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THE PRICE TRANSMISSION IN EUROPEAN STOCK MARKETS

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Abstract: We investigate the dynamic price relationships among ten major stock indexes in Europe before, during and after the recent financial crisis. Using an error-correction model we find that the stock markets are cointegrated with three cointegrating vectors before the crisis and only one cointegrating vector during and after the crisis. We further use directed acyclic graph (DAG) analysis to explore the instantaneous transmission pattern. Contrary to previous research, the UK market is consistently mapped as being caused by several other markets, and France and Spain appear to share leadership roles before the crisis, while leadership is less evident during and post crisis. We also find a decreasing number of instantaneous casual relationships between the markets after the crisis, indicating that the markets are becoming more independent. This result is corroborated by a decline in the number of cointegrating vectors from pre to post crisis.

Keywords: error correction model (ECM), cointegration, directed acyclic graphs (DAG), financial crisis

1. Introduction

Several studies in the financial literature have investigated market linkages and price transmission mechanisms in the major international equity markets, employing the analytical framework of the vector auto-regression (VAR) or the error correction model (ECM). However, virtually all of these models rely on some form of temporal causality. Yang and Bessler (2004) extended the literature by using the method of directed acyclic graphs (DAGs) in combination with error correction modelling to explore evidence of contemporaneous causal patterns in international equity market data.

This paper extends this literature by adopting the techniques in Bessler and Yang (2004) to provide evidence of structural change in stock market linkages and price transmission in response to the 2007-2012 financial crisis. We first divide post-2000 weekly stock index data from ten prominent European markets into three periods representing pre-crisis (2000-2006), crisis (2007-2012), and post-crisis (2013-2016). We then evaluate price transmission between these markets during these three periods using an error-correction model to compute an innovation correlation matrix for each period and corresponding DAG and compare the results.

The paper is organized as follows. Section 2 provides data and summary statistics. Section 3 discusses methodology. Section 4 explains the empirical results of our error correction modelling and DAG analysis. Section 5 presents the conclusions.

2. Data

We use weekly time series for ten European equity indexes in local currency terms (Belgium: BEL 20, France: CAC 40, Germany: DAX, Greece: ASE, Ireland: ISEQ, Italy: FTSE MIB, Netherlands: AEX, Spain: IBEX 35, Switzerland: SMI, and the UK: FTSE 100), from January 2000 to May 2016 (857 observations for each index). All indices are rescaled to start at 100 at the beginning of the period. Figure 1 depicts weekly time series for the ten indices. All markets experienced a substantial run-up prior to 2007, and precipitous decline during financial crisis through 2012. Beginning 2012, all markets (with the exception of Greece and Italy), participated in a recovery, with the German index showing the strongest upward trend. Table 1 provides the corresponding summary statistics. Note that Ireland's market exhibits the greatest volatility, and Greece exhibits the worst performance (pre and post crisis).

