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Measuring the impact of the EU health emergency response authority on the economic sectors and the public sentiment

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ABSTRACT

We present the main findings of an extensive quantitative analysis aimed at quantifying the correlated risk and the effects, on the most important economic sectors, of the Covid-19 pandemic and of a list of actions undertaken at the EU level. The considered data relates to the time series of equities and public sentiment of 89 top-listed companies from EuroStoxx 600. We show the relevant impact of the events both at the companies and sector levels. The results show that the actions produce an effect on the economic sector differentiated in terms of magnitude and reaction times.

1. Introduction

Crisis events that have upset the economic, financial, and social ecosystems have been several and particularly severe in the last 30 years. Whatever the origins of the crisis, purely macro or microeconomic (like the financial bubbles or the global financial crisis), climate change driven (Katrina hurricane, drought), or due to pandemics (Ebola, Covid-19), scholars have extensively studied the short-term and long-term effects either on the whole system or on specific sub-sectors. In such complex scenarios, it becomes crucial to deeply understand the nexus between the specific shock event and the triggered effects at different levels – economic, financial, social, and organizational – to envisage the proper countermeasures to be undertaken in the event of a new (likely) crisis. This was the case after the 2008 global financial crisis which highlighted the strong interconnection among financial institutions and the need for the introduction of a set of approaches able to model, assess and mitigate the systemic risk effect (see [1–3]). The report by the Financial Crisis Inquiry Commission [3] reveals that the impact of the global financial crisis was driven by distress in one area of the financial markets, the housing market, that led to failures in other areas by way of interconnections and vulnerabilities that bankers, government officials, and others had missed or dismissed.

Therefore, systemic risk has become essential when quantifying either the performance or the global risk expressed by financial institutions, large medium, or small enterprises, countries, and financial markets. Indeed, this is particularly true when endogenous or exogenous shocks hit the system. Highly interconnected systems are prone to propagate and amplify effects triggered by endogenous shocks, increasing costs and damages more than expected (see, for example [4–13]). However, if global financial models properly take into account the systemic component, stakeholders can diversify their investments or take advantage of the proper mix of actions.

The Covid-19 crisis, whilst not the first pandemic event, posed a formidable challenge to all the countries in the world. We, all of a sudden, discovered that no one was properly prepared to cope with such a huge shock. Thus, countries, institutions, and companies were exposed for the first time to costs and risks unexpected and, most of all, without mitigation, organizational, or recovery plans. School closures, curfews, lockdowns, mobility restrictions, NPIs (aka non-pharmaceutical interventions), restructuring, and reorganization of hospitals happened everywhere without a specific and controlled road map, at least in the early stage of the pandemic. Experts and citizens experienced directly the importance of coordination and centralization when anomalous, unexpected global events affect the regular life course, economic activities, and subsequent decisions.

In this paper, we investigate through a quantitative scenario analysis, the possible impact induced by a supranational agency on the different economic sectors. The content of this paper is the result of a close collaboration between the European project Periscope,[1] we

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[1] PERISCOPE investigates the broad socio-economic and behavioral impacts of the Covid-19 pandemic, to make Europe more resilient and prepared for future large-scale risks. It collects data on social, economic, and behavioral impacts, and assesses policy measures from all levels of government during the pandemic. It maps impacts on mental health, health inequalities, and the capacity and resilience of health systems.

[2] See https://hadea.ec.europa.eu/about/vision-mission-and-values_en.

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are involved in, the HaDEA (European Health and Digital Executive Agency) which has a mission 'to implement' actions that strengthen Europe in the domains of health, food safety, digital technologies and networks, industrial capacities, and space. To provide high-quality and service-oriented support, to enable European society to become healthier, more resilient, and fair, and for European industry to become more competitive'.[2] In particular, at the beginning of 2021, after one year of the Covid-19 pandemic, HaDEA decided to establish an authority called 'HERA' - Health Emergency Preparedness and Response Authority, able to prevent, detect, and rapidly respond to health emergencies. However, before launching HERA, HaDEA asked Periscope project coordinators, to run a quantitative impact assessment of the different levels of interventions and policies the agency could have put in place. The final aim of such analysis is the evaluation of the different levels of interventions that could be subsumed by the newborn agency, to establish the ideal authority perimeter and the more efficient action plan. For the above reasons, the following research questions appear relevant to HaDEA:

- Is there any impact on the economic sectors of countermeasures undertaken at the supranational level, namely by the European Union?
- Could the presence and intervention of a European agency avoid the jeopardized responses of the different countries and facilitate a more effective and less expensive reaction to the shock?
- Could a European agency advocate and centralize the acquisition of fundamental tools during a pandemic like vaccines, facial masks, and swabs to avoid scarcity issues and uncontrolled price rises?
- What is the induced effect on the economic sectors and the public audience's perception of centralized actions?
- Can a supranational agency, taking care of preparedness and emergency responses, induce a more robust reaction from the economic sectors?

To address the aforementioned research questions, we considered an advanced econometric model, the Bayesian graphical structural vector autoregressive (BGSVAR) to explore the interconnections among top-listed companies from EuroStoxx 600.

This paper proceeds as follows: in Section 2 we describe the relevant literature, in Section 3 we present the methodology employed, in Section 4 we extensively describe the data, in Section 5 we report our main results and in Section 6 we draw our conclusions.

2. Background

When scholars aim at measuring or quantifying the effects of events or shocks on the economic systems, they typically consider financial/economic data like market prices, credit default swaps, macroeconomic time series (GDP, Industrial Production, unemployment rate) (see [5,8,14–16]). Koopman et al. [14] developed a macro-financial econometric framework that allows for default correlations to originate from macroeconomic and financial conditions, frailty risk, and industry sector dynamics. Mare [15] investigated the relationship between the environmental economic conditions and the probability of small bank failures. They found evidence supporting the economic vulnerability hypothesis since macroeconomic factors, both at the regional and the national level, are significantly related to the risk of failure among cooperative banks. Billio et al. [8] studied the market data on hedge funds, banks, broker/dealers, and insurance companies showing that banks are the most important players in transmitting shocks than others. Steinbacher et al. [16] studied models of credit contagion related to the banking system to analyze the effect of shocks on the financial system.

On the other hand, numerous studies take advantage of the usage of unstructured data as an alternative or supplementary source of information to capture the moods, perceptions, and expectations of consumers, stakeholders, and populations. There exist many important papers on the statistical/econometric analysis of non-conventional data: Loughran and McDonald [17], Tetlock et al. [18], Cerchiello and Giudici [19], Bollen et al. [20], Bordino et al. [21], Choi and Varian [22], Feldman [23], Cerchiello and Giudici [24] and Ahelegbey et al. [25], who all show the added value of textual data, in economics and finance. Loughran and McDonald [17] reviewed textual analysis literature in accounting and finance. Tetlock et al. [18] showed that language content can capture relevant information, not otherwise captured, which is incorporated into stock prices quickly. Cerchiello and Giudici [19] demonstrated how tweet data can be relevant in determining systemic risk networks and stressed that such type of data has the advantage of capturing even unlisted institutions in the networks. Souza et al. [26], analyzing listed retail brands, demonstrated through Twitter analysis that social media is essential in financial dynamics even in comparison to more traditional news sources such as newspapers. Tetlock [27] analyzed the link between media and the stock market by pointing out how pessimism is related to a decrease in stock prices and to an increase in trading volume. Joshi et al. [28] studied the relationship between news and stock trends noting that the polarity of news (positive and negative) impacts the market. Ranco et al. [29] analyzed relationships between 30 stock companies from the Dow Jones Industrial Average (DJIA) index and the blogging platform Twitter and found a significant dependence, particularly during the peaks of Twitter volume.

