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Abstract

How much the largest worldwide companies, belonging to different sectors of the economy, are suffering from the pandemic? Are economic relations among them changing? In this paper, we address such issues by analysing the top 50 S&P companies by means of market and textual data. Our work proposes a network analysis model that combines such two types of information to highlight the connections among companies with the purpose of investigating the relationships before and during the pandemic crisis. In doing so, we leverage a large amount of textual data through the employment of a sentiment score which is coupled with standard market data. Our results show that the COVID-19 pandemic has largely affected the US productive system, however differently sector by sector and with more impact during the second wave compared to the first.

Keywords: COVID-19 Pandemic, Textual analysis, Financial risk, Network model

1. Introduction

Covid-19 is not the first pandemic that the world has been experiencing but the conditions we are in, changed our lives permanently and have consequences in every field. If, from the social point of view, the generated change is visible, the impact triggered at the macroeconomic level needs some time to be appreciated and quantified. As never before, the "on-line" life is so intensive, the entire world has the urgency to communicate. From the perspective of the economic market, as information spreads out, the associated sentiments change and increase the impact on the market trends. In the era of social networks, the information moves instantaneously and can amplify or damper the dynamics of the financial markets. Not only purely financial information that has an impact on the economic trend, but the price is also more and more affected by the sentiment of people. The

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mechanisms involved are many, from the purely economic aspects to the sociological and psychological ones. This is the reason why, at the beginning of the 2000s, sentiment analysis has been developed and largely employed, involving different sectors from marketing to politics, passing through psychology and finance.

This paper focuses specifically on the latter and, indeed, it is well known that market prices originate from complex interaction mechanisms that often reflect speculative behaviours, rather than the fundamentals of the companies to which they refer. Market models and, specifically, financial network models based on market data may, therefore, reflect spurious components that could bias results and relative discussion. This weakness of the market suggests to enrich financial market data with data coming from other, complementary, sources. It is a fact that, market prices represent only one source of information, used for evaluating financial institutions; other relevant ones include ratings issued by rating agencies, reports of qualified financial analysts and opinions of influential and specialized media. Most of the previous sources are private, not available for data analysis. However, summary reports from them are now typically reported, almost in real time, in social networks and, in particular, in Twitter and Stocktwits.

Hereafter, we aim at investigating how and how much the interconnections among largest USA companies (top 50), have been impacted, modified and eventually reshaped, both from the financial market and the public sentiment perspectives because of the COVID-19 pandemic outbreak. To achieve the 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. Moreover we compare the pre-Covid-19 pandemic period with the still ongoing one, considering the 2 waves of the outbreak which have affected the USA. Data are up to date and referred to the last available day (November 17th, 2020). Our results clearly show a number of interesting facts:

- Financial market data and sentiment based data induce different behaviours in the networks structure either before and during the pandemic;
- The density of the networks evidently increases with the outbreak of the pandemic suggesting that an exogenous and rather homogeneous diffused shock produces more interconnections among the entities which may lead to a more vulnerable financial system in terms of systemic risk;
- It appears how the system shows a certain amount of resilience as the first wave comes but, with the second one, the interconnections among the agents change largely.
- It is evident a difference among the sectors that reacts in their own ways considered the type of business and the role played in the pandemic.
- The shock produces an effect in the positioning of the companies within the network:

hub and authority scores experience not only a change in the top 5 rankings but also the appearance of now comers.

The paper is organized as follows: Section 2 presents the literature review, Section 3 presents the network VAR model and discusses the Bayesian estimation mechanism. Section 4 presents a description of the data, in Section 5 we report the results and in Section 6 we discuss our findings.

2. Literature Review

Numerous studies analyze the impact of sentiment in finance. Important papers on the statistical/econometric analysis of non conventional data are available: see, for example, Bollen et al. (2011), Bordino et al. (2012), Choi and Varian (2012), Feldman (2013), Cerchiello and Giudici (2016a), who all show the added value of tweets and, more generally, of textual data, in economics and finance. Loughran and McDonald (2016) review textual analysis literature in accounting and finance, Tetlock et al. (2008) find that language content is able to capture relevant information, not otherwise captured, which is incorporated into stock prices quickly. Cerchiello and Giudici (2016c) demonstrate how tweet data can be relevant in determining systemic risk networks and stress that such type of data has the great advantage of being able to include even unlisted institutions in the networks.

Aste (2019), analyzing the cryptocurrency market, demonstrates how prices affect sentiment and vice versa, with differences in intensity and number of significant interactions. Souza et al. (2015), analyzing listed retail brands, demonstrate through twitter analysis that social media are very important in financial dynamics even in comparison to more traditional news sources such as newspapers. Tetlock (2007) analyzes the link between media and stock market pointing out pessimism and demonstrating the relationship between pessimism and a decrease in stock prices and pessimism and an increase in trading volume. Joshi et al. (2016) study the relationship between news and stock trends noting that the polarity of news (positive and negative) impacts the market. Ranco et al. (2015) analyze relationships between 30 stock companies from Dow Jones Industrial Average (DJIA) index and the blogging platform Twitter and find a significant dependence particularly during the peaks of Twitter volume.

Algaba et al. (2020) recently presented an overview of sentiment analysis related to the econometric field calling this specific research stream "sentometrics". Larsen and Thorsrud (2019), using textual analysis on a Norwegian newspaper, construct a new index and prove that it can be useful to predict key quarterly economic variables, including assets.

Our paper supports the recent literature on the impact of Covid-19 using text analysis. We focus on the most recent papers which takes explicitly into account the effects of Covid-19 pandemic. Costola et al. (2020) examined the relationship between stock market reactions and news of COVID-19 obtained from three platforms: MarketWatch.com, Reuters.com, and NYtimes.com. They report a positive association between sentiment score and market returns and illustrate this result also applying principal component analysis on the sentiment database showing that the first principal component is positively related to the financial market. Looking at the Bitcoin market, Chen et al. (2020) studied the impact of fear sentiment, affected by pandemic, on Bitcoin prices in a period from 15 January 2020 to 24 April 2020, using vector autoregressive (VAR) models and show that the fear related to pandemic channels to negative Bitcoin returns and high trading volume. Using twitter platform, Derouiche and Frunza (2020) studied the relationship between tweets sentiment, related to sports companies and their stock prices using the Granger causality test of tweets on stocks and the event study related to Covid-period. Valle-Cruz et al. (2020) analyzed the link between some twitter accounts and financial indices. They show 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. Considering the statistical analysis of the twitter messages, Yin et al. (2020) analyzing 13 million of tweets for 2 weeks, noted a stronger ratio of positive sentiment than negative one with particular attention to some specific topics such as "staying at home". Rajput et al. (2020), considering tweets from January 2020 until March 2020, show that most of the tweet are positive, only about 15% negative.

