it}, usual unit root test can have problems with determining the true order of integration, i.e. unit root test can be oversized, while stationarity tests can lack power (Ng and Perron, 2001).

The crucial step to testing for the presence of a unit root in the common and idiosyncratic components, which are both unobserved, is their consistent estimation when it si not known a priori whether they are I(0) or I(1). Bai and Ng (2001) show how this can be done by the method of principal components on differenced data. Differencing is the key trick in the procedure as present econometric technology does not allow for the consistent estimation of the factors when idiosyncratic components are I(1). The estimates of factors and idiosyncratic components are then obtained by re-integration. Large panel dimensions are required for this; large N permits consistent estimation of the factors whether they are stationary or not, while large T allows for the use of appropriate large-sample theory in the derivation of the tests.

In the derivation of the PANIC procedure the data are assumed (1) to admit a factor structure, and (2) factors and idiosyncratic components follow an AR(1) process with serially uncorrelated errors: $F_{mt} = \alpha_m F_{mt-1} + u_{mt}$, and $e_{it} = \rho_i e_{it-1} + \varepsilon_{it}$. This simple structure led Bai and Ng (2001) to consider the classical unit root test of Dickey and Fuller (1979). In real applications, it si unlikely to find all series in a panel to follow a simple AR(1) process. PANIC allows for weak dependence in u_{mt} and ε_{it}. With the true order of error autocorrelation unknown, the ADF test can be used in accordance with the results of Said and Dickey (1984), who show that the ADF test remains valid provided the order of the augmented autoregressions, M, is chosen such that $M^3/T \to 0$ as M and $T \to \infty$. Hence, Bai and Ng (2001) claim that their main theorems remain valid also with weak serial correlation in u_{mt} and ε_{it}.

Keeping in mind that the factors and idiosyncratic components are estimated assuming a static factor structure, unit root testing with PANIC is invalid if the true data are generated by a dynamic factor model. Indeed, it is more likely to find panel data being consistent with a dynamic factor model and not with the static one. As noted by Stock and Watson (1998), when factor models are used for forecasting purposes the choice between the two is an empirical issue. However, if a factor structure is used to devise unit root test, this becomes a crucial issue. Estimated common components are then not the true ones, which implies that if pooling of X_{it} for a unit root test is not valid because of significant cross correlation, it remains so also for pooling idiosyncratic components e_{it}. If the possibility that also lagged values of factors significantly affect X_{it} cannot be simply ruled out, then the identified idiosyncratic components are not truly idiosyncratic and could remain strongly correlated. In short, in order to justify the underlying assumption of PANIC - static factor structure - a formal test for the presence of moving average components of factors in the model should also be available. If factors entered the model in moving average form, the factors have to be estimated using a methodology different from ordinary method of principal components. Forni at al. (2000), for example, describe the estimation procedure in this case. However, apart from the estimation issues, the inference on the order of integration of the common and idiosyncratic components would remain largely unaltered. The same type of ADF test could be used for the individual ICs, and any of available panel unit root tests for the pooled ICs. More importantly, given that the common components now take the form of an infinite order AR process, the results of Said and Dickey (1984) can be used for unit root testing provided that the finite order lag in the test equation is chosen in accordance with the T dimension.

3 Estimation of the common components and determining the number of factors

The literature presented in this paper considers three different methods for the estimation of the common components - factors. As emphasized above, PANIC is based on a static factor model, which allows for a simpler estimation method than the methods required for the estimation of a dynamic factor models (see Stock and Watson, 1998; Forni et al., 2000).[1] In static form the factor model can be estimated by the method of principal components. Let k denote the number of factors, then the $(N \times k)$ loading matrix Λ, and the $(T \times k)$ matrix of common components F are obtained by solving the following optimization problem

$$V(k) = \min_{\Lambda, F} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i F_t)^2 \tag{2}$$

subject to normalization $\Lambda' \Lambda / N = I_k$ or $F' F / T = I_k$. Using the latter, the estimated factor matrix, $\widetilde{F}$, is $\sqrt{T}$ times the eigenvectors corresponding to the k largest eigenvalues of XX'. The factor loadings are then obtained as $\widetilde{\Lambda} = \widetilde{F}' X / T$. Alternatively, using the first normalization, $\widehat{\Lambda}$ can be calculated as $\sqrt{N}$ times the k largest eigenvectors corresponding to the k largest eigenvalues of $X'X$. The factors are then estimated as $\widehat{F} = X\widehat{\Lambda}/N$. Stock and Watson (1998) estimate the factor matrix using the normalization $F'F/T = I_k$, and obtain the estimate of factor loadings by OLS regression of X_{it} on $\widetilde{F}_t$. Apart from computing convenience that depends on which dimension, N or T, is smaller, the two approaches yield results that do not differ when a factor model is used for unit root testing.

