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Financial Contagion and Duration: Evidence from International Financial Markets

Samuel Tabot Enow*

Research Associate, IIE Varsity College, South Africa. *Email: enowtabot@gmail.com

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ABSTRACT

The overlapping claims of susceptible shocks affecting multiple financial markets have been well documented in finance literature. These shocks are channelled through several propagation mechanisms due to global integration. The purpose of this study was to investigate financial contagion and the relative duration effect. A variance decomposition blueprint was applied to achieved the objective of this study for a sample of five financial markets. The sampling timeframe was from January 01, 2017 to December 31, 2018 characterised by pre Covid-19 pandemic era and January 01, 2020-December 31, 2021 for the Covid-19 pandemic. The results indicate weak endogenous relationship between financial markets before the pandemic. However, significant contagion was observed during the Covid-19 pandemic which last for several periods in some markets. In line with this findings, there may be no portfolio diversification benefits during periods of financial distress. In essence, central banks should implement mechanism absorb economic shocks and facilitate easy access to liquidity during periods of financial distress.

Keywords: Financial Contagion, Variance Decomposition, Financial Markets, Market Shocks, Duration
JEL Classifications: G1, G2, G4

1. INTRODUCTION

Financial market contagions have always spell bad news in many economic setting because global economies and financial markets are arguably more interconnected than any point in history (Claessens, 2019). Although there might be a lot of benefits to this interconnectedness, problems that may arise can outweigh the benefits. This is because issues in one part of the globe can have unexpected consequences elsewhere. The 2007-2008 financial crisis seemed to be contained in one market but spread overwhelmingly to unrelated markets (Gilson and Kraakman, 2014). Also, the 2007-2008 financial crisis had a ripple effect globally as a result of the wider spread in the debt ownership linked to the US mortgage. This resulted in the fall in US house prices and debt value which caused panic as investors sold their assets indiscriminately. In essence, contagion risk emanates from a localised starting point and spreads to other financial markets. According to Bai et al. (2020) financial contagion can be classified as either;

- Exogenous originating from natural disasters
- Market specific originating from subprime policies
- Country specific such United States (US) monetary policies and China-US trade wars.

Although many theories have been attributed to financial contagion in security markets, empirical evidence points to common knowledge symmetry which enhances herding behaviour as the main cause (Goldsteina and Pauzner, 2004). Specifically, financial contagion surfaces when common knowledge prevailing in a stock market is quickly transmitted to the other markets especially in an integrated financial system (Hansen, 2021). This was evident in the Latin America and East Asia crisis in the early 80's and late 90's respectively. There is a vast amount of research on the idiosyncratic effects of financial contagion mirrored in the rich literature on financial markets (Seth and Sighania, 2017; Paskaleva and Stoykova, 2021; Nguyen et al., 2022; Hsiao and Morley, 2022; Siddiqui et al., 2022; Lee and Kim, 2022; Uddin et al., 2022). However, it is still not clear if these market forces filter through the system for multiple periods. In essence, the relative duration of these contagions have not been well investigated in the literature. Therefore, the aim of this study was to investigate financial contagion between financial markets and its duration. Specifically, this study investigates the following questions; Are there variations in financial contagions across financial markets for different periods? Do some markets experience greater degrees of contagion in terms of duration than others? This study contributes to the frontier of market contagion by empirically investigating contagions between financial markets and their relative duration for pre and post financial distress periods, hence a notable contribution. This next section highlights the literature review followed by the methodology, results and discussion and conclusion.

2. LITERATURE

Financial contagions are disruptions that spreads between security markets usually with negative effects (Dornbusch et al., 2000). This is as a consequence of the continuous integration financial markets. Many theories such as fundamental channels, investor based theories and liquidity based models have been attributed to financial contagion (Acharya and Yorulmazer, 2008). Empirical evidence points to common information symmetry as the main cause of financial contagion (Aslam et al., 2022; Pineda et al., 2022). In essence, market turbulence prevailing in a particular market quickly propagate to other stock markets. These transmissions are mainly due to signal extraction issues arising from symmetry information. Consequently, these transmissions in turn gives rise to contagion risk which spreads across financial markets usually within the same jurisdiction. Market contagion has the potential to hamper economic and financial activities. However, market contagions are also as a result of policy driven issues such as market regulations which could be identified as;

- Simultaneous decrease in multiple asset prices
- When the percentage of decrease in asset prices is significantly different from normal times
- Asset prices cannot be explained by their fundamentals.

The table summarises the most recent study as per authors knowledge on financial market contagion.