Figure 1: Index Performance 2000-2016

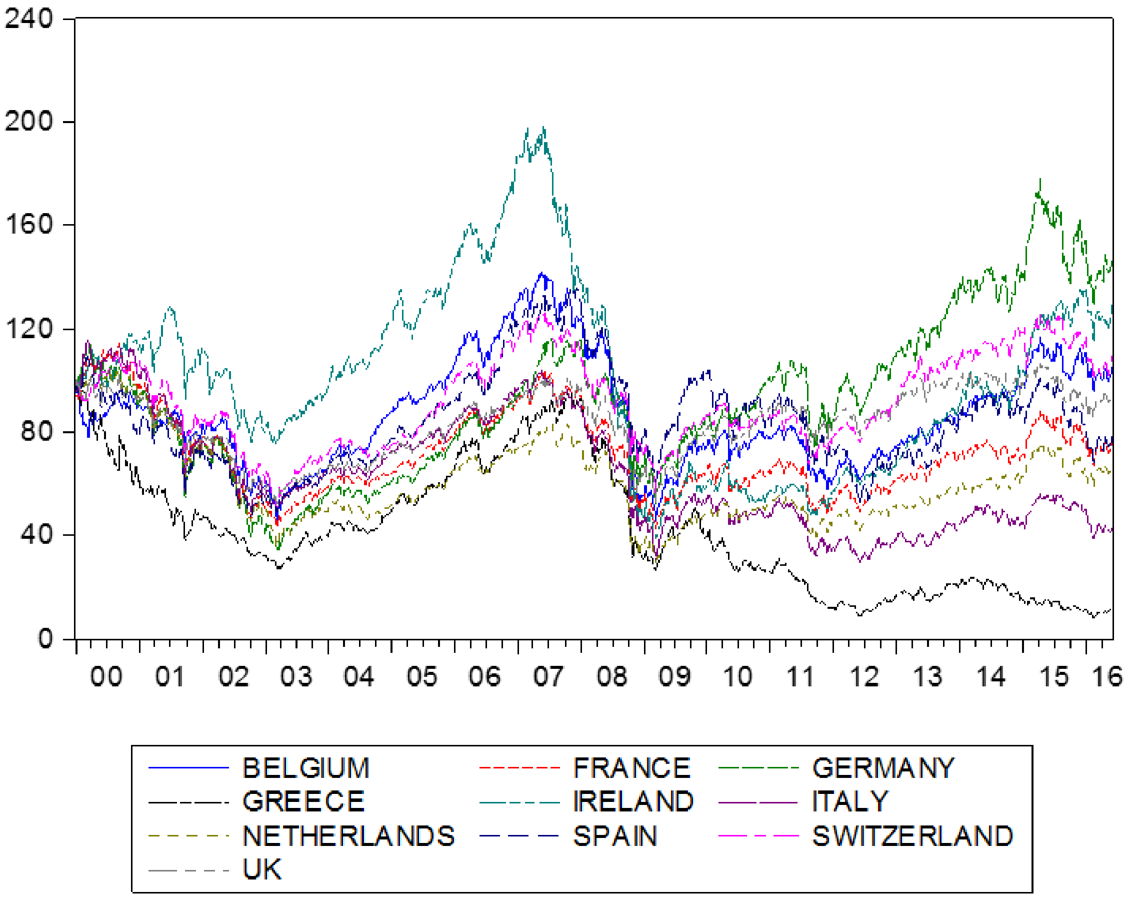


Table 1: **Summary statistics. All indexes are rescaled to start with 100 at the beginning of January 2000**

	BE	FR	DE	GR	IE	IT	NL	ES	CH	UK
Mean	86.8	71.9	92.7	41.8	100.9	63.8	60.9	84.6	92.1	83.9
Median	83.6	69.9	89.7	38.8	99.7	56.1	57.9	83.4	90.0	86.2
Max	142.2	114.4	177.8	100.0	198.6	115.8	103.5	135.9	125.9	106.4
Min	45.7	42.5	34.5	8.2	38.9	29.9	29.7	47.2	51.3	52.4
Stdev	20.6	15.6	30.4	24.0	35.5	21.7	15.8	18.8	17.4	12.9
Skew	0.6	0.6	0.5	0.5	0.5	0.6	0.8	0.6	0.0	-0.5
Kurt	2.8	2.6	2.7	2.2	2.8	2.2	3.2	3.0	2.0	2.2
#Obs.	857	857	857	857	857	857	857	857	857	857

Source: finance.Yahoo.com

3. Methodology

3.1 Error Correction Modelling

Following Yang and Bessler (2004) and Refalo (2009), we first apply a cointegrated VAR model to evaluate the data. Letting X_t denote a vector of ten indexes (k=10), the corresponding vector ECM is specified as:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \, \Delta X_{t-i} + \mu + \varepsilon_t \quad (t = 1, \dots, T) \qquad (1)$$

$$\varepsilon_t \sim iid(0, \Sigma) \qquad (2)$$

μ is a (k by 1) vector of intercepts, ε_t is the corresponding vector of white noise disturbance terms, and Γ_i are (k by k) coefficient matrices defining the short-run adjustments to changes in the price process. Of interest is evidence of a price transmission mechanism contributing to deviations in long-run relationships between market indexes. If the indexes are cointegrated, Π can be factored into two matrices, $\Pi = \alpha\beta'$, where β is the cointegrating vector and α indicates the speed of adjustment to the previous period's deviation from the cointegrating relationship. The rank of Π determines the number of cointegrating vectors.