Special attention is devoted to the determination of the number of factors. Some recent papers consider solutions to this problems for panels with non-fixed dimensions. Forni at al (1998) note for fixed T and $N \to \infty$ that the number of factors can be asymptotically determined by observing the behavior of recursively estimated eigenvalues of $X'X$: first k (dynamic) eigenvalues diverge to infinity while others stay bounded. In finite samples this indication might not be useful. For this reason, they determine the number of factors by considering a 5% threshold of variance explained by the i^{th} factor.

Stock and Watson (1998) assume $N, T \to \infty$ with $\sqrt{N}/T \to \infty$ and estimate the dimension of F using a criterion that minimizes the mean squared forecast error in the model. A procedure for consistent estimation of the number of factors, $r \leq k$, that puts no restriction on the rate of convergence of N and T has been recently proposed by Bai and Ng (2002). They propose three different information criteria that minimize (2) with a penalty term depending both on T and N. This procedure has been used also by Marcellino et al. (2000). It is important to note that Monte Carlo evidence in Bai and

[1] Under suitable assumptions about e_{it}, a dynamic factor model can be estimated by ML using the Kalman Filter (Stock and Watson, 1998). This procedure if difficult with non-balanced panels and large N. Forni et al. (2000) propose a more feasible approach to estimation based on spectral decomposition of the panel.

Ng (2002) shows that their procedure should yield quite consistent estimates also for relatively small panels with $N = 40$, and even $T = 50$.

In this paper, special attention is devoted to difficulties we might encounter in applied work. In particular, the procedure of Bai and Ng (2002) for the estimation of the dimension of F is underlying the procedure in PANIC. Provided that the true number of factors is known, it is shown by Bai and Ng (2001) that PANIC has very good size and power properties also for panels with $N = 20$ and $T = 100$, which is very close to the dimension of data sets I use in this paper. Such cross-section dimension is also very common in macroeconomic analysis. As will be argued below, high volatility of few series that is not uncommon in typical macro panel, causes the three information criteria to give quite inconclusive results. Moreover, the estimated factors instead of representing the common components can be in such cases quite strongly associated with the most idiosyncratic variability. The problem is less severe when the data are properly standardized; however, the three information criteria still show discrepancies in the estimated number of factors that are incompatible with Monte Carlo evidence in Bai and Ng (2002). This implies that PANIC crucially depends on the knowledge of the true number of factors. The difficulties in the determination of this number, and lack of strong evidence that estimated factors really represent the common components in a panel with quite volatile series, decrease the usefulness of PANIC for panel unit root testing.

4 Excessively volatile series

In empirical applications of factor models for time series analysis, a proper handling of excessively volatile series is crucial. Since the factor estimation procedure is the result of minimizing expression (2), it is evident that the presence of some excessively volatile series will result in estimated factors that "accommodate" this volatility. If estimated factors can still be perceived as representing the common components of the data or not, becomes an important issue.

In applications of Stock and Watson (1998) and Marcellino, Stock and Watson (2000) the data are checked for outliers according to a selected multiplicator of the inter-quartile range. The data are then handled in two different ways, first, by dropping the whole series, or second, by treating the outlying observations as missing data. Consequently to the second strategy, the EM algorithm for factor estimation in unbalanced panels has to be used. Stock and Watson (1998) report that the two methods yield similar results in terms of forecasting performance of the model. While the two procedures proposed by Stock and Watson seem very appealing for forecasting purposes, their appropriateness for unit root testing can be seriously questioned. Dropping a series from a panel leaves the question of the order of integration of that series open. Eliminating some observations, on the other hand, effectively changes the series of interest, which may again leave the question of the order of integration of the original series unanswered. One posibility is also to treat all outliers as breaks in the original series so that we are actually investigating the orfedr of integration of series with structural breaks. However, in the examples used in this paper the number of outliers can be so high that it is highly unlikely that they all represent structural breaks.

Forni et al. (2000), and Bai and Ng (2001) recommend a different approach: standardization of the data, without any argument being made, however, on why this is necessary.[2] In particular, the derivation of PANIC procedure does not impose the necessity of data standardization. In empirical applications, PANIC used on standardized or non-standardized data gives quite different results.

