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Ghassan, Hassan and Boulanouar, Zakaria and Hassan,
Kabir Mohammed

Umm Al-Qura University, KSA, High Colleges of Technology, Dubai,
UAE, University of New Orleans, USA

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Revisiting Banking Stability Using a New Panel Cointegration Test

Hassan B. Ghassan^{1,§} Zakaria Boulanouar^{2,*} and Kabir M. Hassan³

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¹ Department of Economics, Umm Al-Qura University, KSA, Mecca 24230, Saudi Arabia

² Department of Finance, Higher Colleges of Technology, Dubai 25026, United Arab Emirates

³ Department of Economics and Finance, College of Business Administration, University of New Orleans, New Orleans, LA 70148, USA

* Author to whom correspondence should be addressed.

§ Current Address: Quantitative Solutions for Economics Research, 91260 Paris, France.

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Abstract

Using the new panel cointegration test that considers serial correlation and cross-section dependence (Hadri, Kurozumi and Rao 2015) on a mixed and heterogenous sample of Saudi banks, we revisit the cointegrating equation of the z-score index of banking stability. We found that in the medium term, some banks aren't cointegrated, although unidentified, meaning that the remaining banks contribute to banking stability. We also found the entire panel of banks to be cointegrated in the long run. We attribute this last outcome to the fact that the memory of the process may lead to long run relationship.

JEL Classification. C51, G21, G28

Keywords. Panel Cointegration, Banking stability, Z-score.

1. Introduction

To date, banking stability studies such as Carreras et al. (2018) have used conventional panel cointegration tests¹ such as Kao (1999) and Pedroni (2004). However, these tests have been criticized for hypothesizing the homogeneity of the cointegration equation (Westerlund 2008), which is too restrictive since many units are, in effect, heterogeneous and interdependent. For instance, Kao (1999) test supposes homogeneity of the slopes across units of the panel while Pedroni (2004) test doesn't explicitly allow for the interdependence between the panel units in the modeling specifications. The use of such tests would lead to spurious long-run relationships.

To revisit banking stability considering the above criticism and technical assumptions that are closer to the aforementioned banking realities, for the first time, we use the new panel cointegration test developed by Hadri, Kurozumi and Rao (2015-henceforth HKR) with a heterogeneous sample of Saudi banks. For comparison purposes we also use Westerlund (2008) test. While the latter allows for serial correlation and assumes the cross-section dependence through the unobserved common factors of error terms, it allows for units of the panel to be independent. The former, however, supposes the cross-section dependence of arbitrary form between time series of the units and treats non-parametrically the serial correlation of the panel error terms.

Furthermore, while Westerlund adopts the null hypothesis of **no** panel cointegration, HKR assumes the null hypothesis of panel cointegration. Thus allowing the treatment of financial stability of banks not as a binary question of 'full panel financial stability versus no panel stability at all' as is the case with Westerlund. This makes HKR more suitable since the rejection of null hypothesis would often mean the existence of panel cointegration among some units.

Other contributions of our research to the stability literature include, a- unlike most of the previous papers, we use quarterly data that we hand collected from banks' balance sheets. Quarterly data fluctuate more than yearly data and provides opportunities to capture the position changes of banks' managers. This is because targets are usually set annually in banks and bank managers change their positions quarterly to achieve annual targets². a- We limit our study to

¹ The long-run relationship detected through a cointegration test is used to mean, in financial terms, that there is stability among banking units.

² For example, a bank that meets its annual loan volume target early in the year, may display more relaxing attitude. However, a bank that finds itself below the target may exhibit a more aggressive attitude to meet its annual performance in other quarters.

one country and as such we isolate any confounding variables and we avoid the heterogeneity bias of the other economies.

Our results show that even when cross-section dependency and serial correlation of the errors are considered, there is possibility for long-run relationship to exist as found with our sample. However, in the medium term, the rejection of null hypothesis means that some banks contribute to banking stability. Consequently, there exists at least one bank that acts as a destabilizer and the challenge for the financial regulators is to identify which bank(s).

