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Analyis of Relationship between Selected Stock Exchanges in Euro Area Countries: A Quantitative Approach

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Abstract:

Purpose: *The purpose of this paper is to carry out an analysis of relationship between stock exchanges in Italy and Germany.*
Design/Methodology/Approach: *The study employs a literature and methodology review in researching relationships between selected stock exchanges along with its own analysis of relationship between Italian and German stock exchanges with the use of Vector Autoregreesion method (VAR).*
Findings: *From the theoretical analysis and carried out research it can be assessed that there is no long term relationship between German and Italian stock exchange, although shocks from German stock exchange are rather to be more influential on Italian stock exchange than vice versa.*
Practical Implications: *Findings can be of use to teachers, academics and policy decision-makers. Originality/Value: The research can spur further discussion about the methods and measures of assessing the interconnectness between stock exchanges.*

Keywords: *Stock market integration, spillovers, connectedness, segmentation, Granger causality, VAR, stock market development.*

JEL Codes: *O16, G19, E44, C58; F36, G15.*

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1. Introduction

The interconnectedness of financial markets has been a valid topic of research for decades and is believed to be one of the pillars of modern finance. Understanding the nature of these linkages = whether they are bi-directional (interdependent), uni-directional, or non-existent (independent) - can be crucial for investors seeking diversification, regulators aiming to mitigate systemic risk, as well as for academics modeling asset pricing. The literature has evolved significantly, moving from early studies on market correlation to more advanced analyses of volatility spillovers and dynamic contagion

This paper aims to analyse possible relationship between stock exchanges of Italy and Germany focusing on the econometric methodologies, and findings that have shaped the understanding of how stock exchanges relate to one another.

2. Literature Review

The dominant finding in the literature, particularly since the 1990s, is that major stock exchanges exhibit significant bi-directional relationships. This interdependence is driven by globalization, the integration of economies, real-time information flows, and the behavior of multinational investors.

The concept of "contagion" was explored by King and Wadhwani (1990), who argued that market downturns are transmitted globally like a "meteor shower," affecting all markets simultaneously rather than through a slower, country-specific "heat wave" process.

Using data around the 1987 crash, they found a significant increase in the correlation between major markets. This work established that linkages are not static and intensify during periods of high volatility. Longin and Solnik (1995, 2001) expanded this topic even further. They utilized a multivariate GARCH model to show that the correlation coefficient between major stock markets is not constant but conditional on market volatility. Specifically, they found that "correlation increases in periods of high volatility", particularly during market downturns directly challenging at the same time the benefits of international diversification.

The literature on regional integration provides further evidence. Studies on the European Union often find strong bi-directional spillovers, especially after implementation of Monetary Union. Baele (2005) analyzed the integration of European stock markets and found that both global and regional sgocks, significantly impact market volatility, indicating deep co-movement. Thalassinos (2008), Thalassinos and Politis (2011) and Thalassinos and Thalassinos (2006) analyzed the integration in the European financial sector, the stock market integration and the international stock markets co-integration.

Similarly, Christiansen (2007) examined the linkages between the US, UK, German, and Japanese bond and stock markets, finding significant evidence of volatility spillovers in both directions, particularly between the stock markets.

The 2008 Global Financial Crisis (GFC) reinforced these findings. Dimitriou, Kenourgios, and Simos (2013) studied six developed and emerging markets during the GFC, using a dynamic conditional correlation (DCC) GARCH model. Their findings confirmed that "interdependence among all markets increases significantly" during crisis periods. Bekaert *et al.* (2014) further explored this, concluding that while global risk aversion is a primary driver, contagion effects beyond fundamental channels were present during the GFC, confirming strong bidirectional feedback loops.

While interdependence might seem as a widespread phenomenon, a significant portion of the literature identifies a clear directional flow of influence, typically from larger, more developed markets to smaller or emerging ones. The US market is almost universally identified as the primary global leader.

