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PRICE CLUSTERING IN INTERNATIONAL FINANCIAL MARKETS DURING THE COVID-19 PANDEMIC AND ITS IMPLICATIONS

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Abstract

The proliferation of trading strategies in many security markets has led to intense scrutiny of market price movements and their distribution. The increase in trading activities across financial markets around the world has enhanced the likelihood of behavioral biases and the tendency for stock prices to cluster around certain intervals. The purpose of this study was to investigate price clustering and psychological barriers in the NASDAQ Index, CAC 40 Index, DAX Index, JPX-Nikkei Index 400, SSE Index, and the JSE Index from 2/01/2020 to 31/12/2021, during the height of the COVID-19 pandemic. Using chi-square and a Kolmogorov-Smirnov tests, the findings revealed evidence of price clustering in the JPX-Nikkei 400 and JSE Index, with further evidence of psychological barriers in the form of support and resistance in the JSE Index. This result implies that a retracement entry strategy is suitable for the JPX-Nikkei Index 400 and JSE Index, and a breakout strategy should be used in the NASDAQ Index, CAC 40 Index, DAX Index, and SSE Index. Security markets should actively promote UTP in order to promote price efficiencies.

Keywords: Price Clustering, Psychological Barrier, Market Efficiency, Chi-Square, Kolmogorov-Smirnov Test, Financial Markets

JEL Classifications: D53, G15, G32

1. Introduction

Many theorists have actively argued that the behavior of security market prices in financial markets has trends that give clues to the behavior of future market prices (Wong *et al.* 2003; Lin *et al.* 2010; Monteiro, 2014; Stankovic *et al.* 2015). Advocates of this theory argue that security market prices can be predicted, provided that the patterns can be appropriately understood (Fama, 1965). As such, this concept has been coined as technical analysis, which looks at historical price data as a guide for future price movements (Shynkevich *et al.* 2017). In technical analysis, price charts are used as a valuable tool to interpret the direction of trade and entry and exit points in the market. Despite its relevance, the technical approach involves a much subjective judgment. Many investment practitioners and analysts still believe that stock prices can never be predicted because they are not set as a result of some underlying factors but merely statistical ups and downs, known as a random walk (Caporin *et al.* 2011; Shah *et al.* 2019). The random walk hypothesis proposes that the behavior of security prices is unpredictable and that there is

no meaningful relationship between the past market price behavior and future prices (Fama, 1965). The argument that market prices for securities are independent was supported by Kendall and Hill (1953), who claimed that stock prices behave as though they were produced by a planned roulette wheel, with each outcome being statistically independent of the past. The evidence of cyclical security prices is merely statistical and unconnected (Rozeff, 1975). The proposition put forward by Kendall and Hill (1953) accedes to the efficient market hypothesis theory, where all available sensitive information is reflected in security prices. Therefore, no investor can consistently outperform the market because stock prices are appropriate based on the available information (Nwaolisa and Kasie, 2012). In other words, investors cannot consistently beat the market, which makes it impossible to purchase undervalued stocks and sell overvalued stocks using real-time information. Hence, fundamental analysis and market timing are not helpful. In sharp contrast to the efficient market hypothesis and random walk, price clustering has been widely observed in many financial markets (Ascioglu *et al.* 2007; Lobão *et al.* 2019; Blau and Griffith, 2016; Hu *et al.* 2017).

Price clustering is a phenomenon where security prices tend to conglomerate more around certain intervals and deviate from other intervals (Holý and Tomanová, 2022). According to Blau and Griffith (2016, there are mainly two reasons for price clustering: the preference for round-digits figures to attenuate cognitive processing cost and a preference to mitigate negotiated cost. The presence of price clustering in a market has both positive and negative effects. Where empirical evidence supports price clustering, investors, analysts, and investment practitioners can take advantage of market price aggregation around certain intervals and trade with the information (Ma and Tanizaki, 2022). That is to say, investors can purchase stock below the grouping price and sell when the prices move to the group. However, price clustering severely disrupts equilibrium prices, which may seriously impact financial markets (Blau and Griffith, 2016).