The rest of the paper is organized as follows. Data, variables and model are presented in Section 2. In Section 3 we present our main findings. Section 4 concludes the paper.

2. Data and Model

Covering the period $t = 2005:q_1 - 2011:q_4$, we use a heterogonous sample of banks that are listed in the Saudi stock market, *Tadawul*, and altogether represent 64% of the Saudi banking sector (

Table1).

Following the literature including Phan et al. (2019) and Shim (2019), the financial stability index is determined as a function of three types of variables, which are detailed in Table 2. Banks and banking sector are the first two types both of which are constructed and collected from *Tadawul* using the banks' own balance sheets. The last type is macroeconomic variables that were sourced from the National Accounts of the Saudi General Authority of Statistics.

Table1: Sample

Bank	Type			
	Domestically oriented	Overseas oriented	Conventional	Islamic
AlBilad	✓			✓
AlRajhi	✓			✓
Riyad	✓		✓	
Saudi American		✓	✓	
Saudi British		✓	✓	
Saudi Investment	✓		✓	

Following previous studies including Ghassan & Fachin (2016), banking stability is evaluated using the following dynamic z-score equation:

$$z_{it} = \mu_i + \beta_i' B_{it-1} + \gamma_i' S_{t-1} + \omega_i' M_{t-1} + \pi_i D_{it} + \varepsilon_{it}$$

where B_{it-1} represents individual bank variables, S_{t-1} and M_{t-1} stand for the banking sector and macroeconomic variables, respectively. Two dummy variables D_{it} as a binary variable are used to distinguish between the impacts of CBs and IBs on the financial stability of bank i . The estimation of the z-score equation is done by the two-stage Generalized Least Squares with cross-section Seemingly Unrelated Regressions (GLS-SUR).

Table 2: Banks, banking sector and macroeconomics variables

Variables	Description
<i>Bank</i>	
LZSCO	log of z-score
LAST	log of total assets measuring bank size
RCA_C	Ratio of credits to assets for conventional banks (CBs)
RFA_I^3	Ratio of financing activities to assets for Islamic banks (IBs)
RCI	Ratio of operating costs to income
IDV	Income diversity
<i>Banking sector</i>	
LHHI	log of Herfindahl index, measuring the banking sector competitiveness
SHIB _A	share of IBs as ratio of IBs' assets to total assets of banking sector
SHIB _D	Share of CBs as ratio of CBs' deposits to total deposits of banking sector
<i>Macroeconomic</i>	
GRW	Real economic growth, measured using the real GDP growth
INF	Inflation measured using consumer price index growth

3. Empirical results

Westerlund (2008) uses an Autoregressive process for the idiosyncratic errors assuming heterogeneous slope coefficients across units of the panel. He proposes two different Durbin-Hausman (DH) statistics, panel DH (DH_p) and group mean DH (DH_g). The DH_g does not require homogeneity for all units of the panel, but only for some units meaning that the alternative hypothesis is $\phi_i < 1$ for at least some $i = 1, 2, \dots, n$. He asserts that if the null hypothesis of no cointegration is rejected, the test continues by applying a panel unit root test to check if the dependent variable has a unit root. If so, then there is a cointegration relationship. By running Westerlund (2008) panel cointegration test on the residuals of the z-score equation, and by considering constant and trend terms in the long-run equation, we find that $DH_p = 3.139$ and $DH_g = 1.372$ with P-values $8.48E-04$ and $8.50E-02$, respectively. This indicates

³ Instead of interest income (commissions) and interest charges, which are used in CBs, we use finance income and finance charges for IBs.

the existence of a cointegrating relationship between units of the panel. Furthermore, the group-test is in favor of accepting the alternative hypothesis of cointegration for some banks.

