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Investigating Causality And Market Contagion During Periods Of Financial Distress And Its Implications

Samuel Tabot Enow[a]

[a] Research Associate, The IIE VEGA School, enowtabot@gmail.com

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Abstract

Purpose: A notable observation in the literature of financial markets is the debate on market contagion and causality. During periods of financial distress, global financial markets experience record low market prices partly due to the spread of fear. It was therefore necessary to investigate market contagions using causality relationships during periods of financial distress.

Methodology: A unit root test, Granger causality and Test for equality of means was used as the blueprint. The sample periods where December 1, 2007 to June 30, 2009 and January 1, 2020 to December 31, 2021.

Findings: Contrary to the perceptions that prevails in most stock markets during distress, there was little empirical evidence to support market contagions. Although very few markets are indeed related.

Originality/Value: The implications of this study extends the efficient market hypothesis concept to market efficiency during periods of financial distress. It is evident that financial markets display greater efficiencies during periods of financial distress. This study is the first to investigate market contagion during periods of distress as per author's knowledge.

1. Introduction

The dynamics of pricing financial markets revolves around three important pillars which are; the price taking investor, macroeconomics factors and portfolio choice alternative (Campbell, 2017). In essence, rationality is a valuable attribute because of irrational optimizers (Mongin, 2000). In the 50's, market participants thought tracing the evolution of economic variables over time would assist in forecasting the performance of financial markets through bullish and bearish episodes. However, as pointed by Fama (1970), financial markets only react to new information which is in themselves unpredictable proposing the concept of market efficiency. Far from the concept of market efficiency, irrationalities still dominate many financial markets today (Enow, 2022; Enow, 2021). These irrationalities continue to dominate financial markets because of randomly evolving security prices resulting from new information and price discovery (Shiller, Fischer & Friedman, 1984). These irrationalities have resulted in contagions where financial markets are perceived to be significantly related (contagion studies). In many instance, market participants believe that there are mysterious factors that explain this interrelatedness without empirical facts (Szolosi, Watson & Ruddell, 2014). This alleged perception has resulted in the difficulty in reconciling price discovery mechanisms with market efficiency and behavioural finance (Lo, 2004). Also, the presence of these irrationalities have led to intangible connections rather than causal empirical evidence. There are several instances in the chronicles of financial indexes where market shocks filters through several financial markets as a result of fear and greed (Westerhoff, 2004). This was evident in United States Federal Reserve chairman's speech in August 2022 where he cautioned on;

- Persistent inflation
- Softening of Labour market policies leading to increasing unemployment
- Gradual hike in interest rates (Powel, 2022)

As a result, there will be unfortunate costs that needs to considered in order to curb these market forces. Powell's (2022) speech drove many financial markets to their lowest points since the beginning of the year. It is important to note that negative market sentiments that are exacerbated across financial markets during periods of financial distress may not have any bearings. With this line of thought, investors and market participants need to consider if there is any empirical evidence to support their sentiments. Although prior literature has continuously categorized international financial markets as a global village where markets are integrated (Roach, 1997; Labonté, 2022), it is still not clear whether events in a financial market affects another market during periods of distress. In other words, market participants should have answers for the following questions; is there any form of market efficiency during periods of financial distress? Is there any empirical evidence to support the notion that spill overs from one market affects the other during financial distress? In essence, investors should be able to ascertain market contagions and causality relationships among stock markets as its understanding during periods of financial distress can assist in providing new information that will mitigate risk and improve portfolio diversification. Therefore, the aim of this study was to investigate causality relationships during financial distress. This appealing study contributes not only to the limited literature on financial market causality and contagions but it is the first as per the author's knowledge to empirically investigate stock index causality during financial distress, hence a noteworthy contribution. The next section highlights the literature review followed by the methodology, results and analysis and conclusions.