Eun and Shim (1989) using a VAR model on daily data from nine major stock markets, found that the US market was the most influential, with innovations in the US significantly impacting almost all other markets. However, the feedback from other markets to the US was minimal, establishing a clear unidirectional relationship.

This US-centric leadership turns out to be persistent one. Hamao, Masulis, and Ng (1990) used a GARCH model to study volatility spillovers between New York, Tokyo, and London. They found significant spillovers from New York to Tokyo and from London to Tokyo, but not in the reverse direction, coining the terms "heat wave" and "meteor shower" slightly differently to describe how volatility is transmitted from one market's close to another's open.

Masih and Masih (1997) applied cointegration and VECM to Asian markets (Hong Kong, Singapore, Taiwan, South Korea) and found that they were predominantly led by the US and UK markets in the long run. With the fast emergence of China as a global power more and more studies have focused on chinese stock exchanges and their influence on neigbouring countries and their stock exchanges.

Liu and Pan (1997) demonstrated a one way volatility spillover from the S&P500 to the Japanese and Hong Kong markets. Similarly, Arouri, Bellalah, and Nguyen (2010) found that the US stock market's influence on the Chinese market was significant and uni-directional, especially after China's accession to the WTO. During the COVID-19 pandemic, Akhtaruzzaman *et al.* (2021) showed that financial contagion flowed uni-directionally from China and the US to other G7 countries.

On the other hand, some markets seem to be segmented or operate independently from the global system. This statement formed the basis of international diversification, as outlined in Solnik (1974). While complete independence is rather rare today, a body of literature has explored this concept, particularly through the "decoupling hypothesis."

Early studies often found correlations, which implied a degree of independence. Makridakis and Wheelwright (1974) found relatively low correlations among major markets, though this was largely a feature of the pre-globalization era.

The "decoupling hypothesis" gained prominence in the early XXI century. It postulated that emerging markets, particularly in Asia, had become resilient enough to grow independently of business cycles in developed nations like the US. Kose, Otrok, and Prasad (2008) analyzed business cycles and found evidence that the correlation between emerging and industrial country business cycles had decreased in the 1990s, lending support to the decoupling theory.

However, the 2008 GFC served as a powerful counterargument. Dooley and Hutchison (2009) explicitly tested the decoupling hypothesis during the GFC and found it to be a "mirage", demonstrating that emerging markets were severely affected by the crisis originating in the US. Their analysis showed a "re-coupling" as the crisis intensified. Waltia (2009) found similar evidence for India, showing its market was significantly integrated with and affected by the US market during the GFC.

One might argue that "no relationship status" is a thing of the past or perhaps only of isolated, illiquid "frontier" markets. For most investable markets, independence is a short-lived phenomenon that vanishes during global stress. As Pukthuanthong and Roll (2009) demonstrate, while some country indices appear to have low correlations on the surface, a deeper factor analysis reveals they are often driven by the same underlying global risk factors.

Various studies tackled this issues with various methods, tools and measures. Network and spillover studies show dense, reciprocal ties among major exchanges; centrality often highest for US and Europe, with two-way spillovers intensifying during stress times (e.g., COVID-19), reducing diversification (Liu, Xu, and Xie, 2024, Li *et al.,* 2023). Liu, Xu, and Xie (2024) cover 20 major stock markets in their research.

Using Diebold—YiImaz spillover indices (time/frequency), structural change detection and identifying potential TVP/rolling windows, they conlude that predominantly bi-directional spillbover happen among major hubs. They identify time-varying intensity with stress-time peaks and some uni-directional flows into emerging markets.

Intra-regional clusters (EU, Asia-Pacific) research captures stronger two-way links within regions, especially trading hours overlap or cross-listing is high (Li *et al.,* 2023). Frequency-domain evidence often shows stronger bi-directional dependence at short horizons during crises and reversion at longer horizons. Directional spillover indices and Granger frameworks frequently identify leadership from US/Europe into BRICS/ASEAN/MENA, with some feedback emerging as markets mature (Liu, Xu and Xie, 2024).

