International Journal of
Financial Studies

Article

Revisiting Banking Stability Using a New Panel Cointegration Test

Hassan B. Ghassan [1,§], Zakaria Boulanouar [2,*] and Kabir M. Hassan [3]

1 Department of Economics, Umm Al-Qura University, KSA, Makkah 24230, Saudi Arabia; hbghassan@uqu.edu.sa or hbghassan@yahoo.com
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; mhassan@uno.edu
* Correspondence: zboulanouar@hct.ac.ae; Tel.: +971-2206-4687
§ Current Address: Quantitative Solutions for Economics Research, 91260 Paris, France.

Abstract: Using a new panel cointegration test that considers serial correlation and cross-section dependence on a mixed and heterogenous sample of Saudi banks, we revisit the cointegrating equation of the z-score index of banking stability. Our results show that even when we consider the cross-section dependency and serial correlation of the errors, there is a possibility of a long-run relationship, which holds in our sample of banks. Furthermore, in the medium term, we found some banks to be integrated, whereas others were non-cointegrated. We interpret this to suggest that some banks contribute to banking stability, whereas others do not. In other words, there exists at least one bank that acts as a destabilizer and the challenge for financial regulators is to identify which banks these are. However, the current version of the Hadri et al. test does not allow for the identification of the non-cointegrated banks. If the test was able to do that, the regulatory authorities would be able to develop corrective policies/measures specifically tailored to the non-cointegrated units.

Keywords: panel cointegration; banking stability; z-score

Citation: Ghassan, Hassan B., Zakaria Boulanouar, and Kabir M. Hassan. 2021. Revisiting Banking Stability Using a New Panel Cointegration Test. *International Journal of Financial Studies* 9: 21. https://doi.org/10.3390/ijfs9020021

Academic Editor: Rob Hull

Received: 1 February 2021
Accepted: 24 March 2021
Published: 7 April 2021

1. Introduction

To date, banking stability studies such as those of Anastasiou et al. (2019), Zhou and Tewari (2019), Carreras et al. (2018) and Illes et al. (2019) have used conventional panel cointegration tests[1] such as those of Kao (1999) and Pedroni (2004). However, these tests have been criticized for hypothesizing the homogeneity of the cointegration equation. This hypothesis is too restrictive since many units are, in effect, heterogeneous and interdependent. For example, the Kao (1999) test supposes the homogeneity of the slopes across units of the panel, whereas the Pedroni (2004) test does not explicitly allow for the interdependence between the panel units in the modeling specifications to be taken into consideration. By assuming homogeneity, independence and the non-correlation between bank-units, the outcomes of any kind of cointegration would lead to a spurious long-term relationship of banking stability.

To revisit banking stability considering the above criticism and technical assumptions that are closer to the aforementioned banking realities, for the first time[2], we have used the new panel cointegration test developed by Hadri, Kurozumi and Rao (Hadri et al. 2015) with a heterogeneous sample of Saudi banks. For comparison purposes, we have also used the Westerlund (2008) test. While the latter allows for serial correlation and

[1] It is worth noting from the outset that, in panel data studies, the long-run relationship detected through a cointegration test is used to mean, in financial terms, that there is stability among the panel of units (banks) (Di Iorio and Fachin 2014).

[2] As far as we know, the Hadri et al. (2015) panel test has never been used in empirical banking stability studies or in any other published empirical papers to date.

assumes cross-sectional dependence through the unobserved common factors of error terms, it allows for units of the panel to be independent. The former, however, supposes cross-sectional dependence of an arbitrary form between time series of the units and treats the serial correlation of the panel error terms non-parametrically.

Furthermore, while Westerlund adopts the null hypothesis of no panel cointegration, HKR assumes the null hypothesis of panel cointegration, thus not treating financial stability of banks 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 the null hypothesis would often imply the existence of panel cointegration among some units.