2. Literature Review

Financial markets are controlled by greed and fear which are sometimes factored in the valuation process (Lo, Repin & Steenbarger, 2005; Enow, 2022). These market forces have had profound effects on global financial markets recently. Market participants tend to over value their portfolios when they are caught up by greed which creates a sense of positivity. As such, more securities with similar valuation are added to the portfolio regardless of their true fair values. This irrational exuberance sometimes leads to market bubbles such as the United States (US) 2008 housing bubble. During the early 2000's, housing prices in the US increased sharply due to higher expectations leading to overpricing. As a result, most US banks engaged in excess lending to individuals even though they did not qualify. Back then, housing properties were seen as safe bets because banks thought they could recover their loans from the sale of the underlying in case of default. The aggressive subprime lending resulted in disregard for securitization of housing loans, collaterised debt obligations (CDO), synthetic CDOs, insurance products and credit default swaps (CDS). With the passage of time, there was a lot of defaults as some investors failed to keep up with their loans. This led to the value of the housing properties in the US to fall sharply relative to the loans resulting in a systemic collapse. The US market experienced a sharp decline which spread across the globe. International financial markets dived to their lowest points as a result of fear. However, one important consideration is whether there was any empirical basis for market shocks to spill over several stock indexes. How does the housing crises in the US related to financial markets in Europe, Asia and Africa? Is there any empirical evidence to support some of these narratives? The table below highlights prior studies on causality and market contagions.

Table 1: Prior literature on market causality

Study	Model	Period	Country	Findings
Lee & Yang (2013)	Granger Causality test	January 3, 1995 – December 31, 2005.	US, Japan and United Kingdom (UK)	Significant causality between US, Japan and UK stocks.
Bhunia & Yaman (2017)	Correlation test	January 2, 1991- March 31, 2016	US and Asian markets	US and Asian markets are significantly correlated in the long and short run.
Abdennadher & Hellara (2018)	Granger Causality test	April, 2005 – March, 2015	Bahrain, Dubai, Egypt, Jordan, Kuwait, Oman, Saudi Arabia, South Africa, Turkey, Tunisia and US	Evidence of volatility transmission from one market to the other leading to the conclusion that markets are related.
Xu & Gao (2019)	Granger Causality test	January 2006 - December 2018	US, UK, China, Japan, India, Brazil, Russia & South Africa	There was a spillover effect from the Chinese Stock market to other markets.
Tan et al., (2022)	Conditional value-at-risk	October 12, 2017- January 22, 2020 and January 23, 2020 and May	12 developing and developed financial markets	The level of spill over risk has greatly increased with Brazil, Canada and Russia absorbing most of the

		20, 2022		risk from other financial markets.
Siddiqui et al., (2022)	Markov regime-switching model	23 January 2020 - 30 June 2020 and 1 April 2019 - 31 December 2019	3 developed and 8 developing markets	Emerging financial markets are the center of contagions from developed markets.
Nguyen et al., (2022)	E-GARCH model	2005 to 2021	US, Japan, Chinese and Asian stock markets	Strong correlation between the US and Japan stock markets with the Asian markets.

Source: Author

The studies in table 1 above summarises prior literature on causality and market contagion in financial markets. From these studies, it is perceptible that causality exist between financial markets and hence contagions. However, the gap in literature still remained because the question on causality relationship and market contagion during periods of distress is unanswered. Hence, this study tries to fill in the gap in literature.

3. Research Methodology

The choice of methodology was informed by the epistemological perspective of the research question highlighted in section 1. To this end, the sample periods were from December 1, 2007 to June 30, 2009 (the 2007-2008 financial crisis) and from January 1, 2020 to December 31, 2021 (The novel Covid-19 pandemic). These sample periods were selected because they were the crux of the financial crisis and Covid-19 pandemic respectively. It was necessary to begin with unit root testing in order to determine the nature of the data relating to stationary time series. As documented by Van Greunen et al., (2014), non-stationary time series have a non-constant mean and variance which leads to spurious regressions. In this case, there will be no empirical basis for making statistical decisions about a time series. Therefore, it is paramount to have a stationary time series. To this end, an Augmented Dickey Fuller (ADF) test and Phillip Perron Test was used to ascertain stationarity in the time series. The three levels of unit root testing are

- Stationary at levels (p-value less than 5% at first analysis)
- Stationary at first differencing

- Stationary at second differencing

An ADF and Phillip Perron test are given by;

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

$y_t = \alpha + \sigma y_{t-1} + \varepsilon_t$ respectively (Tam, 2013)

where

H_0: Stationary time series data at levels (*P-values* less than 5%).