During acute shocks, leadership may flip temporarily (e.g., local/regional hubs transmitting to neighbors), creating transient uni-directional episodes within otherwise bi-directional systems (Li *et al.,* 2023). Studies of integration and market development document phases of partial segmentation (e.g., frontier markets, policy regimes), and show that "no relationship" conclusions can be frequency-specific (long horizons remain segmented while short-run co-movements are present, Stawarz, 2025). Stawarz (2025) concludes with evidence of rising but time-varying integration and segmentation pockets as a useful background for interpreting bi-/uni-/no-relationship findings.

Senna and Mendonca Souza (2023) analyze data from 21 stock exchanges plus 3 major cryptocurrencies. With the use of cointegration study/ARDL methods for long-run versus short-run links and causality tests they identify cross-market dependence that tightens in stress, equity-crypto uni-directional/two-way episodes occuring and potential segmentation in normal periods at long horizons.

In addition, research in recent years is also concentrating on volatility spillover effects, methods and measures across different asset classes and markets (Alimi and Adediran, 2023, Liu, Xu and Xie, 2024, Hussain, Bashir and Rehman, 2023, Saranj and Zolfaghari, 2025, El-Diftar, 2023)

Some sectoral or cross-asset relationships with exchanges weaken outside stress regimes; several papers note that once crisis periods are excluded, certain pairs exhibit weak or no dependence over selected frequencies, consistent with episodic decoupling.

3. Research Methodology

The data for the study is obtained from stooq.pl website. The indexes of 2 Euro Area stock exchanges serve as endogenous variables: Germany and Italy. They are blue chip indexes (DAX for Germany and FTSEMIB for Italy), which means they cover selected number of companies from each stock exchange. Those tend to be most traded companies with a high level of capitalization and liquidity of their shares. The author utilizes 324 monthly observations for the sample period from 1998:01 to 2024:12.

The following model is built in compliance with the literature and data availability. Two variables are under study, so it is required to estimate 2 equations as listed below:

$$lnGER_t = \mu_1 + \sum_{i=1}^{k} \alpha_{1i} lnGER_{t-i} + \sum_{i=1}^{k} \beta_{1i} lnITA_{t-i} + \varepsilon_{1t} \quad (1)$$

$$lnITA_t = \mu_2 + \sum_{i=1}^{k} \alpha_{2i} lnGER_{t-i} + \sum_{i=1}^{k} \beta_{2i} lnITA_{t-i} + \varepsilon_{2t} \quad (2)$$

where:
k – the number of lags,
$lnGER_t$ – the natural logarithm of German stock exchange index in time t,
$lnITA_t$ – the natural logarithm of Italian stock exchange index in time t,
$lnGER_{t-i}$ – the lagged value of German stock exchange index up to the lag order of i,
$lnITA_{t-i}$ – the lagged value of Italian stock exchange index up to the lag order of i
α_{1i}, α_{2i} – structural parameters, where the first subscript denotes the number of equation and the second subscript, the number of lags,
β_{1i}, β_{2i} – structural parameters, where the first subscript denotes the equation number and the second subscript, the number of lags,
γ_{1i}, γ_{2i} – structural parameters, where the first subscript denotes the equation number and the second subscript, the number of lags,
μ_1, μ_2 - the intercept, where the subscript denotes the equation number,
$\varepsilon_1, \varepsilon_2$ – error term (called shock, innovation or impulse in the VAR nomenclature), where the subscript denotes the equation number.

The basic condition for building a VAR model is the stationarity of the variables. In the first step, the stationarity is examined and a results can be seen in Table 1).

