Peer-Reviewed Article

Jurnal Keuangan dan Perbankan
Volume 27, Issue 2 April 2023, 263-271
ISSN: 1410-8089 (Print), 2443-2687 (Online)
DOI: 10.26905/jkdp.27i2.9777

Exploring The Relation between Realised Volatility and Trading Volume: Evidence From International Stock Market

Samuel Tabot Enow

Research Associate, IIE VEGA School. South Africa

Article history:
Received: 2023-03-08
Revised: 2023-04-17
Accepted: 2023-04-30

Corresponding Author:
Name author: Samuel Tabot Enow
E-mail: enowtabot@gmail.com

Abstract

The sequential information theory and mixed distribution hypothesis contends that there exists a bi-directional relation between realised volatility and trading volume. This position has led to the proposition that new information spreads sequentially and reaches market participants and investors at varying times. The purpose of this study was to re-examine these theories using the most recent data. A Granger causality test, Mean Square Error and Mean Average error models where applied to investigate the relationship between realised volatility and trading volume for a sample of five international stock markets from March 5, 2018 to March 5, 2023. The findings of this study contradict the proposition put forth by the sequential information theory and mixed distribution hypothesis where no meaningful relationship was observed except for the CAC 40. Hence, new information rather filters through financial markets at the same time. The finding of this study maybe the explanation for the ever-increasing financial contagion between financial markets.

Keywords : Realised volatility, Trading volume, Granger causality test, Sequential information theory, Mixed distribution hypothesis.
JEL Classification : G11, G15, G17

This is an open-access article under the CC–BY-SA license

1. Introduction

Stock market microstructure involves understanding several complicated layers of traditional trading functions in order to provide a vivid understanding of the price formation system. Till date, market participants and investors are interested in the price discovery system for better capital allocation. Modelling the relationship between realised volatility and trading volume encapsulates a major part of price formation due to the volume of information flow in financial markets (O'Hara, 2015). This idea is postulated by the sequential information flow hypothesis which contends that new information is transmitted systematically to market participants trading in financial markets (Gueyie, Mouhamadou & Mamadou, 2022). In essence, new information reaches security traders at varying times giving rise to information asymmetry (An, Huang & Li, 2022). This leads to disequilibrium in security markets where market prices will enhance the direction of trade and trading volume. That is to say, information and parameters of previous trading volumes can be used to forecast and predict price volatility and vice versa. The sequential information flow hypothesis is supported by the mixed distribution theory which contends that stock price returns and trading volumes are related (He & Velu, 2014). The main bone of contention from these theories is that trading in financial markets is based on new information which ultimately affects market prices and trading volumes (Preis, Moat & Stanley, 2013).

Considering the heterogeneity of market participants, new information can also be used for trading signals. The above theories however contradict the market efficiency hypothesis where the theory maintains that stock prices tend to follow a stochastic process (Enow, 2021). Till date, prior empirical literature on the relationship between RV and VOL focused mainly on time series models such as GARCH and causality effect where a significant relationship between the variables was observed (Adhikari, 2020; Ozdemir, 2020; Choi, Kang & Yoon, 2022). Despite the perceived relevance, more recent forecasting models such as the Mean Square Error (MSE) and Mean Average error (MAE) are now prevalent in empirical research (Hodson, 2022). Hence, the dynamic relationship between RV and VOL can be better explained using the MSE and MAE. Specifically, this study investigates the following research question; using the most recent data, is there any contemporaneous relationship between RV and VOL? Is there any evidence of causality between RV and VOL in financial markets? Can RV and VOL be used as predictors of each other? In providing answers to the above questions, this study makes a significant contribution to the frontier of the dynamic relationship between RV and VOL as well as the literature of price formation and transmission mechanism in international financial markets. This study is structured as follows, section 2 outlines the literature review followed by the methodology, results and discussion in section 3 and 4 respectively. Section 5 which is the conclusion provides recommendations from the study.