Against this background, there is a growing interest among finance researchers in the impact of COVID-19 on financial markets that may be associated with price resolution (Demir *et al.* 2020). As well documented by Mandel and Veetil (2020), economic recovery is based on the formation of equilibrium prices. In line with the study of Hsu *et al.* (2018), this study contributes to the growing call for unlisted trading privileges (UTP) in markets where price clustering is discernible as fundamental prices are distorted due to cognitive biases. Promoting UTP serves as a measure to enhance price and market efficiency, which is essential for asset pricing. In addition, this study proposes a suitable trading strategy in which price clustering is evident. Finally, the study advances the literature on cognitive biases observed in financial markets during the COVID-19 era. As documented by Alzyadat and Asfoura (2021), the pandemic has disrupted many financial markets where price clustering is perceived to be present. The rationale of this study stems from the concept of market efficiency, which states that active managers cannot consistently outperform the market because prices tend to adjust to new information. However, there has been empirical evidence of price clustering in many financial markets for periods. This study also advances this frontier to the COVID-19 era to validate or disapprove the market efficiency hypothesis in another, to make suitable recommendations for investment practitioners. The next section highlights the literature review followed by the methodology, findings, and conclusion.

2. Literature review

The theoretical foundation used in this study is the hypothesis of market efficiency. The market efficiency theory states that all available information is already built into the current market price of financial security. Investment practitioners, market participants, and investors cannot consistently outperform the market (Fama, 1965). According to this theory, prices will adjust quickly to any new information in the market (Fama, 1965). Also, price aberrations are corrected quickly because investors will buy and sell incorrectly priced assets in a concise period. Market efficiency does not imply that security prices cannot deviate from the true market value. On the contrary, there can be high deviations, but this divergence is purely random and will quickly adjust to its original value. Also, investors can beat the market, but no particular investor can consistently

outperform the market (McManus, 2020). Given the number of investors in financial markets, the law of probability, in congruence with the market efficiency theory, suggests that market participants can beat the market consistently over a long period only by chance and not because of any investment strategy. To this end, it can be gleaned that market inefficiencies justify active management (Ang *et al.* 2011). With market efficiencies, fundamental analysis is ineffective and irrelevant. Therefore, relying on public information for investment appraisal decisions is not likely to be of significant help (Malkiel, 1989).

On the contrary, some experts still believe that market analysis and information about security are essential ingredients in the stock selection process (Petrusheva and Jordanoski, 2016). According to Kelikume *et al.* (2020), financial markets are not efficient because fundamentals still drive markets in the long term. The expectations of these fundamentals still move the market considerably (Teles and Leme, 2009). Trading on undervalued fundamentals drivers may seem beneficial in the future because investors perceive that these values may increase. The aspect of market sentiments further compounds the debate that markets are rarely efficient because the concepts of pessimism and optimism cannot be overlooked. Therefore, we expect to see price clustering in financial markets, especially during the era of COVID-19, where there is a possibility that investors may have been driven by behavioral biases such as greed and fear. As already mentioned in the introduction, price clusters have pros and cons. Table 1 highlights empirical studies that implement similar methods to arrive at findings on price clustering conducted during the COVID-19 pandemic.

Table 1. List of studies on price clustering

Study	Model	Period	Country	Findings
Ascioglu *et al.* (2007)	Multivariate analysis	01/2003-10/2003	Japan	Significant evidence of price clustering, but not associated with direct negotiations.
Lobão *et al.* (2019)	Univariate and multivariate analysis	31/07/2007-25/03/2009.	Austria, Denmark, Finland, Germany, Greece, Italy, Portugal, Romania, United States, and Spain.	Evidence of price clustering across the United States and European markets contradicts the market efficiency theory.
Blau and Griffith (2016)	Multivariate test	1995-2012	United States	Presence of price clusters that is related to volatility.
Hu *et al.* *(2017)*	Multivariate test	2003-2009	China	No evidence of price clustering for high-frequency trading, which is in line with efficient market hypothesis.
Ma and Tanizaki (2022)	Linear model with hour dummies	2015-2020	Japan	Presence of clusters around the '00' digits.