Table 1. *Selected factors of stock market development*

Augmented Dickey-Fuller test for dl_DAX	**Augmented Dickey-Fuller test for dl_FTSEMIB**
testing down from 16 lags, criterion AIC sample size 322 unit-root null hypothesis: a = 1 test with constant including 0 lags of (1-L)ld_DAX model: (1-L)y = b0 + (a-1)*y(-1) + e estimated value of (a - 1): -0.948082 test statistic: tau_c(1) = -17.0007 asymptotic p-value 9.268e-41 1st-order autocorrelation coeff. for e: -0.001	testing down from 16 lags, criterion AIC sample size 320 unit-root null hypothesis: a = 1 test with constant including 2 lags of (1-L)ld_FTSEMIB model: (1-L)y = b0 + (a-1)*y(-1) + ... + e estimated value of (a - 1): -0.935117 test statistic: tau_c(1) = -9.60171 asymptotic p-value 6.19e-18 1st-order autocorrelation coeff. for e: -0.004

Source: *The author's own compilation using Gretl.*

In order to test for the stationarity of variables, they are subjected to the augmented Dickey-Fuller test (ADF) with the intercept. For the purposes of the ADF test, 16 lags suggested by the GRETL program are adopted. The variables turn out to be stationary (integrated of order 1 I(I)), as the obtained p-values are lower than the accepted significance level of 0.05.

At the next stage, the length of the lags that will be used to build the model is determined. The Akaike (AIC), Hannan-Qiunn (HQC), and Schwartz information criteria (BIC) are most often used. In order to estimate the number of lags, all three information criteria are taken into account. The maximum lag of 12 lags is implemented. The function with the intercept is used.

Having stationary variables and selected lag order, the model is estimated. The tests of autocorrelation, the test of ARCH effect, and the test for the normality of residuals should be performed then. This is also where Granger causality is defined. Engle-Granger cointegration can also be examined to determine if there is a statistically significant long-term relationship between the variables under study (Table 2).

Table 2. *Engle-Granger test for cointegration*

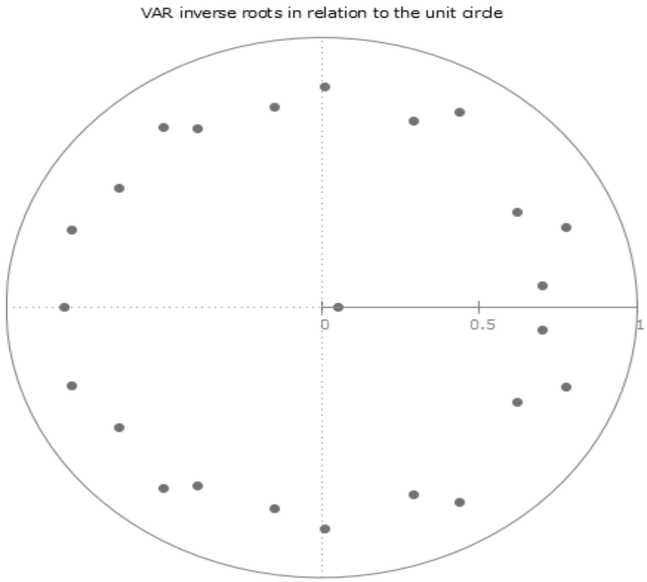
Step 1: testing for a unit root in l_DAX Augmented Dickey-Fuller test for l_DAX including 12 lags of (1-L)l_DAX sample size 311 unit-root null hypothesis: a = 1 with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e estimated value of (a - 1): -0.0492549 test statistic: tau_ct(1) = -2.86323 asymptotic p-value 0.1747 1st-order autocorrelation coeff. for e: 0.002 lagged differences: F(12, 296) = 0.621 [0.8245] **Step 2: testing for a unit root in l_FTSEMIB** Augmented Dickey-Fuller test for l_FTSEMIB including 12 lags of (1-L)l_FTSEMIB sample size 311 unit-root null hypothesis: a = 1 with constant and trend model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e estimated value of (a - 1): -0.0272637 test statistic: tau_ct(1) = -1.82101 asymptotic p-value 0.6947 1st-order autocorrelation coeff. for e: -0.000	**Step 3: cointegrating regression** Cointegrating regression - OLS, using observations 1998:01-2024:12 (T = 324) Dependent variable: l_DAX coefficient std. error t-ratio p-value --- const 2.83910 0.392284 7.237 3.40e-012 *** l_FTSEMIB 0.518761 0.0376991 13.76 3.48e-034 *** time 0.00529153 0.000120889 43.77 2.27e-137 *** Mean dependent var 8.960969 S.D. dependent var 0.477478 Sum squared resid 10.26383 S.E. of regression 0.178814 R-squared 0.860620 Adjusted R-squared 0.859752 Log-likelihood 99.50698 Akaike criterion −193.0140 Schwarz criterion −181.6717 Hannan-Quinn −188.4868 rho 0.973721 Durbin-Watson 0.046880 **Step 4: testing for a unit root in uhat** Augmented Dickey-Fuller test for uhat including 12 lags of (1-L)uhat sample size 311 unit-root null hypothesis: a = 1 test without constant model: (1-L)y = (a-1)*y(-1) + ... + e estimated value of (a - 1): -0.0287614 test statistic: tau_ct(2) = -2.1706 asymptotic p-value 0.6941 1st-order autocorrelation coeff. for e: 0.008 lagged differences: F(12, 298) = 0.710 [0.7420] There is evidence for a cointegrating relationship if: (a) The unit-root hypothesis is not rejected for the individual variables, and (b) the unit-root hypothesis is rejected for the residuals (uhat) from the