The studies above summarises prior literature on financial market contagion in the international scale. Despite their relevance, none of the studies cited in Table 1 investigates the duration of financial contagion. Hence, this study attempt to fill in the gap in literature. The section below highlights the research methodology.

3. METHODOLOGY

A threefold blueprint was applied to achieve the objective of this study. Firstly, an Augmented Dickey Fuller unit root test was first conducted to ascertain the nature of the variables. In essence, a unit root test was required to ensure that the characteristics equation of the polynomial lie outside the unit circle or are greater than 1 which is a pre requisite for any time series modelling (Zhong, 2015). Accordingly, a stationary time series is ascertained when the P-values of the test statistics is less than or equal to the threshold level of 5% (Di Leo and Sardanelli, 2020). Secondly, a vector autoregression (VAR) regression was conducted to capture the joint dynamics of the different financial markets. VAR captures each endogenous variable in the model as a function of the lagged values of its self thus offering a simple and flexible alternative to the traditional multiple equation models (Chen et al., 2011). In so doing, the lagged values were used to determine the extent to which financial markets affect one another. A VAR model is given below;

$$\ln CAC\,40_t = a_1 + \sum_{t=1}^{n} a_{1i} lnCAC\,40_{t-1} + \sum_{t=1}^{n} b_{1i} lnDAX_{t-1}$$

$$+\sum_{t=1}^{n} d_{1i} lnJSE_{t-1} + \sum_{t=1}^{n} f_{1i} lnNASDAQ_{t-1} + \sum_{t=1}^{n} h_{1i} lnNikkei\,225_{t-1} + \varepsilon_{1t}$$

$$\ln DAX_t = a_2 + \sum_{t=1}^{n} a_{2i} lnCAC\,40_{t-1} + \sum_{t=1}^{n} b_{2i} lnDAX_{t-1}$$

$$+\sum_{t=1}^{n} d_{2i} lnJSE_{t-1} + \sum_{t=1}^{n} f_{2i} lnNASDAQ_{t-1}$$

$$+\sum_{t=1}^{n} h_{2i} lnNikkei\,225_{t-1} + \varepsilon_{2t}$$

Table 1: Summary of prior studies on financial contagion

Study (Author and year of study)	Model	Period	Findings
Seth and Sighania (2017)	Meta-analysis	2011-2015	Significant evidence of market contagion between 2011 and 2015
Paskaleva and Stoykova (2021)	TGARCH and autoregressive model	March 3, 2003-June 30, 2016	Evidence of market contagion from the united states and german market to the bulgaria stock exchange.
Nguyen et al. (2022)	DCC-EGARCH	2005-2021	Financial contagions are not related to global integration.
Hsiao and Morley (2022)	Multiple channel test	2007-2021	Debt crisis is the main transmitter of financial contagion
Siddiqui et al. (2022)	Markov switching model	January 23, 2020-June 30, 2020.	Emerging markets experience significant contagion from developed markets.
Lee and Kim (2022)	Bayesian model	2007-2009	The findings revealed market contagion between European financial markets during 2007 and 2009.
Uddin et al. (2022)	Time varying dynamic conditional correlation	January 2018-December 2020	Significant co-movement between stock markets during the Covid-19 pandemic.

Source: Author

$$\ln JSE_t = a_3 + \sum_{t=1}^{n} a_{3i} lnCAC40_{t-1} + \sum_{t=1}^{n} b_{3i} lnDAX_{t-1} + \sum_{t=1}^{n} d_{3i} lnJSE_{t-1} + \sum_{t=1}^{n} f_{3i} lnNASDAQ_{t-1} + \sum_{t=1}^{n} h_{3i} lnNikkei225_{t-1} + \varepsilon_{3t}$$

$$\ln NASDAQ_t = a_4 + \sum_{t=1}^{n} a_{4i} lnCAC40_{t-1} + \sum_{t=1}^{n} b_{4i} lnDAX_{t-1} + \sum_{t=1}^{n} d_{4i} lnJSE_{t-1} + \sum_{t=1}^{n} f_{4i} lnNASDAQ_{t-1} + \sum_{t=1}^{n} h_{4i} lnNikkei225_{t-1} + \varepsilon_{4t}$$

$$\ln Nikkei225_t = a_5 + \sum_{t=1}^{n} a_{5i} lnCAC40_{t-1} + \sum_{t=1}^{n} b_{5i} lnDAX_{t-1} + \sum_{t=1}^{n} d_{5i} lnJSE_{t-1} + \sum_{t=1}^{n} f_{5i} lnNASDAQ_{t-1} + \sum_{t=1}^{n} h_{5i} lnNikkei225_{t-1} + \varepsilon_{5t}$$