Algaba et al. [30] recently presented an overview of sentiment analysis related to the econometric field calling this specific research stream "sentometrics". Larsen and Thorsrud [31], using textual analysis of a Norwegian newspaper, constructed a new index and proved its usefulness in predicting key quarterly economic variables, including assets. Costola et al. [32] examined the relationship between stock market reactions and news of Covid-19 obtained from three platforms, namely, MarketWatch.com, Reuters.com, and NYtimes.com. They reported a positive association between sentiment score and market returns and illustrated the result by applying principal component analysis on the sentiment database, and showing that the first principal component is positively related to the financial market. Using the Twitter platform, Derouiche and Frunza [33] studied the relationship between tweets sentiment, related to sports companies and their stock prices. Valle-Cruz et al. [34] analyzed the link between some Twitter accounts and financial indices by showing that the market reaction is delayed by 6–13 days after the information publication and that the link between these two actors is very high. Yin et al. [35] analyzed 13 million tweets for 2 weeks, and noted a stronger ratio of positive sentiment than negative ones. Rajput et al. [36], considering tweets from January 2020 until March 2020, showed that most of the tweets are positive, only about 15% negative.

Mamaysky [37] examining the financial markets, noted that until mid-March 2020 the markets was hypersensitive and overreacting to news. From mid-March onwards, the markets showed a structural break by reducing the hypersensitive trait. Gormsen and Koijen [38] analyzed the equity market and dividend futures, and showed how these move in response to investors' expectations of economic growth. They noted that the programs implemented by governments have not improved growth expectations in the short term. Baker et al. [39], analyzing the previous pandemics (1918, 1957, and 1968), showed how the Covid-19 pandemic had unprecedented effects on the US market. The authors noted that the market reactions was attributable to government restrictions on commercial activities and social distancing. The socioeconomic effects of Covid-19 on every aspect of the economy have been reviewed by Nicola et al. [40] and Zhang et al. [41] with a map of general risk patterns and systemic risks in markets worldwide.

Reactions of economies and financial markets to the pandemic, caused by the widespread Covid-19, have ignited discussions on the effects of general news and sentiment on equity returns in financial markets and interconnectedness among sectors (see [25,42–47]). Lee [45] explored the correlation between sentiment score and 11 indices sector-based of the US market through a set of t-tests with different lags. Their results demonstrate that all sectors present a significant boost in volatility due to the pandemic. Looking at the correlation between Covid-19 sentiment and stock prices, they showed that the link is different across sectors; in particular, consumer, industrial, energy, and communication services are in the group of the high-medium level of correlation, utility sector in the low-level group, while tech and healthcare in the high, medium, and low group. Chen et al. [46] showed the "disconnection" between stock market and real economy by highlighting that high-price stocks, in particular tech stocks (Facebook, Amazon, Apple, Netflix, and Google), performed better throughout the pandemic while low-price stocks performed worse, loss 10% of their pre-pandemic values. Ahmed et al. [47] analyzed the impact of Covid-19 on Emerging Market Economies (EMEs) with a focus on the relationship between pandemic outcomes and financial developments considering 22 financial indicators. They showed that the access of EMEs to international capital markets is determined by the spread of the virus and in particular by the lockdown measures adopted to deal with it, rather than the strength of their economies. Maghyereh and Abdoh [44] studied how sentiment relates to volatility during crises by comparing the global financial crisis and the Covid-19 pandemic. Ahelegbey et al. [25] analyzed how interconnections among the largest US top-50 companies have been impacted by the Covid-19 pandemic from the financial market and public sentiment perspectives. Mattera et al. [42] proposed composite confidence indicators, based on mixed-frequency data, with the aim of better measuring the evolution over time of public sentiment. For a comprehensive review of the impact of the Covid-19 pandemic on business via text mining analysis, see [43].

In this exercise, we aim to investigate how and how much the interconnections among the largest EU companies have been impacted from the financial market and the public sentiment perspectives, because of the actions undertaken at the EU level in response to the Covid-19 pandemic outbreak. To achieve a full and deep understanding of the market reactions to external shocks, we take advantage of advanced graphical models to efficiently estimate the interconnections among companies leveraging and comparing the two data sources. We completely exploit the temporal dimension by using appropriate rolling windows that reflect the market dynamics and the public perception shaping mechanism.

Since market prices of financial securities usually come in time series observations, the most used model adopted to approximate the dynamic interactions among asset returns or volatilities is the vector autoregressive (VAR) representation. This class of models presents a convenient framework to capture the serial correlation in the return or volatility of financial assets, and has been extensively applied to analyze financial networks (see [8,9,12,48–50]). Giudici and Abu-Hashish [48] proposed a correlation network VAR model to explain the structure between bitcoin prices and classic assets. Billio et al. [8] constructed Granger-causality networks to identify the systemic importance of financial institutions. Giudici and Spelta [49] improved financial network models by applying Bayesian graphical models and dynamic Bayesian graphical models. Diebold and Yilmaz [9] developed various measures of connectedness using forecast error variance decomposition to quantify the network among financial institutions. Ahelegbey et al. [12] proposed a Bayesian graphical structural VAR (BGSVAR) for analyzing interconnectedness in the context of systemic risk. Ahelegbey et al. [50] extended the BGSVAR methodology to understand the extent to which contagion spillovers (from one country to another) arise from financial markets, bank lending, or both.

3. Methodology

3.1. Graphical SVAR model formulation

A network model is a convenient representation of the relationships among a set of variables. They are defined by nodes joined by a set of links, describing the statistical relationships between a pair of variables. The use of networks in VAR models helps to interpret the temporal and contemporaneous relationships in a multivariate time series. Let R_t denote the returns of the stock market prices of n institutions at time t, and S_t denote the sentiment of the institutions. Let $Y_t = (R_t, S_t)$ be a $N \times 1$, $N = 2n$, vector whose dynamic evolution can be described by a SVAR(p) process:

$$Y_t = \sum_{l=1}^{p} B_l \; Y_{t-l} + U_t \tag{1}$$

$$U_t = B_0 \; U_t + \varepsilon_t \tag{2}$$

where p is the lag order, $B_l, l = 1, \dots, p$, is $N \times N$ matrix of coefficients with $B_{ij,l}$ measuring the effect of $Y_{j,t-l}$ on $Y_{i,t}$, U_t is a vector of independent and identically normal residuals with covariance matrix Σ_u, B_0 is a zero diagonal matrix where $B_{ik,0}$ records the contemporaneous effect of a shock to Y_k on Y_i, and ε_t is a vector of orthogonalized disturbances with covariance matrix Σ_ε. From (2), the Σ_u can be expressed in terms of B_0 and Σ_ε as $\Sigma_u = (I - B_0)^{-1} \Sigma_\varepsilon (I - B_0)^{-1'}$. The expressions in (1) and (2) can be written in a more compact form as

$$Y_t = B_+ X_t \; + \; (I - B_0)^{-1} \varepsilon_t \tag{3}$$

where $B_+ = (B_1, \dots, B_p)$ is $N \times Np$ matrix of coefficients, and $X_t = (Y'_{t-1}, \dots, Y'_{t-p})'$ is $Np \times 1$ vector of stacked lagged observation of Y_t. It can be shown that the matrix $(I - B_0)^{-1}$ records the (in)direct contemporaneous effect of ε_t on Y_t. A shock to Y_{jt} can only affect Y_{it} if there is a contemporaneous link from Y_{kt} to Y_{it}.