lagged differences: $F(12, 296) = 0.884$ [0.5640]	cointegrating regression.

Source: *The author's own compilation using Gretl.*

The results of the Engle-Granger test indicate that there is no cointegration among the variables. We can now proceed with an estimation of VAR model. After the VAR is estimated the unit roots of the equation are estimated (Figure 1), followed by the impulse response function (Figure 2). Finally, variance decomposition is carried out for individual variables (Table 3).

Figure 1. *Unit Root Test*



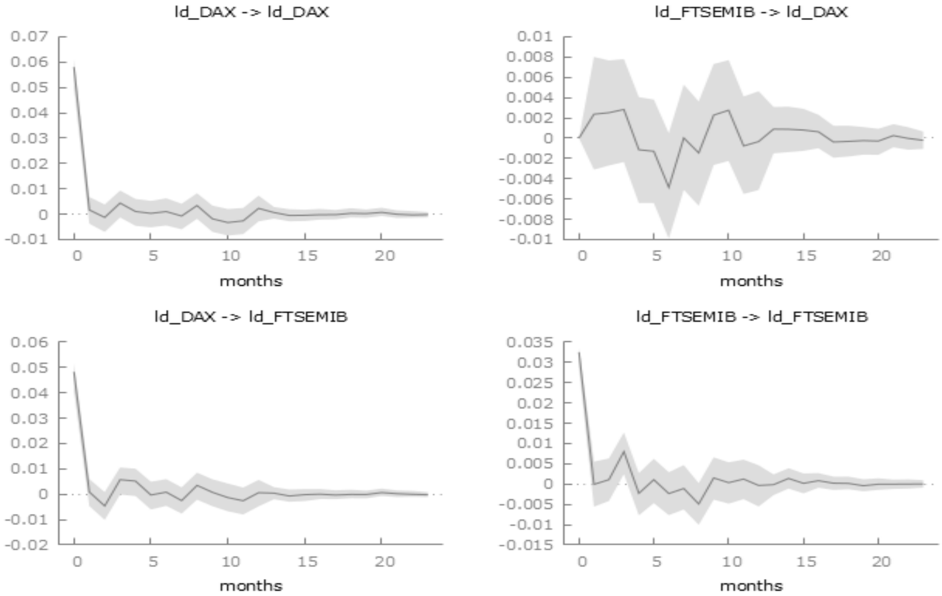
Source: *The author's own compilation using Gretl.*

After a positive verification of the aforementioned tests for the given VAR model, the unit roots of the characteristic equation are to be determined. In Gretl, the unit roots of the characteristic equation are estimated automatically. All the unit roots of the characteristic equation are to be less than one in terms of the modulus.