2. Hypotheses Development

The Theoretical underpinning of this study is the market efficiency theory. The main idea of this hypothesis is that security prices reflect all available information (Fama, 1965). Accordingly, investing based on public information cannot systematically outperform the market overtime (Enow, 2021). Also, it is impossible to forecast stock price returns based on new information arriving the market as it will be quickly reflected in the stock price (Duarte, Montenegro González & Cruz, 2021). Hence price signals from volume trading will be unfruitful, at least in the long run. Future price movements are expected to continue in a stochastic manner as investors are unlikely to beat the market. The market efficiency principle also underpins the Arbitrage pricing theory (APT), Capital asset pricing model (CAPM) and concepts such as beta (Roll & Ross, 1980). However, the market efficiency hypothesis developed by Fama (1965) has received several criticisms among academics and industry experts especially with the emergence of behavioural finance in the early 90s. The fact that security prices are far more volatile appeared to be justified by new information. The main assumption of market efficiency is also challenged on the premise that investors are not always rationale (Enow, 2022). Also, new information is not always free and it is at times costly to obtain, hence it is unlikely that all available information will be reflected in the security price. From the above proposition put forth by the market efficiency theory, it can be suggested that there may be no relationship or causation effect between RV and VOL considering the randomness in price pattern. However, more recent prior literature has suggested otherwise. The table below summarises the most recent studies on the relationship between RV and VOL.

Table 1 above presents the findings of the most recent studies from 2018. From the findings, the authors contend that there is a relationship between RV and VOL using different methods. The studies in table 1 infers that, the concept of market efficiency is not relevant. However, none of the studies indicated the predictive proportion between stock price returns and trading volume. In other words, the forecasting proportion between the dependent and independent variables. Hence, this study will attempt to extend the findings of prior literature.

Table 1: Summary of prior studies on the relationship between RV and VOL

Study	Model	Period	Findings
Gupta, Das, Hasim & Tiwari (2018)	MODWT-VAR approach	January 4, 2002 – September 18, 2017 and January 1, 2001- September 18, 2017	A significant by directional relationship between trading volume and price returns
Ligocká (2019)	Correlation analysis and Granger Causality test	January 1, 2008 – December 31, 2018	Significant positive relationship between volatility and trading volume.
Bajzik (2020)	Meta-Analysis	44 studies in the literature	An inverse relationship exists between trading volumes and price returns. Stock price returns decreases as trading volume increases.
Adhikari (2020)	Granger Causality and VAR	July 2011 - July 2018	A unidirectional relationship between VOL and security price return.
Ozdemir (2020)	Causality test	January 02, 1997− December 29, 2017	A significant bi-directional relationship between price volatility and trading volume
Choi, Kang & Yoon (2022)	GARCH	January 2, 2004 – September 28, 2012	Price volatility is partly explained by trading volume

3. Method, Data, and Analysis

To achieve the objective of this study, two variables were used which were RV calculated as the natural log of today's closing price divided by yesterday's price and VOL which was the daily trading volumes for the JSE (Johannesburg Stock Exchange), the Borsa Istanbul 100 (BIST 100), CAC-40 (the French Stock Market Index), the DAX (the German blue-chip companies) and the Nasdaq Index. All the required data was retrieved from yahoo finance which provides credible and real time data sets. The sample period was the most recent 5 years (March 5, 2018 to March 5, 2023). The data analysis process was in four stages, firstly a descriptive statistic was first conducted to glean the stylist facts of RV and VOL followed by a unit root test. This unit root test was conducted to ensure that RV and VOL were stationary. RV and VOL are said to be stationary if their statistical properties such as the mean, variance and covariance are constant overtime or no trends exist (Nkoro & Uko, 2016). As described in prior literature (Holder, Leon & Wood, 1990), a stationary test is important because non-stationary variables produce spurious results. Accordingly, an Augmented Dickey Fuller (ADF) test was applied to determine the stationarity status of the variables. Where the p-values were less than 5%, RV and VOL were confirmed to be stationary and vice versa. According to Tam, (2013) an ADF test is given by:

$$\Delta y_t = \alpha + \ \delta y_{t-1} + \sum_{i=1}^{n} \beta_i \Delta y_{t-1} + \varepsilon_t$$

$$y_t = \alpha + 6 y_{t-1} + \ \varepsilon_t$$

H_0: Stationary variable if the P-value is less than 5%.
H_1: Non- Stationary variables if the P-values is more than 5%.

