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DOI: 10.15290/oes.2025.03.121.04

USING NETWORK ANALYSIS AND ECONOMETRIC MODELLING TO MAP THE STOCK MARKET DURING CRISES: THE CASE OF THE GERMAN DAX INDEX[1]

Summary

Purpose | The aim of this paper is to test a hypothesis stating that it is possible to use past crises as indicators of the key stock market movers for future crises by applying a two-step identification procedure based on network and econometric analysis. DAX has been selected since it is attached to the biggest European economy and Covid-19 as it is the most recent crisis to end.

Research method | A two-step analysis is proposed based on a combination of the minimum spanning tree (MST) methodology and econometric modelling. After identifying focal firms for the DAX index during DOTCOM, GLOBAL, and EUROZONE events, we have used these firms as explanatory variables for the value of the studied index during the Covid-19 crisis.

[1] This article was financed from funds received as part of statutory research conducted at the Warsaw School of Economics, Global Economic Interdependence Department.

Results | Our results show that only one focal firm was not considered as a statistically significant explanatory variable for the DAX Kursindex. This indicates that the applied procedure allowed to explain over 90% of dynamics in the DAX Kursindex during the recent pandemic crisis.

Originality/value/implications/recommendations | We demonstrate that focal firms of past crises can be used in the analysis of future crises. Stock markets reflect investor's sentiments towards individual firms and the economy in which these firms operate. Despite the fact that a part of prices and index values comes from fundamental analysis, there is a part of valuation that is derived from the subjective interpretation of data and individual belief. Focal firms become the biggest movers of the market in the time of a crisis.

Keywords: correlation network, minimum spanning tree, financial market, economic crisis, DAX

JEL classification: D85, G10, G11, G32, L14

1. Introduction

Stock markets reflect investor's sentiments towards individual firms and the economy in which these firms operate. Despite the fact that a part of prices and index values comes from fundamental analysis, there is a part of valuation that is derived from subjective interpretation of data and individual belief. Escapism towards safe heavens during unsure times reflects such behaviour. These safe harbours become the biggest movers of the market in the time of a crisis, i.e. focal firms. The aim of this paper is to test a hypothesis stating that it is possible to use past crises as indicators of key stock market movers for future crises by applying a two-step identification procedure based on network and econometric analysis. DAX has been selected since it is attached to the biggest European economy and Covid-19 as it is the most recent crisis to end.

The DAX was officially launched on 1 July 1988 with a press release from the three project sponsors (Frankfurter Börse, Börsen-Zeitung and Arbeitsgemeinschaft der Deutschen Wertpapierbörsen). The daily closing price on

1 July 1988 was 1163.52 points. The start date of the DAX was then calculated back to 1 January 1988 and set at 1000 points. Since its launch, the index has increased sixteen-fold, which corresponds to an average annual return of 8.1%.

The applied empirics consist of two steps, during which the results of the network analysis serve as input into the following econometric modelling. Firstly, network analysis is applied to three past crises (DOTCOM, GLOBAL, EUROZONE) to identify focal firms for those events. Secondly, the identified firms are used as independent variables trying to explain the value of the DAX index during the Covid-19 crisis. The minimum spanning tree (MST) methodology in stock market analysis can be traced to Mantegna [1999]. The characteristics of MST networks are shown to be of great interest to financial markets [Bonanno et al., 2004; Onnela, Chakraborti, Kaski, and Kertész, 2003; Onnela, Chakraborti, Kaski, Kertész, et al., 2003]. The history of MSTs as a tool of financial analysis and the application of econometric modelling using obtained central firms is presented in more detail by Tomeczek and Napiórkowski [2024].

The article is structured as follows. Firstly, we present a literature review on the behaviour of financial markets during recent global crises. Next, the applied empirical methods – network analysis and econometric modelling – are described in detail; followed by the presentation of the obtained statistical results. The article ends with a discussion of these results in the light of the German economy and overall conclusions to the study.

2. Literature review

An economic crisis refers to "a rapid negative change in the economic framework… [that] can be caused by both human error and natural disasters… [and] can have a long-term impact on the financial market, exchange rates, the gross national product or the labour market" [Mahlbacher and Schön, 2009]. An economic crisis can also be understood as a conspicuous deterioration in the state of the entire economic system that goes beyond regular fluctuations ("business cycles") and persists over a longer period of time [Koch and Jung, 2013]. A specific version of the economic crisis is financial crises. Gabler Wirtschaftslexikon defines financial crises as a "serious and non-temporal deteriorations in the characteristics of key financial market indicators (…) that usually occur within a short period of time and can have massive and lasting consequences for the real economy" [Budzinski, 2020].