The number of roots of the characteristic equation for the model consisting of 2 variables for 12 lags is 24. All the roots of the characteristic equation are inside the circle, so this condition has been met. Model is stable.

The impulse is set at one standard error of the residuals. The response from Germany in the first equation, Italy in the second equation to the shock from individual variables are statistically significant in the initial period, but after tgird month effect dies out and is statistically insignificant. This is illustrated in detail for all the equations in Figure 2.

Figure 2. *Impulse Response Function*



Source: *The author's own compilation using Gretl.*

Table 3. *Variance Decomposition*

Period	Decomposition of variance for dl_DAX			Decomposition of variance for dl_FTSEMIB		
	std. error	**dl_DAX**	**dl_FTSEMIB**	**std. error**	**dl_DAX**	**dl_FTSEMIB**
1	0.0580709	100.0000	0.0000	0.0582423	68.7894	31.2106
2	0.0581429	99.8346	0.1654	0.0582489	68.7963	31.2037
3	0.0582114	99.6490	0.3510	0.058445	68.9716	31.0284
4	0.0584434	99.4173	0.5827	0.0592672	68.0033	31.9967
5	0.0584639	99.3794	0.6206	0.0595371	68.1441	31.8559
6	0.0584791	99.3307	0.6693	0.0595475	68.1230	31.8770
7	0.0586894	98.6496	1.3504	0.0595991	68.0228	31.9772
8	0.058694	98.6498	1.3502	0.0596634	68.0577	31.9423
9	0.0588103	98.5937	1.4063	0.0599661	67.7055	32.2945
10	0.0588833	98.4479	1.5521	0.0599897	67.6675	32.3325
11	0.0590403	98.2387	1.7613	0.0600057	67.6814	32.3186
12	0.0591048	98.2257	1.7743	0.0600747	67.7137	32.2863
13	0.0591495	98.2251	1.7749	0.0600785	67.7146	32.2854
14	0.0591597	98.2029	1.7971	0.0600801	67.7156	32.2844
15	0.0591686	98.1814	1.8186	0.0601002	67.6846	32.3154
16	0.0591757	98.1636	1.8364	0.0601007	67.6843	32.3157
17	0.0591795	98.1526	1.8474	0.0601064	67.6715	32.3285

18	0.0591811	98.1486	1.8514	0.0601077	67.6717	32.3283
19	0.0591829	98.1458	1.8542	0.060108	67.6713	32.3287
20	0.0591837	98.1441	1.8559	0.0601095	67.6683	32.3317
21	0.0591886	98.1421	1.8579	0.0601128	67.6718	32.3282
22	0.0591892	98.1403	1.8597	0.0601131	67.6721	32.3279
23	0.05919	98.1404	1.8596	0.0601131	67.6721	32.3279
24	0.0591907	98.1391	1.8609	0.0601135	67.6725	32.3275

Source: *The author's own compilation using Gretl.*

The final step in presenting the VAR model is the variance decomposition. Table 3 presents its course for German and Italian stock exchanges. The standard error of changes in the German stock exchange index of blue chips companies depends primarily on this variable.

In the case of variance decomposition for the Italian stock exchange, after some initial fluctuations the variables are fairly stable since the 9th month. The standard error of changes in the stock exchange index in Italy depends only in 32% on changes in this variable and to a greater extent on changes in other variable – in almost 68% on the changes in the stock exchange index in Germany.

4. Research Results and Discussion

The primary tools for identifying bi-directional relationships are multivariate GARCH (MGARCH) models, such as the BEKK-GARCH (Engle and Kroner, 1995) and DCC-GARCH (Engle, 2002), which can model time-varying correlations and simultaneous volatility transmission. Vector Autoregression (VAR) and Vector Error Correction Models (VECM), based on the work of Sims (1980) and Johansen (1991), are used to analyze dynamic feedback loops in returns and volatilities.