Although studies listed in Table 1 are relevant, there is still a gap in the literature on whether there is any evidence of price clustering during the COVID-19 pandemic, which could have significant implications for asset pricing. Therefore, this study fills the knowledge gap by exploring the concept of price clustering in financial markets from January 2020 to December 2021, which is linked to the COVID-19 pandemic. The presence of price clustering during periods of uncertainty such as the pandemic results in averaging down, where market participants use

round numbers as a proxy for the true value of the security (Bourghelle and Cellier, 2007). This behavior is usually a result of a lack of knowledge and greed, leading to serrated price distribution (Bourghelle and Cellier, 2007). The following section outlines the blueprint used in investigating this behavioral abnormality.

3. Methodology

The sample consists of the NASDAQ Index, the French stock market index (CAC 40 Index), Frankfurt stock exchange index (DAX Index), Japanese stock index (JPX-Nikkei Index 400), Shanghai stock exchange (SSE Index), and Johannesburg stock exchange (JSE Index). These markets represent the largest financial markets in the world on four continents. The opening, highest, and closing prices for each index are retrieved from Yahoo Finance from 02/01/2020 to 31/12/2021. This period formed the crux of the COVID-19 pandemic. The empirical distribution of the opening, highest, and closing prices are compared to a uniform distribution to determine whether they occur at whole numbers and to analyze price clustering (Kong *et al.* 2011). More specifically, price clustering is evident when there is a significant rounding up or -down in the observed price distribution of security prices, resulting from a lack of knowledge about the asset price (Harris, 1991).

For the analysis, chi-square and Kolmogorov-Smirnov tests are appropriate because the former compares the square deviation between the expected and observed price distributions, while the latter is suitable for investigating the distribution of data sets (Lanzante, 2021). Chi-square and Kolmogorov-Smirnov tests are deemed appropriate because the latter compares the square deviation between the expected and observed price distributions, while the Kolmogorov-Smirnov test is suitable for investigating the distribution of data sets (Mitchell, 1971). These methods are suitable for analyzing discrete sets of prices with a uniform distribution (Harris, 1991). The findings of the Kolmogorov-Smirnov test and the chi-square test are in harmony, demonstrating robust results and meaningful inference. Both Kolmogorov-Smirnov and chi-square tests report significant positive results, indicating the presence of price clustering. A psychological barrier test is also carried out using the support and resistance level to determine if there are points in the market where prices change repeatedly. A bullish run in financial markets turns bearish when it meets resistance, and a bearish move turns bullish when it meets support. Chi-square and a Kolmogorov-Smirnov tests are also used to investigate psychological barriers. The formulas for a chi-square test and a Kolmogorov-Smirnov test are shown in Equations (1) and (2), respectively.

$$\sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \sim x^2(n-1) \tag{1}$$

, where O_i is the observed frequency and $E_i$is the expected frequency, whereas n is the number of variables and *x* is the random variable.

$$\text{Max} \mid F_0(X) - F_r(X) \mid \sqrt{n} \tag{2}$$

, where $F_0(X)$ is the observed frequency distribution and $F_r(X)$ is the theoretical frequency distribution, and n is the number of variables and *x* is the random variable. The results of the empirical analysis are presented in the next section.

4. Findings

Table 2 presents the findings from the chi-square and Kolmogorov-Smirnov tests. From the results, price clustering was evident in the JPX-Nikkei 400 and JSE during the period considered. The significance is evident in the p-values that are less than 5% from the chi-square and Kolmogorov-Smirnov test, hence inferring the presence of price resolution in these markets. These findings agree with the findings of Ascioglu *et al.* (2007), Lobão *et al.* (2019), and Ma and Tanizaki (2022) but contradict the findings of Hu *et al.* (2017), although they were not explicitly

conducted during the pandemic era. Results also support the findings of Enow (2021), stating that the JPX-Nikkei Index 400 is informationally inefficient, and investors can use fundamental analysis to profit. However, findings in the NASDAQ Index, CAC 40 Index, DAX Index, and SSE Index are mixed since the Kolmogorov-Smirnov test reported a significant positive result, whereas the chi-square test revealed an insignificant finding. These findings are also in line with the results of Enow (2021), which revealed that the NASDAQ Index, CAC 40 Index, and DAX Index are informationally efficient during the pandemic, and therefore price clusters are not expected.