The financial crisis which started in 2008 was caused by the inappropriate lending policies of commercial banks, which provided housing loans to people who lacked creditworthiness.

In practice, the global financial crisis was just preceded by a property crisis in the USA. Since the beginning of the millennium, the money supply in the United States has expanded, while interest rates fell at that time. This made it possible for low-income households, sometimes without collateral, to take out loans to finance the purchase of a house. These property loans, the repayment of which was often uncertain, were bundled with other – better – securities and sold on. The credit default risk was thus transferred to other banks. These "bad loans" put into circulation created a property bubble. As interest rates rose again, many borrowers were no longer able to pay their mortgages and had to sell their homes. As a result of the increased supply on the property market, prices fell and the sales proceeds were no longer sufficient to pay off the loans. The banks could no longer get the money they had lent back – the property bubble burst. The result was a large number of bank failures. On 15 September 2008, Lehman Brothers became the first global investment bank to file for insolvency. Events then came thick and fast – the share prices of global banks collapsed. European banks were also affected and in some cases even had to be supported by their respective governments [de.statista.com, 2025].

The bursting of the bubble also influenced the global economy in the case of the so-called dotcom crisis. The term dotcom bubble was coined by the media for a speculative bubble that burst in March 2000 [Meshnuni, 2012]. The starting point of this process was a large uptake in start-ups associating themselves with the Internet and mobile telephones technology boom that started in the second half of the 1990s [Gorthmanns, 2008]. Rapid growth was the primary goal for the majority of Internet companies. As a result, it was not uncommon for the newly founded companies to go public in order to raise growth capital. IPOs were driven by a high level of investor interest in these companies. They saw a “future” in these companies and wanted to participate in future profits [Glebe, 2008; Meshnuni, 2012]. Furthermore, strong media promotion of the new sector coupled with low savings interest rates also attracted many previously uninvolved investors to the securities markets [Putnoki, 2010]. Belief in new technology coupled with high sales and profit expectations became more important than fundamental valuation ratios, and share prices rose to unprecedented heights [www2]. In some cases, New Economy companies multiplied their value [Dittmann, 2009]. Although many of them were unable to demonstrate a sustainable corporate strategy. From 2000 onwards, warnings of a bubble became louder, and the first company bankruptcies led to share price losses [Fastercapital, 2024].

Another crisis that led to share price falls on stock markets was the debt crisis. It erupted in Greece already in October 2009 after the country’s deficit totalled 15.9% instead of the planned 3%. This did not fulfil the Maastricht criteria. This has led to a situation where Greece’s debt amounted to 120% of the country’s gross domestic product, which was more than double the authorised volume. [Dinov, 2014].

Development in Greece had turned into a crisis of confidence from which the country was no longer able to free itself on its own. Contagion effects and loss of confidence also occurred in other members of the single currency area. This led to a worsening of the situation in the markets for government bonds in these countries. It was equivalent to a drastic slump in government bond prices in various eurozone countries and an unprecedented spread in yields. The threat to the stability of the financial systems in the countries affected weighed on the European and international equity markets [Deutsche Bundesbank, 2011].

The euro countries created the European Financial Stability Facility (EFSF) in 2010 and the European Stability Mechanism (ESM) in 2012 to provide the crisis countries and their economies with further loans on favourable terms. These financial instruments with reduced interest rates for indebted countries did not stop equity markets from falling, with losses disproportionately on bank securities [Deutsche Bundesbank, 2011].

The last crisis, the global coronavirus pandemic originated in Wuhan, China. Since December 2019, the virus has been spreading in China and around the world. As of mid-September, there were more than 29 million new infections and more than 924 thousand deaths worldwide. The lockdowns and the strict measures taken by many governments to contain the pandemic have paralysed the global economy [Beer, 2020]. The spread of the novel coronavirus brought additionally massive uncertainty and volatility to the global equity markets. During the first half of the year 2020, there were massive sell-offs as the threat of the virus became real. The global economy came to a near standstill and markets recorded some of the sharpest falls in recent history [www3]. For example, the MSCI World, a share index that tracks over 1,600 shares from 23 industrialised countries, fell by over 30 per cent from its high in February in euro terms by mid-March [Corona-Krise, 2021]. In turn, the stock markets in New York, London and Frankfurt am Main plummeted at record speed between mid-February and mid-March 2020: share valuations fell by more than 20 per cent within 19 days. In comparison: during the global economic crisis, the stock markets only reached this negative mark after 43 days [Dohmen, 2024].