As will be shown below, standardization in fact improves the empirical performance of PANIC to some extent, but it is not necessarily sufficient. In order to demonstrate how important standardization is, the results reported below contain examples of panels with standardized and non-standardized data that demonstrate how even different conclusions on the order of integration of some variables can be obtained in the two different cases.

5 Some examples of empirical applications of PANIC

In this section I present some examples of how PANIC performs with real data. In particular, I consider 5 different macro panels with monthly data from 1992 to 2001. Each panel is considered twice; firstly with standardized data (labeled with "s"), and secondly with unstandardized data. The first, labeled $REER$, consists of OECD data on real effective exchange rate series for 29 countries. Used on this panel, PANIC will provide yet another test of PPP hypothesis. The second, labeled π_{oecd},is a panel of OECD CPI inflation data for 28 countries. This panel has in addition been expanded with the data from the same source for 4 additional countries: Romania, Estonia,

[2] As required by identificetion restrictions, factors are assumed to be orthonormal in all cases discussed here.

Lithuania and Russian Federation (label $\pi_{oecd}\,(+4)$). These countries have exhibited in the period under analysis particularly high and volatile inflation rates.

The fourth panel labeled π_{slo} replicates to some extent the empirical exercise in Bai and Ng (2001). There the authors show PANIC results for a panel of 21 industry level inflation rates for the US. Here I consider a similar panel, consisting of 29 industry level inflation rates for Slovenia, which exhibits more volatile industry level inflation rates. The results for these 4 panel are reported in Table 4. The results for the 5th panel will be briefly discussed in the text. I refer to this panel as "heterogeneous" panel as it does not consist of data of only one type e.g. price indexes, exchange rates, etc., but rather contains data on industrial production, real exchange rate, inflation and short-term interest rates for 6 countries: Germany, United Kingdom, Sweden, Denmark, the Czech Republic, Hungary, Poland and Slovenia. The aim of reporting the results for this panel also is twofold. First, panel unit root testing in heterogenous panels is instructive since in macroeconomic analysis data of only one type are rarely used. In particular, such a panel could be used to test real and/or nominal convergence, business cycle sychronization between two groups of countries, etc. Second, results show that some of the problems with volatile series become even more serious if heterogeneous data is used.

5.1 Negative sides of PANIC

The major challenge of applying PANIC on a typically sized macro panel can be seen already from the first four lines of Table 1. The lines labeled IC1, IC2 and IC3 correspond to the number of factors given by 3 information criteria proposed by Bai and Ng (2002) for consistent estimation of the number of factors. For all cases with non-standardized data the first two criteria, IC1 and IC2, fail completely. For any choice of the maximum number of factors, $k_{\max}$, both IC1 and IC2 always choose $k_{\max}$. Given that there is no theory available to determine the proper choice of $k_{\max}$,this represents a serious problem. With standardized data the criteria give different suggestions. While the first two always choose the same number of factors, the third criterion suggests zero factors in all cases, which would imply that all series are idiosyncratic. In the heterogenous panel (see above for description), however, the first two criteria again perform badly even with standardized data. In this case $k_{\max}$ is always chosen, while IC3 gives a choice of 2.

Table 1: PANIC results for real effective exchange rates (REER), OECD inflation (π_{oecd}) and industry inflation for Slovenia (π_{slo})

		REER_s[1]	REER	π_{oecd}_s	π_{oecd}	π_{oecd} _s (+4)[2]	π_{oecd} (+4)	π_{slo}_s	π_{slo}
No. of factors	**IC1**	3	k_{max}	3	k_{max}	3	k_{max}	0	k_{max}
	IC2	3	k_{max}	3	k_{max}	3	k_{max}	0	k_{max}
	IC3	0	0	0	3	0	7	0	4
	Chosen	3	3	3	3	3	3	4	4
Stationary factors		0/3	0/3	3/3	1/3	3/3	2/3	4/4	3/4
X_{it} with $\sigma_F^2 > \sigma_e^2$		13/29	3/29	11/28	6/28	12/32	4/32 (“+4”)	6/29	3/29
Stationary ICs		2/29	1/29	5/28	5/28	6/32	6/32	11/29	14/29
ADF[3] test	**Correct**	28/29	28/29	11/28	9/28	16/32	11/32	11/29	7/29
	Missed	1/29	1/29	17/28	19/28	16/32	21/32	18/29	22/29
DFGLS test[4]	**Correct**	29/29	29/29	21/28	20/28	23/32	24/32	19/29	28/29
	Missed	0/29	0/29	7/28	8/28	9/32	8/32	10/29	1/29
Pooled test	X_{it}	I(1) ✓	I(1) ✓	I(0) ✓	I(0) X	I(0) ✓	I(0) X	I(0) ✓	I(0) X
	e_{it}	I(1) X	I(1) X	I(0) ✓	I(0) ✓	I(0) ✓	I(0) ✓	I(0) ✓	I(0) ✓
Cointegration[5]		0/29	1/29		9/28		22/32		17/29
N, T		29, 105	29, 105	28, 114	28, 114	32, 114	32, 114	29, 72	29, 72
Factors mostly associated with			MEX, TY, NL		TY, CEEC-3, GR		“+4”		3 series
		PPP fails	PPP fails	π mostly I(1)	π I(1)	π mostly I(1)	π I(1)	π_{slo} I(1)	π_{slo} I(1)
German inflation				I(1)	I(1)	I(0)	I(1)		