Other contributions of our research to the stability literature include the following. (A) Unlike most of the previous papers, which used yearly data, we used quarterly data that we hand-collected from banks' balance sheets. Quarterly data fluctuate more (in terms of risk and return) than yearly data and so the fluctuations observed provide 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 targets. For example, a bank that meets its annual loan volume target early in the year may display a more relaxing attitude. However, a bank that finds itself below the target may exhibit a more aggressive attitude in order to meet its annual performance targets in other quarters. (B) We limited our study to one country to isolate any social, legal and other confounding variables. This is because when a panel of countries is used, there is a methodological problem due to the heterogeneities that affect the outcomes of regressions. Therefore, by focusing on one country, we avoided the heterogeneity bias of the other economies. (C) We contribute to the stability literature by showing that even when cross-section dependency and serial correlation of the errors are considered, there is a possibility for a long-run relationship to exist, which we found to be the case in our sample. However, in the medium term, the rejection of the 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 banks these are.

In terms of implications, the evidence of banking stability through the new panel cointegration test means that policies administered by monetary authorities 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 addition, financial stability could exist between some units of banks when there is no financial stability in the banking system as a whole.

2. Data, Variables and Model

To revisit banking stability using the new cointegration test of (Hadri et al. 2015), a heterogeneous sample of Saudi main banks was used (Table 1). Altogether, these banks represent 64% of the mixed Saudi banking sector and are listed on the Saudi stock market, Tadawul. The sample covers the period from t = 2005:q_1 to 2011:q_4, encompassing the events of the 2008 global financial crisis.

Following the literature, including Del Gaudio et al. (2020); 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 the banking sector are the first two types, both of which were constructed and collected from the Saudi financial market "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.

Table 1. The sample banks.

Bank Name and Abbreviation	Types of Banks			
	Domestically Oriented	Overseas Oriented	Conventional	Islamic
AlBilad bank (BLD)	✓			✓
AlRajhi bank (RJH)	✓			✓
Riyad bank (RYD)	✓		✓	
Saudi American (SAM)		✓	✓	
Saudi British (SAB)		✓	✓	
Saudi Investment Bank (SIB)	✓		✓	

Source: Authors' data processing.

Table 2. Banks, banking sector and macroeconomics variables.

Variable	Description
Bank variables	
LZSCO	log of z-score
LAST	log of total assets, measuring bank size
RCA_C	Ratio of credits to assets for conventional banks
RFA_I [a]	Ratio of financing activities to assets for Islamic banks
RCI	Ratio of operating costs to income
IDV [b]	Income diversity
Banking sector variables	
LHHI	log of Herfindahl index, which measures the banking sector competitiveness that ranges between zero for highly competitive and 10,000 for the least competitive
$SHIB_A$	share of Islamic banks (IBs) in the Saudi banking sector as a ratio of IBs' assets to total assets of the banking sector
$SHIB_D$	Share of conventional banks (CBs) in the Saudi banking sector as ratio of CBs' deposits to total deposits of the banking sector
Macroeconomic variables	
GRW	Real economic growth, measured using the real GDP growth

Notes: [a] Instead of interest income and interest charges, used in conventional banks, we used finance income and finance charges for Islamic banks. [b] Income diversity is defined as idv = 1 − | Net interest income-Other operating income/Total operatimg income | where the net interest income for Islamic banks includes positive and negative income flows related to the profit and loss sharing (PLS) system. A higher value of this index indicates a higher income diversity.

Following previous studies, including Ariss (2010), Čihák and Hesse (2010) and Ghassan and Fachin (2016), and using the previously defined determinants, banking stability is evaluated using the following dynamic z-score equation:

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

where B_{it-1} represents individual bank variables, and 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 conventional banks (CBs) and Islamic banks (IBs) on the financial stability of bank i.

It is worth noting that the estimation of the z-score equation is carried out using the two-stage generalized least squares-seemingly unrelated regressions (GLS-SUR) method. This procedure performs pooled instrumental variables and two-stage GLS with cross-section SUR.