3. Research methods

In this study, an MST is a subgraph of a correlation network that is constructed by filtering the edges. Correlation networks are undirected complete graphs that represent the correlation between stock returns (i.e., the *n x n* correlation matrix). The MST filtering procedure of a weighted correlation network minimises the sum of its edges, while retaining the characteristic of a single component. Both correlation networks and MST networks consist of nodes (representing firms) and edges (representing the correlation between stock returns of two firms). The correlation network has $\frac{n(n-1)}{2}$ edges and the MST network has n–1edges, where n is the number of nodes.

Financial MST analyses still primarily follow the methodological framework outlined by Mantegna [1999], which is referenced by numerous studies [Coelho et al., 2007; Huang et al., 2022; Jung et al., 2006; Onnela, Chakraborti, Kaski, and Kertész, 2003; Onnela, Chakraborti, Kaski, Kertész, et al., 2003; Tomeczek, 2022]. After collecting the stock market data, the first step is to construct a *n x n* Pearson correlation matrix based on log-returns of firms' stock prices (in this article we focus on the daily close prices of the DAX index constituents). Secondly, the correlations are converted into distance using the following formula: $d_{ij} = \sqrt{2(1-r_{ij})}$, where d_{ij} is the distance between firms *i* and *j* and r_{ij} is the correlation coefficient between firms *i* and *j* Perfect correlation occurs if $d_{ij} = 0$ and perfect anticorrelation occurs if $dij = 2$ (lower distance indicates stronger correlation). Thirdly, the symmetric distance matrix can be represented as a complete graph and filtered using an MST algorithm that minimises the sum of edge weights. The result of these steps is an MST network that can be analysed using standard network centrality measures (e.g., degree centrality or betweenness centrality).

PageRank is a popular measure of network centrality devised by Brin and Page [1998] that served as Google's webpage ranking algorithm. Its current applications in network science extend beyond its original use as this measure can be applied to other kinds of data [Gleich, 2015; Lü et al., 2016]. The PageRank-based procedure of identifying focal (central) firms of a stock market is proposed by Tomeczek and Napiórkowski [2024], who show that focal firms can be used to explain at least 90% of Nasdaq-100 index dynamics. In short, the assumption is that some firms have a strong influence on the stock market. These firms can be selected using PageRank scores and community detection algorithms that identify clusters of nodes.

This study expands on Tomeczek and Napiórkowski [2024] by demonstrating that focal firms of past crises can be used in the analysis of future crises. Four MST networks are constructed for four crises (DOTCOM, GLOBAL, EUROZONE, COVID). The first three are used for the selection of the focal firms that are then applied to the COVID network to check whether the focal firms of the past crises can be used in the analysis of a future crisis. Focal firms are defined as the $c_r + 1$ firms with the highest PageRank for each crisis, where c_r is the number of network communities identified for each crisis.

The analysed crises follow the dates of German recessions available in the FRED database [Federal Reserve Bank of St. Louis, 2024]. The list of DAX Kursindex constituents is taken from the official STOXX website [STOXX, 2024]. The daily close prices of DAX Kursindex (DAXK) and its constituents are downloaded from the Yahoo Finance database [Yahoo Finance, 2024]. A small number of missing daily observations for DHL are downloaded from the Investing.com database www4]. Network calculations and visualizations are made using the open-source software Gephi [Bastian et al., 2009]. For MST filtering we use the popular Kruskal's algorithm [Kruskal, 1956]. For community detection, we use the Leiden algorithm [Traag et al., 2019], with the following parameters: quality function = Constant Potts Model (CPM), resolution = 0.01, number of iterations = 10.

We show that the DOTCOM crisis has three focal firms, the GLOBAL crisis has three focal firms, the EUROZONE crisis has four focal firms, and the COVID crisis has four focal firms. In total, seven unique firms are identified as focal for at least one of the selection crises (DOTCOM, GLOBAL, EUROZONE). We apply these firms to the econometric modelling of the COVID crisis.