H_1: Non- Stationary time series data (*P-values* more than 5%).

The next data analysis tool was a granger causality and a test of equality of mean between series. Regression analysis are mainly used to investigate the dependence of one variable to the other but not useful in determining the direction of influence or causation. The existence of a relation between variables doesn't necessary imply causation. In essence shocks in financial markets may not necessary spill over to the other without determining the causality effect and the direction of influence. Hence, a Granger causality test was used to quantify the usefulness of the past values in selected financial markets. Granger (1969) introduced a causality test to investigated inter relation between variables in order to make significant inferences in his novel model. According the Granger (1969), two time series y_t and x_t display causality if the past values of x_t helps predict the future values of y_t and vice versa. This causality effect has distinct characteristics about the futures values of its effect which can be used to explain bi-directional causality between variables. A Granger model is given by;

$y_t = a_0 + a_1 y_{t-1} + a_2 x_{t-1}$ (Song & Taamouti, 2019)

Where y_t and x_t are the time series dependent and independent variables and a_x are the coefficients.

H_0: No Granger Causality

H_1: Granger Causality, hence reject the null hypothesis

The decision criteria: H_0 is rejected if the p-value is less than 5%. The third analysis performed was the Test for Equality of Means between the financial markets. The aim of this Test was to determine whether the mean values of the financial markets are equal. Hence the following hypothesis where developed;

H_0: The mean between the financial markets are equal ($u_1 = u_2$).

H_1: The mean between the financial markets not are equal, reject H_0

In the decision criteria for the equality of mean test, H_0 is rejected if the p-value is more than 5% and vice versa. The five international financial markets used in this study where the CAC-40 (the French Stock Market Index), the DAX (the German blue chip companies), the JSE (Johannesburg Stock Exchange), the Nikkei-225 (Nikkei Stock Average) and the Nasdaq Index. The required data was sourced from Yahoo finance and were mainly daily share prices for the selected stock exchanges. The results and output results are presented in the next section.

4. Findings and Discussion

As already indicated in the blueprint, a unit root test is needed to ascertain whether the data collected is stationary before proceeding with the Granger causality testing. The findings from the unit root test is presented below.

Table 2: Unit root test results

ADF Test results

	T-Statistic (1% CV)	*T-Statistic (5% CV)*	*T-Statistic (10% CV)*	*ADF T-statistics*	*P-value*
CAC-40	-3.446608	-2.868601	-2.570597	-21.93967	0.0000*
DAX	-3.446777	-2.868676	-2.570637	-20.54363	0.0000*
JSE	-3.446862	-2.868713	-2.570657	-16.12698	0.0000*
Nasdaq	-3.446777	-2.868676	-2.570637	-17.06123	0.0000*
Nikkei-225	-3.447259	-2.868888	-2.570751	-20.74724	0.0000*

Phillip Perron Test results

	T-Statistic (1% CV)	*T-Statistic (5% CV)*	*T-Statistic (10% CV)*	*PP T-statistics*	*P-value*
CAC-40	-3.455685	-2.872586	-2.57273	-16.26657	0.0000*
DAX	-3.455887	-2.872675	-2.572778	-16.4044	0.0000*
JSE	-3.456514	-2.87295	-2.572925	-20.14024	0.0000*
Nasdaq	-3.456302	-2.872857	-2.572875	-16.13717	0.0000*
Nikkei-225	-3.457286	-2.873289	-2.573106	-15.83095	0.0000*

CV= Critical Value; *significant at 5%

The table 2 above, the p-values for the ADF and Phillip Perron test are both significant at 5%, indicating that the time series data for CAC-40, DAX, JSE, Nasdaq and Nikkei-225 are all stationary at order 0. In this case, shocks in the financial markets under consideration in the short run quickly adjust to the long run. From these results, all the data is integrated at order zero and requires no further differencing. Therefore, using a Jansen cointegrated test will be inappropriate. A Granger Causality test and an independent mean test was therefore conducted to investigated the dependence of financial markets during periods of financial distress. The results of the Granger causality and test for equality of mean for the 2007-2008 financial crisis and Covid-19 pandemic is presented below.