The slope coefficients and shock dependence matrices of (1) and (2) can be specified through network graphs by assigning to each $B_{ij,l}$ a corresponding latent indicator in $G_{ij,l} \in \{0, 1\}$, such that for $i, j = 1, \dots, N$, and $l = 0, 1, \dots, p$:

$$B_{ij,l} = \begin{cases} 0 & \text{if} \quad G_{ij,l} = 0 \quad \Longrightarrow \quad Y_{j,t-l} \nrightarrow Y_{i,t} \\ \beta_{ij,l} \in \mathbb{R} & \text{if} \quad G_{ij,l} = 1 \quad \Longrightarrow \quad Y_{j,t-l} \rightarrow Y_{i,t} \end{cases} \tag{4}$$

where $Y_{j,t-l} \nrightarrow Y_{i,t}$ means that Y_j does not influence Y_i at lag l, including $l = 0$, which correspond to contemporaneous dependence.

Let $\bar{B}_{ij} = \sum_{l=0}^{p} B_{ij,l}$ and $\bar{G}_{ij} = \sum_{l=0}^{p} G_{ij,l}$. Following Eq. (4), we define two null-diagonal matrices $A \in \{0, 1\}^{N \times N}$ (adjacency matrix) and $W \in \mathbb{R}^{N \times N}$ (weighted adjacency matrix), whose ijth element is given by:

$$A_{ij} = \begin{cases} 0, & \text{if } \bar{G}_{ij} = 0 \\ 1, & \text{otherwise} \end{cases}, \qquad W_{ij} = \bar{B}_{ij} \tag{5}$$

This interpretation of the weighted adjacency matrix W helps the construction of a contagion effect model that can "modify" the "merit" of a company with the effect of contagion from the companies to which it is connected, in a level specified by the coefficients.

For our analysis, we are interested in the sector-specific blocks of these matrices, which give specific insights into the dynamic behavior of a subset of companies linked by similar activities. For this reason, we are going to analyze $\bar{B} = [\bar{B}_{ij}]$ in sub-blocks, identified by the sector of interest, and then define a class of indices grounded on Network Theory, useful to give further insights on the topological structure of the system.

Let $S_k \subset S$ be the set of the indices $i = 1, \dots, N$ related to the sector k, $\forall k \in [1, 5]$. For what follows, we define $|S_k|$ to be the cardinality (i.e. the number of its elements) of set S_k. Consider the following sector-specific measures:

- *Number of Links*: an unnormalized measure that reflects the total number of connections in a network. It is calculated as:

$$\sum_{i \in S_k} \sum_{j \in S_k} A_{ij}$$

- *Density*: it describes the portion of the potential connections in a network that are actual connections. Being a variable connected with at maximum $S_k - 1$ other variables, the density is simply the number of links normalized for all the possible combinations among S_k variables. It is calculated as:

$$\frac{1}{|S_k|^2 - |S_k|}\sum_{i\in S_k}\sum_{j\in S_k} A_{ij}$$

- *Strength in (out)*: Averaged sum of the weights of inward (outward) edges for a set of nodes. It is calculated as:

$$\frac{1}{|S_k|}\sum_{i\in S_k} W_{ij} \quad \text{(in)}, \qquad \frac{1}{|S_k|}\sum_{j\in S_k} W_{ij} \quad \text{(out)}$$

- *Average Degree*: is the average number of edges per node in the graph. It is calculated as:

$$\frac{1}{|S_k|}\sum_{i,j\in S_k} A_{ij}$$

In the analysis, the second class comes from the generalized forecast error variance decomposition (GFEVD) matrix. Once B_+ and B_0 are estimated, the model in Eq. (1) can be rewritten in the Moving Average (MA) representation, which is useful to highlight the role of the various shocks appearing in the system, as well as their relative contributions. Let $Y_t = \sum_{i=0}^{+\infty}\theta_i\varepsilon_{t-i}$ be the forecast error of predicting Y_t conditional on the information at time $t-1$, where θ_i is derived recursively as $\theta_i = B_1\theta_{i-1} + B_2\theta_{i-2} + \cdots + B_p\theta_{i-p}$, with $\theta_0 = I_N$ and $\theta_i = 0$ for $i < 0$. Then the H-step GFEVD, first introduced by Pesaran and Shin [51], is calculated as:

$$d_{ij}^H = \frac{\tilde{d}_{ij}^H}{\sum_{j=1}^N \tilde{d}_{ij}^H}, \qquad \text{where} \qquad \tilde{d}_{ij}^H = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(\mathfrak{e}_i'\theta_h\Sigma_u\mathfrak{e}_j)^2}{\sum_{h=0}^{H-1}(\mathfrak{e}_i'\theta_h\Sigma_u\theta_h'\mathfrak{e}_j)} \tag{6}$$

where d_{ij}^H measures the proportion of the H-step ahead forecast error variance of the ith element of Y_t accounted for by the innovations in the jth element of Y_t, $\mathfrak{e}_i$ is a selection vector with ith element unity and 0 elsewhere. By pooling together d_{ij}^H for each i, j, the $[N \times N]$ H-step GFEVD matrix is easily obtained: $D^H = [\tilde{d}_{ij}^H]$.

The nice property of the GFEVD is that it can be naturally interpreted as a weighted, directed network, where the edges represent the quota of forecast error variance explained by each node. Nevertheless, even though B_+ and B_0 are sparse, the endogeneity of the system implies that the coefficients of the MA representations, as well as the GFEVD, are dense. As a direct consequence, the above-mentioned indicators lose their explanatory power, given the lack of sparsity in the transformed system.

To better analyze these objects we then rely on two simple indicators, originally introduced by Diebold and Yilmaz [9]. We define the *total directional connectedness from others to i* (SPILLOVER TO) and the *total directional connectedness to others from j* (SPILLOVER FROM) as

$$\mathcal{F}_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{N} d_{ij}^H, \qquad \mathcal{T}_{\bullet\leftarrow i} = \sum_{i=1,i\neq j}^{N} d_{ij}^H \tag{7}$$

The spillover (TO) index is the central part of the analysis concerning the impact of the events selected (through the corresponding dummies) and is thought to show the connection between a specific variable and the whole system due to shock arising elsewhere. The "TO" in brackets stands for the fact that we are looking at the impact *from* the dummies *TO*, as opposed to the "FROM" spillover. This measure of connection is intimately related to the econometric notion of variance decomposition, in which the forecast error variance of a variable is decomposed into parts attributed to the various variables in the system.

