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Spillovers Between Euronext Stock Indices: The COVID-19 Effect

Luana Carneiro [1], Luís Gomes [2,*], Cristina Lopes [2] and Cláudia Pereira [2]

1 ISCAP, Instituto Politécnico do Porto, 4465-004 S. Mamede Infesta, Portugal; lbeliago@kpmg.com
2 CEOS.PP, ISCAP, Instituto Politécnico do Porto, 4465-004 S. Mamede Infesta, Portugal; cristinalopes@iscap.ipp.pt (C.L.); claudiap@iscap.ipp.pt (C.P.)
* Correspondence: pgomes@iscap.ipp.pt

Abstract: The financial markets are highly influential and any change in the economy can be reflected in stock prices and thus have an impact on stock indices. The relationship between stock indices and the way they are affected by extreme phenomena is important for defining diversification strategies and analyzing market maturity. The purpose of this study is to examine the interdependence relationships between the main Euronext stock indices and any changes caused by an extreme event—the COVID-19 pandemic. Copula models are used to estimate the dependence relationships between stock indices pairs after estimating ARMA-GARCH models to remove the autoregressive and conditional heteroskedastic effects from the daily return time series. The financial interdependence structures show a symmetric relationship of influence between the indices, with the exception of the CAC40/ISEQ pair, where there was financial contagion. In the case of the AEX/OBX pair, the dynamics of dependence may have changed significantly in response to the pressure of the pandemic. On the other hand, the dominant influence of the CAC40 before and the AEX after the pandemic confirms that the size and age of these indices give them a benchmark position in the market. Finally, with the exception of the AEX/OBX and CAC40/ISEQ pairs, the interdependencies between the stock indices decreased from the pre- to the post-pandemic sub-period. This result suggests that the COVID-19 pandemic has weakened the correlation between the markets, making them more mature and independent, and less risky for investors.

Keywords: financial interdependence; financial markets; risk; Euronext; COVID-19; copulas

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1. Introduction

Financial markets play a fundamental role in the global economy, being crucial for allocating resources between different sectors, as well as price formation and risk management. The concept of globalization has strengthened the interconnection between the economies of different countries, making them more interdependent and less different. Studying this phenomenon contributes to identifying the correlation dynamics between different financial markets. Most recent research in this area has focused on the financial contagion of international crises (Forbes & Rigobon, 2002; B. V. M. Mendes, 2005; Rodriguez, 2007; Horta et al., 2010; Zorgati et al., 2019) and on the resilience of financial markets to the COVID-19 pandemic (Alfaro et al., 2020; Ding et al., 2021). However, studies on the impacts of extreme events on market interdependence dynamics are still scarce. This paper aims to fill this research gap. Therefore, the aim of this study is to examine the interdependent relationships between the main Euronext stock indices and the changes caused by an extreme event—the COVID-19 pandemic.

The Euronext is one of the largest international stock exchange platforms, and includes a variety of stock indices that reflect the performances of the respective economies. The size and importance of this platform for investment and potential portfolio risk management, with underlying revenues of EUR 1468 million in 2022, justifies the selection of this sample. Although the stock indices operate independently, they are interconnected in the global economy, and influence each other through complex relationships (Junior et al., 2015).

Previous literature on the analysis of interdependence and financial contagion highlights the copula method as the most appropriate to study these phenomena. The empirical study of this paper defined a pre-pandemic subperiod from 1 June 2013 to 10 March 2020 and a post-pandemic subperiod from 11 March 2020 to 30 June 2023 for the analysis of the following Euronext stock indices: AEX (Dutch), CAC40 (France), BEL20 (Belgium), PSI (Portugal), ISEQ (Ireland) and OBX (Norway). The methodological procedure began with applying ARMA-GARCH models to correct for the effects of autocorrelation and conditional heteroscedasticity usually associated with the volatility of financial time series. Copula models were then estimated for each pair of financial indices in both subperiods.

International stock market co-movement studies that discuss volatility spillovers with the GARCH model framework and in combination with other approaches, including the Vector Autoregressive (VAR) framework, have been widely conducted. This study uses the copula method through five different copula stands—the few that focus specifically on the Euronext stock index. Therefore, the main contribution of the study to the literature is related to the method of measuring international stock market integration, namely, the issue of spillovers from a copula perspective, regional stock market integration between the six Euronext stock indices, the impact of the COVID-19 pandemic, and the implications of international portfolio diversification.

The conclusions of the manuscript are useful for policymakers in anticipating the impacts of extreme events on stock markets and for investment portfolio managers in identifying risk diversification strategies. In addition, the results contribute to deepening the scientific evidence on the complex interdependencies between the main Euronext stock indices, filling some gaps in financial research and stimulating new lines of work.

The structure of the manuscript is organized into five sections. Following the introduction, Section 2 reviews the literature on the impact of the COVID-19 pandemic on the financial market and the evidence for financial interdependence and contagion. Section 3 deals with the methodology used to conduct the empirical study, presenting the ARMA-GARCH model, the copula models, the sample, and the procedures to be developed. Section 4 presents the results and discussion. Section 5 summarizes the main findings of the research.

2. Literature Review

2.1. Impact of the COVID-19 Pandemic on Financial Markets

COVID-19 was the cause of the severe acute respiratory syndrome coronavirus (SARS-CoV-2), identified in Wuhan in December 2019. Three months later, the World Health Organization (WHO) classified the outbreak as a pandemic and urged countries to take strong preventive measures, given the international spread of the infection.

The structure of economies mattered, with countries most dependent on services and foreign markets suffering the most from shockwaves that triggered the most extensive global crisis of the last century. The adverse effects exacerbated inequalities between countries, and the recovery has been as uneven as its initial impact.

Since the beginning of the pandemic, several empirical studies have been published on its impact on financial markets. Alfaro et al. (2020) conducted a study to identify how information about the spread of the disease was incorporated into the stock returns.

The authors found that the sectors most affected were accommodation, entertainment and transport, due to the higher level of exposure. On the other hand, the sectors least affected were education, finance and professional services, due to their ability to operate remotely using technology and the internet. The results also show that firms that are more capital-intensive, more indebted and with lower returns suffer a greater negative impact, as they have less flexibility to reduce costs during the pandemic.

Ding et al. (2021) analyzed the resilience of 6000 listed firms from 56 countries during the first quarter of 2020 in the context of COVID-19 cases. The study results suggest that firms with greater liquidity, lower leverage and better access to credit were less affected by the pandemic than those in countries less affected by the outbreak. In addition, firms with greater social responsibility outperformed those on the stock market. On the other hand, the results also confirm that the financial markets valued flexibility, mainly through mergers, acquisitions and changes in leadership.

Although the effects are predominantly adverse, positive advances have been identified in some research areas, such as the development of digital currencies, technological advances, and the application of artificial intelligence. Therefore, market participants should consider their exposure to a new risk factor in the future: pandemic risk.