Considering the Italian stock market, Colladon et al. (2020) propose a new textual index (ERKs) able to predict stock market prices and demonstrate the improvement using a forecasting model. Mamaysky (2020) examining the financial markets, note that until mid-March 2020 the markets are hypersensitive, that is very volatile and overreacting to news. From mid-March on-wards, the markets show a structural break reducing largely the hypersensitive trait. Gormsen and Koijen (2020), analyzing equity market and dividend futures, show how these move in response to investors' expectations of economic growth. They note that the programs implemented by governments have not improved growth expectations in the short term. Baker et al. (2020), analyzing the previous pandemics (1918, 1957 and 1968), show how the Covid-19 pandemic has unprecedented effects on the US market. The authors note that this is imputable 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. (2020b) and Zhang et al. (2020) map general risk patterns and systemic risks in markets around the world. We pay particular attention to the recent literature that has studied the impact of the pandemic on the US market with a specific focus on sub sectors specificity. Lee (2020) explored the correlation between sentiment score and 11 sector indices of the US Market through a set of t-test with different lags. Results demonstrate that all sectors present a significant boost in volatility due to the pandemic. Looking at correlation between Covid-19 sentiment and stock prices, they show 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. The impact of Covid-19 was stressed also from Federal reserve in some notes. Chen et al. (2020) show the "disconnection" between stock market and real economy. High price stocks, in particular tech stocks (Facebook, Amazon, Apple, Netflix, and Google), have performed better throughout the pandemic while low price stocks performed worse, losing the 10% of their values pre-pandemic. Ahmed et al. (2020) analyze the impact of Covid-19 on Emerging Market Economies (EMEs) in particular relationship between pandemic outcomes and financial developments considering 22 financial indicators. They show 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 by the strength of their economies.

2.1. Background: Network models

We studied the impact of Covid-19 on stocks' relationship through the application of network model. Boccaletti et al. (2006) review the structure of the networks and the applications in the different fields. Related to the financial area, Pantaleo et al. (2011) build a network structure based on covariance estimators to improve the portfolio optimization. Peralta and Zareei (2016) propose a portfolio optimization strategy through network-based method in which the securities are the nodes of the network and the links are the correlations of returns. Pozzi et al. (2008) compare the stability of two graph methods: the Minimum Spanning Tree and the Planar Maximally Filtered Graph using financial data.

Network models approach are commonly used in the field of systemic risk. Sheldon et al. (1998), Upper and Worms (2004), Eisenberg and Noe (2001) and in particular, frequently, are based on correlations between agents. There is a myriad of studies on the application of network models to uncover these vulnerabilities in financial systems to identify channels of shock transmission among financial institutions and markets (Acemoglu et al., 2015; Battiston et al., 2012; Billio et al., 2012; Cerchiello et al., 2017; Diebold and Yilmaz, 2014; Elliott et al., 2014; Nicola et al., 2020a).

Mantegna (1999), studying daily time series, finds a hierarchical arrangement between them through the construction of a graph calculated on the correlations between each pair of actions. Onnela et al. (2004) construct a network using return correlations and explain the methodology for constructing asset graphs. Giudici and Abu-Hashish (2019) propose a correlation network VAR model to explain the structure between bitcoin prices and classic asset. Steinbacher et al. (2013) studied network-based model of credit contagion related to the banking system to analyze the effect of shocks to the financial system. Billio et al. (2012) construct a Granger-causality networks on hedge funds, banks, broker/dealers, and insurance companies showing that banks are the most important actor in transmitting shocks than others, Giudici and Spelta (2016) improve financial network model applying Bayesian graphical models and dynamic Bayesian graphical models. Souza and Aste (2019) demonstrate the predictability of future stock market using a network approach that combines textual information and financial data. Giudici et al. (2020) propose a model for improving the credit risk of peer-to-peer platforms by exploiting the topological information embedded in similarity networks.

In this paper, we propose a network model to stress the relationship among companies in different sectors, considering the dynamic pre and during Covid-19 pandemic. Our study focuses on the top 50 world companies due to their important role in the entire world economy and also due to the amount of available textual information. We want to assess how much the largest worldwide companies are suffering from the pandemic and whether the relationship between them is changing. To answer these questions we build a network model that considers two sources of information: textual data from news and blog and financial stock prices. We decided to analyze separately the different sectors to stress in which sector the pandemic affects more and how.

3. Methodology

3.1. Network VAR Model Formulation

Let R_t denote the returns of the stock market indices of n institutions at time t, and S_t denote the sentiment of the institutions. Let $Y_t = (R_t, S_t)$ be a $2n \times 1$ vector whose dynamic evolution can be described by a VAR(Y_t) process:

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

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

where p is the lag order, B_l is $2n \times 2n$ matrix of coefficients with $B_{ij|l}$ measuring the effect of $Y_{j,t-l}$ on $Y_{i,t}$, U_t is a vector 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

$$\Sigma_u \;=\; (I - B_0)^{-1} \Sigma_\varepsilon (I - B_0)^{-1'} \tag{3}$$

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. To analyze (1) and (2) through networks, we assign to each coefficient in B_l a corresponding latent indicator in $G_l \in \{0,1\}^{2n \times 2n}$, such that for $i, j = 1, \ldots, n$, and $l = 0, 1, \ldots, p$:

$$B_{ij|l} = \begin{cases} 0 & \text{if} \quad G_{ij|l} = 0 \quad \Longrightarrow \quad Y_{j,t-l} \not\rightarrow Y_{i,t} \\ \beta_{ij} \in \mathbb{R} & \text{if} \quad G_{ij|l} = 1 \quad \Longrightarrow \quad Y_{j,t-l} \rightarrow Y_{i,t} \end{cases} \tag{4}$$

where $Y_{j,t-l} \not\rightarrow Y_{i,t}$ means that Y_j does not influence Y_i at lag l. We define two matrices $A \in \{0,1\}^{2n \times 2n}$ and $A^w \in \mathbb{R}^{2n \times 2n}$ such that

$$A = \mathbf{1}\left(\sum_{l=0}^{p} \sum_{ij} G_{ij|l} > 0 \right) = \begin{pmatrix} A_{R|R} & A_{R|S} \\ A_{S|R} & A_{S|S} \end{pmatrix}, \qquad A^w = \sum_{l=0}^{p} \sum_{ij} B_{ij|l} = \begin{pmatrix} A^w_{R|R} & A^w_{R|S} \\ A^w_{S|R} & A^w_{S|S} \end{pmatrix} \tag{5}$$

where $\mathbf{1}(G_{ij} > 0)$ is the indicator function, i.e., unity if $G_{ij} > 0$ and zero otherwise, $A^w_{R|R}$ and $A^w_{R|S}$ are sub-matrices of A^w that measure the cumulative effect of R_{t-l} and S_{t-l} on