A granger causality test was conducted to examine whether the information provided by the lag values of RV allows for a more accurate prediction of VOL and vice versa. In other words, a Granger causality test was used to provide evidence of correlation between RV and VOL. If RV Granger causes VOL, then RV can be used to predict future values of VOL and vice versa (Enow, 2023). Albeit, inference must be done cautiously taking into consideration that Granger causality is used for short run relationships. Mathematically, a granger model is given by:

$$RV_t = a_0 + a_1 RV_{t-1} + a_2 VOL_{t-1} + \epsilon$$

Where a_0 is the coefficient of the intercept and ϵ is the error term (Song & Taamouti, 2019). In essence,

H_0: No Causality effect between RV and VOL because the p-value is more than 5%.
H_1: Granger Causality effect between RV and VOL because the p-value is less than 5%.

Finally, a MSE and MAE model was utilized to provide a forecasted proportion between RV and VOL. These models provide the absolute and average magnitude error generated by a regression model (Chiang, Qiao & Wong (2009). The MSE and MAE also highlights the square differences between the observed and predicted values of RV and VOL, hence a notable advancement from the studies cited in the prior literature (Chiang, Qiao & Wong, 2009). The equations below represent the mathematical expression of MSE and MAE:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(RV - VOL)^2$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|RV - VOL|$$

Adapted from Chiang, Qiao & Wong, (2009). The section below presents the results and analysis.

4. Results

As already alluded in section 1 and 3, the first part of the data analysis was to provide a basic description of RV and VOL. These stylised facts are presented on table 2.

Table 2. Descriptive statistics

	JSE		BIST (100)		CAC 40		DAX		Nasdaq	
	RV (%)	VOL	RV (%)	VOL	RV (%)	VOL	RV (%)	VOL	RV	VOL
Mean	-0.044	180,696	-0.200	26,800,000	0.020	81,599,969	0.020	83,630,964	0.030	38,000,000
Median	0.000	131,102	0.200	22,600,000	0.090	78,157,950	0.070	76,933,300	0.110	40,000,000
Maximum	6.000	1701,513	9.400	94,600,000	8.050	37,100,000	10.400	40,000,000	8.900	11,600,000
Minimum	-10.000	3,895	-4.600	0.000	-13.000	0.000	-13.000	0.000	-13.000	95,900,000
St. Deviation	1.600	165,748.3	13.100	16,200,000	1.290	38,053,315	1.300	37,236,275	1.600	1.540
Skewness	-31.000	3.290	-34.370	1.010	-1.010	1.770	-0.660	2.600	-0.590	0.610
Kurtosis	6.350	19.750	1202.430	3.600	16.630	12.560	15.790	16.400	9.680	3.610
Obs	1250.000	1,250	1,245	1,245	1,282	1,282	1,268	1,268	1,258	1,258

Table 2 provides a comprehensive overview of the descriptive characteristics observed across the sampled financial markets. Notably, the Johannesburg Stock Exchange (JSE) and Borsa Istanbul 100 Index (BIST 100) exhibited the lowest mean price volatilities, indicating relatively stable pricing behaviors. Conversely, markets such as the Nasdaq Composite, the CAC 40, and the DAX demonstrated positive Realised Volatility (RV), suggesting higher levels of price fluctuations. Upon closer examination of Table 2, it becomes apparent that less developed stock markets, exemplified by the JSE and BIST 100, tend to exhibit lower trading volumes compared to their more developed counterparts. This observation underscores the influence of market maturity on trading activity, with developed markets typically witnessing higher levels of investor participation and liquidity.

Furthermore, the analysis reveals a left-skewed distribution of price returns across all sampled financial markets, with the CAC 40 displaying the least variability in this regard. However, it is noteworthy that the price returns of the BIST 100 stand out due to the presence of several extreme outliers, contributing to an exceptionally high kurtosis value of 1202.43. This observation aligns with the elevated level of Realised Volatility (13.1% standard deviation) observed in the BIST 100, indicating heightened price instability within this market segment.

To further explore the dynamic nature of Realised Volatility (RV) and trading volume (VOL) over time, Table 3 is presented below, offering insights into the temporal evolution of these critical market metrics."