2.2. Evidence of Interdependence and Financial Contagion

The interdependence between financial markets is associated with the phenomenon of joint movement between the prices of assets in these markets, and this phenomenon can occur even when there is no economic rationale to justify such a movement. According to Forbes and Rigobon (2002), given the interdependence of markets, joint movement does not arise due to economic shocks such as crises or pandemics, during which contagion occurs. However, contagion between countries can be recognized when there is a significant increase in the movements of the respective markets triggered by a shock to the economy.

According to Eichengreen et al. (1996), the financial contagion effect is related to the fact that the probability of a crisis in one country correlates with the crisis in another country once the political and economic fundamentals have been controlled. This effect could spill over more easily between countries with strong trade links or similar macroeconomic characteristics. However, Pericoli and Sbracia (2003) point out that the existence of financial contagion is subject to the following conditions: (1) the likelihood of crisis in one country rises with the existence of crisis in another country; (2) price volatility spreads from the crisis-affected country to others; (3) fundamentals do not drive the correlation of asset prices; (4) financial asset correlation increases across countries; (5) a change occurs in the transmission mechanism among countries caused by a crisis in one of them, which alters asset price correlations.

According to Ahelegbey et al. (2021), there are various channels through which financial interdependence and contagion effects can occur, with financial markets standing out. The study of this topic continues to attract the attention of international financial researchers.

Forbes and Rigobon (2002) tested the existence of these effects in three different periods: the Asian crisis of 1997, the Mexican economic crisis of 1994, and the US stock market crash of 1987. The authors used heteroscedasticity-biased tests based on correlation coefficients. The results show the existence of contagion between the crisis periods studied.

B. V. M. Mendes (2005) used copula theory to investigate the existence of excessively correlated movements between markets that conventional economic theories cannot adequately explain. The analysis considered seven stock markets in Latin America, Asia and Africa. The research found increased interdependence between these markets, particularly during joint losses, with the Argentina/Mexico and Brazil/Mexico pairs standing out.

Rodriguez (2007) analyzed the returns of five East Asian financial indices throughout the 1997 Asian crisis and four Latin American indices throughout the 1994 Mexican crisis. The author identified financial contagion effects in both crisis periods by applying the Markov switching model through copulas with time-varying parameters. Horta et al. (2010) used the copula method to test for contagion resulting from the subprime crisis in the Belgian, French, Dutch and Portuguese financial markets of Euronext. In terms of the generality of these financial markets, the study confirmed the phenomenon was present everywhere with equal intensity. With the same objective and using the same methodology, Zorgati et al. (2019) also found financial contagion effects in the Americas, Australia, China, Indonesia, Malaysia and Singapore. Most recently, R. Mendes et al. (2022) analyzed the financial contagion effects of the subprime crisis on southern and northern European countries. The authors used the copula method to estimate the interdependence between the PSI20 (Portugal), IBEX35 (Spain), ATHEX (Greece), FTSEMIB (Italy) and OMXH25 (Finland), OMXS30 (Sweden), OMXC20 (Denmark) and OsloOBX (Norway) indices. In parallel, the S&P500 US stock index was also analyzed. The results show that the interdependence between all European countries and the US intensified after the subprime crisis. Moreover, the southern countries, except for Portugal, were less affected by the contagion of the crisis.

In 2020, Zeren and Hizarci (2020) investigated risk diversification in the context of COVID-19 using the Maki cointegration test. The results show levels of causality between the number of daily deaths and six capital markets. Furthermore, a cointegration relationship was found between the number of cases of the disease and the SSE (China), KOSPI (South Korea) and IBEX35 (Spain) indices, but not with the FTSE MIB (Italy), CAC40 (France) and DAX30 (Germany) indices. The authors suggest that investors should avoid investing in stock markets during periods of long-term crisis.

Grima et al. (2021) analyzed the effects of the VIX index (CBOE Volatility Index of the Chicago Board Options Exchange) on major stock markets during the early phase of the COVID-19 pandemic. The authors subjected these data to the Johansen cointegration test and the fully modified least squares (FMOLS) method. The results indicate that there was cointegration between the VIX index and the pandemic, as well as between the VIX index and the country indices of the US (DJI), Germany (DAX), France (CAC40), England (FTSE100), Italy (MIB), China (SSEC) and Japan (Nikkei225). Lee et al. (2023) investigated whether the COVID-19 pandemic caused abnormal returns in the US and Chinese stock markets at the beginning of the outbreak. Using the event study methodology, the authors concluded that there was a significant negative impact on Chinese markets in the immediate aftermath of the shutdown, while US markets were slow to recover. The results also show that the pandemic was important in linking these two stock markets.

Pardal et al. (2020) analyzed financial integration in the stock market indices of Austria, Slovenia, Hungary, Lithuania, Poland, Czech Republic, Russia and Serbia in the context of the COVID-19 pandemic from 2019 to 2020. Using the Gregory and Hansen test, the authors found a very significant level of integration, which decreases the possibility of portfolio diversification in the long term. Suriawinata et al. (2023) used Johansen and Autoregressive Distributed Lag (ARDL) methods to test the integration of the Indonesian capital market with four developed markets, namely, the US, Australia, Hong Kong and the UK, between 2019 and 2020. The results reveal the comovement of the Indonesian stock market, with four comovements occurring during the COVID-19 pandemic. Endri et al. (2024) also examined the integration of the Indonesian stock market with eight major trading partners from 2013 to 2024: China, Japan, USA, Malaysia, India, Singapore, Philippines and South Korea. The analysis of short- and long-term dynamic relationships using the VAR model and multivariate cointegration showed the low integration of the Indonesian market with those of its partners in the long term, suggesting the possibility of portfolio diversification through international investments in these markets.

3. Results and Discussion

The empirical work begins with the methodology proposed by Forbes and Rigobon (2002) to test for contagion between Euronext stock indices. The procedure consists of testing whether the correlation has increased significantly after a pre-specified crisis event. In general, the return time series of the "source of contagion" index and the "index for which we are testing contagion" index are considered. Consider ρ_y as the correlation between the returns of two indices during the crisis period (high volatility) and ρ_x during the pre-crisis period (low volatility). If the volatility of the returns of the "source of contagion" index increases without changing the fundamental relationship between the return dynamics of the two indices, then $\rho_y > \rho_x$, giving a false appearance of contagion. Furthermore, the adjusted correlation ρ_a is considered, which is an unconditional correlation (i.e., a conditional correlation ρ_y scaled by a nonlinear function of the percentage change in volatility of the source index returns), and the underlying adjustment allows for a change in source index return volatility, where $\rho_a = \rho_y$ if there is no fundamental change in the relationship between the two indices.

The test establishes the null hypothesis $H_0 : \rho_a = \rho_x$ to test for a significant change in correlation against the alternative hypothesis $H_1 : \rho_a > \rho_y$, using the *t*-statistic with Fisher's transformation in the procedure.

Table 1 shows the values of the *t*-test statistic for contagion between the Euronext stock return indices.