The output of the network analysis (i.e., firms identified as focal in at least one of the studied crises) has been used to construct an equation of the econometric model, parameters of which have been estimated using Ordinary Least Squares (OLS). The goal of the model is to see if the previously identified focal firms can serve as good future predictors of the stock market's performance (here: during the Covid-19 pandemic).

Equation of the econometric model

$$\ln\left(DAXK\right)_t = \beta_0 + \beta_1 \ln\left(ALV\right)_t + \beta_2 \ln\left(BAS\right)_t + \beta_3 \ln\left(BAYN\right)_t + \\ + \beta_4 \ln\left(BMW\right)_t + \beta_5 \ln\left(DBK\right)_t + \beta_6 \ln\left(MBG\right)_t + \beta_7 \ln\left(SIE\right)_t + \varepsilon_t,$$

where:
$\ln(variable)_t$ – natural logarithm of a given variable in time t
β_1 – coefficient of the Z independent variable
β_0 – constant
ε – error term

The model is estimated over a period of 30/11/2017–29/05/2020, yielding 625 daily observations. This is the most recent recession in Germany and it crucially includes the Covid-19 crisis (dates of the recessions designated using the peak through the trough method by the Federal Reserve Bank of St. Louis [2024]). Prior to estimation, variables were transformed into their natural logarithms form and checked for stationarity using the Augmented Dickey-Fuller test (H_0: unit root is present, STATA code: *dfuller*) and corrected for the presence of a unit root with differencing (*d.*, Table 1). The assumption of linearity has been confirmed with statistically significant at a 1% level of statistical significance, positive and high or very high linear Pearson correlation coefficients (H_0: no statistically significant correlation, *pwcorr*) between the dependent and independent variables (Table 2). The model was also checked for the presence of multicollinearity (Variance Inflation Factor, *vif* – Table 3). Post estimation examination (based, e.g., on [Napiórkowski, 2022]) included tests for autocorrelation (Breusch–Godfrey LM test, H_0: no serial autocorrelation, *estat bgodfrey*, Table 4), heteroskedasticity (given a lack of normal distribution of residuals, White's test was selected over the Breusch–Pagan/Cook–Weisberg test, H_0: homoskedasticity, *whitetst*, Table 4), normal distribution of (Jarque-Bera – *jb*, – and Shapiro–Wilk – *swilk*, Table 4 – tests, H_0: normal distribution) and stationarity (Augmented Dickey-Fuller with MacKinnon approximation of p-value, Table 4) of residuals. Lastly, the Portmanteau test for white noise [Zhu et al., 2017] was conducted (H_0: residuals are white noise, *wntestq*, Table 4).

Results (test statistics = -4.438) of the Engle-Granger test for cointegration suggest that there is no need to distinguish between long- and short-term solutions with the Vector Error Correction model [Maddala, 1992].

TABLE 1

Results (p-values) of the Augmented Dickey-Fuller test for variables

Variable	lnALV	lnBAS	lnBAYN	lnBMW	lnDBK	lnMBG	lnSIE	lnDAXK
I(0)	0.284	0.795	0.764	0.471	0.126	0.718	0.516	0.253
I(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: "ln" represents a natural logarithm of a variable.

Source: the authors' own table based on data from Yahoo Finance [2024].

TABLE 2

Results (p-values) of the Pearson linear correlation coefficient estimations between the dependent and independent variables

Ind. variable	D1.lnALV	D1.lnBAS	D1.lnBAYN	D1.lnBMW	D1.lnDBK	D1.lnMBG	D1.lnSIE
Coefficient	0.8638	0.8644	0.6983	0.8003	0.6988	0.8516	0.8512
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: "D1." represents the process of taking a first difference and "ln" a natural logarithm of a variable.

Source: the authors' own table based on data from Yahoo Finance [2024].

TABLE 3

Variance Inflation Factors

Variable	D1.lnMBGDE	D1.lnBASDE	D1.lnBMWDE	D1.lnSIEDE	D1.lnALVDE	D1.lnDBKDE	D1.lnBAYNDE	Mean VIF
VIF	4.760	4.100	3.760	3.220	3.100	2.060	1.670	3.240
1/VIF	0.210	0.244	0.266	0.311	0.322	0.487	0.599	–

Note: "D1." represents the process of taking a first difference and "ln" a natural logarithm of a variable.