Table 3. Unit root test results

			Test critical Values		
		Augmented Dickey-Fuller test t-Statistic	1% level	5% level	10% level
JSE	RV	-39.54(0.000) *	-3.435	-2.863	-2.567
	VOL	-13.05(0.000) *	-3.435	-2.863	-2.567
BIST 100	RV	-34.97 (0.000) *	-3.435	-2.863	-2.567
	VOL	-3.59(0.005) *	-3.435	-2.863	-2.567
CAC 40	RV	-36.09 (0.000) *	-3.435	-2.863	-2.567
	VOL	-6.92(0.000) *	-3.435	-2.863	-2.567
DAX	RV	-36.54 (0.000) *	-3.435	-2.863	-2.567
	VOL	-6.712(0.000) *	-3.435	-2.863	-2.567
NASDAQ	RV	-11.14(0.000) *	-3.435	-2.863	-2.567
	VOL	-20.68(0.000) *	-3.435	-2.863	-2.567

*MacKinnon (1996) one-sided p-values. *Significant at 5%

From table 3, the mean, variance and covariance of RV and VOL stay constant with time evident in the ADF values which are less than the 5% significance value. Thus, the model used in this study purely captures the relationship between RV and VOL. Therefore, there were no seasonality, error mean or de-trending shortcomings in the variables. Table 4 below presents the findings of the Granger causation effect between RV and VOL for the different financial markets under consideration.

Table 4. Pairwise Granger Causality Tests

	Granger Causality Hypothesis	Observations	F-Statistic	P-value
JSE	VOL does not Granger Cause RV	1248	2.884	0.056
	RV does not Granger Cause VOL		1.674	0.187
BIST 100	VOL does not Granger Cause RV	1243	0.26	0.77
	RV does not Granger Cause VOL		0.995	0.37
CAC 40	VOL does not Granger Cause RV	1280	4.872	0.007*
	RV does not Granger Cause VOL		5.164	0.005*
DAX	VOL does not Granger Cause RV	1266	2.806	0.06
	RV does not Granger Cause VOL		2.418	0.089
Nasdaq	VOL does not Granger Cause RV	1256	1.44	0.237
	RV does not Granger Cause VOL		0.266	0.766

From the results above in table 4, the lag values of RV and VOL do not provide any significant prediction of each other with the exception of the CAC 40. In essence, apart from the CAC 40, the bi-directional relationship between RV and VOL are not significant at 5%. Hence RV and VOL cannot be used to predict each other. This finding contradicts the findings of Adhikari (2020); Ozdemir (2020); and Choi, Kang & Yoon (2022) who found a significant relationship between RV and VOL. However, price patterns in the CAC 40 relays significant volume information and vice versa. The bi-directional effect in the CAC 40 also conveys important information through RV and VOL. These findings extents the proposition put forth by Enow (2022) who contends that the volatility between stock market prices are independent of each other. Considering that some authors (Gueyie, Mouhamadou & Mamadou, 2022; Alhussayen, 2022; Chiang, Qiao & Wong, 2009) also found an insignificant bi-directional relationship between RV and VOL, it can be suggested that the relationship between RV and VOL is not static but dynamic in nature. The table below highlights the forecast proportions for each variable.

Table 5. MSE and MAE PARCH model for RV and VOL

	Model	Forecast variable	MSE	MAE	Forecast proportion (%)
JSE	PARCH	RV	0.016	0.012	0.006
		VOL	1.650	1.040	0.280
BIST 100	PARCH	RV	0.313	0.016	0.0008
		VOL	2.010	1.420	35.430
CAC 40	PARCH	RV	0.012	0.008	0.007
		VOL	3.750	2.280	0.490
DAX	PARCH	RV	0.013	0.0089	0.010
		VOL	3.790	2.370	5.320
Nasdaq	PARCH	RV	0.016	0.011	0.0015
		VOL	1.580	1.290	4.430

Table 5 above presents an alternative model for exploring the relationship between RV and VOL. The MSE values are well greater than the MAE values recorded as seen above. However, the forecasting proportions are very low with 35% being the highest value as seen in the BIST 100. In all the RV cases, the forecasting proportion is close to zero inferring that VOL cannot be used to predict RV. Also, the VOL forecasting proportions are very low with the highest number recorded in BIST 100. This may be due to the higher standard deviation value reported in table 2. The results in table 5 strengthens the findings in table 4 where there are no meaningful relationship and causation between RV and VOL in all the sampled financial markets with the exception of the CAC 40.