Table 1. Values of the *t*-test statistic for contagion between the Euronext stock return indices.

Index	AEX	CAC40	BEL20	PSI	ISEQ
AEX					
CAC40	−8.3014/N				
BEL20	−12.267/N	−7.9601/N			
PSI	−4.3691/N	−3.8765/N	−6.4361/N		
ISEQ	−1.0620/N	1.7943/C	−4.9104/N	−0.7207/N	
OBX	−4.1939/N	−3.5231/N	−4.7188/N	0.4171/N	−3.5157/N

The critical value for the *t*-test at the 5% level is equal to 1.65, so any test statistic greater than this critical value indicates contagion (C), while any lower statistic indicates no contagion (N). The results suggest that contagion only occurred in the case of the CAC40/ISEQ index pair. Therefore, the prevailing relationship between the Euronext stock indices during the period of empirical analysis is characterized by interdependence.

3.1. Removing Autoregressive Effects and Conditional Heteroscedasticity

The procedure begins by calculating daily returns' autocorrelation and partial autocorrelation functions and their squares for each Euronext stock index. It then continues with the Ljung-Box test (for lags 10, 15, and 20) under the null hypothesis of no autocorrelation in the time series, and the Engle test under the null hypothesis of no ARCH effect. The *p*-value close to zero in both tests justifies the rejection of the null hypothesis, suggesting that the six sample stock indices have autoregressive and heteroscedastic effects (results available upon request).

These effects were removed by estimating ARMA-GARCH models on the daily returns of each index and obtaining the residuals, known as filtered returns. This econometric analysis led to the estimation of 94 models, and the most appropriate one was selected for each index based on the AIC, as shown in Table 2.

Table 2. Estimation of ARMA-GARCH models for Euronext stock indices returns.

Index	Model	Persistence	AIC
AEX	ARMA (5,4)-GARCH (2,2)	0.95681	−6.4799
CAC40	ARMA (5,5)-GARCH (2,2)	0.93965	−6.3058
BEL20	ARMA (5,5)-GARCH (2,2)	0.96829	−6.4828
PSI	ARMA (5,5)-GARCH (2,2)	0.94682	−6.3014
ISEQ	ARMA (5,5)-GARCH (2,2)	0.95281	−6.2141
OBX	ARMA (5,5)-GARCH (2,2)	0.93817	−6.3513

Note: ARMA-GARCH models were estimated with autoregressive parameters m and n ranging from 1 to 5 and parameters p and q ranging from 1 to 2.

Since the results of the persistence statistic are close to 1, the shock will remain in the long term for all indices (Zorgati et al., 2019). A high persistence of returns implies a low fluctuation in returns. This means that the higher the daily return, positive or negative, the more stable or persistent the return will be. Furthermore, the potential upward bias in the estimated persistence parameter may be an effect of structural changes in the GARCH parameters w, α and β (Diebold, 1986).

Both the Ljung-Box and Engle's ARCH tests were repeated (for lags 10, 15 and 20) on the six stock indices filtered returns, as shown in Table 3.

Table 3. Ljung-Box and ARCH tests on the filtered returns for Euronext stock indices.

Lag	Ljung-Box Test	*p*-Value	ARCH Test	*p*-Value
AEX				
10	3.46	0.97	10.43	0.40
15	7.92	0.93	13.51	0.56
20	11.82	0.92	24.08	0.24
CAC40				
10	0.72	1.00	9.54	0.48
15	7.93	0.93	11.31	0.73
20	10.73	0.95	16.65	0.68
BEL20				
10	3.86	0.95	12.48	0.25
15	5.47	0.99	26.73	0.03
20	10.87	0.95	30.25	0.07
PSI				
10	3.12	0.98	12.89	0.23
15	9.01	0.88	20.32	0.16
20	11.94	0.92	29.24	0.08
ISEQ				
10	7.47	0.68	6.21	0.80
15	11.69	0.70	22.33	0.10
20	13.36	0.86	25.56	0.18
OBX				
10	6.78	0.75	17.29	0.07
15	10.64	0.78	20.90	0.14
20	13.80	0.84	27.16	0.13

The results of the Ljung-Box and Engle ARCH tests show significant *p*-values above 5%, suggesting the elimination of autoregressive and conditional heteroskedastic problems and providing statistical quality to continue the empirical study.

3.2. Estimation of Copula Models

First, each filtered return time serjhies was divided between the pre-pandemic and post-pandemic subperiods. The empirical values of the tau coefficient for each stock index pair were obtained by subperiod, as shown in Table 4.

Table 4. Kendall's tau coefficient for each Euronext stock indices pair.

	Stock Indices Pairs														
Subperiods	**AEX/ CAC40**	**AEX /BEL20**	**AEX/ PSI**	**AEX/ ISEQ**	**AEX/ OBX**	**CAC40/ BEL20**	**CAC40/ PSI**	**CAC40/ ISEQ**	**CAC40/ OBX**	**BEL20/ PSI**	**BEL20/ ISEQ**	**BEL20/ OBX**	**PSI/ ISEQ**	**PSI/ OBX**	**OBX/ ISEQ**
Pre-pandemic	0.7055	0.6516	0.4755	0.4999	0.4220	0.6602	0.4866	0.5115	0.4131	0.4742	0.5102	0.3804	0.3945	0.3735	0.3178
Post-pandemic	0.6336	0.5682	0.3997	0.4984	0.3846	0.6120	0.4294	0.5493	0.3741	0.4096	0.5004	0.3565	0.3396	0.3482	0.3074

In general, the tau coefficients decrease for all pairs of financial indices from the pre-pandemic subperiod to the post-pandemic subperiod. This decline in correlation suggests a substantial change in the dynamics and interactions between the indices following the pandemic.

The study proceeds by estimating bivariate copula models using the Canonical Maximum Likelihood (CML) method to analyze the dependence structure among each pair of indices. The series of filtered returns were transformed into 12 uniform margins and formed the pairs of stock indices under analysis—AEX/CAC40, AEX/BEL20, AEX/PSI, AEX/ISEQ, AEX/OBX, CAC40/BEL20, CAC40/PSI, CAC40/ISEQ, CAC40/OBX, BEL20/PSI, BEL20/ISEQ, BEL20/OBX, PSI/ISEQ, PSI/OBX and ISEQ/OBX. Kendall's tau coefficient can also be useful in estimating the copula parameter, allowing dependency structures to be compared when the estimated copulas are different (Horta et al., 2010). For those pairs of indices, the Gaussian, t-Student, Clayton, Gumbel and Frank copula models were estimated, including the dependence parameter, tau coefficient and the tail dependence, as shown in Table 5.

The t-Student copula is recommended to describe the influence between pairs of Euronext indices in both analyzed subperiods, except for AEX/OBX.

Table 5. Estimation of copula models for each Euronext stock index pair.