We apply Trace tests developed by Johansen (1991) to determine the number of cointegrating vectors. The test statistics is computed as:

$$Trace = -\sum_{i=r+1}^{k} T ln(1 - \lambda_i^*) \qquad (3)$$

where λ^*_i are the estimated eigenvalue(s), T is the number of observations, and r is the maximum cointegrating rank. Rejection of the hypothesis implies the number of cointegrating vectors exceeds r. In order for the cointegration test to be valid, unit root tests are conducted on each series to test for non-stationarity before we apply the cointegration test.

3.2 Directed Acyclic Graphs

The method of directed acyclic graphs (DAG) uses a series of logic based rules to deduce contemporaneous causal relations from the correlation structure of a dataset. It is applied by first determining which variables are un-conditionally or conditionally correlated, and then by using a series of logic arguments (known as sepset conditions) to determine causal direction of these correlations, creating a causal map linking the variables. The advantage of this method is that it requires no ad-hoc or theoretical restrictions (though such restrictions may be employed) in determining links or causality. This paper uses TETRAD 5.2.1 software for constructing the DAGs.

In our application, one begins with a diagram of the ten markets connected to each other by straight lines (links), each representing the correlation between those markets. Links between markets that are not statistically correlated are eliminated. The remaining links are then turned into arrows (using the sepset conditions in a stage known as orientation) indicating the causal direction of correlation. The resulting graph (or DAG) indicates the pattern of contemporaneous causality between the ten markets. Note that in this paper, we apply no exogenous or structural restrictions in determining our DAGs, and eliminate all links that are not significant at the .01 level.

The method is extensively discussed in science literature in Spirtes et al (2000) and Glymour and Cooper (1999). DAG has been applied to studying financial data in a number of other papers including Bessler and Yang (2003), Yang and Bessler (2004), Haigh et al (2004), and Li et al (2008), and Refalo (2009). The latter two papers provide a detailed overview of the algorithm (Li et al 2008 illustrate how the algorithm works graphically). More recently Jayech (2011) studies the August 2011 stock market crash with a DAG-copula based approach using daily returns of stock indices and bonds.

4. Empirical analysis

4.1 Error Correction Modelling and Cointegration Tests

Table 2 presents results from Johansen cointegration tests. The tests are conducted without a drift term in the VAR; all tests assume a constant in the cointegrating vector(s). Testing is ended at the first failure to reject the hypothesis; the Akaike information criterion was used to select the number of VAR lags used (one for pre-crisis period and two for crisis and post-crisis periods). The results are three cointegrating vectors linking the markets in the pre-crisis period, and only one cointegrating vector linking the markets crisis and post-crisis, indicating reduced market cointegration after the crisis began. The cointegrating ranks we observe are consistent with Bessler and Yang (2003) which notes that stock price series tend to exhibit fewer cointegrating vectors, indicating a loose long-run co-movement among stock market prices. Likewise, international equity market studies using cash indices by Francis and Leachman

(1998) and Masih and Masih (2001) find only one (or no) cointegrating vector linking the markets.[1]

Table 2: Johansen's Cointegration Tests

Reported are the Trace test statistics, under a hypothesis H0 of zero to three cointegrating vectors. Where T is the number of observations, r is the maximum number of cointegrating vectors, n is the number of eigenvalues, and λi^* is the estimated eigenvalue, the statistics are given by Equation (3). Results displayed are for the three sub-sample periods 2000-2006, 2007-2012 and 2013-2016.[2]

	2000-2006			2007-2012			2013-2016		
	VAR lag=1			VAR lag = 2			VAR lag = 2		
H0 rank	**Trace**	**C(5%)**	**Decision**	**Trace**	**C(5%)**	**Decision**	**Trace**	**C(5%)**	**Decision**
None	345.6	251.3	R	253.9	251.3	R	263.1	251.3	R
At most 1	249.4	208.4	R	190.7	208.4	F	181.5	208.4	F
At most 2	177.8	169.6	R	150.6	169.6	F	131.8	169.6	F
At most 3	132.4	134.7	F	113.2	134.7	F	98.3	134.7	F