5. Discussion

The present study delves into the nuanced dynamics governing the relationship between realized volatility (RV) and trading volume (VOL) across a spectrum of international stock markets. Departing from conventional scholarly discourse and theoretical frameworks, our research unveils a surprising absence of a significant correlation between RV and VOL across the majority of the sampled markets, with a notable exception found in the CAC 40. This departure challenges established notions such as the sequential information theory and mixed distribution hypothesis, which traditionally propose a bidirectional connection between RV and VOL, suggesting that the sequential release of new information influences both trading volumes and market prices.

The observed divergence from an expected RV-VOL relationship in most markets hints at the limitations in using these metrics as predictive indicators of each other. This departure prompts a critical reevaluation of traditional perspectives on price formation and transmission mechanisms in financial markets. Instead, our findings suggest a scenario wherein new information spreads rapidly and uniformly among market participants, leading to simultaneous reactions in both RV and VOL. This phenomenon likely stems from increased market integration, both regionally and globally, as well as the prevalence of financial contagion, which facilitates swift information dissemination across markets.

Moreover, our study sheds light on the intricate complexities underlying market dynamics, emphasizing the multifaceted nature of RV-VOL interactions. While the absence of a significant relationship between RV and VOL in most markets challenges traditional models, it also underscores the need for more nuanced methodologies that account for evolving market conditions and structural transformations. Furthermore, the identification of a robust RV-VOL relationship in the CAC 40 underscores the potential heterogeneity across markets, highlighting the importance of market-specific analysis in uncovering underlying patterns and predictive relationships. Moving forward, our research serves as a catalyst for future investigations, urging scholars and practitioners alike to delve deeper into the evolving landscape of market dynamics and its implications for investment strategies and risk management practices.

However, it is noteworthy that the CAC 40 stands out as an exception, demonstrating a significant bidirectional relationship between RV and VOL. This finding underscores the intrinsic interconnectedness of price volatility and trading volume within this specific market, highlighting their potential utility as predictive indicators for each other. This underscores the importance of considering market-specific factors and dynamics when analyzing the relationship between RV and VOL, emphasizing the need for nuanced, context-aware approaches in understanding market behavior.

6. Conclusion, Limitations, and Suggestions

Conclusion

The aim of this study was to investigate the relationship between RV and VOL to ascertain or rebut the sequential information and mixed distribution theories, as well as the findings of prior literature using the most recent data. The results of this study reveal that there is no meaningful relationship between RV and VOL; hence, they cannot be used as estimators to predict one another. Contrary to the study of Chiang, Qiao & Wong (2009) and in line with the study of Gueyie, Mouhamadou & Mamadou (2022); Alhussayen (2022), sequential information theory and mixed distribution theory are irrelevant, at least in the current dispensation. The findings of this study suggest that new information entering financial markets tends to be disseminated faster to active market participants, probably due to regional and global integration. Also, financial market contagion, which has increased recently, may also be a propelling factor for new information transmission.

In conclusion, this study challenges the traditional theories of price formation and information dissemination in financial markets by finding no significant relationship between realized volatility and trading volume in most international stock markets. While previous literature and theories have suggested a bi-directional relationship between RV and VOL, the findings of this study indicate that new information may be disseminated more uniformly across market participants, leading to simultaneous reactions in both RV and VOL. However, the CAC 40 exhibited a significant relationship between RV and VOL, suggesting market-specific dynamics at play.

Limitations and suggestions

Despite the insights provided by this study, there are several limitations that should be acknowledged. Firstly, the study focused on a limited number of international stock markets, which may not be representative of global market dynamics. Additionally, the analysis only considered data up to March 2023, and market conditions may have evolved since then. Moreover, the study employed specific methodologies and models, which may have their own limitations and assumptions.

Future research in this area could explore a broader range of international stock markets and consider a longer time horizon to capture evolving market dynamics. Additionally, alternative methodologies and models could be employed to further investigate the relationship between RV and VOL. Furthermore, qualitative research could be conducted to explore the underlying factors driving the observed patterns in RV and VOL, particularly in markets where significant relationships were found. Finally, considering the increasing importance of technological advancements and algorithmic trading in financial markets, future research could examine how these factors influence the relationship between RV and VOL.

References

Adhikari, P. (2020). The dynamic relationship between stock returns and trading volumes in Nepalese stock market. *Management Dynamics, 23*(2), 161–172.