Indices Pairs	Copulas	Dependence Parameter	Degrees of Freedom	tau Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
AEX/ CAC40	Gaussian	0.8950	-	0.7057	-	-	−2788.1390
		0.8409	-	0.6359	-	-	−1029.9690
	t-Student	**0.8954**	**3.7935**	**0.7062**	**0.6267**	**0.5615**	**−2907.6990**
		0.8413	**7.8279**	**0.6364**	**0.7993**	**0.3675**	**−1047.7920**
	Clayton	4.7930	-	0.2944	-	0.1726	−2342.0800
		3.4590	-	0.3664	-	0.2243	−897.5622
	Gumbel	3.1960	-	0.7617	0.6871	-	−2658.1600
		2.4810	-	0.7127	0.5969	-	−918.1527
	Frank	11.5200	-	0.9132	-	-	−2525.8180
		8.7420	-	0.8856	-	-	−930.0824

Table 5. *Cont.*

Indices Pairs	Copulas	Dependence Parameter	Degrees of Freedom	tau Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
AEX/ BEL20	Gaussian	0.8556 0.7721	- -	0.6537 0.5616	- -	- -	−2271.7640 −758.0478
	t-Student	**0.8566** **0.7778**	**5.6497** **5.5199**	**0.6549** **0.5673**	**0.7297** **0.6807**	**0.4336** **0.4160**	**−2338.9440** **−793.7489**
	Clayton	3.7410 2.6320	- -	0.3484 0.4318	- -	0.2109 0.2753	−1793.1760 −682.2807
	Gumbel	2.6930 2.1200	- -	0.7292 0.6795	0.6287 0.5283	- -	−2134.5630 −675.8411
	Frank	9.4270 7.1950	- -	0.8939 0.8610	- -	- -	−2053.7060 −715.3086
AEX/ PSI	Gaussian	0.6743 0.5861	- -	0.4711 0.3987	- -	- -	−1040.7510 −347.7480
	t-Student	**0.6774** **0.5881**	**9.2006** **9.2795**	**0.4738** **0.4002**	**0.7706** **0.7308**	**0.3066** **0.2741**	**−1066.6860** **−360.5709**
	Clayton	1.8140 1.3320	- -	0.5244 0.6002	- -	0.3554 0.4288	−772.5467 −333.8631
	Gumbel	1.7870 1.5540	- -	0.6412 0.6085	0.4404 0.3565	- -	−942.9273 −283.0906
	Frank	5.3460 4.1840	- -	0.8129 0.7610	- -	- -	−977.8034 −323.6561
AEX/ ISEQ	Gaussian	0.7111 0.7091	- -	0.5036 0.5018	- -	- -	−1210.2510 −582.2332
	t-Student	**0.7109** **0.7089**	**11.3598** **10.5728**	**0.5034** **0.5016**	**0.8251** **0.8114**	**0.2961** **0.3022**	**−1225.7880** **−589.2550**
	Clayton	1.9990 1.9870	- -	0.5001 0.5016	- -	0.3334 0.3348	−802.8557 −498.1848
	Gumbel	1.9050 1.8600	- -	0.6558 0.6503	0.4751 0.4624	- -	−1134.6680 −505.5395
	Frank	5.7220 5.7130	- -	0.8252 0.8250	- -	- -	−1092.4490 −529.7518
AEX/ OBX	Gaussian	0.6218 0.5680	- -	0.4272 0.3846	- -	- -	−837.4154 −321.4303
	t-Student	**0.6214** 0.5706	**7.3665** 6.6246	**0.4269** 0.3866	**0.6820** 0.6095	**0.3104** 0.3007	**−867.6490** −341.0885
	Clayton	1.4600 **1.2500**	- **-**	0.5780 **0.6154**	- **-**	0.4065 **0.4444**	−698.5630 **−343.7520**
	Gumbel	1.6540 1.5260	- -	0.6232 0.6041	0.3954 0.3447	- -	−746.1579 −261.4406
	Frank	4.5410 4.0020	- -	0.7798 0.7501	- -	- -	−753.7622 −298.5445
CAC40/ BEL20	Gaussian	0.8646 0.8219	- -	0.6649 0.6141	- -	- -	−2374.8960 −943.0930
	t-Student	**0.8643** **0.8221**	**6.1967** **6.3428**	**0.6645** **0.6144**	**0.7571** **0.7434**	**0.4143** **0.4014**	**−2424.4990** **−963.2706**
	Clayton	3.8870 3.1550	- -	0.3397 0.3880	- -	0.2046 0.2407	−1906.6850 −788.6469
	Gumbel	2.7560 2.3900	- -	0.7338 0.7050	0.6372 0.5816	- -	−2210.1020 −856.8523
	Frank	9.6640 8.2370	- -	0.8965 0.8786	- -	- -	−2122.5120 −857.5837

Table 5. *Cont.*

Indices Pairs	Copulas	Dependence Parameter	Degrees of Freedom	tau Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
CAC40/PSI	Gaussian	0.6893 0.6194	- -	0.4842 0.4252	- -	- -	−1106.7890 −400.8251
	t-Student	**0.6920** **0.6235**	**7.2390** **5.2834**	**0.4865** **0.4286**	**0.7161** **0.5584**	**0.3399** **0.3572**	**−1142.3630** **−431.2179**
	Clayton	1.8960 1.5060	- -	0.5133 0.5705	- -	0.3453 0.3990	−875.8155 −375.0491
	Gumbel	1.8310 1.6540	- -	0.6468 0.6232	0.4539 0.3954	- -	−1005.6440 −355.5108
	Frank	5.5330 4.6500	- -	0.8193 0.7849	- -	- -	−1029.7910 −378.0829
CAC40/ISEQ	Gaussian	0.7238 0.7593	- -	0.5152 0.5489	- -	- -	−1275.4440 −717.7577
	t-Student	**0.7237** **0.7609**	**10.0324** **6.6759**	**0.5151** **0.5505**	**0.8065** **0.7279**	**0.3113** **0.3753**	**−1294.0190** **−740.7025**
	Clayton	2.0940 2.4380	- -	0.4885 0.4507	- -	0.3232 0.2909	−861.2939 −640.7915
	Gumbel	1.9540 2.0470	- -	0.6615 0.6718	0.4882 0.5115	- -	−1199.8760 −634.6999
	Frank	5.9370 6.6890	- -	0.8316 0.8505	- -	- -	−1151.1540 −659.1173
CAC40/OBX	Gaussian	0.6111 0.5593	- -	0.4186 0.3778	- -	- -	−800.5750 −309.2969
	t-Student	**0.6103** **0.5584**	**11.5257** **5.2223**	**0.4179** **0.3772**	**0.7924** **0.4923**	**0.2649** **0.3257**	**−812.6181** **−337.2313**
	Clayton	1.4080 1.1950	- -	0.5869 0.6260	- -	0.4153 0.4556	−650.6740 −331.9872
	Gumbel	1.6170 1.5230	- -	0.6179 0.6036	0.3816 0.3434	- -	−693.6911 −260.9647
	Frank	4.3810 3.8670	- -	0.7717 0.7414	- -	- -	−716.9635 −280.9884
BEL20/PSI	Gaussian	0.6749 0.5990	- -	0.4716 0.4089	- -	- -	−1043.2350 −367.6508
	t-Student	**0.6775** **0.5999**	**6.4887** **7.1174**	**0.4739** **0.4096**	**0.6748** **0.6570**	**0.3497** **0.3054**	**−1084.4770** **−384.2308**
	Clayton	1.8040 1.3880	- -	0.5258 0.5903	- -	0.3566 0.4188	−809.7707 −362.8322
	Gumbel	1.8040 1.5870	- -	0.6434 0.6135	0.4457 0.3699	- -	−966.0578 −305.8225
	Frank	5.3300 4.3260	- -	0.8124 0.7688	- -	- -	−970.9994 −339.9377
BEL20/ISEQ	Gaussian	0.7239 0.7103	- -	0.5153 0.5029	- -	- -	−1275.6410 −585.0522
	t-Student	**0.7234** **0.7112**	**8.8632** **5.9964**	**0.5148** **0.5037**	**0.7809** **0.6689**	**0.3247** **0.3755**	**−1299.6420** **−608.6568**
	Clayton	2.0830 2.0040	- -	0.4898 0.4995	- -	0.3244 0.3329	−914.4944 −506.6758
	Gumbel	1.9470 1.8920	- -	0.6607 0.6542	0.4864 0.4715	- -	−1190.1000 −526.3663
	Frank	5.9190 5.7900	- -	0.8311 0.8273	- -	- -	−1145.0760 −533.6685