Moreover, we are also interested in comparing different VAR specifications and thereby assessing which accounts for the best explanatory power. To this extent, we define *Relative performance* indicator: is the ratio of the Root Mean Squared Error (RMSE) between model p and q: a measure of the relative goodness of fit of model p compared to that of model q (baseline model). Calculated as:

$$\frac{\sum_{t=1}^T\sum_{i=1}^N (Y_{i,t} - \hat{Y}_{i,t}^q)^2}{\sum_{t=1}^T\sum_{i=1}^N (Y_{i,t} - \hat{Y}_{i,t}^p)^2} \in \mathbb{R}^+$$

where $\hat{Y}_{i,t}^j$ is the in sample forecast of $Y_{i,t}$ performed using model j. A value below 1 means that model q outperforms model p, and vice versa.

4. Data description

We recall that the aim of this paper is the assessment and quantification of the possible impacts of a supranational agency which is supposed to centralize decisions and actions as countermeasures to pandemic events. As it is well known, such an agency was not in place at the time of the explosion of the pandemic, thus we decided to take advantage of a scenario analysis by using some relevant events that occurred during the first year and half of the pandemic as proxies of the supranational institution in charge of addressing countermeasures organization.

To this end, we consider the 89 top companies from EuroStoxx 600, which is made up of several economic sectors and we consider the period October 1st, 2018 - April 27th, 2021 (940 days). The variables of interest are the financial equity prices and the sentiment scores produced by the research company Brain,[3] based on the analysis of 2000 global sources (regular news, bulletin, etc.) written in 33 different languages. Brain specializes in the production of alternative datasets and in the development of proprietary algorithms for investment strategies in financial markets. The Brain Sentiment Indicator dataset[4] comprises a daily sentiment indicator for the largest listed worldwide companies. Such an indicator represents a score that ranges between −1 and +1 and is based on financial news and blogs written in English. Each news is pre-analyzed to assign the corresponding company through the use of a dictionary of company names; then the news is categorized using syntactic rules or machine learning classifiers. If this step fails a dictionary-based approach is used. The data are collected using data mining and filtering techniques to assess the pertinence of news to a specific company. Also, the similarity and repetition of news on the same topic are taken into account and weighted in the final calculation of the sentiment. The Brain sentiment score should not be confused with the Economic Sentiment indices survey data provided by EUROSTAT.

The classification of the 89 companies available in Table 1 is based on the Statistical classification of economic activities in the European Community (NACE). Without loss of generality, we have decided to restrict the number of sectors by grouping similar ones, to create four macro-sectors, and letting the remaining ones be grouped into "others" group. The division is done as follows: (i) Financial: Banking, Financial Services, and Insurance; (ii) Consumer: Consumer Defensive and Consumption; (iii) Health: Health sector; (iv) Technological: Technological sector; (v) Other sectors: Chemical, Industrial, Oil-Gas, Telecommunication, and Utility-Energy.

The main goal of the analysis is twofold:

1. to quantify dynamically the impact of the waves/phases of the Covid-19 pandemic on some economic sectors;
2. to quantify the impact of a list of relevant events referred to as actions undertaken at the EU level, which could be considered a proxy of the agency's role.

[3] https://braincompany.co.

[4] Brain has developed a proprietary sentiment indicator (BSI) based on natural language processing approaches to collect and classify the company news from a series of providers. The user can access the BSI through a Dashboard, API, FTP service, or a report sent by email.

Table 1
The list of considered 89 companies extracted from EuroStoxx 600.

No.	Stock	Ticker	No.	Stock	Ticker
Banking			**Health care**		
1	BNP PARIBAS	BNP	21	AMBU A/S-B	AMBUB
2	DANSKE BANK A/S	DANSKE	22	ASTRAZENECA PLC	AZN
3	DNB ASA	DNB	23	COLOPLAST-B	COLOB
4	HSBC HOLDINGS PLC	HSBA	24	DEMANT A/S	DEMANT
5	INTESA SANPAOLO	ISP	25	ESSILORLUXOTTICA	EL
6	SVENSKA HANDELSBANKEN-A SHS	SHBA	26	GENMAB A/S	GMAB
			27	GN STORE NORD A/S	GN
Chemical			28	GLAXOSMITHKLINE PLC	GSK
7	KONINKLIJKE KPN NV	KPN	29	MERCK KGAA	MRK
Consumer defensive			30	NOVARTIS AG-REG	NOVN
8	ADIDAS AG	ADS	31	NOVOZYMES A/S-B SHARES	NZYMB
9	BRITISH AMERICAN TOBACCO PLC	BATS	32	ROCHE HOLDING AG-GENUSSCHEIN	ROG
10	LVMH MOET HENNESSY LOUIS VUI	MC	33	SANOFI	SAN
11	L'OREAL	OR	**Industrial**		
12	PANDORA A/S	PNDORA	34	DASSAULT AVIATION SA	AM
13	HERMES INTERNATIONAL	RMS	**Insurance**		
14	UNILEVER PL	ULVR	35	ALLIANZ SE-REG	ALV
Consumption			36	AXA SA	CS
15	INDUSTRIA DE DISENO TEXTIL	ITX	37	ZURICH INSURANCE GROUP AG	ZURN
16	KERING	KER	**Oil & Gas**		
			38	AKER BP ASA	AKERBP
Financial services			39	BP PLC	BP.
17	INVESTOR AB-A SHS	INVEA	40	ENI SPA	ENI
18	KINNEVIK AB - B	KINVB	41	TOTAL SE	FP
19	LONDON STOCK EXCHANGE GROUP	LSEG	42	GALP ENERGIA SGPS SA	GALP
20	UBS GROUP AG-REG	UBSG	43	NESTE OYJ	NESTE
			44	OMV AG	OMV
			45	ROYAL DUTCH SHELL PLC-A SHS	RDSA
46	REPSOL SA	REP	68	ILIAD SA	ILD
47	RUBIS	RUI	69	ORANGE	ORA
48	SNAM SPA	SRG	70	SWISSCOM AG-REG	SCMN
49	VESTAS WIND SYSTEMS A/S	VWS	71	TELEFONICA SA	TEF
Tech			72	TELENOR ASA	TEL
50	AMADEUS IT GROUP SA	AMS	73	TELE2 AB-B SHS	TEL2B
51	ASML HOLDING NV	ASML	74	TELIA CO AB	TELIA
52	AVEVA GROUP PLC	AVV	75	TEMENOS AG - REG	TEMN
53	BECHTLE AG	BC8	76	TELECOM ITALIA SPA	TIT
54	CAPGEMINI SE	CAP	77	VODAFONE GROUP PLC	VOD
55	DASSAULT SYSTEMES SE	DSY	**Utility-Energy**		
56	ERICSSON LM-B SHS	ERICB	78	EDP-ENERGIAS DE PORTUGAL SA	EDP
57	HEXAGON AB-B SHS	HEXAB	79	ENDESA SA	ELE
58	INFINEON TECHNOLOGIES AG	IFX	80	ENEL SPA	ENEL
59	LOGITECH INTERNATIONAL-REG	LOGN	81	ENGIE	ENGI
60	NOKIA OYJ	NOKIA	82	E.ON SE	EOAN
61	SAP SE	SAP	83	FORTUM OYJ	FORTUM
62	SIMCORP A/S	SIM	84	IBERDROLA SA	IBE
63	STMICROELECTRONICS NV	STM	85	NATIONAL GRID PLC	NG.
			86	ORSTED A/S	ORSTED
TLC			87	RWE AG	RWE
64	BT GROUP PLC	BT.A	88	VERBUND AG	VER
65	CELLNEX TELECOM SA	CLNX	89	VEOLIA ENVIRONNEMENT	VIE
66	DEUTSCHE TELEKOM AG-REG	DTE			
67	ELISA OYJ	ELISA			

To this end, we estimate in a statistically robust way, the structure of interconnectedness among the companies, considering both market reactions and public sentiment. The structure of interconnectedness considered in this study is based on a Bayesian Graphical SVAR model which guarantees statistically sound estimation of the significant links among the entities taking into account the contemporaneous and temporal dynamics.