[1] A “_s” indicates that the data have been standardized.
[2] 4 countries added to the panel: Romania (59.7%), Estonia (32.3%), Lithuania (43.3%), Russian Federation (84.3%) (average inflation rate in brackets).
[3] If all factors are I(0), the stationarity of the ICs is checked. If the IC is I(0) and the ADF or DFGLS tests reject the null, this is classified as “correct”, and “missed” otherwise. If the IC is I(1) and the ADF or DFGLS tests accept the null, this is classified as “correct”, and “missed” otherwise. If at least on factor is I(1), every rejection by ADF or DFGLS tests is classified as “missed”.
[4] A more powerful unit root test by Eliott, Rothemberg, Stock (1996).
[5] In case of an I(1) factor, it is tested whether individual series cointegrate with the factor. The DF test statistic is compared to Phillips and Ouliaris (1990) critical values.

In subsequent analysis I have based my decision on the number of factors on the results reported by the first two criteria for standardized data. In addition, it was checked whether this was approximately in accordance with the 10% limit share of total variation explained by eigenvectors corresponding to the largest eigenvalues individually. The same choice on the number of factors has been used for standardized and non-standardized data.

The order of integration of estimated factors is also conditional on standardization. With the exception of the real effective exchange rate panel, the number of I(1) factors is always larger in non-standardized panels than in standardized panels, a result that could be expected. In all three inflation panels the factors are shown to be stationary if standardization is applied. With non-standardized data at least one factor becomes nonstationary, which has an important consequence: every individual inflation series becomes automatically I(1) by construction due to the presence of an I(1) common component.

As expected, standardization also significantly increases the number of series in a panel with explained variation attributed to the common components (factors) larger than the explained variation attributed to the idiosyncratic components (the line labeled X_{it} *with* $\sigma_F^2 > \sigma_e^2$). This number more than doubles on average and may even become four times as large in the case of REER. This clearly reflects the fact that estimated factors become heavily influenced by excessively volatile series, which is more pronounced with non-standardized data.

For illustration, for non-standardized data is the ratio σ_F^2/σ_e^2 very low for a majority of the series, while it extremely high (exceeding 5 in all cases) for Turkey, Mexico and Netherlands in the case of REER panel; Turkey, Greece, Poland, Hungary and the Czech Republic for the smaller OECD inflation panel, and the 4 subsequently added countries (Romania, Estonia, Lithuania and Russian Federation) in the larger OECD inflation panel. These are all countries with very high relative volatility in the corresponding panel.

It has also been checked whether allowing for a larger number of factors results in estimated common components that capture the variability more evenly across series. The answer is negative. For example, increasing the number of factors from 3 to 7 in a larger OECD inflation panel adds also Greece and Turkey (the two countries that have been standing out already in a smaller panel) to the group of 4 countries with initially high ratio σ_F^2/σ_e^2; however, the ratios for the initial 4 countries reach tremendous levels, for Russia as high as 293. It is clear that in such cases the factors can be associated more with few idiosyncratic components than with the common components.

In order to illustrate how severe this problems can become when PANIC is used for making some economic conclusions, I have tracked conclusions being made on the order of integration of German inflation. As reported in the last line of Table 1 there is no uniform conclusion. Three cases indicate that German inflation contains a unit root, but in the standardized larger panel we would conclude that it is stationary.

In the standardized heterogeneous panel[3] an even more confusing result emerges. Given the difficulties with the determination of the number of factors described at the beginning of this section, I have performed the analysis with $r = 2$ and $r = 4$ (both could be possible according to the ratio of eigenvalues). The first two factors are both I(0), and with $r = 2$ the German idiosyncratic component is also I(0). This implies that German inflation is I(0). However, with $r = 4$ the two additional factors are I(1). The 4th factor is also very important for German series as it significantly increases its σ_F^2/σ_e^2 ratio. The idiosyncratic component of German inflation suddenly becomes I(1), which would imply that German inflation is I(1) due to both common and idiosyncratic component. It is worth emphasizing that this finding is extremely counter-intuitive: removing the influence of two I(1) factors results in I(1) idiosyncratic component, which was previously shown to be I(0).