Table 5. *Cont.*

Indices Pairs	Copulas	Dependence Parameter	Degrees of Freedom	tau Coefficient	Upper Tail Dependence	Lower Tail Dependence	AIC
BEL20/OBX	Gaussian	0.5731 0.5406	- -	0.3885 0.3636	- -	- -	−680.7532 −284.5132
	t-Student	**0.5707** **0.5369**	**7.1039** **5.3144**	**0.3867** **0.3608**	**0.6359** **0.4785**	**0.2929** **0.3119**	**−712.8526** **−307.5239**
	Clayton	1.2280 1.1080	- -	0.6196 0.6435	- -	0.4488 0.4744	−601.8386 −300.4890
	Gumbel	1.5520 1.4960	- -	0.6082 0.5994	0.3557 0.3316	- -	−598.3160 −241.3552
	Frank	3.9640 3.6690	- -	0.7477 0.7274	- -	- -	−602.8683 −254.9061
PSI/ISEQ	Gaussian	0.5855 0.5092	- -	0.3982 0.3401	- -	- -	−718.2271 −246.3568
	t-Student	**0.5852** **0.5112**	**11.2549** **5.3334**	**0.3980** **0.3416**	**0.7767** **0.4511**	**0.2580** **0.2977**	**−731.4442** **−273.6517**
	Clayton	1.3030 1.0290	- -	0.6055 0.6603	- -	0.4342 0.4929	−561.8356 −252.6712
	Gumbel	1.5760 1.4550	- -	0.6118 0.5927	0.3655 0.3127	- -	−636.3604 −212.4668
	Frank	4.1150 3.4660	- -	0.7570 0.7115	- -	- -	−649.7576 −229.2870
PSI/OBX	Gaussian	0.5518 0.5243	- -	0.3721 0.3513	- -	- -	−620.1367 −264.1531
	t-Student	**0.5537** **0.5241**	**10.9131** **5.5931**	**0.3736** **0.3512**	**0.7547** **0.4909**	**0.2486** **0.2985**	**−633.9519** **−286.5113**
	Clayton	1.1930 1.0690	- -	0.6264 0.6517	- -	0.4560 0.4833	−499.3047 −280.2284
	Gumbel	1.5180 1.4700	- -	0.6029 0.5951	0.3412 0.3197	- -	−539.2102 −223.4428
	Frank	3.8420 3.5580	- -	0.7397 0.7189	- -	- -	−576.7862 −241.6733
ISEQ/OBX	Gaussian	0.4893 0.4684	- -	0.3255 0.3103	- -	- -	−466.1361 −202.3359
	t-Student	**0.4855** **0.4683**	**7.7879** **6.2938**	**0.3227** **0.3103**	**0.6021** **0.4879**	**0.2457** **0.2566**	**−491.7319** **−224.9201**
	Clayton	0.9319 0.8879	- -	0.6822 0.6925	- -	0.5176 0.5297	−426.0756 −219.7671
	Gumbel	1.4170 1.3870	- -	0.5863 0.5811	0.2943 0.2790	- -	−396.2354 −166.7752
	Frank	3.1890 3.0290	- -	0.6864 0.6699	- -	- -	−412.0625 −183.6187

Note: Based on the lowest AIC value, the best-fitting copula model (in bold) was selected for each subperiod. For each copula model, the pre-pandemic subperiod is shown in the top row and the post-pandemic subperiod is shown in the bottom row.

Table 6 divides the Kendall's tau coefficients estimated in each selected copula model by the pairs of stock indices for the pre-pandemic subperiod (panel A) and the post-pandemic subperiod (panel B). Since the identification of different copulas does not allow the comparison of dependence parameters, Table 6 also calculates the variation in tau coefficient between the pre- and post-pandemic subperiods for each pair of stock indices (panel C).

Table 6. Financial effect of the pandemic event on Euronext stock indices pairs.

Panel A—Kendall's tau Coefficient in the Pre-Pandemic Subperiod						
Index	**AEX**	**CAC40**	**BEL20**	**PSI**	**ISEQ**	**OBX**
AEX	–	0.7062	0.6549	0.4738	0.5034	0.4269
CAC40	0.7062	–	0.6645	0.4865	0.5151	0.4179
BEL20	0.6549	0.6645	–	0.4739	0.5148	0.3867
PSI	0.4738	0.4865	0.4739	–	0.3980	0.3736
ISEQ	0.5034	0.5151	0.5148	0.3980	–	0.3227
OBX	0.4269	0.4179	0.3867	0.3736	0.3227	–
Panel B—Kendall's tau Coefficient in the Post-Pandemic Subperiod						
Index	**AEX**	**CAC40**	**BEL20**	**PSI**	**ISEQ**	**OBX**
AEX	–	0.6364	0.5673	0.4002	0.5016	0.6154
CAC40	0.6364	–	0.6144	0.4286	0.5505	0.3772
BEL20	0.5673	0.6144	–	0.4096	0.5037	0.3608
PSI	0.4002	0.4286	0.4096	–	0.3416	0.3512
ISEQ	0.5016	0.5505	0.5037	0.3416	–	0.3103
OBX	0.6154	0.3772	0.3608	0.3512	0.3103	–
Panel C—Variation of Kendall's tau Coefficient Between Pre- and Post-Pandemic Subperiods						
Index	**AEX**	**CAC40**	**BEL20**	**PSI**	**ISEQ**	**OBX**
AEX	–	−0.0698	−0.0875	−0.0735	−0.0018	0.1885
CAC40	−0.0698	–	−0.0501	−0.0580	0.0354	−0.0407
BEL20	−0.0875	−0.0501	–	−0.0643	−0.0111	−0.0258
PSI	−0.0735	−0.0580	−0.0643	–	−0.0564	−0.0224
ISEQ	−0.0018	0.0354	−0.0111	−0.0564	–	−0.0125
OBX	0.1885	−0.0407	−0.0258	−0.0224	−0.0125	–

A visual inspection suggests that the CAC40 was the most influential index, especially on the AEX and BEL20 in the pre-pandemic subperiod, followed by the AEX (see panel A). However, the extreme event led to a change in dominance, with the AEX becoming the most influential index, especially over the CAC40 and OBX in the post-pandemic subperiod, followed by the CAC40 (see panel B).