In terms of Covid-19 outbreaks, we identify the following 4 phases (plus the pre-Covid period): (A) "Pre-Covid" period to indicate period until the end of February 2020; (B) "First wave" - from the beginning of March 2020 to the end of May 2020; (C) "Phase 1" - from the beginning of June 2020 to the end of September 2020, this window is not called "wave" since it was a period with a particularly low incidence of the pandemic; (D) "Second wave" - from the beginning of October 2020 to the end of December 2020; (E) "Third wave" - from the beginning of January 2021 till the end of April 2021.

The waves are important as reference points for evaluating the role of a possible agency as in our simulation study. In particular, we assume that the first wave (March–May 2020) represents the lowest level of preparedness and response to the crisis induced by the Covid-19 pandemic. Countries, at that time were facing severe shortages of personal protective equipment (PPE), medical devices and in vitro medical devices (including tests and testing materials), available therapies, vaccines, and essential medicines. Such a situation represents the worst scenario and, in this sense, it can be assumed as a benchmark (Policy option 0: Baseline scenario). All the subsequent waves, although severe in terms of the number of cases and deaths, witnessed an increased reaction capacity of the European countries, thanks to the coordinated actions undertaken at the EU level. In this sense, we assume that waves 2 and 3 can mimic different levels of agency interventions.

The events of interest, which we explicitly consider in our analysis, are the following ones: (1) 17th June 2020 - First action: Establishment of EU vaccines strategy; (2) 14th August 2020 - Second action: First

APAs under the vaccines strategy; (3) 17th Feb 2021 - Third action: Establishment of the Vaccelerate trial network; (4) 16th March 2021- Fourth action: Additional purchase agreements of BioNTech-Pfizer and Moderna vaccines.

Such actions can be subsumed as levels of intervention alternative to Policy Option 0. More specifically and by the HaDEA agency, we assume the following analogies: (I) The first action would represent the **Policy Option 1** (Strengthened coordination for threat assessment and knowledge generation based on joint undertakings and other mechanisms); (II) The second action would represent the **Policy option 2.1**: Operational Authority; (III) The third action would be considered as an example of **Policy option 2.2**: Operational and Infrastructure Authority; (IV) Lastly, the fourth event which represents a long-term action, can be considered as an example of **Policy option 3**: Full end-to-end Authority & streamlining of EU level initiatives on medical countermeasures for serious cross-border threats to health.

For purposes of robustness checks, we considered 3 supplementary events, namely: 28th of July 2020 - Securing EU access to Veklury (Remdesivir) treatment, 21st of December 2020 - the EU Commission authorizes first safe and effective vaccine against Covid-19, and 17th of February 2021 Launch of the "HERA Incubator".

To assess correctly the impact of these events on the economic sectors, we control for the number of Covid-19 cases aggregated at the European level. We summed up all the daily cases of the European countries and categorized the counts variable according to some standard statistical distribution (first quartile and third quartile). Specifically, we define classes as follows: (a) Below 10 893 daily cases as **low impact**; (b) 10 893 – 153 250 daily cases as **medium impact**; (c) Above 153 250 daily cases as **high impact**.

From a methodological point of view, to quantify the impact of the waves and the events/actions, we split the exercise into two sub-analysis:

1. Spillover analysis at the sector level (averaging data at the companies level) to quantify the specific impact of each event onto the economic sectors considering both market and public sentiments;
2. Interconnectedness analysis at the companies level, considering both the waves and the events.

To assess and compare networks, we use several indicators: (i) Number of Links; (ii) Density: number of actual links over the possible links; (iii) Average Degree: average number of links for each node; (iv) Strength: the number of links weighted for the relative coefficients; (v) Spillover (TO) index: The quota of variance explained by the event in influencing the whole system, within a generalized forecast error variance decomposition (GFEVD); (vi) Ratio of the Root Mean Squared Error (RMSE): A goodness of fit measure.

5. Results

The first analysis is based on the spillover index. In Table 2 we report the overall Spillover impact from the specific events to the considered sectors. Such an index accounts for the quota of variability explained by the specific event (through the dummy variable) in influencing the equity and sentiment time series. Since such analysis is dynamic and depends upon the specific time horizon, we considered a temporal window of up to 14 days. For the sake of comparison, we report in Fig. 1 results of the aggregated Spillover index (in percentages on the y-axis) at the 1st, 7th, and 14th horizon and we can infer that: (1) There is an ordering in the impact of the events: the Vaccelerate trial (in blue) and the First EU Vaccine Strategy (yellow) are the most impacting events; (2) The first APAs (red) appears as the least effective event on day 1 but it rapidly converges to the other two important events on day 14; (3) The Additional purchase of Pfizer/Moderna (green) is less impacting especially on days 1 and 7; (4) The cases variable (dashed black line) seems to rise at an increasing rate with a peak at the 7th horizon, after which the multiplier effect begins to fall. This can be attributed to the rise in the two vaccine-related events.

The analysis reveals that all the considered events have some significant impact on the sectors, although with different magnitudes. The vaccine-related events are the most important ones, regardless of the horizon, and they also overcome the Covid-19 cases effect in many scenarios. Considering how relevant and impacting are the waves of the pandemic, the presence of significant spillovers due to the actions (signaled through the events analysis) undertaken at the EU level, proves the importance of a coordinated and centralized organization. More precisely, based on the previous assumptions, we can infer that the Vaccelerate trial network (Policy option 2.2) has the highest impact, although partially overcome at the longest horizon by the event EU vaccines strategy (Policy Option 1). First APAs under the vaccine strategy, although starting with a particularly low impact on day 1, rapidly reach the highest levels of influence on day 14. The last event (additional purchase agreements) being a long-term action has a low impact on day 1 but it increases rapidly at the longest horizon.

A more detailed analysis is available in Table 2. According to the considered events (temporally ordered) and the analyzed horizon (1, 7, and 14 days), we list the 3 top sectors in terms of spillover impact. First of all, we can notice that both equities and sentiments are affected by the events. This means that both the time series can be considered as transmission channels as strictly interconnected according to a sort of feedback loop scheme. The consumer sector is ranked first (either the equity or the sentiment component) about all the events but second on the Vaccelerate trial. The technological sector is first in that category, even though we should stress that the relative numbers are close to each other (0.26 and 0.25). The health sector is particularly relevant in Event 1 (EU vaccine strategy), Event 2 (first APAs), and Event 4 (Additional Purchase) while Event 3 and Event 4 (respectively Vaccelerate trial and Additional Purchase) have more impact on the financial and technological sectors.