3. A Previous Panel Cointegration Test of Bank Stability

The banks in our dataset are heterogeneous but not independent. Furthermore, the cross dependence and the common factors that exist between the banks are related to the banks' activities and typology, and therefore such panel data requires suitable tests. 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 $\left(DH_p\right)$ and group mean DH $\left(DH_g\right)$. 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 $i = 1, 2, \ldots, n$. 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 the Westerlund panel cointegration test on the residuals of the z-score equation, and by considering constant and trend terms in the long-term equation, we find that $DH_p = 3.139$ and $DH_g = 1.372$ with based-asymptotic normal p-values 8.48×10^{-4} and 8.50×10^{-2}, respectively. The panel test outcomes indicate the existence of a cointegrating relationship between units of the panel. This provides evidence in favor of rejecting the null hypothesis of non-cointegration for all the banks of the panel. Furthermore, the group test is in favor of accepting the alternative hypothesis of cointegration for at least some banks.

These results mean that some panel banks show long-term financial stability. However, the Westerlund test does not indicate explicitly which sub-panels are cointegrated, that is to say, contributing to financial stability.

Technically, it is worth noting that the common factors approach used by Westerlund to correct for the cross-section dependence proceeds by defactoring data using the principal components estimates. However, in the residual equation, this procedure leads to the loss of some information concerning the underlying variables. In contrast, the Hadri et al. (2015) panel test, by using a non-parametric approach in order to accommodate cross-section dependence and serial correlation, avoids any potential misspecification of related dependencies and considers a fixed cross-section dimension. Hadri et al. (2015) works with standardized residuals obtained from an individual regression, augmented by the leads and lags of v_{it-j} i.e., using dynamic OLS regression. Next, we run the HKR test.

4. The New Test of Panel Cointegration of Bank Stability

4.1. The Test

With the Hadri et al. (2015) test, the null hypothesis (H_0), $\rho_i < 1$ for all i is that all the units are cointegrated, whereas the alternative hypothesis $\rho_i = 1$ for $i = 1, \ldots, N_1$ with $1 \leq N_1 \leq N$ is that at least one unit is not cointegrated. That is to say, due to 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.

Hadri et al. (2015) defines two statistics, $\hat{S}_K$ and its bias-corrected $\widetilde{S}_K$, which are based on a simple average of the auto-covariances of individuals, and do not need to be weighted since the errors of the main regression are normalized by the standard deviation. However, because the test-statistic is based on the auto-covariance, it suffers from under-size distortion. This requires the construction of a bias-corrected version of the test-statistic. Furthermore, as the finite sample performance essentially depends on the lag order K of auto-covariances, (Hadri et al. 2015) considers 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 $\widetilde{S}_K$ in terms of size and power.[3] However, 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 (Hadri et al.

[3] This procedure is explained in detail in Harris et al. (2003) in the framework of the auto-covariance-based test for a panel stationarity test.

2015). Consequently, to avoid a drop in the power of the test, HKR suggests using the bias-corrected test with $a = 2, 3$ and $\delta = 1/2$. Our test results are summarized in Table 3.

Table 3. Hadri et al. panel cointegration tests.[4]

δ	1/4		1/2			3/4
a	**1 and 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)
$\widetilde{S}_K$	0.374 (0.646)	−0.447 (0.328)	0.384 (0.649)	2.790 (0.997)	2.249 (0.988)	3.229 (0.999)

Source: Authors' data processing, and the computation was implemented using the Gauss program. The one-tailed p-values from N (0,1) are presented in brackets. For the BLD unit, the cointegrating regression contains a trend term.

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, using the bias-corrected statistic $\widetilde{S}_K$. For $a = 3$ and $\delta = 1/4$, by smoothing the lag length and without bias correction, there is no panel cointegration at the 10% significance level. Furthermore, for $\hat{S}_K = 1.116$ with a p-value equal to 0.868, we can accept the null hypothesis of cointegration between banks; and the type 2 error has greater power when we choose the lag length $K = (3T)^{1/2}$ instead of $K = (2T)^{1/2}$ (HKR 2015)[5]. Without bias correction, the statistic $\hat{S}_K$ tends to under-reject the null hypothesis. Using the bias-corrected statistic $\widetilde{S}_K$, 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, and consequently all the units of banks can be cointegrated. 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. This outcome means that there are some banks that contribute to financial instability, whereas others contribute to stability.