A psychological barrier is also established to determine the presence of support and resistance in the selected markets. As seen in Table 2, there is sufficient evidence of psychological barriers in the JSE, which is supported by significant p-values for both the chi-square and a Kolmogorov-Smirnov tests. In rare scenarios, the presence of psychological barriers may also be inferred to the JPX-Nikkei 400 because of mixed results in chi-square and a Kolmogorov-Smirnov tests. Therefore, price clustering in the JSE and JPX Nikkei Index 400 and psychological barriers in the JSE exist.

Table 2. Findings from the chi-square and Kolmogorov-Smirnov tests

Nasdaq Index				
	Open	High	Low	Close
Chi-square	10.35	6.74	5.52	4.81
P-value	0.32	0.66	0.79	0.85
Kolmogorov-Smirnov	70.72	72.19	71.56	117.67
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance	2.85	5.94		
P-value	0.97	0.00		
Support	1.31	3.63		
P-value	0.998	0.00		
CAC 40 Index				
	Open	High	Low	Close
Chi-square	7.76	10.51	10.31	12.59
P-value	0.56	0.31	0.33	0.18
Kolmogorov-Smirnov	70.24	71.02	74.40	105.33
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance level	1.281	3.768		
P-value	0.998	0.000		
Support level	2.03	5.27		
P-value	0.99	0.00		
JPX-Nikkei Index 400				
	Open	High	Low	Close
Chi-square	219.90	230.98	205.32	207.60
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
Kolmogorov-Smirnov	69.16	69.91	73.60	118.06
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance level	0.42	2.04		
P-value	0.99	0.02		
Support level	1.08	2.97		
P-value	0.99	0.00		

Note: * denotes significance at 5%.

Tabe 2. Continued

DAX Index				
	Open	High	Low	Close
Chi-square	5.64	13.22	4.89	11.10
P-value	0.78	0.15	0.84	0.27
Kolmogorov-Smirnov	72.24	71.75	78.90	114.95
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance level	2.72	7.22		
P-value	0.97	0.00		
Support level	0.75	2.75		
P-value	0.99	0.00		
JSE Index				
	Open	High	Low	Close
Chi-square	527.64	58.33	100.17	262.26
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
Kolmogorov-Smirnov	96.00	79.15	220.96	161.16
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance level	29.88	20.30		
P-value	*(0.00)	*(0.00)		
Support level	19.85	15.91		
P-value	*(0.02)	*(0.00)		
SSE Index				
	Open	High	Low	Close
Chi-square	13.69	6.70	9.53	7.01
P-value	0.13	0.67	0.39	0.64
Kolmogorov-Smirnov	73.31	71.74	81.92	117.83
P-value	*(0.00)	*(0.00)	*(0.00)	*(0.00)
	Psychological Barriers			
	Chi-square	Kolmogorov-Smirnov		
Resistance level	2.12	6.16		
P-value	0.99	0.00		
Support level	2.01	5.32		
P-value	0.99	0.00		

Note: * denotes significance at 5%.

5. Conclusion

The purpose of this study was to investigate the presence of price clustering and psychological barriers in the NASDAQ Index, CAC 40 Index, DAX Index, JPX-Nikkei Index 400, SSE Index, and JSE Index from a period of 0f2/01/2020 to 31/12/2021, which is associated with the COVID-19 pandemic. The study used a combination of Chi-square and Kolmogorov-Smirnov tests to document a robust finding. The results indicated that there was no evidence of price clustering in the NASDAQ Index, CAC 40 Index, DAX Index, and SSE Index, but significant price clustering in the JPX-Nikkei Index 400 and JSE Index with further evidence of psychological barriers in the form of support and resistance in the JSE Index.

From these findings, investors and market participants can trade profitably in the JSE and JPX-Nikkei 400 using a retracement entry strategy to profit from price movements. Retracements, which are short-term price corrections in the upward and downward trends, will be of significant value in the JSE and JPX-Nikkei 400 financial markets because they provide profitable

opportunities by entering into trades in the original trend direction at a better price before the run continues. However, a breakout strategy will be preferred in the NASDAQ Index, CAC 40 Index, DAX Index, and SSE Index because of the absence of price clustering and psychological barrier. Additionally, advisory authorities should actively promote the concept of UTP to promote market efficiency.