4.2 Error Correction Modelling and Cointegration Tests

The ECM yields the innovation correlation matrices (4.1-4.4), with the markets listed in the order Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, Switzerland, and UK, for pre-crisis, crisis, post-crisis, and all periods combined:

$$\Sigma_{precrisis} = \begin{bmatrix} 1 \\ 0.66 & 1 \\ 0.67 & 0.89 & 1 \\ 0.32 & 0.41 & 0.39 & 1 \\ 0.58 & 0.58 & 0.60 & 0.25 & 1 \\ 0.66 & 0.87 & 0.85 & 0.38 & 0.57 & 1 \\ 0.76 & 0.89 & 0.87 & 0.40 & 0.60 & 0.86 & 1 \\ 0.63 & 0.80 & 0.79 & 0.38 & 0.53 & 0.78 & 0.77 & 1 \\ 0.76 & 0.72 & 0.71 & 0.30 & 0.56 & 0.72 & 0.79 & .64 & 1 \\ 0.68 & 0.84 & 0.81 & 0.31 & 0.57 & 0.79 & 0.83 & 0.72 & 0.76 & 1 \end{bmatrix} \quad (4.1)$$

$$\Sigma_{crisis} = \begin{bmatrix} 1 \\ 0.90 & 1 \\ 0.82 & 0.92 & 1 \\ 0.70 & 0.67 & 0.60 & 1 \\ 0.74 & 0.72 & 0.65 & 0.59 & 1 \\ 0.87 & 0.93 & 0.84 & 0.67 & 0.67 & 1 \\ 0.90 & 0.93 & 0.87 & 0.68 & 0.72 & 0.86 & 1 \\ 0.79 & 0.87 & 0.81 & 0.63 & 0.59 & 0.86 & 0.78 & 1 \\ 0.83 & 0.87 & 0.81 & 0.60 & 0.70 & 0.83 & 0.85 & 0.75 & 1 \\ 0.86 & 0.93 & 0.89 & 0.63 & 0.70 & 0.86 & 0.91 & 0.79 & 0.86 & 1 \end{bmatrix} \quad (4.2)$$

[1] We also test whether each price series is itself stationary and conduct additional tests for the restrictions on the cointegration space.

[2] Johansen's cointegration tests are also performed with the whole sample 2000-2016. Trace test indicates two cointegrating equations at the 0.05 level with two VAR lags.

$$\Sigma_{postcrisis} = \begin{bmatrix} 1 \\ 0.92 & 1 \\ 0.89 & 0.92 & 1 \\ 0.39 & 0.41 & 0.37 & 1 \\ 0.73 & 0.74 & 0.72 & 0.38 & 1 \\ 0.80 & 0.85 & 0.79 & 0.56 & 0.66 & 1 \\ 0.89 & 0.94 & 0.90 & 0.39 & 0.73 & 0.82 & 1 \\ 0.80 & 0.86 & 0.78 & 0.54 & 0.60 & 0.88 & 0.82 & 1 \\ 0.64 & 0.62 & 0.61 & 0.25 & 0.51 & 0.50 & 0.62 & 0.56 & 1 \\ 0.76 & 0.82 & 0.77 & 0.34 & 0.58 & 0.70 & 0.84 & 0.70 & 0.65 & 1 \end{bmatrix} \quad (4.3)$$

$$\Sigma_{all} = \begin{bmatrix} 1 \\ 0.81 & 1 \\ 0.77 & 0.89 & 1 \\ 0.50 & 0.51 & 0.43 & 1 \\ 0.68 & 0.66 & 0.61 & 0.43 & 1 \\ 0.76 & 0.89 & 0.78 & 0.50 & 0.61 & 1 \\ 0.83 & 0.91 & 0.83 & 0.49 & 0.65 & 0.85 & 1 \\ 0.75 & 0.83 & 0.78 & 0.51 & 0.59 & 0.82 & 0.76 & 1 \\ 0.76 & 0.76 & 0.72 & 0.42 & 0.60 & 0.71 & 0.76 & 0.68 & 1 \\ 0.79 & 0.86 & 0.81 & 0.45 & 0.62 & 0.78 & 0.84 & 0.75 & 0.78 & 1 \end{bmatrix} \quad (4.4)$$

Unconditionally the correlations between countries are similar in magnitude to the results of Yang and Bessler (2004), which uses country stock future index data. This result is unsurprising given the degree of economic integration among markets in this study.