Except for pairs AEX/OBX and CAC40/ISEQ, the decrease in tau coefficient suggests that the dependence relationships among the stock indices deteriorated from the pre-pandemic to the post-pandemic subperiod (see panel C). Concretely, the decrease in the tau coefficient was greater for the AEX/BEL20, AEX/PSI, AEX/CAC40 and BEL20/PSI pairs, reflecting their decreasing interdependence.

Interestingly, the increase in the coefficient for the pairs with the latest Euronext indices (ISEQ and OBX) indicates that the correlations with the largest indices (CAC40 and AEX) intensified, reinforcing the joint post-pandemic movement.

4. Materials and Methods

The copula method is used to analyze the influence relationships between the Euronext stock indices, and the possible changes caused by an extreme event—the COVID-19 pandemic. As a first step, any problems related to the volatility of the financial series are corrected by estimating ARMA-GARCH models and obtaining the daily returns of the indices filtered for autoregressive effects and conditional heteroscedasticity.

4.1. Limitations of the ARCH and ARMA-GARCH Models

Engle (1982) introduced the ARCH (AutoRegressive Conditionally Heteroscedastic) model to explain some of the statistical properties of financial time series and clarify the volatility associated with chronological data. Financial time series data often exhibit unstable behavior characterized by the presence of autoregressive and conditional heteroscedasticity effects. Although the ARCH model is simple to calculate, it requires many parameters to describe the evolution of volatility (Tsay, 2005).

As an alternative, Bollerslev (1986) proposed the GARCH(p,q) (Generalized AutoRegressive Conditional Heteroscedasticity) model, which is more practical to use and more stable to estimate, and it describes the variance of the current error term as a function of the actual sizes and variances of the error terms from previous periods,

$$\sigma_t^2 = w + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

where the model coefficients must satisfy the conditions $w > 0$, $\alpha_i \geq 0$ $(\text{with} i = 1, \cdots, p)$ and $\beta_j \geq 0$ $(\text{with} j = 1, \cdots, q)$ to ensure that the conditional variance σ_t^2 remains non-negative at all times t, and has finite expected value or higher moments. If $q = 0$, this corresponds to an ARCH model of p-order. In this context, the estimate of the "persistence parameter" is given by $\alpha + \beta$.

In turn, this empirical work uses a GARCH model extension that is given by the ARMA-GARCH (AutoRegressive Moving Average-Generalized AutoRegressive Conditional Heteroscedasticity) model. This formulation combines the properties of the ARMA model, which allows the modeling of a linear time series, with those of the GARCH model, which allows the modeling of the non-linearity of the residual series, giving greater reliability to the results.

In the $\mathrm{AR}(m)$ model, the m-order is the number of AutoRegressive terms corresponding to lags in the Y_t time series; in the $\mathrm{MA}(n)$ model, the n-order is the number of Moving Average terms corresponding to lags in the ε_t random errors. The $\mathrm{ARMA}(m, n)$ model is expressed by

$$y_t = \mu + \sum_{i=1}^{m} \phi_i y_{t-i} + \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{2}$$

where μ is a constant term, ϕ_i are the parameters of the autoregressive terms, θ_j are the parameters of the moving average terms, and m and n are non-negative integer values, being $E(\varepsilon_t) = 0$ and $V(\varepsilon_t) = \sigma^2$.

In order to correct for the above effects, we use the ARMA-GARCH model via the following procedures:

(i) Conditional mean is represented by the $\mathrm{ARMA}(m, n)$ model, formalized in (2);
(ii) Conditional variance is represented by the $\mathrm{GARCH}(p, q)$ model, formalized in (1).

Once the candidate ARMA-GARCH models have been estimated, the most appropriate structure is selected based on the lowest value obtained from the Akaike Information Criterion (AIC),

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{3}$$

where L is the likelihood function value obtained by parameter estimation with k parameters.

4.2. Copula Models

Several studies have proposed the copula method to study the effects of contagion or financial dependence (Costinot et al., 2000; Embrechts et al., 2003; Hu, 2006; Horta et al., 2010; R. Mendes et al., 2022). A copula is a multivariate distribution function on $[0, 1]^n$

with uniform marginal distributions (Embrechts et al., 2003; Boubaker & Salma, 2011). The models link such distributions of two variables to obtain their joint distribution for analyzing the levels and structures of those effects (Hu, 2006).

Since X and Y are random variables with a copula C, the variable Y will be a function of X if C lies between the two Fréchet–Hoeffding limits,

$$W(u, v) = \max(0, u + v - 1) \text{ and } M(u, v) = \min(u, v), \quad (u, v) \in [0, 1] \tag{4}$$

where a copula C translates a dependency structure model between X and Y,

$$W(u, v) \le C(u, v) \le M(u, v) \tag{5}$$

The following asymptotic tail coefficients λ_u and λ_l can be used as measures of local dependence between variables (Horta et al., 2010). Both coefficients can be expressed as a function of a copula C,

$$\lambda_u = \lim_{u \to 1} \frac{1 - 2u + C(u, u)}{1 - u}, \lambda_l = \lim_{u \to 0} \frac{C(u, u)}{u} \tag{6}$$

The tail dependency coefficients indicate the likelihood of one variable reaching an extreme value, given that another variable has already attained it. In this context, they can assess the probability of the markets crashing together, through the lower asymptotic tail λ_l, or booming together, through the upper asymptotic tail λ_u. Therefore, the higher the coefficients, the greater the likelihood of market interactions, both in downturns, which in this case means an increased risk of losses, and in upturns.

The Gaussian copula is expressed by

$$C(u_1, u_2; \rho) = \Phi_2\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \rho\right) \tag{7}$$

where Φ^{-1} is the inverse of the univariate normal distribution function $N(0, 1)$ and Φ_2 is the bivariate normal distribution function with mean 0, variance 1 and correlation coefficient ρ (Czado, 2019).