R_t for $l = 0, \ldots, p$, respectively. The sub-matrices of A reports the following:

$$A_{R|R}(i,j) = \begin{cases} 1, & \text{if } R_j \to R_i \\ 0, & \text{if } R_j \not\to R_i \end{cases}, \qquad A_{R|S}(i,k) = \begin{cases} 1, & \text{if } S_k \to R_i \\ 0, & \text{if } S_k \not\to R_i \end{cases} \tag{6}$$

$$A_{S|R}(q,j) = \begin{cases} 1, & \text{if } R_j \to S_q \\ 0, & \text{if } R_j \not\to S_q \end{cases}, \qquad A_{S|S}(q,k) = \begin{cases} 1, & \text{if } S_k \to S_q \\ 0, & \text{if } S_k \not\to S_q \end{cases} \tag{7}$$

where $R_j \to R_i$ exist if there is a contemporaneous or lagged directed link from R_j to R_i. Similar reasoning holds for $S_k \to R_i$, $R_j \to S_q$, and $S_k \to S_q$. Thus, $A_{R|R}$ specifies adjacency matrix of equity-to-equity connections, $A_{R|S}$ for sentiment-to-equity, $A_{S|R}$ for equity-to-sentiment, and $A_{S|S}$ for sentiment-to-sentiment linkages. $A^w = (A^w_{R|R}, A^w_{R|S}, A^w_{S|R}, A^w_{S|S})$ specifies the weights of the relationship in $A = (A_{R|R}, A_{R|S}, A_{S|R}, A_{S|S})$ obtained as a sum of the estimated contemporaneous and lagged coefficients. The correspondence between (G, B) and (A, A^w) is such that the former captures the short-run dynamics in $Y_t = (R_t, S_t)$ while the latter can be viewed as long-term direct relationships when $Y_t = Y_{t-1} = \ldots = Y_{t-p}$. Defining a sparse structure on (G, B) induces parsimony of the short-run model and sparsity on the long-run relationship matrices (A, A^w).

3.2. Bayesian Graphical Vector Autoregression

The model specification in (1) and (2) combines to form the structural VAR model which is well documented to exhibit identifiability problems. To circumvent this problem, we apply the Bayesian graphical vector autoregressive (BGVAR) approach of Ahelegbey et al. (2016) to separate and estimate the contemporaneous and lagged interactions associated with the VAR. We complete the Bayesian formulation with prior specification and posterior approximations to draw inference on the model parameters.

3.2.1. Prior Specification

We specify the prior distributions of $(p, G, B, \Sigma_\varepsilon)$ as follows:

$$p \sim \mathcal{U}(1, \bar{p}), \qquad [B_{ij}|G_{ij} = 1] \sim \mathcal{N}(0, \eta), \qquad G_{ij} \sim \text{Ber}(\pi_{ij}), \qquad \Sigma_\varepsilon^{-1} \sim \mathcal{W}(\delta, \Lambda_0)$$

where $\bar{p}, \eta, \pi_{ij}, \delta$, and S_0 are hyper-parameters. The specification for p is a discrete uniform prior on the set $\{1, \ldots, \bar{p}\}$, $1 < \bar{p}$. The specification for B_{ij} conditional on G_{ij} follows a normal distribution with zero mean and variance η. Thus, relevant explanatory variables that predict a response variable must be associated with coefficients different from zero and the rest (representing not-relevant variables) are restricted to zero. We consider G_{ij} as Bernoulli distributed with π_{ij} as the prior probability. We assume Σ_ε^{-1} is Wishart distributed with prior expectation $\frac{1}{\delta}\Lambda_0$ and $\delta > n$ the degrees of freedom parameter.

3.2.2. Posterior Approximation

Let $X_t = (Y'_{t-1}, \ldots, Y'_{t-p})'$ be an $np \times 1$ vector of lagged observations, denote with $Y = (Y_1, \ldots, Y_N)$ a $N \times n$ matrix collection of all observations, and $X = (X_1, \ldots, X_N)$ be an $N \times np$ matrix collection of lagged observations. We fixed $p = 5$ to allow us select the relevant variables in different equations of the system. Following the Bayesian framework of Geiger and Heckerman (2002), we integrate out the structural parameters analytically to obtain a marginal likelihood function over graphs. Following Ahelegbey and Giudici (2020), we approximate inference of the parameters via a collapsed Gibbs sampler such that the algorithm proceeds as follows:

1. Sample via a Metropolis-within-Gibbs $[G_0, G_{1:p}|Y, p]$ by
   (a) Sampling from the marginal distribution: $[G_{1:p}|Y, p]$
   (b) Sampling from the conditional distribution: $[G_0|Y, p, G_{1:p}]$
2. Sample from $[B_0, B_{1:p}, \Sigma_\varepsilon|Y, \hat{G}_0, \hat{G}_{1:p}, p]$ by iterating the following steps:
   (a) Sample $[B_{i,\pi_i|1:p}|Y, \hat{G}_{1:p}, \hat{G}_0, B_0, \Sigma_\varepsilon] \sim \mathcal{N}(\hat{B}_{i,\pi_i|1:p},\ D_{\pi_i})$ where

$$\hat{B}_{i,\pi_i|1:p} = \sigma_{u,i}^{-2} D_{\pi_i} X'_{\pi_i} Y_i, \qquad D_{\pi_i} = (\eta^{-1} I_{d_x} + \sigma_{u,i}^{-2} X'_{\pi_i} X_{\pi_i})^{-1} \tag{8}$$

   where $X_{\pi_i} \in X$ corresponds to $(\hat{G}_{y_i, x_\pi|1:p} = 1)$, $\sigma_{u,i}^2$ is the i-th diagonal element of $\hat{\Sigma}_u = (I - \hat{B}_0)^{-1} \hat{\Sigma}_\varepsilon (I - \hat{B}_0)^{-1'}$, and d_x is the number of covariates in X_{π_i}.
   (b) Sample $[B_{i,\pi_i|0}|Y, \hat{G}_0, \hat{G}_{1:p}, B_{1:p}, \Sigma_\varepsilon] \sim \mathcal{N}(\hat{B}_{i,\pi_i|0}, Q_{\pi_i})$ where