Source: the authors' own table based on data from Yahoo Finance [2024].

TABLE 4

Model tests' results

Test	p-value
Breusch–Godfrey LM test for autocorrelation	0.536
White's general test	4.30E-08
Jarque-Bera normality	2.80E-19
Shapiro–Wilk W test for normal data	0.000
Dickey–Fuller test for unit root (residuals)*	0.0000
Portmanteau test for white noise	0.978

* MacKinnon approximate p-value for Z(t) = 0.0000.

Source: the authors' own table based on data from Yahoo Finance [2024].

Since there was no issue of multicollinearity (all VIF-s are less than 5.000 – [Studenmund, 2009; Wooldridge, 2014] – Table 3) or autocorrelation (p-value = 0.536), residuals were identified as stationary (p-value = 0.000) and confirmed as white noise (p-value = 0.978), estimation had to only be corrected for the presence of heteroskedasticity (p-value = 0.000) – Table 4. The lack of normal distribution of residuals with such a large number of observations is not a problem impacting the validity of obtained results [Stock and Watson, 2006]. Robust standard errors were achieved with the *regress..., vce(robust)* command [Stata, 2022].

4. Results

The results of the network modelling are shown in Table 5 (general network statistics of every MST network) and Table 6 (the list of all analysed firms and their PageRank scores). The MST networks are presented in Graphs 1–4; the colours represent clusters (based on the co-movement of stock prices) and labels represent focal firms (nodes with the highest PageRank). Firms in the same cluster are considered to have stronger co-movement in their stock prices. Cluster membership is often associated with firms belonging to the same industry (e.g., in all four networks MBG and BMW are neighbours). The number of clusters is determined by the Leiden algorithm, as detailed in the research methods. The number of nodes in each network corresponds to the data availability of current DAX firms (as of April 2024). Average edge weights show the strength of connections, i.e., lower values indicate stronger co-movement of stock prices. In the context of the most significant recession in Germany, the strongest impact on the stock market is observed for the COVID network.

Firm-level results point to ALV as the most consistent performer and the most important firm in the networks. ALV is the only firm selected as focal in all four networks. In general, there is a remarkable degree of consistency. Three firms are focal in two networks: BASF, MBG, and SIE. Four firms are focal in one network: BAYN, BMW, DBK, and SY1. This level of consistency, perhaps characteristic of the German stock market, allows us to use the past crises in the analysis of the most recent one. Three of the focal firms of the COVID network (ALV, BAS, MBG) are predicted by our selection process; the fourth unpredicted focal firm SY1 is a large chemical manufacturer.

TABLE 5
Network statistics

Name	Start	End	Total weight	Nodes	Edges	Average edge weight
DOTCOM	1-May-2001	28-Feb-2005	26.62	29	28	0.95
GLOBAL	1-Mar-2008	30-Jun-2009	26.09	31	30	0.87
EUROZONE	1-Aug-2011	31-May-2015	26.23	33	32	0.82
COVID	1-Dec-2017	31-May-2020	28.20	36	35	0.81

Source: the authors' own table based on data from Yahoo Finance [2024].

TABLE 6
PageRank scores of the analysed firms (focal firms are marked in grey)