Dividing the data into pre-crisis, crisis, and post-crisis periods, we find that the instantaneous correlations are greater during the crisis period. To test the significance of this change in correlation between periods, we employ the Z-test with the Fisher transformation, Fisher (1921). First, we transform each correlation coefficient using Equation (5):

$$\rho' = 0.5 \ln\left(\frac{1+\rho}{1-\rho}\right) \quad (5)$$

We then test for statistical significance in the difference in correlation for each element of the innovation correlation matrix between any two periods by computing the z-statistic and corresponding p-value:

$$z = \frac{\rho_1' - \rho_2'}{\sqrt{\frac{1}{N_1 - 3} + \frac{1}{N_2 - 3}}} \quad (6)$$

Matrices 7.1-7.3 display changes in the correlation coefficients from pre-crisis to crisis, crisis to post-crisis, and pre-crisis to post-crisis, which are significant at the 5% significance level. A 1 for an increase, -1 for a decrease, and 0 for no statistically significant change:

$$\Sigma_{crisis} - \Sigma_{precrisis} = \begin{bmatrix} NA & & & & & & & & & \\ 1 & NA & & & & & & & & \\ 1 & 1 & NA & & & & & & & \\ 1 & 1 & 1 & NA & & & & & & \\ 1 & 1 & 0 & 1 & NA & & & & & \\ 1 & 1 & 0 & 1 & 1 & NA & & & & \\ 1 & 1 & 0 & 1 & 1 & 0 & NA & & & \\ 1 & 1 & 0 & 1 & 0 & 1 & 0 & NA & & \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & NA & \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & NA \end{bmatrix} \tag{7.1}$$

$$\Sigma_{postcrisis} - \Sigma_{crisis} = \begin{bmatrix} NA & & & & & & & & & \\ 0 & NA & & & & & & & & \\ 1 & 0 & NA & & & & & & & \\ -1 & -1 & -1 & NA & & & & & & \\ 0 & 0 & 0 & -1 & NA & & & & & \\ -1 & -1 & 0 & 0 & 0 & NA & & & & \\ 0 & 0 & 0 & -1 & 0 & 0 & NA & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & NA & & \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & NA & \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & NA \end{bmatrix} \tag{7.2}$$

$$\Sigma_{postcrisis} - \Sigma_{precrisis} = \begin{bmatrix} NA & & & & & & & & & \\ 1 & NA & & & & & & & & \\ 1 & 0 & NA & & & & & & & \\ 0 & 0 & 0 & NA & & & & & & \\ 1 & 1 & 1 & 0 & NA & & & & & \\ 1 & 0 & -1 & 1 & 0 & NA & & & & \\ 1 & 1 & 0 & 0 & 1 & 0 & NA & & & \\ 1 & 1 & 0 & 1 & 0 & 1 & 0 & NA & & \\ -1 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & NA & \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & -1 & NA \end{bmatrix} \tag{7.3}$$

Compared with pre-crisis levels, 38 out of 45 correlation coefficients are statistically greater during the crisis. The majority of the correlation coefficients then decrease following the crisis. Comparing pre-crisis and post crisis pairwise correlations, the Belgian, Irish, and Greek markets generally exhibit greater correlation with the other markets post-crisis, and the Swiss and UK markets show evidence of reduced post-crisis pairwise correlation.