$$\hat{B}_{i,\pi_i|0} = \sigma_{\varepsilon,i}^{-2} Q_{\pi_i} \hat{U}'_{\pi_i} \hat{U}_i, \qquad Q_{\pi_i} = (\eta^{-1} I_{d_u} + \sigma_{\varepsilon,i}^{-2} \hat{U}'_{\pi_i} \hat{U}_{\pi_i})^{-1} \tag{9}$$

   where $\hat{U} = Y - X\hat{B}'_{1:p}$, $\hat{U}_{\pi_i} \in \hat{U}_{-i}$ is the set of contemporaneous predictors of $\hat{U}_i$ that corresponds to $(\hat{G}_{y_i, y_\pi|0} = 1)$, and d_u is the number of covariates in U_{π_i}
   (c) Sample $[\Sigma_\varepsilon^{-1}|Y, \hat{G}_{1:p}, \hat{G}_0, B_{1:p}, B_0] \sim \mathcal{W}(\delta + N,\ \Lambda_N)$ where

$$\Lambda_N = \Lambda_0 + (\hat{U} - \hat{U}\hat{B}'_0)'(\hat{U} - \hat{U}\hat{B}'_0) \tag{10}$$

See Ahelegbey and Giudici (2020) for a detailed description of the network sampling algorithm and convergence diagnostics.

For our empirical application, we set the hyper-parameters as follows: $\pi_{ij} = 0.5$ (which leads to a uniform prior on the graph space), $\eta = 100, \delta = n + 2$ and $\Lambda_0 = \delta I_n$. We set the number of MCMC iterations to sample 200,000 graphs and we ensured that the convergence and mixing of the MCMC chains are tested via the potential scale reduction factor (PSRF) of Gelman and Rubin (1992).

4. Data

For our analysis, we focus on some of the most important American companies: the top 50 of the S&P. We obtain the daily stock prices of these companies from yahoo finance covering a period that ranges from August 2016 to November 17th, 2020. We also employ a sentiment index referred to the same companies and period produced by Brain[1].

[1]https://braincompany.co

No.	Stock	Ticker
	Communication	
1	AT & T Inc.	T
2	Verizon Comm. Inc.	VZ
	Consumer	
3	Amazon.com Inc.	AMZN
4	Comcast Corp.	CMCSA
5	Walt Disney Co.	DIS
6	Home Depot Inc.	HD
7	McDonald's Corp.	MCD
8	Netflix Inc.	NFLX
9	Costco Wholesale Corp.	COST
10	Coca-Cola Co.	KO
11	PepsiCo Inc.	PEP
12	Procter & Gamble Co.	PG
13	Philip Morris Int. Inc.	PM
14	Walmart Inc.	WMT
	Financial	
15	Bank of America Corp	BAC
16	Berkshire Hathaway Inc.	BRK.B
17	Citigroup Inc.	C
18	JPMorgan Chase & Co.	JPM
19	Wells Fargo & Co.	WFC
	Industrial	
20	Boeing Co.	BA
21	Honeywell Int. Inc.	HON
22	Union Pacific Corp.	UNP
23	Raytheon Technologies	RTX

No.	Stock	Ticker
	Energy	
24	Chevron Corp.	CVX
25	Exxon Mobil Corp.	XOM
	Health Care	
26	AbbVie Inc.	ABBV
27	Abbott Laboratories	ABT
28	Amgen Inc.	AMGN
29	Bristol-Myers Squibb Co.	BMY
30	Johnson & Johnson	JNJ
31	Medtronic Plc	MDT
32	Merck & Co. Inc.	MRK
33	Pfizer Inc.	PFE
34	Thermo Fisher Scientific Inc.	TMO
35	UnitedHealth Group Inc.	UNH
	Tech	
36	Apple Inc.	AAPL
37	Accenture Plc	ACN
38	Adobe Inc.	ADBE
39	Broadcom Inc.	AVGO
40	Salesforce.com inc.	CRM
41	Cisco Systems Inc.	CSCO
42	Facebook Inc.	FB
43	Alphabet Inc.	GOOGL
44	Intel Corp.	INTC
45	Mastercard Inc.	MA
46	Microsoft Corp.	MSFT
47	NVIDIA Corp.	NVDA
48	Oracle Corp.	ORCL
49	PayPal Holdings Inc.	PYPL
50	Visa Inc.	V

Table 1: Detailed description of the top 50 S&P companies.

Brain is a research company specialized in the production of alternative datasets and in the development of proprietary algorithms for investment strategies on financial markets. The Brain Sentiment Indicator dataset comprises of a daily sentiment indicator for the largest listed worldwide companies. Such 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 news are categorized using syntactic rules or machine learning classifiers. If this step fails a dictionary based approach is used.

The final dataset is composed of 1021 observations and 100 variables (for each company we have two columns: one for the closing market price and one for the sentiment score). The complete list of companies is available in Table 1. Since the companies under