It is important to stress that the last action (Additional Purchase - Policy Option 3) is the one showing the highest spillover effect in particular on the consumer sector. This is a relevant result that highlights the importance of the undertaken action in a phase of the pandemic where European countries were ready to begin a massive vaccination campaign but were experiencing a severe shortage in the supply of doses. Indeed, the consumer sector is one of the most affected by the pandemic, therefore, the announcement of additional purchases, which represents a long-term action and, in this sense, evidence of an EU strategy in place (Policy Option 3), is perceived as a particularly fortunate action by such an affected sector.

5.1. Companies level analysis

In Fig. 2 we show the temporal evolution of the network density index which, for the sake of clarity, is aggregated at the sector level using an arithmetic average. The graph reports both the five considered periods and the four events. First, we notice that each sector shows its density level, in particular, the technological sector is, by far, the most connected one until the second wave. In the first wave, three sectors recorded a decrease in their network density except the health sector. Each sector then responded differently to the events under consideration and in line with the specific product characteristics of each of them. The first event (the EU vaccine strategy) had an interesting impact on the consumer sector which dropped sensibly after a sharp increase started in the first period. The second event (first APAs) instead shows a diversified effect: the technological sector reported a delayed reaction with a decrease in density while all the other sectors kept increasing. During the second wave (Oct–Dec 2020) we do not have events and indeed the density patterns are rather chaotic without a clear and consistent trend. The last two actions implemented during the third wave seem to be relevant for the technology sector which recorded a decline in density again while the other sectors maintained

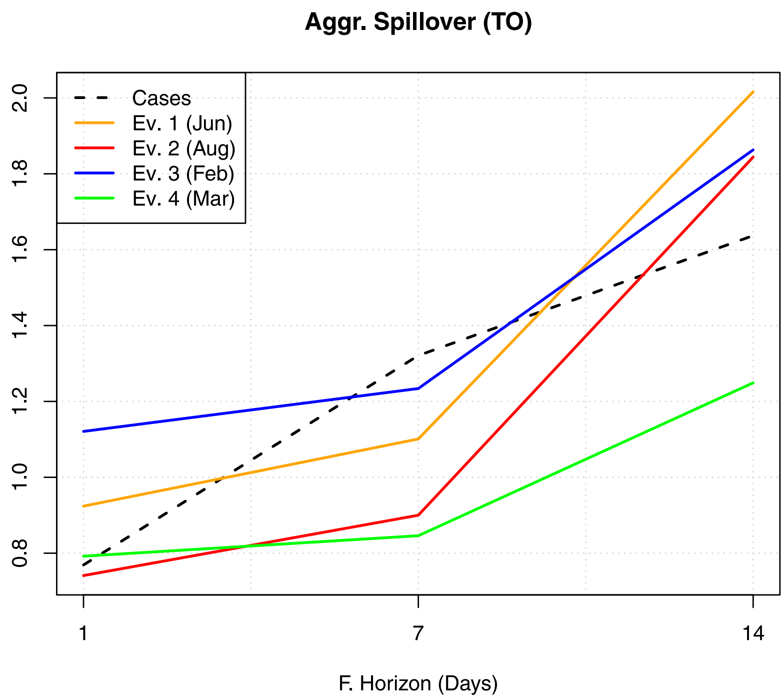

Fig. 1. Aggregated Spillover (TO) evolution according to the events, the daily Covid-19 cases, and the temporal horizon (1, 7, and 14 days).

Table 2
Spillover impact of each event on considered sectors. The top 3 sectors are listed. In parenthesis, E stands for equity data and S for sentiment data.

F. Horizon	EU vax strategy		First APAs		Vaccelerate trial		Add. Purchase	
1 day	CONS(S)	0.30	CONS(S)	0.35	TECH(E)	0.26	CONS(E)	0.42
	HLT(E)	0.25	HLT(S)	0.27	CONS(S)	0.25	TECH(E)	0.19
	FIN(S)	0.17	TECH(E)	0.21	FIN(E)	0.18	HLT(E)	0.15
7 days	CONS(S)	0.25	CONS(S)	0.29	TECH(E)	0.26	CONS(E)	0.41
	CONS(E)	0.19	HLT(S)	0.22	CONS(S)	0.25	TECH(E)	0.18
	HLT(E)	0.18	TECH(E)	0.21	FIN(E)	0.18	HLT(E)	0.14
14 days	CONS(E)	0.22	TECH(E)	0.23	TECH(E)	0.26	CONS(E)	0.32
	TECH(E)	0.19	CONS(E)	0.19	CONS(S)	0.25	TECH(E)	0.23
	HLT(E)	0.16	FIN(E)	0.17	FIN(E)	0.18	FIN(E)	0.19

their patterns. It is worth noticing the density evolution of the health sector. That is, there is a clear and consistent increasing trend in their network density. At the end of the third wave, we see that the health sector is the most connected one; this is a reasonable reaction to the huge solicitation experienced from the beginning of the pandemic either for medicament or for vaccine research. In summary, we notice that all the considered events had an impact that interacts differently according to the specific sector.

As a final analysis, we calculated the delta variation of some network-based measures, namely: the number of links, the density, and the average degree. The deltas have been calculated by taking the first wave as the reference phase. The underlying hypothesis is that the first wave represents the no supranational agency intervention (Policy option 0), in other words, the lowest levels of preparedness and the reaction of the countries.

From Table 3, we notice negative deltas for the consumer and technological sectors while the other two sectors increase their complexity. It is important to remember that a decrease in the density and the related indexes, is an indication of a less densely interconnected system, less vulnerable to shocks and systemic risk. Such analysis, which we remind is based on the networks estimated on the equity, sentiment, and events variables, suggests that a strong coordinated intervention, like the four considered actions, is necessary to help the recovery of the economic sectors. Indeed the health sector, as already stated above, has a different pattern due to its specific and unique role in the pandemic. The increase in the complexity of the network can be considered a positive reaction since a higher level of collaboration and interconnections among the pharmaceutical companies can improve the reaction and preparedness of the whole system. Moreover, the reaction of the financial sector is in line with its typical behavior which is a system particularly interconnected and more resilient to external non-financial shocks. Finally, since each sector responds differently in magnitude and reaction time to each action, only an ensemble of differentiated and coordinated actions (Policy Option 3) could ensure an effective impact on all the economic sectors.