References

Alzyadat, J.A. and Asfoura, D., 2021. The effect of COVID-19 pandemic on stock market: an empirical study in Saudi Arabia. *Journal of Asian Finance, Economics and Business,* 8(5), pp. 913-921. https://doi.org/10.13106/jafeb.2021.vol8.no5.0913

Ang, A., Goetzmann, W.N., and Schaefer, S.M., 2010. The efficient market theory and evidence: implications for active investment management. *Foundations and Trends in Finance,* 5(3), pp. 157-242. http://dx.doi.org/10.1561/0500000034

Ascioglu, A., Comerton-Forde, C., and McInish, T., 2007. Price clustering on the Tokyo Stock Exchange. *The Financial Review,* 42, pp. 289-301. https://doi.org/10.1111/j.1540-6288.2007.00172.x

Blau, B.M. and Griffith, T.G., 2016. Price clustering and the stability of stock prices. *Journal of Business Research,* 69(10), pp. 3933-3942. https://doi.org/10.1016/j.jbusres.2016.06.008

Bourghelle, D. and Cellier, A., 2007. *Limit order clustering and price barriers on financial markets: empirical evidence from Euronext*. Working Paper. Lille: University of Lille. [online] Available at: <https://www.semanticscholar.org/paper/Limit-Order-Clustering-and-Price-Barriers-on-from-Cellier-Bourghelle/472e9c0b09515c256b96db6ee1ae3684ab09f2fc> [Accessed on 4 May 2022].

Caporin, M., Ranaldo, A., and Magistris, P.S., 2011. On the predictability of stock prices: a case for high and low prices. *Journal of Banking and Finance,* 37(12), pp. 5132-5146. https://doi.org/10.1016/j.jbankfin.2013.05.024

Demir, E., Bilgin, M.H., Karabulut, G., and Doker, A.C., 2020. The relationship between cryptocurrencies and COVID-19 pandemic. *Eurasian Economic Review*, 10, pp. 349-360. https://doi.org/10.1007/s40822-020-00154-1

Enow, S.T., 2021. The impact of COVID-19 on market efficiency: a comparative market analysis. *Eurasian Journal of Economics and Finance,* 9(4), pp. 235-244. https://doi.org/10.15604/ejef.2021.09.04.003

Fama, E.F., 1965. The behavior of stock-market prices. *The Journal of Business,* 38(1), pp. 34-105. https://doi.org/10.1086/294743

Harris, L., 1991. Stock price clustering and discreteness. *The Review of Financial Studies*, 4(3), pp. 389-415. https://doi.org/10.1093/rfs/4.3.389

Holý, V. and Tomanová, P., 2022. Modeling price clustering in high-frequency prices. *Quantitative Finance*, pp. 1-15.https://doi.org/10.1080/14697688.2022.2050285

Hsu, S., Chung, H., and Chen, W., 2018. Market competition and price clustering: evidence from the ETF market. *Journal of Financial Studies*, 26(4), pp. 1-44. http://dx.doi.org/10.6545%2fJFS.201812_26(4).0001

Hu, B., Jiang, C., McInish, T., and Zhou, H., 2017. Price clustering on the Shanghai Stock Exchange. *Applied Economics,* 49(28), pp. 2766-2778. https://doi.org/10.1080/00036846.2016.1248284

Kelikume, I., Olaniyi, E., and Iyohab, F.A., 2020. Efficient market hypothesis in the presence of market imperfections: evidence from selected stock markets in Africa. *International Journal of Management, Economics and Social Sciences,* 9(1), pp. 37-57. https://doi.org/10.32327/IJMESS/9.1.2020.3

Kendall, M.G. and Hill, A.B., 1953. The analysis of economics time series, part i: prices. *Journal of the Royal Statistical Society. Series A (General)*, 116(1), pp. 11-34. https://doi.org/10.2307/2980947

Kong, V.X., Leung, C.C.H., Tse, W.M., and Zheng, T.X., 2011. Price clustering in earning announcements and trading time in Hong Kong stock market. *Investment Management and Financial Innovations*, 8(1), pp. 219-233.