	Equity Returns					Sentiment Scores			
	Mean	Std	Skew	Kurt		Mean	Std	Skew	Kurt
AAPL	0.14	1.94	-0.38	7.76	S_AAPL	0.06	0.12	-0.62	1.43
ABBV	0.06	1.87	-1.12	16.06	S_ABBV	0.16	0.28	-0.85	0.78
ABT	0.09	1.60	-0.11	7.29	S_ABT	0.21	0.28	-0.88	0.79
ACN	0.08	1.61	0.00	9.24	S_ACN	0.27	0.26	-0.71	1.11
ADBE	0.14	2.08	-0.01	10.02	S_ADBE	0.18	0.27	-0.74	0.72
AMGN	0.04	1.67	0.13	6.62	S_AMGN	0.18	0.26	-0.48	0.34
AMZN	0.13	1.90	0.09	4.31	S_AMZN	0.14	0.27	-0.61	0.53
AVGO	0.09	2.29	-1.33	15.83	S_AVGO	0.14	0.29	-0.45	-0.04
BA	0.05	3.01	-0.61	19.53	S_BA	0.03	0.21	0.03	-0.28
BAC	0.06	2.19	-0.12	13.08	S_BAC	0.10	0.20	-0.32	0.48
BMY	0.02	1.67	-1.51	11.08	S_BMY	0.17	0.29	-0.77	0.30
BRK.B	0.04	1.40	-0.41	13.60	S_BRK.B	0.13	0.30	-0.51	-0.39
C	0.02	2.38	-0.81	16.76	S_C	0.08	0.27	-0.55	0.35
CMCSA	0.04	1.67	-0.11	6.16	S_CMCSA	0.14	0.26	-0.54	0.32
COST	0.09	1.37	-0.17	8.80	S_COST	0.13	0.28	-0.48	0.09
CRM	0.11	2.15	0.50	17.83	S_CRM	0.15	0.31	-0.76	0.61
CSCO	0.04	1.77	-0.57	10.44	S_CSCO	0.19	0.23	-0.74	0.95
CVX	0.00	2.13	-1.44	35.74	S_CVX	0.07	0.29	-0.49	-0.09
DIS	0.04	1.76	0.24	14.49	S_DIS	0.09	0.21	-0.40	1.05
FB	0.07	2.11	-1.20	14.38	S_FB	-0.07	0.16	0.16	-0.23
GOOGL	0.07	1.71	-0.43	6.85	S_GOOGL	0.04	0.15	-0.18	0.51
HD	0.07	1.70	-2.15	34.62	S_HD	0.16	0.25	-0.60	0.66
HON	0.07	1.64	-0.27	14.71	S_HON	0.20	0.27	-0.74	0.87
INTC	0.04	2.18	-0.85	18.17	S_INTC	0.11	0.19	-0.29	0.00
JNJ	0.03	1.31	-0.68	11.50	S_JNJ	0.13	0.28	-0.62	0.32
JPM	0.06	1.95	-0.12	16.96	S_JPM	0.08	0.24	-0.43	0.80
KO	0.03	1.31	-1.03	11.96	S_KO	0.13	0.25	-0.48	0.29
MA	0.12	1.89	0.03	11.77	S_MA	0.20	0.24	-0.87	1.21
MCD	0.07	1.51	-0.29	35.34	S_MCD	0.03	0.27	0.05	-0.10
MDT	0.03	1.60	-0.54	12.25	S_MDT	0.20	0.28	-0.39	0.08
MRK	0.04	1.41	-0.20	6.33	S_MRK	0.21	0.24	-0.65	0.61
MSFT	0.13	1.78	-0.36	12.06	S_MSFT	0.15	0.15	-0.56	2.27
NFLX	0.15	2.49	0.24	4.76	S_NFLX	0.09	0.18	-0.38	0.62
NVDA	0.21	3.10	-0.14	10.20	S_NVDA	0.16	0.21	-0.66	0.87
ORCL	0.04	1.68	0.49	23.15	S_ORCL	0.16	0.26	-0.86	1.08
PEP	0.04	1.37	-0.65	25.77	S_PEP	0.14	0.28	-0.56	0.19
PFE	0.02	1.43	-0.19	7.41	S_PFE	0.16	0.24	-0.63	0.75
PG	0.06	1.32	0.23	14.34	S_PG	0.14	0.31	-0.54	0.03
PM	0.00	1.74	-1.76	17.71	S_PM	0.07	0.32	-0.52	-0.30
PYPL	0.15	2.18	0.01	8.84	S_PYPL	0.15	0.27	-0.69	0.52
RTX	0.01	2.03	-0.38	14.71	S_RTX	0.14	0.30	-0.54	0.02
T	-0.01	1.53	-0.64	8.04	S_T	0.10	0.21	-0.24	0.09
TMO	0.11	1.61	-0.26	5.14	S_TMO	0.21	0.28	-0.91	1.13
UNH	0.09	1.89	-0.56	16.71	S_UNH	0.17	0.28	-0.55	0.30
UNP	0.08	1.80	-0.64	11.80	S_UNP	0.11	0.31	-0.40	-0.41
V	0.09	1.68	-0.22	13.19	S_V	0.15	0.27	-0.77	1.08
VZ	0.03	1.23	0.16	5.42	S_VZ	0.14	0.23	-0.48	0.52
WFC	-0.05	2.17	-0.49	12.61	S_WFC	-0.01	0.24	-0.02	0.40
WMT	0.08	1.41	0.70	15.61	S_WMT	0.08	0.23	-0.48	0.73
XOM	-0.06	1.83	-0.24	11.34	S_XOM	0.04	0.25	-0.15	-0.06

Table 2: Descriptive Statistics for Equity returns and Sentiment scores.

analysis belong to different sectors, we have divided them into sub groups according to the S&P's division that considers 11 sectors: Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Materials, Real

Estate, Technology, Utilities. 3 sectors (namely materials, real estate and utilities) are not represented in our dataset, in addition we decided to unify the two consumer categories thus obtaining 7 final groups.

Table 2 reports the summary statistics of the first four moments (i.e., mean, standard deviation, skewness and excess kurtosis) of the equity returns and sentiment scores. The statistics show that almost all the equity returns and sentiment scores have a near-zero mean. The equity returns, however, appear more volatile than the sentiment scores. That is, the standard deviation of the equity returns are relatively higher (greater than 1) compared to that of the sentiment scores (less than 1). A greater majority of the returns and sentiments exhibit fairly symmetric behaviour, i.e., they are characterized mostly by small but consistent positive outcomes and, occasionally, large negative returns. The excess kurtosis of the sentiment scores are largely less than 3, which indicates that the sentiments data are approximately normal (via skewness-kurtosis summary), while that of the equity returns confirms the stylized facts of leptokurtic behavior of daily return series.

5. Results

We apply the BGVAR estimation methodology to study the dynamics of interconnectedness among the top 50 of S&P companies and the sub-sectors via a two-and-half year (approximately 504 days) rolling window. Our choice of window size is motivated by the need to have enough data points to capture 24-months dynamic dependence among the companies. We set the increments between successive rolling windows to one month. The first window covers August 2016 – July 2018, followed by September 2016 – August 2018, and the last from December 2018 – November 2020. In total, we have 29 rolling windows.

To unify the dataset, we compute the daily returns as the log difference of successive daily adjusted close prices of the companies equities. Since stock prices are not recorded for weekends, we consider the weekend sentiment scores in the computation of the Monday sentiment via a simple mean of the three days. In this way, both R_t and S_t express time variations: in the equity price and in the sentiment scores, respectively, for each company.

We study the equity-sentiment interconnectedness of the top 50 of S&P companies by considering them jointly as well as sub-sectors separately. Following the sector division of the companies in Table 1, we created five categories, namely: Consumer, Financial, Health Care, Tech and Miscellaneous and analyzed the interconnectedness for each sub-sector. Due to the low number of companies in the communication, energy and industrial sector, we combined them to create a unique sub-sector, which we refer to as "Miscellaneous".