3.1 Panel cointegration test

Technically, the common factors approach used by Westerlund to correct for the cross-section dependence proceeds by defactoring data using the principal components estimates. But in the residual equation, this procedure leads to drop some information of the underlying variables. In contrast, by using a non-parametric approach to accommodate cross-section dependence and serial correlation, HKR panel test avoids any potential misspecification of related dependencies and considers a fixed cross-section dimension. HKR work with standardized residuals obtained from an individual regression augmented by the leads and lags of v_{it-j} i.e. using Dynamic OLS regression.

With HKR, the null hypothesis (H_0) of cointegration $\rho_i < 1$ for all i , whereas the alternative hypothesis $\rho_i = 1$ for $i = 1, \dots, N_1$ with $1 \leq N_1 \leq N$ is that at least one unit is not cointegrated. Due to the cross-section dependence and serial correlation, if one unit is not integrated, we can reject the null hypothesis. The rejection of the null hypothesis could imply the existence of sub-panel cointegration.

HKR define two statistics, \hat{S}_K and its bias-corrected \tilde{S}_K , which are based on a simple average of the auto-covariances of individuals. Knowing that the test-statistic is based on the auto-covariance, it suffers from under-size distortion, and then requires to construct a bias-corrected version of the test-statistic. As the finite sample performance essentially depends on the lag order K of auto-covariances, they consider nine lag orders in their simulations from $K = (aT)^\delta$, for $a = 1, 2, 3$ and $\delta = 1/4, 1/2, 3/4$, to evaluate the performance of the statistics \hat{S}_K and \tilde{S}_K in terms of size and power. But, with a strong serial correlation between the residuals for the small (1/4) and large (3/4) smoothing parameters δ , there is an over-size distortion through the significance level in the tests (HKR). Consequently, to avoid a drop in the power of the test, HKR suggest using the bias-corrected test with $a = 2, 3$ and $\delta = 1/2$. Our test results are summarized in Table 3.

Table 3: HKR panel cointegration tests

δ	1/4		1/2			3/4
a	1 & 2	3	1	2	3	1
\hat{S}_K	-1.057 [0.145]	-1.425 [0.077]	-0.574 [0.283]	0.206 [0.582]	1.116 [0.868]	0.983 [0.837]
\tilde{S}_K	0.374 [0.646]	-0.447 [0.328]	0.384 [0.649]	2.790 [0.997]	2.249 [0.988]	3.229 [0.999]

Note: In brackets the one-tailed p -values from $N(0, 1)$. The computation is implemented using Gauss program.

For $a = 3$ and $\delta = 1/4$, by smoothing the lag length and without bias-correction, there is no panel cointegration at 10% significance level. While, for $\hat{S}_K = 1.116$ with P-value equals to 0.868, we can accept the null hypothesis of cointegration between banks; and type 2 error has higher power when we choose lag length $K = (3T)^{1/2}$ instead of $K = (2T)^{1/2}$. Without bias correction, the statistic \hat{S}_K tends to under-reject the null hypothesis. By using the bias-corrected statistic \tilde{S}_K , considering $\delta = 1/2$ for $a = 2, 3$ and $\delta = 3/4$ for $a = 1$, i.e. long-memory for the residuals and powered test, we accept at the 1% significance level that all banks are cointegrated.

Our results show that as the lag order K and its smooth parameter δ increase, the memory of the process may increase in the long run. This means that even if some banks are not individually contributing to the stability, the entire panel of banks taken together can build a stable banking system. However, in the medium-term, as the parameter δ gets smaller, our results show that the null hypothesis can be rejected. Such outcome means that there exist some banks that contribute to instability while others contribute to stability.

3.2 Monte Carlo simulations and HKR cointegration test

Basically, the S -statistic of HKR test has a limiting distribution of standard normal that gives the asymptotic critical values (CV) under the null hypothesis of cointegration ; therefore there is no need to compute bootstrap critical values. But the Monte Carlo simulations are implemented by HKR to control and evaluate the size distortion of S -statistic. They show that the bias-corrected statistics work well in controlling the empirical size of the tests.