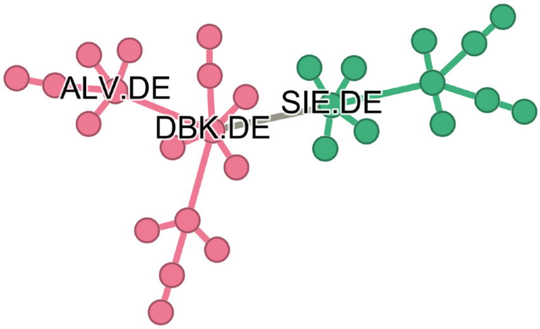
Ticker	Name	DOTCOM	GLOBAL	EUROZONE	COVID
1COV.DE	COVESTRO	..	..	..	0.0149
ADS.DE	ADIDAS	0.0185	0.0338	0.0163	0.0151
AIR.DE	AIRBUS	0.0375	0.0177	0.0166	0.0291
ALV.DE	ALLIANZ	**0.0840**	**0.0812**	**0.0574**	**0.1026**
BAS.DE	BASF	0.0678	0.0466	**0.1520**	**0.0888**
BAYN.DE	BAYER	0.0196	0.0180	**0.0752**	0.0149
BEI.DE	BEIERSDORF	0.0195	0.0186	0.0180	0.0165
BMW.DE	BMW	0.0194	0.0338	**0.0726**	0.0148
BNR.DE	BRENNTAG	..	..	0.0163	0.0275
CBK.DE	COMMERZBANK	0.0185	0.0343	0.0183	0.0165
CON.DE	CONTINENTAL	0.0194	0.0174	0.0475	0.0148
DB1.DE	DEUTSCHE BOERSE	0.0185	0.0177	0.0163	0.0151
DBK.DE	DEUTSCHE BANK	**0.1103**	0.0609	0.0323	0.0289
DHL.DE	DEUTSCHE POST	0.0195	0.0178	0.0163	0.0148
DTE.DE	DEUTSCHE TELEKOM	0.0189	0.0361	0.0173	0.0291
DTG.DE	DAIMLER TRUCK	..	..	..	..

Ticker	Name	DOTCOM	GLOBAL	EUROZONE	COVID
ENR.DE	SIEMENS ENERGY	..	..	..	..
EOAN.DE	E.ON	0.0372	0.0478	0.0323	0.0171
FRE.DE	FRESENIUS	0.0195	0.0184	0.0173	0.0151
HEI.DE	HEIDELBERG MATERIALS	0.0205	0.0186	0.0180	0.0148
HEN3.DE	HENKEL PREF	0.0196	0.0174	0.0315	0.0289
HNR1.DE	HANNOVER RUECK	0.0359	0.0186	0.0183	0.0416
IFX.DE	INFINEON TECHNOLOGIES	0.0189	0.0194	0.0169	0.0309
MBG.DE	MERCEDES-BENZ GROUP	0.0835	**0.1336**	0.0569	**0.0876**
MRK.DE	MERCK	0.0210	0.0190	0.0173	0.0151
MTX.DE	MTU AERO ENGINES	..	0.0174	0.0169	0.0166
MUV2.DE	MUENCHENER RUECK	0.0374	0.0186	0.0323	0.0160
P911.DE	DR ING HC F PORSCHE PREF.	..	..	..	..
PAH3.DE	PORSCHE AUTOMOBIL HLDG PREF	..	..	0.0184	0.0425
QIA.DE	QIAGEN	0.0189	0.0202	0.0173	0.0167
RHM.DE	RHEINMETALL	0.0211	0.0192	0.0166	0.0162
RWE.DE	RWE	0.0210	0.0499	0.0183	0.0305
SAP.DE	SAP	0.0189	0.0174	0.0163	0.0165
SHL.DE	SIEMENS HEALTHINEERS	..	..	..	..
SIE.DE	SIEMENS	**0.0971**	**0.0759**	0.0163	0.0289
SRT3.DE	SARTORIUS PREF.	0.0210	0.0192	0.0180	0.0167
SY1.DE	SYMRISE	..	0.0177	0.0163	**0.0443**
VNA.DE	VONOVIA SE	..	..	..	0.0166
VOW3.DE	VOLKSWAGEN PREF	0.0372	0.0174	0.0325	0.0268
ZAL.DE	ZALANDO	..	..	..	0.0173

Source: the authors' own table based on data from Yahoo Finance [2024].

GRAPH 1

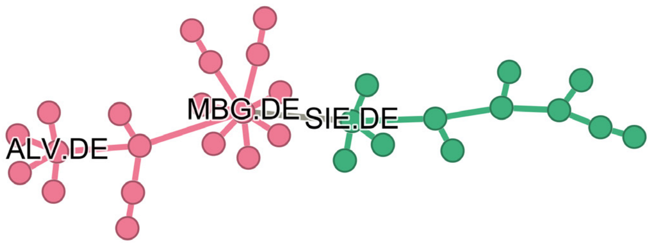
DOTCOM network



Source: the authors' own table based on data from Yahoo Finance [2024].