4.2. Monte Carlo Simulations and the New Cointegration Test

It is worth noting that the S-statistic of the Hadri et al. (2015) test has a limiting distribution of standard normal distribution that gives asymptotic critical values (CVs) under the null hypothesis of cointegration. Therefore, there is no need to compute bootstrap critical values. However, Monte Carlo simulations are implemented by Hadri et al. (2015) to control and evaluate the size distortion of the S-statistic. Furthermore, the authors of the test showed that the bias-corrected statistics work well in controlling the test's empirical size.

In finite samples, the empirical size under the null hypothesis will generally differ from the nominal p-value (as 0.05), where the null distribution is derived asymptotically. By comparing the CV of finite sample simulations to the CV of the asymptotical distribution, the fraction of rejections (rejection rates) corresponds to the empirical size, and the difference relative to 0.05 is called the size distortion. When the exact finite sample distribution is unknown, 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-term variance estimation and leads–lags truncation parameter $M = 2(T/100)^{1/5}$ are set

[4] We thank Professor Kurozumi for sharing the Gauss code for their specific panel cointegration tests.

[5] The bias-corrected statistic $\widetilde{S}_K$ is required in the panel cointegration test when the test suffers from severe size distortion under the null hypothesis; such corrections improve the finite sample properties, because the test statistic based on auto-covariances has a negative bias (as per Table 3), making the test conservative (Hadri et al. 2015).

such that the empirical size and power are sufficiently close to the nominal one, designated as 0.05, compared to other choices. Moreover, as a based-auto-covariances test, Hadri et al. (2015) investigates the effect of lag order $K = (aT)^{\delta}$ on the S-statistic because the finite sample performance decisively depends on K, which is calculated using $a = 1,\ 2,\ 3$ and $\delta = 1/4,\ 1/2,\ 3/4$. Hadri et al. (2015) also evaluates the performance of the statistics $\hat{S}_K$ and $\widetilde{S}_K$ in terms of size and power, considering the assumptions of the cross-sectional dependency and a mild serial correlation, 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, Hadri et al. (2015) establishes 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.

Following the test's authors, who investigate the performance of the S-statistic using finite sample simulations from $T = 100$, and because our sample has around 30 temporal observations and 6 units, we ran Monte Carlo replications to gain further insights into the empirical size and power of our S-tests. By considering the assumptions of cross-cointegration, cross-correlation and a diversified serial correlation case with a linear trend component, as is credible in our banking sample, we expanded the simulations to sample $T = 30,\ 50$ with $N_1/N = 0$ to obtain the results presented in Table 4.

Table 4. Rejection rates under H_0: Empirical size [a] and power [b] of panel cointegration tests.

T	N	LM	$\hat{S}_K^{ols}(1)$	$\hat{S}_K^{ols}(2)$	$\hat{S}_K^{ols}(3)$	$\hat{S}_K(1)$	$\hat{S}_K(2)$	$\hat{S}_K(3)$	$\widetilde{S}_K(1)$	$\widetilde{S}_K(2)$	$\widetilde{S}_K(3)$	$d\widetilde{S}_K(1)$	$d\widetilde{S}_K(2)$	$d\widetilde{S}_K(3)$
30	10	0.049	0.007	0.007	0.014	0.004	0.005	0.007	0.059	0.072	0.092	0.010	0.023	0.043
30	20	0.042	0.006	0.004	0.015	0.002	0.002	0.006	0.060	0.081	0.113	0.018	0.039	0.071
30	30	0.054	0.000	0.003	0.004	0.001	0.001	0.003	0.057	0.091	0.118	0.003	0.037	0.065
50	10	0.051	0.008	0.008	0.014	0.004	0.005	0.008	0.063	0.075	0.095	0.012	0.024	0.044
50	25	0.046	0.007	0.005	0.016	0.002	0.002	0.007	0.066	0.088	0.124	0.020	0.042	0.078
50	50	0.061	0.000	0.004	0.005	0.001	0.001	0.003	0.065	0.104	0.135	0.004	0.043	0.074
100	10	0.053	0.009	0.008	0.015	0.005	0.006	0.009	0.066	0.078	0.099	0.013	0.025	0.046
100	25	0.049	0.008	0.005	0.017	0.003	0.003	0.007	0.070	0.094	0.132	0.021	0.045	0.083
100	50	0.063	0.001	0.004	0.005	0.001	0.002	0.003	0.067	0.107	0.139	0.004	0.044	0.076
100	100	0.060	0.001	0.003	0.004	0.001	0.001	0.002	0.064	0.103	0.164	0.004	0.043	0.104