In finite samples, the empirical size under the null hypothesis generally will differ from the nominal p -value (as 0.05) where the null distribution is derived asymptotically. The fraction of rejections or rejection rates, by comparing the CV of finite sample simulations to CV of asymptotical distribution, corresponds to the empirical size; and the difference to 0.05 is called size distortion. When, we don't know the exact finite sample distribution, the alternative is to use simulation to compare the exact CV to the asymptotic CV. Throughout the simulations, the bandwidth $J = 12(T/100)^{1/4}$ for long-run variance estimation and leads-lags truncation parameter $M = 2(T/100)^{1/5}$ are set such that the empirical size and power are sufficiently close to the nominal one, as 0.05, compared to other choices. Moreover, as a based-auto-covariances test, HKR investigate the effect of lag order $K = (aT)^\delta$ on S -statistic because the

finite sample performance decisively depends on K , which is calculated using $a = 1, 2, 3$ and $\delta = 1/4, 1/2, 3/4$. They evaluate the performance of the statistics \hat{S}_K and \tilde{S}_K in terms of size and power. They consider the assumptions of the cross-section dependency mild, diversified and strong serial correlation. Based on a specified data generating process, and considering the effect of cross-dependency and serial correlation on the tests under the null hypothesis, HKR establish the rejection frequencies of the cases where $T = 100, 300, 500$, $N = 10, 25, 50, 100$ and $N_1/N = 0, 0.2, 0.5$. The number of replications is 5000 and the significance level is set to 0.05.

As the paper of HKR investigate the performance of the S -statistic, by using finite sample simulations from $T = 100$ and as our sample has around 30 temporal observations and 6 units, we have run a Monte Carlo replications to get more insights on the empirical size and power of our S -tests. By considering the assumptions of cross-cointegration, cross-correlation and diversified serial correlation case with linear trend component, as credible in our banking sample, we expand the simulations to sample $T = 30, 50$ with $N_1/N = 0$ to obtain the following Table 4.

The rejection rates of \hat{S}_K mostly suffer from under-size distortion in small finite samples. Such results lead to select the bias-corrected \tilde{S}_K statistic in testing for panel-cointegration. The \tilde{S}_K is more powerful than the other statistics. Also, $\tilde{S}_K(1)$ and $\tilde{S}_K(2)$ relatively perform well in comparison to $\tilde{S}_K(3)$ from the case when small T as $T = 30$ and $N = 10$, but $\tilde{S}_K(3)$ display more power as its distortion is more large in comparison to $\tilde{S}_K(1)$ and $\tilde{S}_K(2)$.

We can conclude that a random sample will be practically informative when we consider bias-corrected statistic \tilde{S}_K . Even if the sample is small, the testing methods can be used to subtract intelligible information from data. The main comments on the power of HKR test are that as autocovariances-based test, the bias-corrected statistics $\tilde{S}_K(a)$ are more effective than $\hat{S}_K(a)$ in terms of size and power. Although, the decision on HKR panel cointegration test depend on the parameters involved in evaluating the S -statistic including the lag-leads length, we find that Table 3 indicates the stability of banks in the long-run.

Table 4: Rejection rates under H_0 : Empirical size⁴ and power⁵ of panel cointegration tests

T	N	LM	$\hat{S}_K^{ols}(1)$	$\hat{S}_K^{ols}(2)$	$\hat{S}_K^{ols}(3)$	$\hat{S}_K(1)$	$\hat{S}_K(2)$	$\hat{S}_K(3)$	$\tilde{S}_K(1)$	$\tilde{S}_K(2)$	$\tilde{S}_K(3)$
30	10	0.049	0.007	0.007	0.014	0.004	0.005	0.007	0.059	0.072	0.092
30	20	0.042	0.006	0.004	0.015	0.002	0.002	0.006	0.060	0.081	0.113
30	30	0.054	0.000	0.003	0.004	0.001	0.001	0.003	0.057	0.091	0.118
50	10	0.051	0.008	0.008	0.014	0.004	0.005	0.008	0.063	0.075	0.095
50	25	0.046	0.007	0.005	0.016	0.002	0.002	0.007	0.066	0.088	0.124
50	50	0.061	0.000	0.004	0.005	0.001	0.001	0.003	0.065	0.104	0.135
100	10	0.053	0.009	0.008	0.015	0.005	0.006	0.009	0.066	0.078	0.099
100	25	0.049	0.008	0.005	0.017	0.003	0.003	0.007	0.070	0.094	0.132
100	50	0.063	0.001	0.004	0.005	0.001	0.002	0.003	0.067	0.107	0.139
100	100	0.060	0.001	0.003	0.004	0.001	0.001	0.002	0.064	0.103	0.164