We compare the sub-period networks, the pre-COVID-19 phase and the COVID-19 (Wave-1 and Wave-2) phase in terms of the number of links, the network density, the average degree, the clustering coefficient, and the average path length. We characterize, through numerical summaries, the time-varying nature of interconnections by monitoring the network density, average degree, clustering coefficient and average path length. In Figure 1, we report the evolution of the density of equity-sentiment interconnectedness along the analyzed period. Two curves are compared, different in terms of employed lags, 1 vs 5. It clearly emerges the presence of two separated periods as of starting from late

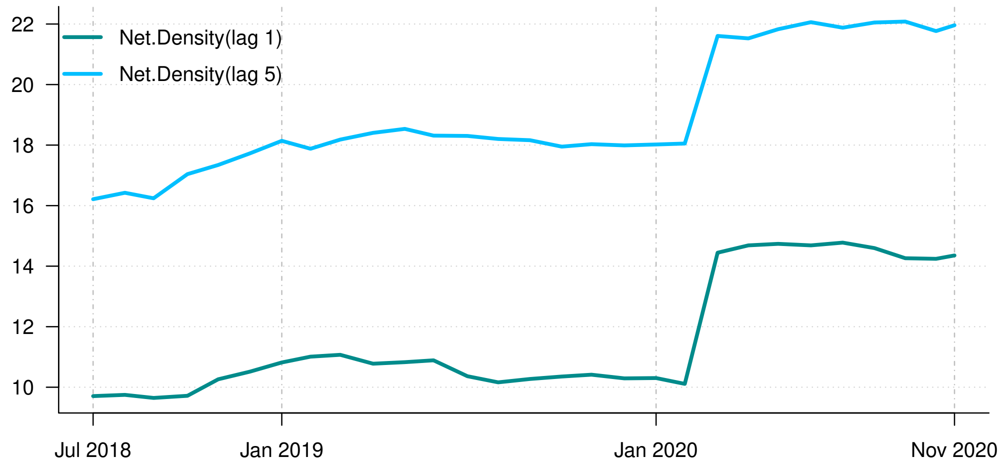
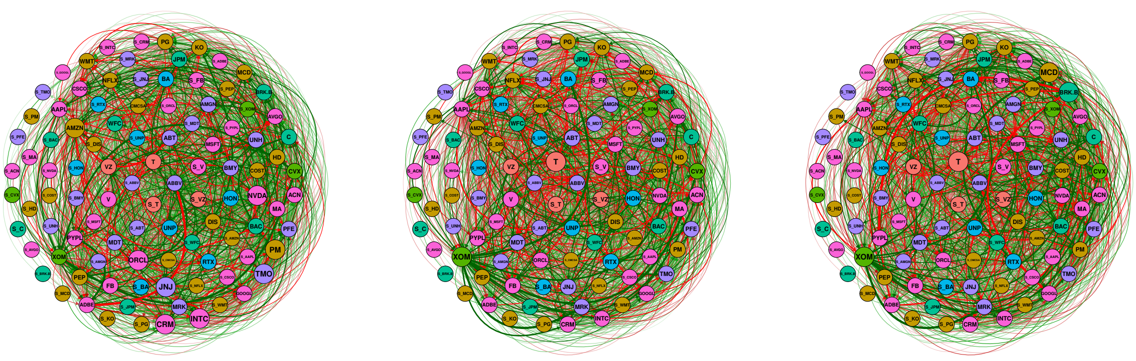


Figure 1: Density of equity-sentiment interconnectedness among top 50 S&P companies.

June 2020. The density increases by a factor of 6.5 – 8 points. As the pandemic enters in the most hitting phase, all the connections increase greatly, meaning that the exogenous shock affects the entire system as a whole, increasing the vulnerability as well. Indeed, a more interconnected system amplifies more and more any impact through a contagion spreading mechanism (see Cerchiello and Giudici (2016b)).

If we focus on the three periods of the data at hand (pre-pandemic, first wave, second wave), we can visualize the networks in Figure 2 and the metrics in Table 3. If the difference between the pre-covid and the first wave is not so evident, we notice a change in the values of the number of links, the density, average degree and average path length during the second wave. This suggest that, although the system appears resilient as the first wave arrives, with the prolongation of the pandemic, companies can not stand any longer the shock.



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

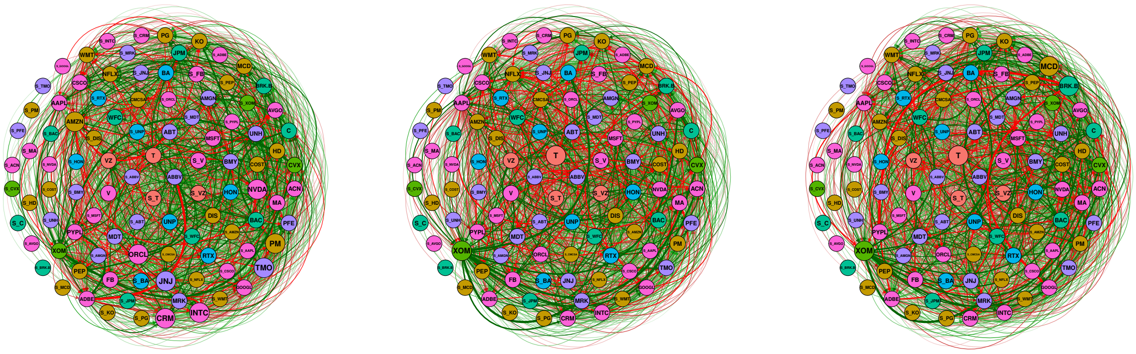
Figure 2: Sub-period network before and during COVID-19 period

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	2437	24.616	24.37	0.964	1.451
COVID-19 Wave-1	2401	24.253	24.01	0.994	1.131
COVID-19 Wave-2	2335	23.586	23.35	0.991	1.139

Table 3: The network statistics for sub-period interconnectedness before and during COVID-19 period.

5.1. Equity-to-Equity Networks

To further analyze the Covid-19 pandemic effects on the system, we split the analysis in the two components: equity data on one hand and sentiment data on the other. In particular we investigate what happens to the Equity to Equity connections, that is focusing only on the intra-equities layer linkages. As far as we are concerned with the equity market,



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

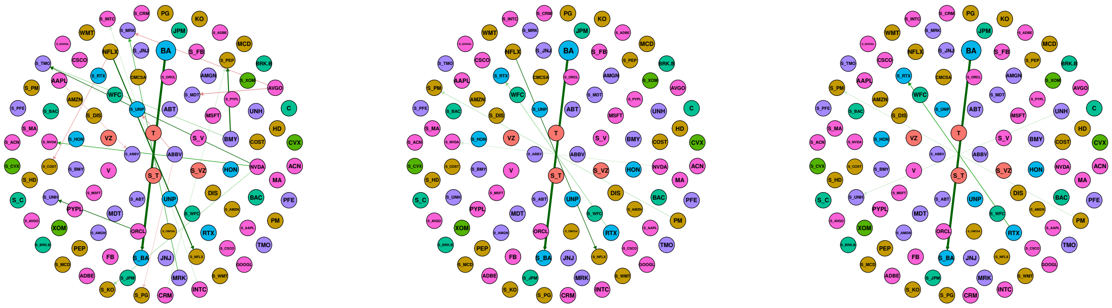
Figure 3: Equity-to-Equity sub-period network before and during COVID-19 period

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	2392	97.633	47.84	0.997	1.024
COVID-19 Wave-1	2395	97.755	47.90	0.999	1.022
COVID-19 Wave-2	2330	95.102	46.60	0.995	1.049

Table 4: Statistics for sub-period Equity-to-Equity interconnectedness before and during COVID-19 period.