Finally, a Variance decomposition test was also conducted. The aim of this test was to provide the forecast error of the percentage of unexpected variations that are induced by shocks from other financial markets. These shocks indicate the relative impact that one financial market has on the other. Also, the variance decomposition enables assessment of economic significance as a percentage of the forecast error for a specific stock market (Campbell, 1991). Empirically, the forecast error in variance decomposition model is given by;

$$X_{t+h} - X_t\ (h) = a_4 + \sum_{t=0}^{n-1} \varnothing_i \omega_{t+h-i}$$

Where $X_t\ (h)$ is the forecast variance for period t in X_{t+h} (Seymen, 2008). The sample period was from January 1, 2017 to 31 December 2018 (Pre Covid-19 pandemic) and January 1, 2020 to 31 December 2021 (Covid-19 pandemic). The returns of the daily closing prices for five financial markets namely the the French Stock Market Index (CAC 40), the German blue chip companies (DAX), Johannesburg stock exchange (JSE), Nasdaq Index and the nikkei stock average (Nikkei 225) was used as the matrix of analysis. The section below highlights the findings.

4. RESULTS AND DISCUSSION

As already indicated in the methodology, a unit root test was first required before standard VAR regression and variance decomposition testing. From Tables 2 and 3 above, all the variables were stationary at levels which can be seen in the significant P-values for all the financial markets under consideration before and during the Covid-19 pandemic. The Tables 4-7 highlights the VAR and Variance decomposition outputs.

The VAR results and the variance decomposition results before and during the pandemic are presented in Tables 2-7. The results and interpretation of the variance decomposition are the main findings although the VAR results were used to supplement the analysis. From Table 4, there is a weak endogenous relationship between the lag values of the CAC 40 and the DAX, JSE, Nasdaq and Nikkei 225 as shown in their coefficients and t-values of 6% (1.52), −2.2% (−1.01), 4.3% (1.41) and 4.3% (1.26) respectively. This implies that the past realisation of the CAC 40 is associated with only 6%, −2.2%, 4.3% and 4.3% in the DAX, JSE, NAASDAQ and Nikkei 225 respectively. A similar finding, was observed between the CAC 40, JSE and Nasdaq as indicated in Table 4. The same observations can also be seen for the JSE, Nasdaq, and Nikkei 255 where they account for <20% of the movements in the other financial markets. A weekly endogenous relationship was also observed between the DAX and JSE as seen in Table 4. Looking at the variance decomposition results for pre-crisis era in Table 5, the forecasting error for all the financial markets under consideration is explained by itself from period 1 through period 10. In other words, the CAC 40, DAX, JSE Nasdaq and Nikkei 225 doesn't have strong influence on each other hence, exhibit strong exogenous impact. Hence the contagion effect is not significant before the covid-19 pandemic. The results of the covid-19 pandemic present a slightly different picture. The VAR estimates in Table 6 indicates that the lag values of the DAX accounts for up to 44.3% of movements in the CAC 40 with a t-value of 8 which is far greater than the pre pandemic values. The same can be observed between the Nasdaq and the DAX as shown in Table 6 although the results showed lower pandemic results in some cases. These findings are further strengthen by the Variance

Table 2: Unit root test before the covid-19 pandemic

Lag Length: 0 (Automatic - based on SIC, maxlag=18)				
Stock markets	Augmented dickey-fuller test t-statistic	Test critical values		
		10% level	1% level	5% level
CAC 40	−22.57 (0.000)*	−3.4425	−2.8668	−2.5696
DAX	−24.25 (0.000)*	−3.4426	−2.8668	−2.5696
JSE	−24.37 (0.000)*	−3.4426	−2.8668	−2.5696
NASDAQ	−23.95 (0.000)*	−3.4426	−2.8668	−2.5696
NIKKEI 225	−22.66 (0.000)*	−3.4430	−2.8670	−2.5697

*MacKinnon (1996) one-sided P-values

Table 3: Unit root test during the covid-19 pandemic

Lag Length: 0 (Automatic - based on SIC, maxlag=18)				
Stock markets	Augmented dickey-fuller test t-statistic	Test critical values		
		1% level	5% level	10% level
CAC 40	−14.159 (0.000)*	−3.442919	−2.86698	−2.56973
DAX	−14.301 (0.000)*	−3.443046	−2.86703	−2.56976
JSE	−22.771 (0.000)*	−3.443228	−2.86711	−2.5698
NASDAQ	−6.650 (0.000)*	−3.443361	−2.86717	−2.56983
NIKKEI 225	−21.202 (0.000)*	−3.443607	−2.86728	−2.56989