Table 3: Granger Causality output results during the Covid-19 pandemic

2 Lags Pairwise Granger Causality Tests during the Covid-19 Pandemic			
Null Hypothesis:	**Observations**	**F-Statistic**	**P-value**
DAX does not Granger Cause CAC_40	254	350.898	0.000*
CAC_40 does not Granger Cause DAX		0.07195	0.9306
JSE does not Granger Cause CAC_40	248	0.58660	0.557
CAC_40 does not Granger Cause JSE		0.18669	0.8298
NASDAQ does not Granger Cause CAC_40	250	1.41072	0.2459
CAC_40 does not Granger Cause NASDAQ		0.29359	0.7458
NIKKEI_225 does not Granger Cause CAC_40	241	2.09532	0.1253
CAC_40 does not Granger Cause NIKKEI_225		0.00276	0.9972
JSE does not Granger Cause DAX	248	3.09041	0.0473
DAX does not Granger Cause JSE		0.02886	0.9716
NASDAQ does not Granger Cause DAX	250	10.7710	0.000*
DAX does not Granger Cause NASDAQ		0.29363	0.7458
NIKKEI_225 does not Granger Cause DAX	241	1.17636	0.3102
DAX does not Granger Cause NIKKEI_225		0.43095	0.6504
NASDAQ does not Granger Cause JSE	248	0.80719	0.4473
JSE does not Granger Cause NASDAQ		2.23567	0.1091
NIKKEI_225 does not Granger Cause JSE	241	0.78965	0.4552
JSE does not Granger Cause NIKKEI_225		0.21498	0.8067
NIKKEI_225 does not Granger Cause NASDAQ	241	0.60421	0.5474
NASDAQ does not Granger Cause NIKKEI_225		1.19473	0.3046

Table 4: Test for Equality of Means Between Series

Method	***df***	***Value***	***P-value***
Anova F-test	(4, 1254)	0.171826	0.9528
Welch F-test*	(4, 624.672)	0.14245	0.9663

Category Statistics

Variable	***Count***	***Mean***	***Standard Deviation***	***Standard Error of Mean***
CAC_40	258	-0.00021	0.014219	0.000885
DAX	256	-0.00063	0.014724	0.00092
JSE	250	-2.91E-05	0.016853	0.001066
NASDAQ	252	-0.00104	0.019051	0.0012
NIKKEI_225	243	-0.00019	0.013101	0.00084
All	1259	-0.00042	0.015717	0.000443

Table 5: Granger Causality results during the financial crisis

2 Lags Pairwise Granger Causality Tests			
Null Hypothesis:	**Observations**	**F-Statistic**	**P-value**
DAX does not Granger Cause CAC_40	392	159.603	0.000*
CAC_40 does not Granger Cause DAX		3.52726	0.0303*
JSE does not Granger Cause CAC_40	390	4.43947	0.0124*
CAC_40 does not Granger Cause JSE		0.34287	0.7099
NASDAQ does not Granger Cause CAC_40	393	16.4934	0.000*
CAC_40 does not Granger Cause NASDAQ		1.28097	0.2789
NIKKEI_225 does not Granger Cause CAC_40	381	4.88732	0.008*
CAC_40 does not Granger Cause NIKKEI_225		0.40385	0.668
JSE does not Granger Cause DAX	390	9.45161	0.0001*
DAX does not Granger Cause JSE		0.6555	0.5198
NASDAQ does not Granger Cause DAX	392	13.6565	0.000*
DAX does not Granger Cause NASDAQ		7.45876	0.0007*
NIKKEI_225 does not Granger Cause DAX	381	4.2518	0.0149*
DAX does not Granger Cause NIKKEI_225		0.79103	0.4541
NASDAQ does not Granger Cause JSE	390	1.9562	0.1428
JSE does not Granger Cause NASDAQ		8.15921	0.0003*
NIKKEI_225 does not Granger Cause JSE	381	1.24521	0.2891
JSE does not Granger Cause NIKKEI_225		0.99896	0.3692
NIKKEI_225 does not Granger Cause NASDAQ	381	0.94155	0.3909
NASDAQ does not Granger Cause NIKKEI_225		2.91421	0.0555