The t-Student copula is expressed by

$$C^t_{v,R}(u) = t^n_{v,R}\left(t_v^{-1}(u_1), \cdots, t_v^{-1}(u_n)\right) \tag{8}$$

where $t^n_{v,R}$ is the multivariate t_v-Student distribution, t_v^{-1} is the inverse of the t-Student distribution with v degrees of freedom, and $R_{ij} = \Sigma_{ij} / \sqrt{\Sigma_{ii}\Sigma_{jj}}$ is the correlation matrix.

The Clayton copula presents dependence on the lower limit of the distribution,

$$C_\theta(u, v) = \max\left(\left[u^{-\theta} + v^{-\theta} - 1\right]^{-1/\theta}, 0\right) \tag{9}$$

where $\varphi(t) = \left(t^{-\theta} - 1\right)/\theta$ and $\theta \in [-1, \infty) \setminus \{0\}$.

The Gumbel copula presents dependence on the upper limit of the distribution,

$$C_\theta(u, v) = \varphi^{-1}(\varphi(u) + \varphi(v)) = \exp\left(-\left[(-\ln u)^\theta + (-\ln v)^\theta\right]^{1/\theta}\right) \tag{10}$$

The Frank copula presents relatively weak values of symmetric dependence at the limits of the distribution,

$$C_\theta(u, v) = -\frac{1}{\theta} \ln\left(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v} - 1\right)}{e^{-\theta} - 1}\right) \tag{11}$$

where $\varphi(t) = -\ln \frac{e^{-\theta t}-1}{e^{-\theta}-1}$ and $\theta \in \mathbb{R} \setminus \{0\}$.

Since the bivariate copula models have distribution functions that range within $[0,\ 1]^2$, the filtered return series are transformed into uniform margins $\hat{u}_{i,j}$ using the empirical distribution function $\hat{F}_{j,n}(x_{i,j})$,

$$\hat{u}_{i,j} = \hat{F}_{j,n}(x_{i,j}) \qquad \text{and} \qquad \hat{F}_{j,n}(x_{i,j}) = \frac{1}{n+1}\sum_{i=1}^{n} I_{[x_{ij} \leq x]} \tag{12}$$

A parametric family of copulas is used to estimate the interdependence between the marginal distributions (Kim et al., 2007). Given the copula $C(u_1, u_2, \ldots u_m; \theta)$ and its density function $c(u_1, u_2, \ldots u_m; \theta)$, θ represents the vector of parameters estimated by the Maximum Likelihood method,

$$\hat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmax}} \sum_{i=1}^{n} \log c(\hat{u}_{i1}, \ldots, \hat{u}_{im}; \theta) \tag{13}$$

4.3. Sample, Data and Procedures

The main stock indices on the Euronext platform were selected to form the sample—AEX (Dutch), CAC40 (France), BEL20 (Belgium), PSI (Portugal), ISEQ (Ireland) and OBX (Norway). The daily closing levels of each index were obtained from the Yahoo Finance platform (https://finance.yahoo.com/world-indices/) (accessed on 9 March 2025), and the respective daily returns were calculated as follows:

$$\text{return}_t = \frac{\text{price}_t - \text{price}_{t-1}}{\text{price}_{t-1}} \tag{14}$$

The empirical study has a reference date of 11 March 2020, when the World Health Organization declared the outbreak of the pandemic. The ten-year time horizon is separated into a pre-pandemic subperiod from 1 June 2013 to 10 March 2020 and a post-pandemic subperiod from 11 March 2020 to 30 June 2023.

The methodological procedure for studying the relationships of influence between the main Euronext stock indices and identifying the changes caused by the extreme event—the COVID-19 pandemic—is as follows:

(1) Remove autoregressive and conditional heteroscedastic effects using ARMA-GARCH models, obtaining the filtered returns of the financial index time series. The AIC criterion is used to select the most appropriate model for each index;
(2) Divide each series into the pre-pandemic subperiod and the post-pandemic subperiod. Transform the respective filtered returns into uniform margins for each subperiod;
(3) Estimate the Kendall's tau (τ) correlation coefficient (as a measure of dependence that can overcome some of the limitations of linear correlation) and the copulas for both subperiods of each index from the uniform distributions;
(4) Select the best model to infer the influence relationships between the indices through the AIC criterion.

5. Conclusions

Financial markets play an essential role in the global economy, serving as engines for allocating resources, setting prices and managing risk. Euronext distinguishes itself in the international financial markets by bringing European stock indices together on a single platform so that they can interact and influence each other. Understanding these relationships and the underlying dynamics is crucial for researchers and those involved in the financial markets. Severe events such as the COVID-19 pandemic can trigger significant changes in a globalized world. For this reason, studying these interactions becomes even more important in order to anticipate and manage the risks that can affect economies.

Contagion was found only in the case of the CAC40/ISEQ pair. Therefore, the empirical study proceeded using the copula method to analyze the dependency relationships between six Euronext stock indices and any changes impacted by the extreme event—the COVID-19 pandemic. Recent studies have also used this modeling approach to investigate interdependencies between financial markets (Rodriguez, 2007; Horta et al., 2010; Zorgati et al., 2019; R. Mendes et al., 2022). The t-Student copula was chosen for most financial index pairs, except for the AEX/OBX pair. This suggests that for most pairs, the interdependence structures exhibit a symmetric relationship with influence between the indices, both upwards and downwards. Other studies have also found interdependencies between stock indexes, especially during joint losses (B. V. M. Mendes, 2005), and contagion during extreme events such as economic crises (Rodriguez, 2007; Horta et al., 2010; Zorgati et al., 2019). In the case of the AEX/OBX pair, the t-Student copula fits better for the pre-pandemic period, and the Clayton copula fits better for the post-pandemic period. This evidence suggests that interdependence dynamics have undergone significant changes in response to the pressures arising from the COVID-19 pandemic. Similar conclusions were drawn by Zeren and Hizarci (2020), Grima et al. (2021) and Lee et al. (2023). The change means that the two indices have moved from a symmetric dependence relationship to a stronger dependence at the lower end of the distribution, i.e., when the market falls, as identified by B. V. M. Mendes (2005).

In addition, the dominant influences of the CAC40 and the AEX before and after the pandemic confirm that the size and age of these indices give them a benchmark position in the market.

Except for the AEX/OBX and CAC40/ISEQ pairs, the decrease in tau coefficient shows that the interdependences among the stock indices decreased from the pre- to the post-pandemic subperiod. Similar evidence was reported by Endri et al. (2024). This behavior also suggests that the pandemic event weakened the correlation between markets, making them more mature, independent and efficient, according to Gomes et al. (2022). This also means that investing in these indices can mitigate portfolio risk by diversifying into assets that have reduced correlation dynamics. However, these results contrast with those of Pardal et al. (2020) and Lee et al. (2023), who found greater interdependence between stock markets after the pandemic, and with those of R. Mendes et al. (2022) after the subprime crisis.