Alhussayen, H. (2022). The Relationship Between Trading Volume and Market Returns: A VAR/Granger Causality Testing Approach in the Context of Saudi Arabia. *Organizations and Markets in Emerging Economies*, 13(1), 260-275.

An, Y., Huang, L., & Li, Y. (2022). The Asymmetric Overnight Return Anomaly in the Chinese Stock Market. *Journal of Risk and Financial Management*, 15(11), 534.

Bajzik, J. (2020). Trading Volume and Stock Returns: A Meta-Analysis. IES Working Paper, No. 45/2020, Charles University in Prague, Institute of Economic Studies (IES), Prague.

Chiang, T.C., Qiao, Z., & Wong, W.K. (2009). New Evidence on the Relation between Return Volatility and Trading Volume. *Journal of Forecasting*, 1-14.

Choi, K.H., Kang, S.H., & Yoon, S.M. (2022). Relationship between Stock Returns and Trading Volume: Domestic and Cross-Country Evidence in Asian Stock Markets. *International Journal of Electrical Engineering*, 2, 57-63.

Duarte, J.J., Montenegro González, S. & Cruz, J.C. (2021) Predicting Stock Price Falls Using News Data: Evidence from the Brazilian Market. *Comput Econ,* 57, 311–340.

Enow, S.T. (2021). The impact of covid-19 on market efficiency: a comparative market analysis. *Eurasian Journal of Economics and Finance*, 9(4), 235-244

Enow, S.T. (2022). Price Clustering in International Financial Markets during the Covid-19 Pandemic and its implications. *Eurasian Journal of Economics and Finance*, 10(2), 46-53.

Enow, S.T. (2023). Investigating Causality and Market Contagion During Periods of Financial Distress and Its Implications. *Journal of Accounting, Finance and Auditing studies*, 9(1), 140-153

Fama, E.F., 1965. The behavior of stock-market prices. *The Journal of Business,* 38(1),34-105.

Gueyie, J., Mouhamadou, S. D., & Mamadou, F.D. (2022). Relationship between Stock Returns and Trading Volume at the Bourse Régionale des Valeurs Mobilières, West Africa. *International Journal of Financial Studies* 10(113), 1-16.

Gupta, S., Das, D., Hasim, H., & Tiwari, A. (2018). The Dynamic Relationship Between Stock Returns and Trading Volume Revisited: A MODWT-VAR Approach. *Finance Research Letters,* 27*,* 91-98.

He, X., & Velu, R. (2014). Volume and Volatility in a Common-Factor Mixture of Distributions Model. *The Journal of Financial and Quantitative Analysis*, *49*(1), 33–49.

Hodson, T.O. (2022). Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. *Geosci. Model Dev*., 15, 5481–5487.

Holder, C., Leon, H., & Wood, C. (1990). Testing for non-stationarities in macroeconomic time series data. *Social and Economic Studies*, 39(4), 83–105. http://www.jstor.org/stable/27864968

Ligocká, M. (2019). The empirical relationship between stock returns and trading volume: the case of polish companies. *Acta academica karviniensia*, 19(2),42-53

O'Hara, M. (2015). High frequency market microstructure. *Journal of Financial Economics*, 116(2), 257-270.

Nkoro, E., & Uko, A.K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. Journal of Statistical and Econometric, 5(4), 63-91.

Ozdemir, L. (2020). Volatility Spillover Between Stock Prices and Trading Volume: Evidence from the Pre-, In-, and Post Global Financial Crisis Periods. *Front. Appl. Math. Stat*. 5(65), 1-8.

Preis, T., Moat, H. & Stanley, H. (2013). Quantifying Trading Behavior in Financial Markets Using *Google Trends*. *Sci Rep,* 3, 1684.

Roll, R., & Ross, S. A. (1980). An Empirical Investigation of the Arbitrage Pricing Theory. *The Journal of Finance*, *35*(5), 1073–1103. https://doi.org/10.2307/2327087.

Song, X. & Taamouti, A. (2019). A Better Understanding of Granger Causality Analysis: A Big Data Environment. *Oxford Bulletin of Economics & Statistics*, 81(4), 911-936.

Tam, P.S. (2013). Finite-sample distribution of the augmented Dickey–Fuller test with lag optimization. *Applied Economics*, 45(24), 3495-3511.