Figure 3 and Table 4 report the results. In particular, Table 4 discloses the pattern of the network along the three periods: similarly to previous results the financial market reacts more during the second wave. As we would have expected, there is a huge number of links which remains rather stable, confirming once again the deep interconnection of the financial market.

In Figure 4 and Table 5 we report another set of results looking at the effect of equity markets on sentiments, that is capturing sentiment reactions to changes in financial market



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

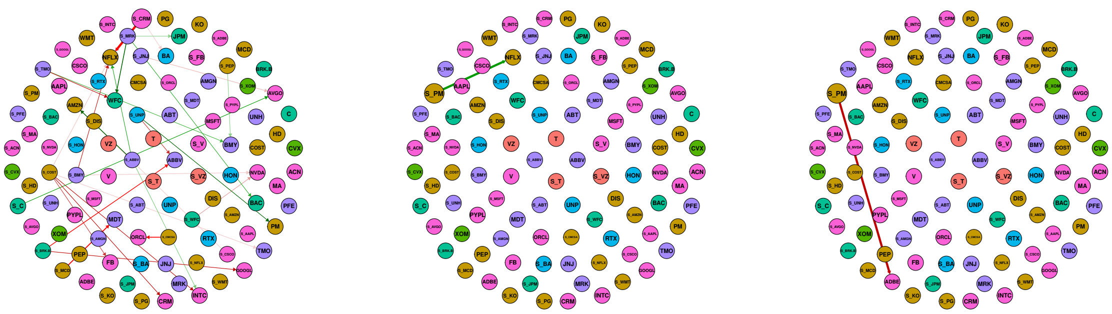
Figure 4: Equity-to-Sentiments sub-period network before and during COVID-19 period

Period	Links	Density	Average Degree
Pre-COVID-19	17	0.68	0.34
COVID-19 Wave-1	5	0.20	0.10
COVID-19 Wave-2	4	0.16	0.08

Table 5: Statistics for sub-period Equity-to-Sentiment network before and during COVID-19 period.

performance. The reader can immediately notice a number of relevant facts: the total number of links is much less. That is to say that the financial market has a lower impact on sentiments and this is consistent along the whole time horizon. However, there is a clear difference in the three periods: the pre-covid period recorded three times higher sentiment reactions to changes in financial market indexes than in the Covid-19 periods. We could say that the influence from the financial world to the public perception one has been frozen by the virus, lowering down largely the influence channel.

Such phenomenon is even more evident if we consider the opposite direction of transmission: from sentiment to equity. Figure 5 and Table 6 contain relative results and confirm the important dampening effect of the pandemic. Just one connection survives



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 5: Sentiment-to-Equity sub-period network before and during COVID-19 period

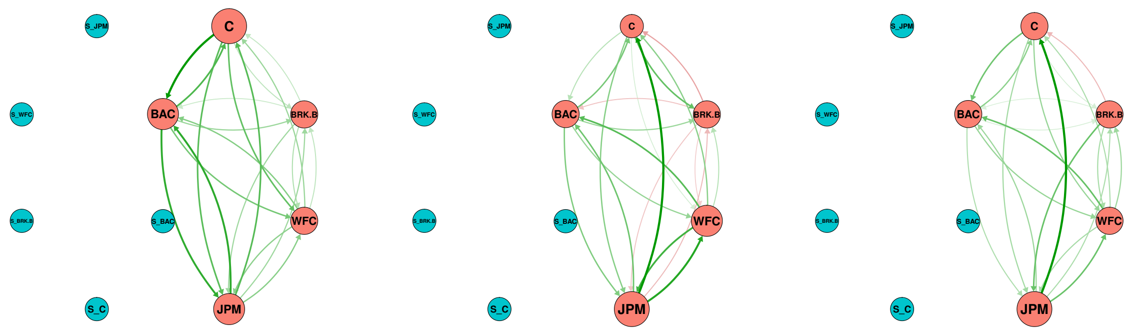
Period	Links	Density	Average Degree
Pre-COVID-19	28	1.12	0.56
COVID-19 Wave-1	1	0.04	0.02
COVID-19 Wave-2	1	0.04	0.02

Table 6: Statistics for sub-period Sentiment-to-Equity network before and during COVID-19 period.

during the first and the second wave. In the first wave, the only surviving linkage is $S\_PM \rightarrow NFLX$, and $S\_PM \rightarrow ADBE$ survived in the second wave. The reaction of Netflix and Adobe to sentiments associated with Philip Morris Int. - a tobacco company, are the only surviving linkages during the Covid pandemic.

Given the heterogeneity of the activities of the 50 companies at hand, it is relevant to deepen the analysis with regards to each specific sub-sector. Starting from the Financial sector, we notice from Figure 6 and Table 7 that all the indexes remains exactly the same.

Our analysis reveals that the linkage among the financial institutions revolve around



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 6: Sub-period Financial sub-sector network before and during COVID-19 period

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	20	22.222	2	1	1
COVID-19 Wave-1	20	22.222	2	1	1
COVID-19 Wave-2	20	22.222	2	1	1

Table 7: Statistics for sub-period Financial sub-sector network before and during COVID-19 period.