GRAPH 2

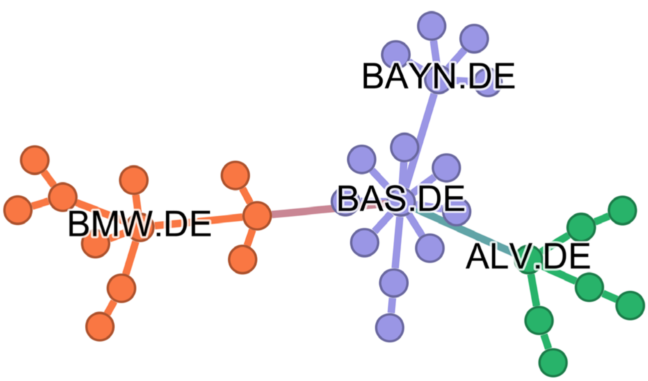
GLOBAL network



Source: the authors' own table based on data from Yahoo Finance [2024].

GRAPH 3

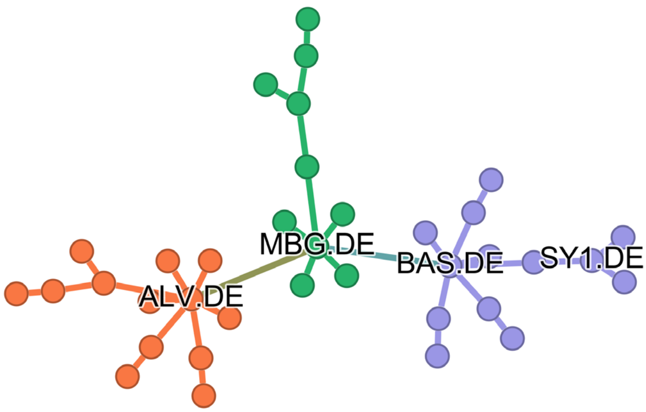
EUROZONE network



Source: the authors' own table based on data from Yahoo Finance [2024].

GRAPH 4

COVID network



Source: the authors' own table based on data from Yahoo Finance [2024].

Moving to the results of econometric modelling, the null hypothesis of all estimated coefficients being equal to zero and to each other has been rejected (Prob > F = 0.000) and the model accounts for 92,7% of the variance in the dependent variable (Table 7). Therefore, the estimated econometric model proved to be a very good fit to data on the DAXK stock index. Only the coefficient of BMW stock was found not to be statistically significant at a 1% level of statistical significance (p-value = 0.172, Table 8). ALV and SIE are shown to be the biggest drivers of DAXK during the Covid-19 pandemic, with DBK being at the other end of this spectrum.

TABLE 7

Quality of fit statistics

F(7, 480)	635.540	R-squared	0.927
Prob > F	0.000	Root MSE	0.004
Number of obs	488	–	–

Note: the number of observation (488) is different than the original one (625) due to the process of differencing.

Source: the authors' own table based on data from Yahoo Finance [2024].

TABLE 8
Econometric modelling results

Explanatory variables	Coeffi-cient	Robust std. err.	t	P>t	[95% conf. interval]	
D1.lnALV	0.220	0.023	9.400	0.000	0.174	0.266
D1.lnBAS	0.138	0.028	4.980	0.000	0.084	0.193
D1.lnBAY	0.119	0.015	8.110	0.000	0.090	0.148
D1.lnBMW	0.035	0.025	1.370	0.172	-0.015	0.085
D1.lnDBK	0.038	0.010	3.880	0.000	0.019	0.057
D1.lnMBG	0.082	0.020	4.140	0.000	0.043	0.121
D1.lnSIE	0.180	0.024	7.380	0.000	0.132	0.227
Constant	0.000	0.000	1.740	0.083	0.000	0.001

Note: the number of observation (488) is different than the original one (625) due to the process of differencing. “D1.” represents the process of taking a first difference and “ln” a natural logarithm of a variable.

Source: the authors’ own table based on data from Yahoo Finance [2024].

Econometric results (very high R^2 and statistically significant coefficients) have proven our hypothesis to be correct. It is possible to use past crises as indicators of key stock market movers for future crises. Secondly, the shown results prove that the presented two-step (network analysis-econometric modelling) approach is successful in identifying those firms.

5. Discussion

The performance of the DAX over the past 36 years suggests that the index is much more than a purely mathematical representation of the value of the now 40 largest companies listed on the Frankfurt Stock Exchange. The index is also a barometer of sentiment, characterised by economic, political and social trends. [Schallmayer and Meyke, 2023]. Since its launch, the index of Europe’s largest economy has increased sixteen-fold, which corresponds to an average annual return of 8.1%. With this history, the DAX has no need to shy away from international comparison, outperforming both the broad European equity market (Stoxx600) and the global equity market (MSCI World) over this period.