*MacKinnon (1996) one-sided P-values

Table 4: Vector autoregression estimates before the Covid-19 pandemic era

VAR estimates					
Stock markets	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
CAC_40 (−1)	0.012159	−0.08373	0.219827	−0.05034	−0.007128
	(0.044)*	(0.048)*	(0.086)	(0.061)	(0.057)
	[27365]	[−1.70933]	[53688]	[−0.81907]	[−0.12448]
DAX(−1)	0.061440	−0.09051	−0.00877	0.200941	0.009215
	(0.040)*	(0.044)*	(0.078)	(0.055)	(0.052)
	[52149]	[−2.03324]	[−0.11140]	[59787]	[17707]
JSE(−1)	−0.02287	0.023290	−0.07025	−0.01107	−0.037654
	(0.022)*	(0.024)*	(0.044)*	(0.031)*	(0.029)*
	[−1.01064]	[93386]	[−1.59217]	[−0.35375]	[−1.29148]
NASDAQ(−1)	0.045842	0.144704	0.041541	−0.08305	−0.044042
	(0.032)*	(0.035)*	(0.063)	(0.044)*	(0.041)*
	[41875]	[06257]	[65927]	[−1.85847]	[−1.05768]
NIKKEI_225(−1)	0.043594	−0.00521	0.001374	0.075727	−0.006741
	(0.034)*	(0.038)*	(0.067)	(0.047)*	(0.044)*
	[26046]	[−0.13667]	[02037]	[58313]	[−0.15124]
R−squared	0.016483	0.042179	0.018244	0.034895	0.005727
Adj. R−squared	0.006668	0.032620	0.008446	0.025263	−0.004195
F−statistic	1.679325	4.412484	1.861981	3.622857	0.577201
Log likelihood	1736.380	1686.976	1397.758	1571.958	1607.784

Source: Author

Table 5: Variance decomposition results before the Covid−19 pandemic era

Variance decomposition of CAC_40						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.007924	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.007990	98.39241	0.707742	0.200712	0.390611	0.308520
3	0.007991	98.38524	0.711735	0.200790	0.391961	0.310277
4	0.007991	98.38513	0.711798	0.200807	0.391968	0.310301
5	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
6	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
7	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
8	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
9	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
10	0.007991	98.38512	0.711799	0.200807	0.391970	0.310302
Variance decomposition of DAX						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.008736	0.178654	99.82135	0.000000	0.000000	0.000000
2	0.008917	0.718519	96.06997	0.193240	3.014728	0.003539
3	0.008925	0.718862	95.95352	0.197167	3.118911	0.011542
4	0.008926	0.719102	95.94649	0.197454	3.124823	0.012132
5	0.008926	0.719120	95.94605	0.197469	3.125204	0.012161
6	0.008926	0.719121	95.94602	0.197469	3.125227	0.012163
7	0.008926	0.719121	95.94602	0.197470	3.125229	0.012163
8	0.008926	0.719121	95.94602	0.197470	3.125229	0.012163
9	0.008926	0.719121	95.94602	0.197470	3.125229	0.012163
10	0.008926	0.719121	95.94602	0.197470	3.125229	0.012163
Variance decomposition of JSE						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.015454	0.017026	0.051008	99.93197	0.000000	0.000000
2	0.015594	1.251001	0.050934	98.61654	0.081445	8.04E-05
3	0.015597	1.255560	0.069950	98.58583	0.081741	0.006918
4	0.015597	1.255717	0.070064	98.58537	0.081914	0.006936
5	0.015597	1.255717	0.070067	98.58535	0.081929	0.006936
6	0.015597	1.255717	0.070067	98.58535	0.081930	0.006936
7	0.015597	1.255717	0.070067	98.58535	0.081930	0.006936
8	0.015597	1.255717	0.070067	98.58535	0.081930	0.006936
9	0.015597	1.255717	0.070067	98.58535	0.081930	0.006936
10	0.015597	1.255717	0.070067	98.58535	0.081930	0.006936
Variance decomposition of NASDAQ						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.010960	0.035656	4.499844	0.036906	95.42759	0.000000
2	0.011146	0.153007	6.415435	0.072351	92.88087	0.478336

(*Contd...*)