4.3 DAG Analysis

To study evidence of instantaneous casualty and structural changes in the pattern of causality for pre-crisis, crisis, and post-crisis periods, we construct DAGs for the innovation correlation matrices 4.1-4.4, respectively. As discussed in section 3.2, all graphs are estimated requiring a .01 significance level for correlation between markets.
Figure 2A presents the DAG for the pre-crisis period. There are ten directional links (including one bidirectional link) and five non-directional links. The graph indicates a direct causal flow from France, Germany, and Switzerland to the UK, with Netherlands and Spain causing UK indirectly via Germany. This result differs from Yang and Bessler (2004), which finds the UK to have a leadership role among the European markets. The difference in findings may be due to the different data span (1997-2007 vs 2000-2006), frequency of the data (daily vs weekly), instrument (index future vs index), and the number of European countries examined in our studies (four versus ten). France and Spain are graphed as having leadership roles. Our DAG also reveals changes in the Italian market to be driven by trading in several other markets. There are links between Switzerland, Netherlands, Belgium, and Ireland, but in general, there is little evidence of a directional causality pattern among those markets.

That Germany is mapped as being caused by several lesser markets may be explained by the one to three hour delay in closing times of the German Exchanges (19:00 and 21:00 UTC) vis-a-vis the other European exchanges, allowing for additional trading in the German market in response to last minute trades in markets that have closed. Our results are consistent with an integrated market prior to the financial crisis – with many market indices moving simultaneously in response to contemporaneous information, and the difference in market closing times explaining why the German index is graphed as a follower. Also note that Greece, the nation which will later face a sovereign debt crisis in 2009, is shown as an outlier in the pre-crisis period, not having any casual flow to or from other countries.

Figure 2B presents the DAG for the crisis period 2007-2012 and has a different structure. Most countries have casual flows to and/or from other countries. The UK market is influenced directly by Germany, Netherlands, France, and Switzerland. Ireland and Greek markets are now part of the causal diagram as being influenced directly or indirectly by trading in virtually all other markets. France has direct links with six markets, though only one causal relationship is mapped – France causing UK. During this period, the German and Netherlands markets are graphed as having leadership roles. The diagram is consistent with centralized government (EU) policy changes and trading in quality markets driving the markets that are in crisis. It is also consistent with investor flight to quality, where the markets in greatest crisis become followers.

Figure 2C presents the DAG for post-crisis period 2013-2016. Only two directional links and seven non-directional links are found. Again, UK is graphed as being caused by the other markets, and France has the greatest number of direct relationships. The Ireland index is graphed as having no causal flow with the other European markets, possibly reflecting that continued domestic policy turmoil has the greatest influence on trading in that market. The reduction in linkages from pre-crisis may indicate a greater degree of independence among these markets and could be the result of reforms implemented after the crisis to reduce risk taking and financial contagion. However, the presence of mostly non-directional links indicates simultaneous price movements and market integration.

Comparing the DAGs for the three periods, we find evidence consistent with centralized government policy making and investor flight to quality influencing the pattern of price information transmission during the crisis, and greater market independence ex-post the crisis, using a contemporaneous time analysis. This is consistent with VAR model analysis in which the number of cointegrating vectors in the data declined from three vectors pre-crisis to one post-crisis.

Figure 4D presents a DAG analysis for the entire sample (2000-2016). While there are a number of bidirectional relationships, what stands out is that the UK market is graphed as being caused by the other key markets. This is consistent with the results of our pre-crisis, crisis, and post-crisis graphs.