5.2 Positive sides of PANIC

If the problems with excessively volatile series could be analytically solved, the qualities of the underlying idea of PANIC could prevail. To demonstrate this, I assume away the problems with the determination of the number of factors and interpret the results of unit root testing as if we have identified the true factor structure of the data i.e. I assume that PANIC captures the true data generating process.

Under this assumption, the advantages of PANIC over the most widely used unit root test - the ADF test, or a more powerful DFGLS test become evident. For the REER panel where all three factors are highly non-stationary this is perhaps not so evident (DFGLS never rejects the null of a unit root, and ADF test does it only once); however it becomes so in the panels with the presence of strong stationary factors. The ADF test missignals the order

[3] The results of unit root testing for this panel are available from the author upon request. For compactness they have not been included in Table 1. Moreover, the estimated factors were not able to capture what was the main purpose of applying PANIC to this panel: different real and nominal trends in the group of four EU countries (Germany, Denmark, the UK and Sweden), compared to four Accession countries (Hungary, the Czech Republic, Poland and Slovenia). This fact is reflected in a low σ_F^2/σ_e^2 ratio for all series.

of integration of individual series in 50 to 76% of the cases (see lines labeled *ADF test* in Table 1). The DFGLS test performs much better, it missignals in 25 to 35% of the cases, which is, however, still very high (see lines labeled *DFGLS test*). It is worth emphasizing that apart from very few cases, these are all rejections of the true null. This confirms the results of Ng and Perron (2001) that univariate unit root tests tend to be over-sized if the series consists of two components with different orders of integration.

Perhaps the most important advantage of PANIC is that it solves the problem of size and power deficiencies of panel unit root tests when cross-unit short-run correlation is present . Pooling of idiosyncratic component is valid, and usual panel unit root test can be applied. Here the version of Maddala and Wu (1999) is considered. The results show that while a panel unit root test applied to the original series always leads to the correct conclusion with standardized data, it fails to do so in 3 out of 4 cases (all 3 inflation panels) for non-standardized data. This polarity is perhaps only a coincidence; however, the over-rejection, documented also by Banerjee et al. (2001), is evident.

Pooling the idiosyncratic component gives, on the other hand, much better results. The presence of stationary series is almost always correctly detected. Wrong conclusion can be based on the two cases of REER panel (see the line in Table 1 labeled $Pooled\ test - e_{it}$), but here we have only 2 and 1 stationary idiosyncratic components in each panel respectively, such that this finding could be also due to a relatively small sample.

Finally, it is worth mentioning that the caveat from section 3 applies here. Pooling of estimated idiosyncratic components is truly valid only if the static factor structure supports the true structure of the data, and if the true number of factors is known. In other words, the advantages of PANIC become evident only when we assume that the static factor structure underlying the PANIC procedure correctly captures the true data generating process.

6 Conclusion

In a controlled experiment, with generated data, PANIC performs very well. The true number of factors is correctly determined, and the true structure of the data generatting process is well captured. With real data this is no loner so. Two problems arise that are probably closely linked to the relative volatility of the series in the panel. The first is the problem with determination of the number of factors in a typical macro panel with N around 30. The criteria proposed by Bai and Ng (2002) for consistent estimation give very inconclusive results even with standardized data.

The second problem arises with the question how well do the estimated factors capture the common components of the panel. It has been shown that the factors can be heavily influenced by few excessively volatile series. Standardization is recommended as a remedy in this case; however, the role of standardization is theoretically not clear. Standardization is perhaps required to scale the variation of the data to the same level required for the identification of the factors. But this should not be the reason as the factor loadings adjust accordingly. In the opposite case the factor loadings can be normalized to have unit variance for identification, which leaves the decomposition into common and idiosyncratic part unchanged.

Both problems are very important when a factor structure is used for unit root testing. The advantages of PANIC crucially depend on the correctness of the decomposition into the common and idiosyncratic components, which are both unobserved. The difficulties emerging in applied work point towards considerable uncertainty with the true representation of the DGP.

A closely related issue is also the choice between a static or a dynamic factor model. It would be preferable if the choice could be based on some information criteria for the determination of the dimension of MA lag in the common part of the panel.

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