Table 5: ***(Continued)***

Variance decomposition of NASDAQ						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
3	0.011155	0.166325	6.459913	0.077616	92.81017	0.485975
4	0.011156	0.166637	6.461723	0.077772	92.80766	0.486209
5	0.011156	0.166647	6.461868	0.077783	92.80747	0.486231
6	0.011156	0.166648	6.461877	0.077784	92.80746	0.486232
7	0.011156	0.166648	6.461878	0.077784	92.80746	0.486233
8	0.011156	0.166648	6.461878	0.077784	92.80746	0.486233
9	0.011156	0.166648	6.461878	0.077784	92.80746	0.486233
10	0.011156	0.166648	6.461878	0.077784	92.80746	0.486233
Variance decomposition of NIKKEI_225						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.010212	0.262658	0.230087	0.104108	0.036682	99.36646
2	0.010241	0.265394	0.228956	0.434063	0.249688	98.82190
3	0.010241	0.268205	0.235212	0.437439	0.250862	98.80828
4	0.010241	0.268324	0.235241	0.437452	0.251178	98.80780
5	0.010241	0.268324	0.235246	0.437453	0.251191	98.80779
6	0.010241	0.268324	0.235246	0.437453	0.251192	98.80779
7	0.010241	0.268324	0.235246	0.437453	0.251192	98.80779
8	0.010241	0.268324	0.235246	0.437453	0.251192	98.80779
9	0.010241	0.268324	0.235246	0.437453	0.251192	98.80779
10	0.010241	0.268324	0.235246	0.437453	0.251192	98.80779

Cholesky one S.D. (d.f. adjusted)
Cholesky ordering: CAC_40 DAX JSE NASDAQ NIKKEI_225

Table 6: Vector autoregression estimates during the Covid-19 pandemic era

Vector autoregression estimates					
Stock markets	**CAC 40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI 225**
CAC 40 (−1)	−0.22341	0.039655	−0.04859	0.037400	−0.024203
	(0.052)	(0.056)	(0.063)	(0.060)	(0.050)
	[−4.23924]	[69676]	[−0.76099]	[62109]	[−0.47968]
DAX (−1)	0.443280	−0.00128	0.001004	−0.00558	−0.044091
	(0.053)	(0.057)	(0.065)	(0.061)	(0.051)
	[26042]	[−0.02211]	[01544]	[−0.09098]	[−0.85819]
JSE (−1)	−0.00295	0.065340	−0.00826	0.097256	−0.053669
	(0.038)*	(0.042)*	(0.047)*	(0.044)*	(0.037)*
	[−0.07563]	[55262]	[−0.17494]	[18427]	[−1.43851]
NASDAQ(−1)	−0.15247	−0.1448	−0.03807	−0.33813	0.026542
	(0.041)*	(0.044)*	(0.049)*	(0.047)*	(0.039)*
	[−3.70414]	[−3.25753]	[−0.76338]	[−7.18963]	[67354]
NIKKEI_2251)	0.030643	0.084260	−0.01751	0.055051	0.032714
	(0.047)*	(0.051)	(0.058)	(0.054)	(0.045)*
	[63989]	[62931]	[−0.30170]	[00614]	[71356]
R−squared	0.129404	0.029903	0.004741	0.110042	0.011414
Adj.R-squared	0.120316	0.019777	−0.00565	0.100752	0.001095
F-statistic	14.23953	2.953000	0.456340	11.84548	1.106128
Loglikelihood	1357.581	1320.289	1264.468	1292.934	1378.698

Source: Author

Table 7: Variance decomposition results during the Covid-19 pandemic era

Variance Decomposition of CAC_40						
Period	**SE**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.0148	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.0158	87.73821	9.922191	0.029273	2.236993	0.073333
3	0.0158	87.16400	10.39501	0.049402	2.277101	0.114482
4	0.0158	87.12536	10.42840	0.053314	2.276708	0.116219
5	0.0158	87.12175	10.43158	0.053673	2.276613	0.116381
6	0.0158	87.12139	10.43188	0.053713	2.276613	0.116399
7	0.0158	87.12135	10.43191	0.053717	2.276615	0.116401
8	0.0158	87.12135	10.43191	0.053718	2.276615	0.116401
9	0.0158	87.12135	10.43192	0.053718	2.276616	0.116401
10	0.0158	87.12135	10.43192	0.053718	2.276616	0.116401

(*Contd...*)