In Figs. 3 and 4 we report a further analysis based on the strength-in and strength-out measures which account for the average of the weights of inward (outward) edges. In other words, such measures account for the power of each company or sector in influencing the related counterparts. It appears an interesting pattern in the relationship between the two quantities as the pandemic evolves. In the pre-Covid period, we have a positive linear correlation which, waves by waves, turns into a non-linear negative one. That is to say that companies relevant in transmitting influence are also those more influenced, they are leaders both at the receiving and at the transmitting level. During the pandemic instead, such a relationship does not hold anymore; the most influencing companies are those less influenced, resulting in a non-linear negative correlation. It seems that polarization occurs in the roles, there are companies pivotal in transmitting influence and others that become mainly receivers. Such phenomenon appears more clearly

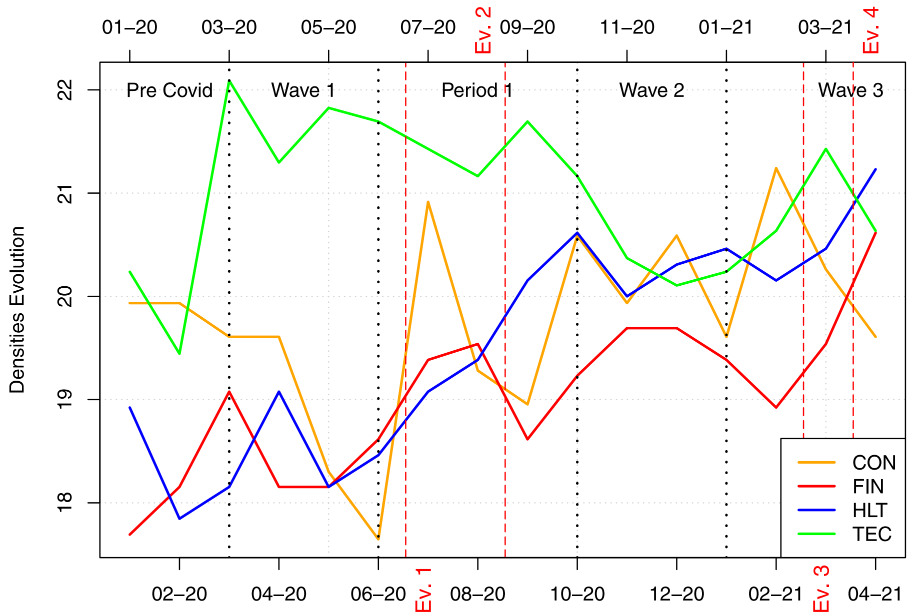

Fig. 2. Temporal evolution of network density according to sectors, periods, and events. Ev.1 = Establishment of EU vaccines strategy, Ev.2 = First APAs under the vaccines strategy, Ev.3 = Establishment of the Vaccelerate trial network, Ev.4 = Additional purchase agreements of BioNTech-Pfizer and Moderna vaccines.

Table 3
Delta variation with regards to the first wave (Mar–May 2020), sector by sector.

Waves	ΔLinks	ΔDensity	ΔAv. Degree	Waves	ΔLinks	ΔDensity	ΔAv. Degree
Consumer sector				**Financial sector**			
Jun–Sep	−5	−1.634	−0.278	Jun–Sep	1	0.154	0.038
Oct–Dec	−4	−1.307	−0.222	Oct–Dec	6	0.923	0.231
Jan–Apr	−3	−0.980	−0.167	Jan–Apr	14	2.154	0.538
Health sector				**Tech sector**			
Jun–Sep	8	1.231	0.308	Jun–Sep	−5	−0.661	−0.179
Oct–Dec	7	1.077	0.269	Oct–Dec	−14	−1.852	−0.500
Jan–Apr	12	1.846	0.462	Jan–Apr	−14	−1.852	−0.500

in Fig. 4, where we notice that in the pre-Covid period, the sectors are very close to each other, meaning that they have similar patterns. Then, a rather stable level of the strength-in index (around 6 and 7) corresponds to a ranking for the strength-out index: the technological sector is the most influencing one while the consumer is the most influenced. We can then conclude that the pandemic had a huge impact on the organization of the economic sectors and their relative roles. The crisis induced a ranking in the sectors led by the tech industries which experienced a boost in development due to the hype in all the online and technological activities.

Table 4
RMSE ratio between each specification and the basic model without events.

Combination	RMSE ratio	Combination	RMSE ratio
No events	1	Second and Third	0.959
First event	0.978	Second and Fourth	0.959
Second event	0.977	First-Second-Third	0.942
Third event	0.977	First-Second-Fourth	0.942
Fourth event	0.977	First-Third-Fourth	0.943
First and Second	0.959	Second-Third-Fourth	0.943
First and Third	0.959	All	**0.917**
First and Fourth	0.959		

5.2. Goodness of fit

Finally, in Table 4 we report the ratio between the RMSE of the basic model (with no events) and all the other models, one for each possible combination of events. The lower the ratio, the greater the predictive accuracy of the model considered. What emerges is that the configuration with the full specification (i.e. all the events contemporaneously), reaches the lowest error rate, suggesting that such configuration produces the best fit to the observed data. Such a result confirms once again the need for an ensemble of actions to be undertaken at the EU level, that is to say, a full policy scenario (Policy 3). Just one action or even a combination of two, is not enough for describing the variability and patterns of the 89 companies during the pandemic.

6. Conclusion

In the current paper, we present an extensive quantitative analysis requested by the EU within the activities of the European project ‘Periscope: Pan-European Response to the Impacts of COVID-19 and Future Pandemics and Epidemics’. In the aftermath of the Covid-19 pandemic, the European Union using the HaDEA agency, launched the establishment of a specific authority HERA - Health Emergency Preparedness and Response Authority, able to prevent, detect, and rapidly respond to health emergencies. Before properly finalizing the role played by such authority, HaDEA wanted to assess either qualitatively or quantitatively the ideal level of intervention of such authority. To this end, we set a quantitative scenario analysis inspecting, in a robust way, the possible impacts of specific actions undertaken at the EU level on a selection of 89 companies listed on the EuroStoxx 600 and divided into 5 sectors.

From a methodological point of view, we evaluated the interconnectedness risk (also referred to as systemic risk) by leveraging traditional and non-traditional data, respectively market prices and sentiment data (based on a huge amount of verified textual sources).