Notes: [a] The empirical size is indirectly related to power, since it deals with rejection rates under the null hypothesis. Thus, if empirical size is greater than nominal size, it will reject too often if the null hypothesis is true, and particularly will also reject more often when the null hypothesis is false, meaning that the test has higher power. [b] The fraction of rejections looks like an empirical measure of the 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. Notes: The rate $d\widetilde{S}_K(a)$ corresponds to the difference between rejection-frequencies of the Lagrange Multiplier statistic (LM)-statistic and $\widetilde{S}_K(a)$; this serves to evaluate the empirical size of the test. All computations were conducted using Gauss software.

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

We can conclude that a random sample will practically be informative when we consider the bias-corrected statistic $\widetilde{S}_K$. Even if the sample is small, the testing methods can be used to gather intelligible information from the data. Our main comments on the power of the Hadri et al. (2015) test are that as an autocovariances-based test, the bias-corrected statistics $\widetilde{S}_K(a)$ are more effective than $\hat{S}_K(a)$ in terms of size and power. However, the decision about the HKR panel cointegration test depends on the parameters used in evaluating the S-statistic, including the lag–leads length, and we thus find that Table 3 indicates stability of banks in the long run.

4.3. Robustness Checks

Hadri et al. (2015) indicates that the S-statistic is robust to the presence of possible cointegration across units. Nevertheless, and due to the size of our sample, we conducted robustness checks by removing one banking unit from the panel. First, we removed one conventional bank, Saudi Investment Bank (SIB), then one Islamic bank, AlBilad Bank (BLD), and lastly one overseas-oriented conventional bank. The results are presented in Table 5.

Table 5. Robustness of HKR panel cointegration tests.

δ	1/4		1/2			3/4
a	**1 and 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)
$\widetilde{S}_K$	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. We obtained similar results by removing other banks, which are omitted to save space (details are available upon request).

The outputs of the robustness checks' showed similar results, which indicate that the results of Table 3 are robust. Consequently, the robustness checks supported the main outcomes of the panel cointegration test, namely, that the bias-corrected S-statistics are more efficient in terms of empirical size and power than the non-bias-corrected S-statistics.

5. Conclusions

Our research shows that, considering the cross-sectional dependency and serial correlation of the errors, and by using the unbiased statistic, the Hadri et al. (2015) test leads us to accept the null hypothesis that all banks in the panel are cointegrated, showing a long-term relationship. Generally speaking, this means that banking stability studies would benefit from the use of Hadri et al. (2015). This is because, unlike the previous tests that hypothesize the homogeneity of the cointegration equation, which is considered to be unrealistic and thus leads to a spurious long-term relationship of banking stability, detecting a long-run relationship through the use of the new test would lead to reliable cointegration results. Furthermore, policy implications flowing from the long-term relationship detected through the test would be more sound.

For our sample, the fact that all banks were found to be cointegrated 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, our results led us to reject the null hypothesis that all banking units in the panel are cointegrated. This particular result, possible by the use Hadri et al. (2015), is also very important for both stability studies and in terms of policy implications.

For the former, rather than to conclude that in the medium-term there is either a cointegration or none, with Hadri et al. (2015), absence of cointegration would mean possibility of existence of partial cointegration between some units of the panel. For the latter, however, the implications for a—our sample, steaming from the new test results, is that while some banks contribute to banking stability, others contribute to banking instability. Moreover, for b—banking stability studies at large, it is possible to use the test to test for potential existence of banking stability between some units of any panel of banks.