T	N	LM	$d\tilde{S}_K(1)$	$d\tilde{S}_K(2)$	$d\tilde{S}_K(3)$
30	10	0.049	0.010	0.023	0.043
30	20	0.042	0.018	0.039	0.071
30	30	0.054	0.003	0.037	0.065
50	10	0.051	0.012	0.024	0.044
50	25	0.046	0.020	0.042	0.078
50	50	0.061	0.004	0.043	0.074
100	10	0.053	0.013	0.025	0.046
100	25	0.049	0.021	0.045	0.083
100	50	0.063	0.004	0.044	0.076
100	100	0.060	0.004	0.043	0.104

Note 1: The rate $d\tilde{S}_K(a)$ corresponds to the difference between rejection-frequencies of LM-statistic and $\tilde{S}_K(a)$; it serves to evaluate the empirical size of the test. All computations are conducted using Gauss software. The four last rows with $T = 100$ are from Table 5 with trend model of HKR paper.

3.3 Robustness checks

The paper of HKR indicate that the S -statistic is robust to the presence of possible cointegration across units. Nevertheless, and due to the size of our sample, we have checked this robustness by removing one unit from the panel. Firstly, we remove one conventional bank SIB, secondly one Islamic bank namely BLD, and lastly one oriented abroad conventional bank. The results are in the following Table 5. The outputs displaying similar results indicate that the results of Table 3 are robust. Consequently, the robustness check support the main outcomes of the panel cointegration test that the bias-corrected S -statistics are more efficient in terms of empirical size and power than no bias-corrected S -statistics.

⁴ The empirical size is indirectly related to power since it deals with rejection rates under the null hypothesis. So, if empirical size is greater than nominal size, it will reject too often if the null is true, and particularly will also reject more often when the null is false, meaning that the test has higher power.

⁵ The fraction of rejections looks like an empirical measure of power of the test. This analysis is used to compare alternative tests and check the possibility that H_1 is true. When this distortion is large, the test will gain power.

Table 5: Robustness of HKR panel cointegration tests

δ	1/4		1/2			3/4
α	1 & 2	3	1	2	3	1
\hat{S}_K	-0.424 [0.336]	-1.488 [0.068]	-0.190 [0.425]	0.622 [0.733]	0.407 [0.658]	-0.288 [0.387]
\tilde{S}_K	1.157 [0.876]	-0.837 [0.201]	1.208 [0.886]	2.711 [0.996]	2.465 [0.993]	2.252 [0.988]

Note: These results are for the panel after removing BLD bank. We obtain similar results by removing other banks, which are omitted to save space (details are available upon request).

4. Conclusions

Our research shows that, considering cross-section dependency and serial correlation of the errors, and by using the unbiased statistic, HKR test leads to accept the null hypothesis that all banks in the panel are cointegrated showing long run relationship. This means that the policies administered by the monetary authority and those of the panel banks are consistent and meaningful in the long-run. Furthermore, in a mixed banking system, banking stability does not depend on the financing model (Islamic or conventional) of the banks, but more on their interdependence.

In the medium-term, the null hypothesis is rejected, meaning that some banks contribute to financial instability while others contribute to stability. The current HKR version, however, doesn't allow identification of the non-cointegrated banks. Had the test been able to do that, the regulatory authorities would be able to develop corrective policies/measures specifically tailored to the non-cointegrated units, which would improve greatly banking stability. We use this occasion to call for further improvement of HKR test to discern between co-integrated and non-cointegrated units.

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