Figure 2A: Pre-Crisis Pattern from TETRAD V

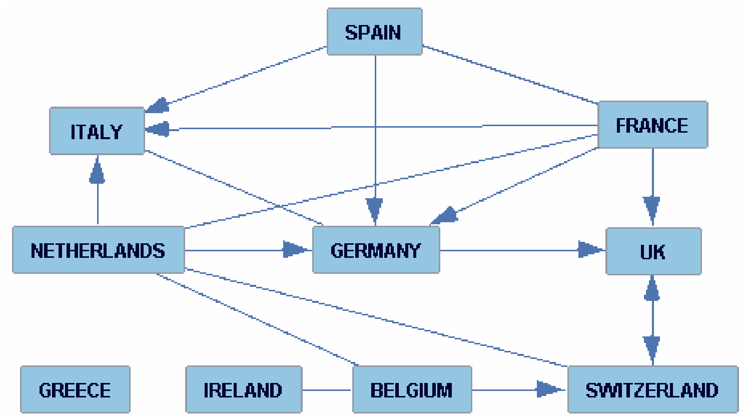


Figure 2B: Crisis Pattern from TETRAD V

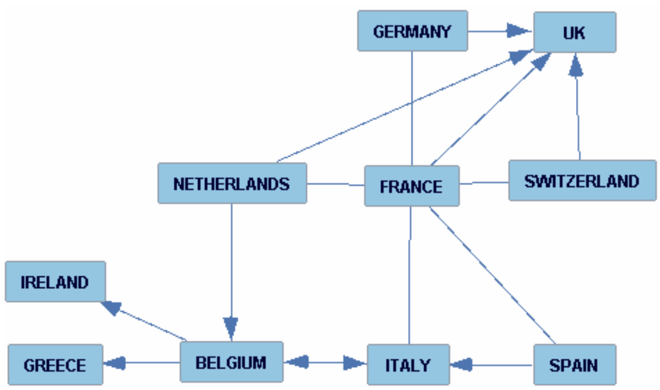


Figure 2C: Post-Crisis Pattern from TETRAD V

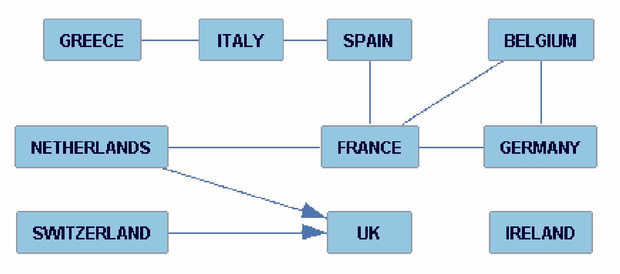
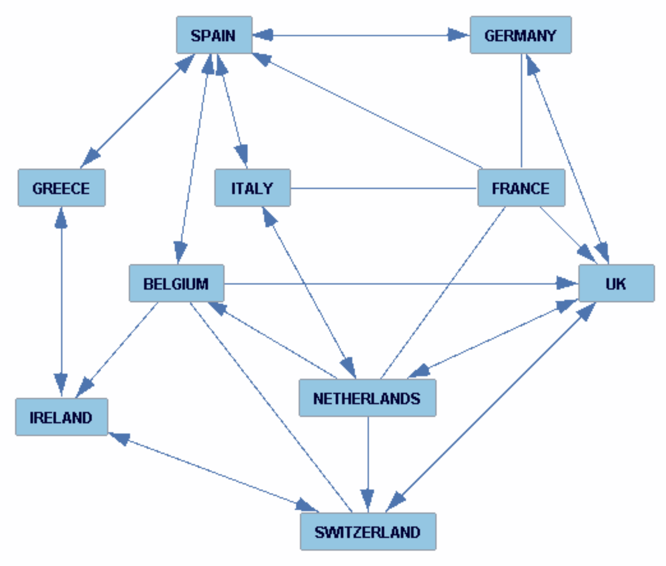


Figure 2D: Whole Sample Pattern from TETRAD V



5. Conclusion

We investigate price transmission patterns in the ten European stock indexes before, during, and after the Great Recession following the approach of Yang and Bessler (2004), which combines cointegration, ECM, and DAG methodologies. Different from recent studies such as Francis and Leachman (1998), Masih and Masih (2001), and Bessler and Yang (2003), where only one cointegrating vector is found among major stock markets, and from Yang and Bessler (2004) where two cointegrating vectors are found, our ECM analysis indicates that there are three cointegrating before the crisis and only one cointegrating vector in the other periods.

We then study instantaneous causality between these markets using DAGs. France and Spain appear to share leadership roles before the crisis while Germany and Netherlands become leaders during the crisis. Contrary to previous research, the UK is consistently graphed as being caused by other markets (though this becomes more pronounced during the crisis), and the Irish and Greek market indices are graphed as being caused by other market indices during the crisis period. We also find a decrease in the number of instantaneous casual links between the markets after the crisis, with most links becoming non-directional, indicating greater independence of the European markets. This result is consistent with the results of our VAR model, and may be a result of post-crisis regulatory reforms to reduce risk taking and potential financial contagion in response to the stock market meltdowns. The impact of reform mechanisms on the European market linkages (and trading) is a sweeping topic that deserves extensive research but is beyond the scope of this paper.

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