It remains to say that the empirical results of this research and the implications that follow should be considered in light of some limitations. One of these limitations is the effects of the sampling period on the results. Another is the fact that the current version of the new test does not allow for the identification of the cointegrated or non-cointegrated banks. If the test was able to do that, our results would allow us to make more precise recommendations, so that regulatory authorities would be able to develop corrective policies/measures specifically tailored to the non-cointegrated units, which would greatly improve banking stability. We use this occasion, therefore, to call for the further improvement of the test to discern between co-integrated and non-cointegrated units. Furthermore, since this research is the first to use the Hadri et al. (2015) panel cointegration test, we call for future research testing with other samples.

Author Contributions: Methodology, H.B.G.; Writing—original draft, H.B.G.; Writing, Review & editing, Z.B. and K.M.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

Anastasiou, Dimitrios, Helen Lour, and Mike G. Tsionas. 2019. Nonperforming loans in the euro area: Are core–periphery banking markets fragmented? *Interational Journal of Finance and Economics* 24: 97–112. [CrossRef]

Ariss, Rima Turk. 2010. Competitive conditions in Islamic and conventional banking: A global perspective. *Review of Financial Economics* 19: 101–8. [CrossRef]

Carreras, Oriol, Philip Davis, and Rebecca Piggott. 2018. Assessing macroprudential tools in OECD countries within a cointegration framework. *Journal of Financial Stability* 37: 112–30. [CrossRef]

Čihák, Martin, and Heiko Hesse. 2010. Islamic Banks and Financial Stability: An Empirical Analysis. *Journal of Financial Services Research* 38: 95–113. [CrossRef]

Del Gaudio, Belinda L., Amith V. Megaravalli, Gabriele Sampagnaro, and Vincenzo Verdoliva. 2020. Mandatory disclosure tone and bank risk-taking: Evidence from Europe. *Economics Letters* 186: 108531. [CrossRef]

Di Iorio, Francesca, and Stefano Fachin. 2014. Savings and investments in the OECD: A panel cointegration study with a new bootstrap test. *Empirical Economics* 46: 1271–300. [CrossRef]

Ghassan, Hassan B., and Stefano Fachin. 2016. Time Series Analysis of Financial stability of banks: Evidence from Saudi Arabia. *Review of Financial Economics* 31: 3–17. [CrossRef]

Hadri, Kaddour, Eiji Kurozumi, and Yao Rao. 2015. Novel panel cointegration tests emending for cross-section dependence with N fixed. *Econometrics Journal* 18: 363–411. [CrossRef]

Harris, David, Brendan McCabe, and Stephen Leybourne. 2003. Some limit theory for auto-covariances whose order depends on sample size. *Econometric Theory* 19: 829–64. [CrossRef]

Illes, Anamaria, Marco J. Lombardi, and Paul Mizen. 2019. The divergence of bank lending rates from policy rates after the financial crisis: The role of bank funding costs. *Journal of International Money and Finance* 93: 117–41. [CrossRef]

Kao, Chihwa. 1999. Spurious Regression and Residual-Based Tests for Cointegration in Panel Data. *Journal of Econometrics* 90: 1–44. [CrossRef]

Pedroni, Peter. 2004. Panel Cointegration; Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Econometric Theory* 20: 597–625. [CrossRef]

Phan, Hien Thu, Sajid Anwar, W. Robert J. Alexander, and Hanh Thi My Phan. 2019. Competition, efficiency and stability: An empirical study of East Asian commercial banks. *The North American Journal of Economics and Finance* 50: 100990. [CrossRef]

Shim, Jeungbo. 2019. Loan portfolio diversification, market structure and bank stability. *Journal of Banking & Finance* 104: 103–15.

Westerlund, Joakim. 2008. Panel cointegration tests of the Fisher effect. *Journal of Applied Econometrics* 23: 193–233. [CrossRef]

Zhou, Sheunesu, and D. D. Tewari. 2019. Shadow banking, risk-taking and monetary policy in emerging economies: A panel cointegration approach. *Cogent Economics and Finance* 7: 1636508. [CrossRef]