Co-integration tests are essential for determining long-run equilibrium relationships. These studies typically use daily or weekly closing price data from major indices like the S&P 500 (USA), FTSE 100 (UK), DAX (Germany), Nikkei 225 (Japan), and MSCI indices for various regions. The timeframes often span several decades to capture various market phases.

The cornerstone method for identifying uni-directional relationships is the Granger Causality test (Granger, 1969), often embedded within a VAR or VECM framework. These tests explicitly assess whether past values of one variable can predict the current values ofanother. Asymmetric GARCH models (e.g., EGARCH) are also used to test if negative news from a dominant market has a stronger effect than positive news.

Impulse Response Functions (IRFs) derived from VAR models are crucial for visualizing the direction and persistence of shocks. These studies often rely on daily data to capture the opening and closing times of different exchanges, which is critical for establishing the sequence of information flow (e.g., news from the US close affecting the Asian open). High-frequency intraday data is increasingly used to trace these effects more precisely (e.g., Engle, Ito, and Lin, 1990).

Generally speaking, the choice of econometric model is fundamentally tied to the research question. To test for long-run equilibrium Co-integration tests (Johansen, 1991) are being employed. To test for lead-lag effects Granger Causality tests within a VAR framework (Eun and Shim, 1989) is used.

To model dynamic feedback loops VAR/VECM architecture with Impulse Response Functions (Sims, 1980) is carried out. To model volatility transmission and time-varying correlations various GARCH are implemented (Bollerslev, 1986; Bollerslev, 1990; Engle and Kroner, 1995; Engle, 2002). The literature itself shows an evolution, moving from static correlation analysis to dynamic, conditional models that better capture the complex, time-varying nature of market relationships (Campbell, Lo, and MacKinlay, 1997; Tsay, 2005).

Regarding the analysis conducted in this article, it seems to be partly consistent with previous research results and partly inconsistent. The German stock exchange is larger in terms of capitalization and turnover than the Italian stock exchange, and at the same time, Germany is the largest economy in the European Union.

The lack of a long-term relationship between the analyzed stock exchanges, as measured by the Engle Granger cointegration test, may be surprising. Variance decomposition results indicate, however, that potential external shocks from Germany may have a greater impact on Italy than other way around.

5. Conclusions, Proposals, Recommendations

The article analyses the relationships among some selected stock exchanges in the Euro Area – Germany and Italy. The VAR method is used to estimate the parameters of the regression equation. When the impulse response function is estimated, the response from the German stock exchange to the shock from independent variables expires after the first month. The response of the Italian stock exchange to the shocks from independent variables expires after the third month.

In the case of variance decomposition for the German stock exchange, the variables are stable. The standard error of changes in the German stock exchange index depends primarily on this variable.

In the case of the Italian stock exchange index, we can notice some small fluctuations. The standard error of changes in the stock exchange index in Italy depends surprisingly on more than 67% on the changes of German stock exchange index. This seems to be a surprising result, but it may arise from the much smaller size of the Italian stock exchange comparing to German stock exchange.

The academic literature demonstrates that global stock exchanges are deeply interconnected. While bi-directional relationships (interdependence) are the norm for developed markets, a uni-directional leadership role for the US market persists, especially in its influence over emerging economies.

The notion of complete independence or decoupling has been largely refuted, especially in light of evidence from the 2008 GFC and subsequent crises, which show that correlations converge to one during systemic events.

Despite this consensus, gaps remain. The impact of high-frequency and algorithmic trading on the speed and nature of information transmission is an area of active research. The evolving role of China's stock exchanges - whether they will remain partially insulated or become new regional/global leaders - is a critical unanswered question.

Finally, the effect of phenomena like unconventional monetary policies, geopolitical shocks, and the rise of decentralized finance presents new and complex challenges for modeling the intricate web of relationships between global stock exchanges.

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