Lanzante, J.R., 2021. Testing for differences between two distributions in the presence of serial correlation using the Kolmogorov–Smirnov and Kuiper's tests. *International Journal of Climatology,* 41(14), pp. 6314-6323. https://doi.org/10.1002/joc.7196

Lin, Z.W., Chen, C., and Huang, C.S., 2010. Profits from technical analysis: an empirical evidence of precious metal markets. *Investment Management and Financial Innovations,* 7(4), pp. 131-141.

Lobão, J., Pacheco, L. and Alves, L., 2019. Price clustering in bank stocks during the global financial crisis. *Scientific Annals of Economics and Business,* 66(4), pp. 465-486. https://doi.org/10.47743/saeb-2019-0043

Ma, D. and Tanizaki, H., 2022. Intraday patterns of price clustering in Bitcoin. *Financial Innovation,* 8(4), pp. 1-25. https://doi.org/10.1186/s40854-021-00307-4

Malkiel, B.G., 1989. Is the stock market efficient? *Science,* 243(4896), pp. 1313-1318. https://doi.org/10.1126/science.243.4896.1313

Mandel, A. and Veetil, V., 2020. The economic cost of COVID lockdowns: an out-of-equilibrium analysis. *Economics of Disasters and Climate Change,* 4, pp. 431-451. https://doi.org/10.1007/s41885-020-00066-z

McManus, P.M., 2020. *How efficient is market pricing: can investors beat the market? Further, are prices always right as stated in the efficient market hypothesis*? Unpublished Honors Theses and Capstones. New Hampshire: University of New Hampshire, United States. [online] Available at: <https://scholars.unh.edu/honors/510> [Accessed on 1 April 2022].

Mitchell, B., 1971. A comparison of Chi-square and Kolmogorov-Smirnov tests. *The Royal Geographical Society*, 3(4), pp. 237-241.

Monteiro, J. D.D., 2014. *Technical analysis: wisdom or wizardry*. Unpublished Master's Thesis. Lisbon: ISCTE Business School, Portugal. [online] Available at: <http://hdl.handle.net/10071/10130> [Accessed on 1 April 2022].

Nwaolisa, E.F. and Kasie, E.G. 2012. Efficient market hypothesis: a historical perspective (a study of Nigerian capital market). *Kuwait Chapter of Arabian Journal of Business and Management Review,* 1(8), pp. 76-86.

Petrusheva, N. and Jordanoski, I., 2016. Comparative analysis between the fundamental and technical analysis of stocks. *Journal of Process Management and New Technologies,* 4(2), pp. 26-31. https://doi.org/10.5937/JPMNT1602026P

Rozeff, M.S., 1975. The money supply and the stock market: the demise of a leading indicator. *Financial Analysts Journal,* 31(5), pp. 18-26. https://doi.org/10.2469/faj.v31.n5.18

Shah, D., Isah, H., and Zulkernine, F., 2019. Stock market analysis: a review and taxonomy of prediction techniques. *International Journal of Financial Studies,* 7(6), pp. 1-22. https://doi.org/10.3390/ijfs7020026

Shynkevich, Y., McGinnity, T.M., Coleman, S.A., Belatreche, A., and Li, Y., 2017. Forecasting price movements using technical indicators: Investigating the impact of varying input window length. *Neurocomputing,* 264, pp. 71-88. https://doi.org/10.1016/j.neucom.2016.11.095

Stankovic, J., Markovic, I., and Stojanovic, M., 2015. Investment strategy optimization using technical analysis and predictive modelling in emerging markets. *Procedia Economics and Finance*, 19, pp. 51-62. https://doi.org/10.1016/S2212-5671(15)00007-6

Teles, V.K. and Leme, M.C., 2009. Fundamentals or market sentiment: what causes country risk? *Applied Economics,* 1(9), pp. 1-11. https://doi.org/10.1080/00036840801964518

Wong, W. K., Manzur, M., and Chew, B.K., 2003. How rewarding is technical analysis? Evidence from Singapore stock market. *Applied Financial Economics*, 13(7), pp. 543-551. https://doi.org/10.1080/0960310022000020906