The conclusions highlight the importance of understanding the complex interactions between stock indices and their ability to adapt to extreme events. In addition, the findings contribute to the improvement of portfolio management strategies as financial markets continue to evolve and face unexpected challenges. A high degree of integration means that markets move in the same way, reducing the usefulness of portfolio diversification (Pardal et al., 2020). Conversely, international investment between stock markets with low correlation dynamics can mitigate portfolio risk (Endri et al., 2024). In the short term, however, it is possible to adopt market momentum strategies under the expectation that interdependencies will increase during extreme events (Forbes & Rigobon, 2002; B. V. M. Mendes, 2005; Rodriguez, 2007; Pardal et al., 2020; Grima et al., 2021; Lee et al., 2023; Suriawinata et al., 2023) and become less intense after shocks (Gomes et al., 2022; Endri et al., 2024). This study also shows that after the pandemic, the AEX/OBX index pair reduced the correlation dynamic in the market's upward behavior. Furthermore, the decrease in interdependencies also suggests that the composition of the investment portfolios in Euronext stock indices, with the exception of the AEX/OBX and CAC40/ISEQ pairs, mitigates risk in both up and down markets.

More comprehensive studies are recommended for future research. For example, implementing a DCC-GARCH model to track the dynamic evolution of interdependencies during the different phases of the crisis would provide a more detailed understanding of how market relationships changed in response to the shocks and the subsequent recovery from the COVID-19 pandemic. On the other hand, the impact of the fear index or the investor sentiment index on the joint movement of international stock indices can be studied.

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References

Ahelegbey, D. F., Giudici, P., & Hashem, S. Q. (2021). Network VAR models to measure financial contagion. *The North American Journal of Economics and Finance*, *55*, 101318. [CrossRef]

Alfaro, L., Chari, A., Greenland, A. N., & Schott, P. K. (2020). *Aggregate and firm-level stock returns during pandemics, in real time.* Working Paper No. 26950. National Bureau of Economic Research. Available online: https://www.nber.org/system/files/working_papers/w26950/w26950.pdf (accessed on 3 February 2025).

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. [CrossRef]

Boubaker, A., & Salma, J. (2011). Detecting financial markets contagion using copula functions. *International Journal of Management Science and Engineering Management*, *6*(6), 443–449. [CrossRef]

Costinot, A., Roncalli, T., & Teiletche, J. (2000). *Revisiting the dependence between financial markets with copulas*. SSRN. [CrossRef]

Czado, C. (2019). Multivariate distributions and copulas. In *Analyzing dependent data with vine copulas* (Vol. 222). Lecture Notes in Statistics. Springer. [CrossRef]

Diebold, F. X. (1986). Modeling the persistence of the conditional variances: A comment. *Econometric Reviews*, *5*(1), 51–56. [CrossRef]

Ding, W., Levine, R., Lin, C., & Xie, W. (2021). Corporate immunity to the COVID-19 pandemic. *Journal of Financial Economics*, *141*(2), 802–830. [CrossRef]

Eichengreen, B., Rose, A., & Wyplosz, C. (1996). *Contagious currency crises.* Working Paper No. 5681. National Bureau of Economic Research. Available online: https://www.nber.org/system/files/working_papers/w5681/w5681.pdf (accessed on 3 February 2025).

Embrechts, P., Lindskog, F., & McNeil, A. (2003). Chapter 8—Modelling dependence with copulas and applications to risk management. In S. T. Rachev (Ed.), *Handbook of heavy tailed distributions in finance* (pp. 329–384). North-Holland. [CrossRef]

Endri, E., Fauzi, F., & Effendi, M. S. (2024). Integration of the Indonesian stock market with eight major trading partners' stock markets. *Economies*, *12*(12), 350. [CrossRef]

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, *50*(4), 987–1007. [CrossRef]

Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance*, *57*(5), 2223–2261. Available online: http://www.jstor.org/stable/3094510 (accessed on 5 February 2025). [CrossRef]

Gomes, L. M. P., Soares, V. J. S., Gama, S. M. A., & Matos, J. A. O. (2022). Efficiency drifts in Euronext stock indices returns. *International Journal Business*, *27*(2), 1–17. [CrossRef]

Grima, S., Özdemir, L., Özen, E., & Romãnova, I. (2021). The Interactions between COVID-19 cases in the USA, the VIX index and major stock markets. *International Journal of Financial Studies*, *9*(2), 26. [CrossRef]

Horta, P., Mendes, C., & Vieira, I. (2010). Contagion effects of the subprime crisis in the European NYSE Euronext markets. *Portuguese Economic Journal*, *9*, 115–140. [CrossRef]

Hu, L. (2006). Dependence patterns across financial markets: A mixed copula approach. *Applied Financial Economics*, *16*(10), 717–729. [CrossRef]

Junior, L. S., Mullokandov, A., & Kenett, D. Y. (2015). Dependency relations among international stock market indices. *Journal of Risk and Financial Management*, *8*(2), 227–265. [CrossRef]

Kim, G., Silvapulle, M. J., & Silvapulle, P. (2007). Comparison of semiparametric and parametric methods for estimating copulas. *Computational Statistics & Data Analysis*, *51*(6), 2836–2850. [CrossRef]

Lee, H.-A., Liew, V. K.-S., Ghazali, M. F., & Riaz, S. (2023). Reaction of US and Chinese stock markets to COVID-19 news. *International Journal of Financial Studies*, *11*(2), 59. [CrossRef]

Mendes, B. V. M. (2005). Asymmetric extreme interdependence in emerging equity markets. *Applied Stochastic Models in Business and Industry*, *21*(6), 483–498. [CrossRef]

Mendes, R., Gomes, L., & Ramos, P. (2022). Financial contagion from the subprime crisis: A copula approach. *Scientific Annals of Economics and Business*, *69*(4), 501–520. [CrossRef]

Pardal, P., Dias, R., Šuleř, P., Teixeira, N., & Krulický, T. (2020). Integration in Central European capital markets in the context of the global COVID-19 pandemic. *Equilibrium*, *15*(4), 627–650. [CrossRef]

Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of Economic Surveys*, *17*(4), 571–608. [CrossRef]

Rodriguez, J. C. (2007). Measuring financial contagion: A Copula approach. *Journal of Empirical Finance*, *14*(3), 401–423. [CrossRef]

Suriawinata, I. S., Setianingrum, P. H., Prastuti, D., Rusli, D., & Pranitasari, D. (2023). COVID-19, structural breaks, and capital market integration: Indonesian evidence. *Journal STEI Ekonomi*, *32*, 1–15. [CrossRef]

Tsay, R. S. (2005). *Analysis of financial time series*. John Wiley & Sons, Inc. ISBN 978-0-471-69074-0.

Zeren, F., & Hizarci, A. (2020). The impact of COVID-19 coronavirus on stock markets: Evidence from selected countries. *Bulletin of Accounting and Finance Reviews*, *3*(1), 78–84. [CrossRef]

Zorgati, I., Lakhal, F., & Zaabi, E. (2019). Financial contagion in the subprime crisis context: A copula approach. *The North American Journal of Economics and Finance*, *47*, 269–282. [CrossRef]