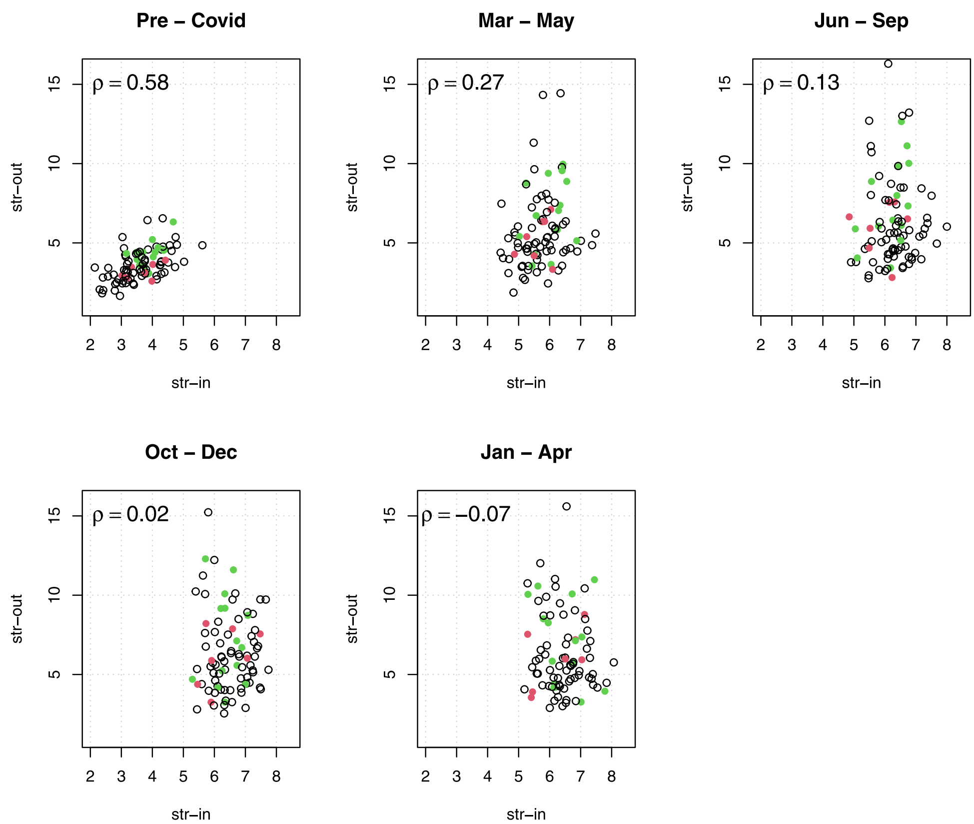

Fig. 3. Relationship between strength-in and -out along the five periods at companies level along with the Spearman's rank correlation coefficient. Green (Red) points belong to the Technological (Consumer) sector.

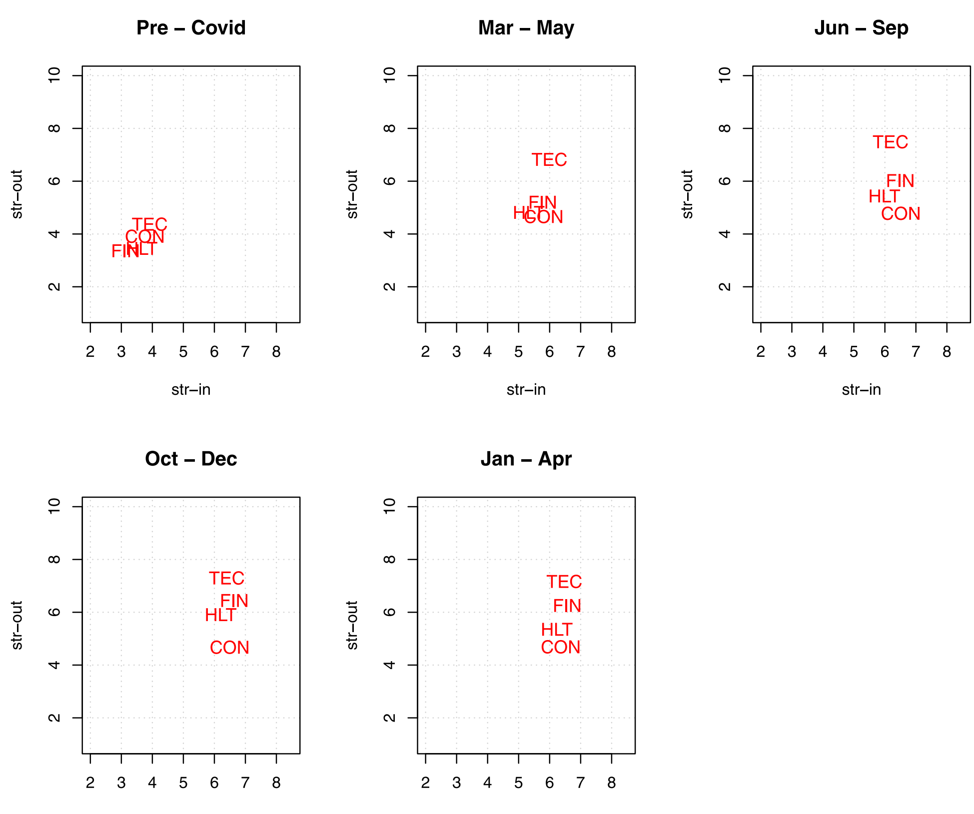

Fig. 4. Relationship between strength in and strength out along the five periods at the sectors level.

The risk is quantified by fitting a Bayesian graphical SVAR model that helps in interpreting the temporal and contemporaneous relationships in multivariate time series. The spillover (TO) index is the central part of the analysis concerning the impact of the events selected. It is thought to show the connection between a specific variable with the whole system due to shock arising elsewhere. Using such analysis, we were able to assess the effects induced by some specific and relevant actions undertaken at the EU level, after controlling for the number of Covid cases, such as the establishment of the EU vaccines strategy, the first APAs under the vaccines strategy, the establishment of the Vaccelerate trial network and the additional purchase agreements of BioNTech-Pfizer and Moderna vaccines.

In light of the research hypothesis we defined in the introduction section, we can infer several implications that can be useful to policymakers and institutions in general. We investigated the possible impact on the economic sectors of countermeasures undertaken at the supranational level, namely by the European Union. The analysis reveals that all the considered events have some significant impact on the sectors, although with different magnitudes. The vaccine-related events are the most important ones, regardless of the horizon, and they also overcome the Covid-19 cases effect in many scenarios. Considering how relevant and impacting are the waves of the pandemic, the presence of significant spillovers due to the actions undertaken at the EU level proves the importance of a coordinated and centralized organization. We also showed that the most impacted sector is the consumer one, highlighting even more the importance of the supranational institutions in the everyday life of European citizens. Indeed the analysis also showed that the events have impacts on both the transmission channels that is equities and sentiment time series. This means that the EU by avoiding the jeopardized and not centralized behavior of the different countries can induce a concrete impact on either the financial markets or the sentiment/perception of European citizens. Moreover, the fact that the most impacting events are the Vaccelerate trial and the First EU Vaccine Strategy proves the importance of coordinated rather than country-based actions. Policymakers should consult among them and converge before undertaking measures. In this sense, a supranational agency can act as a hub to centralize and undertake homogeneous actions, especially those related to vaccination procurement and trials.

The results are interesting and relevant from the policymakers' perspective. In particular, the Vaccelerate trial and the first EU Vaccine Strategy are the most impacting events. On the contrary, the first APA appears the least effective event in the short term (day 1) but rapidly converges with the other two important events on day 14. The analysis reveals that all the considered events have some significant impact on the sectors, although differentiated in magnitude. The vaccine-related events are the most important ones, regardless of the horizon, and they also overcome the Covid-19 cases effect in many scenarios. Considering how relevant and impacting are the waves of the pandemic, the presence of significant spillovers due to the actions (signaled through the events analysis) undertaken at the EU level, proves the importance of a coordinated and centralized organization. In line with previous studies, we also found that the more impacted sector is the Consumer one while the financial sector tends to be more robust and resilient.

In conclusion, our analysis proves that the economic sectors are positively influenced by centralized actions. Sectors tend to react more quickly to exogenous shocks (like the pandemic one) if policymakers arrange advanced protocols, and guidelines and avoid local and disorganized responses. Moreover, the agency HaDEA, used our findings, together with other relevant studies, to establish the optimal level of intervention of HERA that was launched as a new European Commission Directorate-General on September 16th, 2021.

CRediT authorship contribution statement

Daniel Felix Ahelegbey: Data curation, Software, Validation, Writing – original draft, Writing – review & editing. **Alessandro Celani:** Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Paola Cerchiello:** Conceptualization, Project administration, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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