Table 7: ***(Continued)***

Variance decomposition of DAX						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.0160	37.99630	62.00370	0.000000	0.000000	0.000000
2	0.0162	36.96865	60.38607	0.282870	1.835098	0.527313
3	0.0162	36.88153	60.27820	0.312221	1.999932	0.528114
4	0.0162	36.87172	60.27020	0.314505	2.014856	0.528716
5	0.0162	36.87051	60.26933	0.314827	2.016525	0.528808
6	0.0162	36.87036	60.26923	0.314868	2.016714	0.528820
7	0.0162	36.87035	60.26922	0.314873	2.016735	0.528821
8	0.0162	36.87034	60.26922	0.314874	2.016738	0.528821
9	0.0162	36.87034	60.26922	0.314874	2.016738	0.528821
10	0.0162	36.87034	60.26922	0.314874	2.016738	0.528821
Variance decomposition of JSE						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.0179	3.012881	1.935443	95.05168	0.000000	0.000000
2	0.0179	3.280424	1.932761	94.65201	0.116297	0.018510
3	0.0179	3.279432	1.942814	94.61234	0.145982	0.019434
4	0.0179	3.279377	1.943278	94.60972	0.148183	0.019443
5	0.0179	3.279376	1.943289	94.60955	0.148338	0.019443
6	0.0179	3.279376	1.943289	94.60954	0.148351	0.019443
7	0.0179	3.279376	1.943289	94.60954	0.148352	0.019443
8	0.0179	3.279376	1.943289	94.60954	0.148352	0.019443
9	0.0179	3.279376	1.943289	94.60954	0.148352	0.019443
10	0.0179	3.279376	1.943289	94.60954	0.148352	0.019443
Variance decomposition of NASDAQ						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.0169	8.651771	4.840264	0.479786	86.02818	0.000000
2	0.0178	7.988951	4.761758	0.909865	86.15327	0.186160
3	0.0179	7.911344	4.797278	0.978144	86.10969	0.203542
4	0.0179	7.902724	4.810948	0.986699	86.09376	0.205865
5	0.0179	7.901695	4.813554	0.987815	86.09073	0.206206
6	0.0179	7.901570	4.813963	0.987959	86.09026	0.206252
7	0.0179	7.901554	4.814022	0.987978	86.09019	0.206258
8	0.0179	7.901552	4.814030	0.987980	86.09018	0.206259
9	0.0179	7.901552	4.814031	0.987980	86.09018	0.206259
10	0.0179	7.901552	4.814032	0.987980	86.09018	0.206259
Variance decomposition of NIKKEI_225						
Period	**S.E.**	**CAC_40**	**DAX**	**JSE**	**NASDAQ**	**NIKKEI_225**
1	0.0141	1.219085	0.354811	0.861164	0.401720	97.16322
2	0.0142	1.502186	0.538669	1.296085	0.494997	96.16806
3	0.0142	1.502072	0.548684	1.296141	0.496830	96.15627
4	0.0142	1.502062	0.549256	1.296151	0.496865	96.15567
5	0.0142	1.502062	0.549293	1.296155	0.496865	96.15563
6	0.0142	1.502062	0.549296	1.296155	0.496865	96.15562
7	0.0142	1.502062	0.549297	1.296155	0.496865	96.15562
8	0.0142	1.502062	0.549297	1.296155	0.496865	96.15562
9	0.0142	1.502062	0.549297	1.296155	0.496865	96.15562
10	0.0142	1.502062	0.549297	1.296155	0.496865	96.15562

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: CAC_40; DAX; JSE; NASDAQ, NIKKEI_225

Source: Eviews output

decomposition output in Table 7 where the CAC 40 showed strong influence in the DAX from period 1 right through period 10. The DAX showed symptoms of influence, and this observation can be seen between the CAC 40 and the DAX. These findings concur with the study of Enow (2023) who is of the opinion that market shocks are more prevalent during periods of financial distress.

5. CONCLUSION

Financial contagion may not exist in the absence of integrated financial markets where it is directly linked to changes in investors sentiments. The purpose of this study was to empirically explore financial market contagion and its duration pre and during the Covid-19 pandemic in international financial markets. The findings of this study reveals that financial contagion are mainly prevalent through periods of market distress and filters through the system for multiple periods. To this end, country specific mechanisms are required during periods of financial crisis to absorb economic shocks and facilitate easy access to liquidity. Central banks will have to setup a comprehensive capital buffers during market turbulence and promote micro financing which may also prove to be a reliable tool to mitigate financial contagion. Also, portfolio diversification strategies may not be helpful during periods of financial distress.

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