This trend of a German stock market indexinteracted with the behaviour of the share prices of several companies, which are identified as statistically significant in Table 5 (highlighted in grey). Regarding the importance of the companies in the various sectors in the DAX index, this varied over the course of the crises and contributed to the specific behaviour of the prices of these companies. This is evidenced by historical figures compared with more recent ones. Between 2001 and 2021, the weight of financial sector stocks fell from just under 29% to just over 12%. The weighting of the technology sector, in turn, has tripled compared to point in 2007 (currently just under 15%). Similarly the healthcare sector tripled its share of the index [Schallmayer and Meyke, 2023].

Finally, it is worth mentioning the most export-oriented sector of the German economy, i.e. the automotive sector. This includes such companies as Volkswagen, Daimler and BMW. Taken together, the three car manufacturers account for almost 36% of the total turnover of the DAX 30. In terms of sectors, the automotive industry has by far the largest share of the cumulative value created by the DAX 30 and is the sector that has grown the most, doubling its total turnover between 2009 and 2020 [Basic, 2021].

It is also worth noting at this point how revenues have developed in the leading companies in the German automotive sector in recent years. Table 9 shows the sales development of the 13 strongest DAX companies in terms of sales in the period from 2016 to 2021. Volkswagen is in the first place, immediately followed by the Mercedes-Benz Group with sales of just under €170,000 million in 2021. BMW is in the fourth place after Allianz, with sales of over 110,000 million euros in 2021 [Halilagic, 2023]. To summarise the preceding discussion, it is important to note that despite the growth of the financial sector globally, it has reduced its weight in the DAX sector in favour of industry, including the technology, healthcare and automotive sectors.

TABLE 9
DAX firms by sales (in millions of euros)

DAX firms	2016	2017	2018	2019	2020	2021
Volkswagen	217 267	229 550	235 849	252 632	222 884	250 200
Mercedes Benz Group	153 261	164 154	167 362	172 745	154 309	168 000
Allianz	122 416	126 149	130 557	142 369	140 455	148 510
BMW	94 163	98 282	97 480	104 210	98 990	111 200
Deutsche Telekom	73 095	74 947	75 656	80 531	100 999	108 790
Deutsche Post	57 334	60 444	61 550	63 341	66 806	81 747
Basf	57 550	61 223	62 675	59 316	59 149	78 598
E.ON	33 173	37 965	30 084	41 284	60 944	77 358
Siemens	79 644	82 863	55 538	58 483	57 139	62 265
Munich Re	48 900	49 100	49 100	51 500	54 900	59 600
Bayer	34 943	35 015	39 586	43 545	41 400	44 100
Fresenius	29 471	33 886	33 530	35 409	36 277	37 520

Source: [Statista, 2022].

6. Conclusions

Stock markets reflect investor sentiment, and their behaviours are notoriously difficult to predict. The aim of this study was to examine if – based on the past experiences – it is possible to properly identify focal firms in the upcoming crisis on the stock market. To achieve this aim, we have applied our two-step analysis. After identifying the key firms for the DAX index during DOTCOM, GLOBAL, and EUROZONE events, we have used these firms as explanatory variables for the value of the studied index during the Covid-19 crisis. The procedure also identified three out of four focal firms found using actual pandemic data (Table 6). The results of our econometric model, in which only one firm was not considered as a statistically significant explanatory variable for the DAX Kursindex, indicate that the applied procedure allowed to explain over 90% of the dynamics in the DAX Kursindex during the recent pandemic crisis (Table 8). Therefore, this confirms our research hypothesis.

The presented method can be beneficial for identifying future focal firms; hence, for stock and efficient (i.e., build with only a few, instead of hundreds of firms) ETF building. Focal firms become the biggest movers of the market in the time of a crisis. Our study is not without its limitations as it focuses only on one stock index and one crisis. The question remains whether the German stock market has some idiosyncratic or institutional characteristics that cause the focal firms to remain relatively constant between crises. Hence, extrapolation to more markets and more crises requires a series of repeated studies allowing for far more general observations. We find this an interesting area for further research.

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