Table 6: Test for Equality of Means Between Series

Method	***df***	***Value***	***Probability***
Anova F-test	(4, 1957)	0.028786	0.9984
Welch F-test*	(4, 976.559)	0.029611	0.9983

Category Statistics

Variable	***Count***	***Mean***	***Standard Deviation***	***Standard Error of Mean***
CAC_40	398	-0.00115	0.023388	0.001172
DAX	394	-0.00094	0.022693	0.001143
JSE	392	-1.06E-03	0.026918	0.00136
NASDAQ	395	-0.00061	0.024508	0.001233
NIKKEI_225	383	-0.00083	0.026259	0.001342
All	1962	-0.00092	0.024768	0.000559

The tables above present some important findings. During the pandemic it can be gleaned that market shocks in the DAX affects the CAC-40. This was evident in the F-stats and p-value which is less than 5% significance. A similar finding is seen in the causality effect; where the Nasdaq index affects the DAX. These findings were supported by the test of equality between means where the p-values of Anova F-test and Welch F-test is also insignificant. With these findings, it can be concluded that during the Covid-19 pandemic, there was no empirical evidence to support any spillover in international markets. This finding is contrary to the findings of Lee & Yang (2013); Bhunia & Yaman (2017); Abdennadher & Hellara (2018) who found a significant relationship between international markets. It can therefore be suggested that, financial market downturns where country specific not as a result of spill overs or contagions.

However, the findings in table 5 presents a slightly different picture where market events in the DAX affects the CAC-40 and also vice versa. This same pattern was observed between the Nasdaq and the DAX. A unilateral relationship was observed between the JSE and CAC-40, the Nasdaq and CAC-40, the Nikkei-225 and the DAX and between the JSE and the Nasdaq. From the test of inequality in table 6, there is an insignificant relationship between the financial markets. From these findings, it can also be suggested that the CAC-40 was pruned to market shocks and spill over effects in the 2007-2008 financial crises than the Covid-19 pandemic. Also, the efficiency of the CAC-40 has greatly improved where there are fewer causalities from other markets. Parallel to this finding, the Nikkei-225, Nasdaq and JSE display strong resilience to other markets during periods of distress. From this results, it can be observed that there is a perfect flow of information between some financial markets around. This may be as a result of increasing interdependence between international economies. The findings of this study also suggest that some financial markets are fragile and negative shocks in one market may cause severe damages in another.

5. Conclusions

The aim of this study was to investigate market contagion and causality in financial markets during periods of distress. This was to validate to rebuff the psychology of investing where agitations in one markets spills to many other markets especially during periods of financial distress such as the 2007-2008 financial crisis and Covid-19 pandemic. During the pandemic, market shocks in the DAX and Nasdaq affected the CAC-40 and DAX respectively. Conversely, a unilateral relationship was observed between the JSE and CAC-40, the Nasdaq and CAC-40, the Nikkei-225 and the DAX and between the JSE and the Nasdaq during the financial crisis. However, a bilateral relationship was observed between the DAX and CAC-40 as well as the Nasdaq and the DAX. Accordingly, the DAX, the Nasdaq and the CAC-40 displayed similarities during the Covid-19 pandemic and financial crisis. From the findings in tables 2 to 6, it is evident that there is little empirical evidence to support the market contagions. It is surprising to see that market participants are not entirely driven by behavioural anomalies during financial distress which suggest some form of market efficiency. The findings of this study also supports the proposition that markets are not always efficient and inefficient. This can be observed in tables 3 and 5 where the Granger causality p-values are significant in some markets and insignificant in others. Although prior studies have reported on cointegration of financial markets during crises (Pedisic, 2022), it did not address the pricing mechanism in the long run. Also, these studies didn't address the possibility of deviating from the cointegration relationship. Therefore, market efficiency still exists during financial distress and spillover effects are simply as a result of either fear or greed as a result of cynicism. In concluding, financial market prices during periods of distress will not be cointegrated considering the existence of some form of efficiency and no empirical evidence to support contagion of financial markets.

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