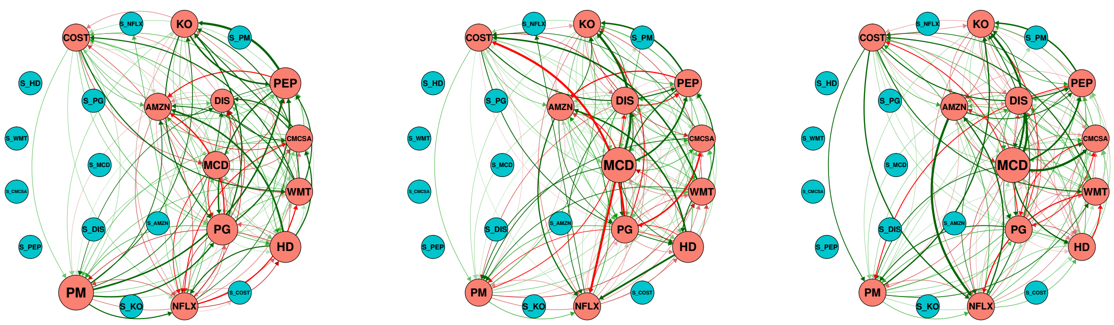
their equity market performance with no effect from sentiments. Thus, the change in the networks structure that we have noticed in the previous tables, is not driven by the financial companies. We, however, notice that although the connections remain unchanged during the pre-covid and covid periods, the sign and magnitude of the interactions seems to change over the sub-periods. More specifically, Citigroup (C) and Berkshire Hathaway

	Pre-COVID-19	COVID-19 Wave-1	COVID-19 Wave-2
		Top 5 Hub-Centrality Score	
1	C (0.579)	JPM (0.684)	JPM (0.758)
2	JPM (0.500)	WFC (0.496)	BAC (0.413)
3	BAC (0.484)	BAC (0.423)	C (0.339)
4	WFC (0.343)	BRK.B (0.275)	BRK.B (0.297)
5	BRK.B (0.250)	C (0.180)	WFC (0.228)
		Top 5 Authority-Centrality Score	
1	BAC (0.572)	C (0.656)	C (0.712)
2	JPM (0.480)	BAC (0.441)	WFC (0.550)
3	WFC (0.438)	WFC (0.435)	BAC (0.354)
4	C (0.407)	JPM (0.388)	JPM (0.233)
5	BRK.B (0.292)	BRK.B (0.187)	BRK.B (0.110)

Table 8: Hub and Authority Centrality of Financial sector network before and during COVID-19 period.

(BRK.B) seem to exhibit bi-directional relationship through out all periods. However, the pre-covid reported an almost equally positive link. The first and second wave of the Covid, however, recorded a positive impact of C on BRK.B, and a negative reverse impact of BRK.B on C. A look at the centrality of the network in terms of Hub and Authority scores (in Table 8) shows that of the 5 companies, Citigroup was central to risk transmission during the pre-covid period, while JPM dominate in the Covid period.

In analyzing the Consumer sub-sector, Figure 7 shows the resulting network structure over the three sub-periods. Unlike, the Financial sub-sector, the Consumer sub-sector network record links are at all levels: equity-equity, equity-sentiment, sentiment-equity. For instance, the sentiment associated with Netflix (S_NFLX) react strongly positive to the equity performance of Netflix (NFLX) during the pre-covid, which reduced slightly in the first wave of the Covid but varnished in the second wave. We also observe a reaction from Netflix (NFLX) to the sentiment associated with Philip Morris Int. (S_PM). From



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 7: Sub-period Consumer sub-sector network before and during COVID-19 period

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	132	23.913	5.500	0.950	1.219
COVID-19 Wave-1	132	23.913	5.500	0.954	1.231
COVID-19 Wave-2	129	23.370	5.375	0.984	1.104

Table 9: Statistics for sub-period Consumer sub-sector network before and during COVID-19 period.

Table 9, we notice a slight variation in the metrics of the second wave Consumer sub-sector network. In particular the clustering coefficient increases and the average path length decreases. Table 10 confirms the different behaviour of the consumer sub-sector: the hub companies during the pandemic change and increase in coefficient magnitude. The consumer system appears less resilient in comparison to the financial one. McDonalds, which is not in the top 5 hubs before the pandemics, not only appears all of a sudden, but it is also first ranked. Also Comcast Corp. and Amazon enter the ranking.

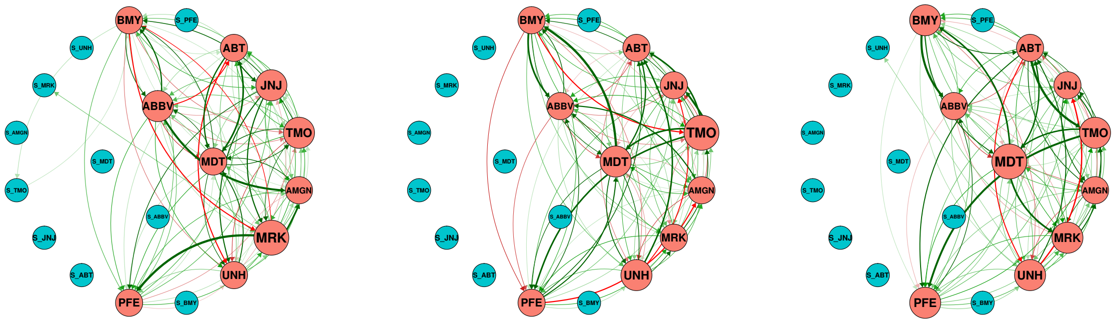
	Pre-COVID-19	COVID-19 Wave-1	COVID-19 Wave-2
		Top 5 Hub-Centrality Score	
1	PM (0.489)	MCD (0.578)	MCD (0.618)
2	PG (0.421)	HD (0.395)	PM (0.293)
3	PEP (0.343)	PG (0.339)	PEP (0.278)
4	HD (0.304)	CMCSA (0.266)	PG (0.276)
5	KO (0.279)	PEP (0.264)	AMZN (0.263)
		Top 5 Authority-Centrality Score	
1	PEP (0.400)	NFLX (0.436)	KO (0.454)
2	AMZN (0.384)	KO (0.385)	CMCSA (0.353)
3	NFLX (0.362)	AMZN (0.338)	PEP (0.345)
4	PG (0.349)	PM (0.289)	DIS (0.326)
5	KO (0.340)	CMCSA (0.288)	NFLX (0.310)

Table 10: Hub and Authority Centrality of Consumer sector network before and during COVID-19 period.

The Health-Care sub-sector network, represented in Figure 8 and Table 11, presents a pattern rather unstable. The indexes change without a common pattern, albeit showing an apparent drop in the magnitude during wave 1 and increasing again in wave 2. Similarly

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	93	24.474	4.65	0.952	1.24
COVID-19 Wave-1	90	23.684	4.50	1.000	1.00
COVID-19 Wave-2	88	23.158	4.40	0.976	1.12

Table 11: Statistics for sub-period Health-Care sub-sector network before and during COVID-19 period.



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 8: Sub-period Health-Care sub-sector network before and during COVID-19 period

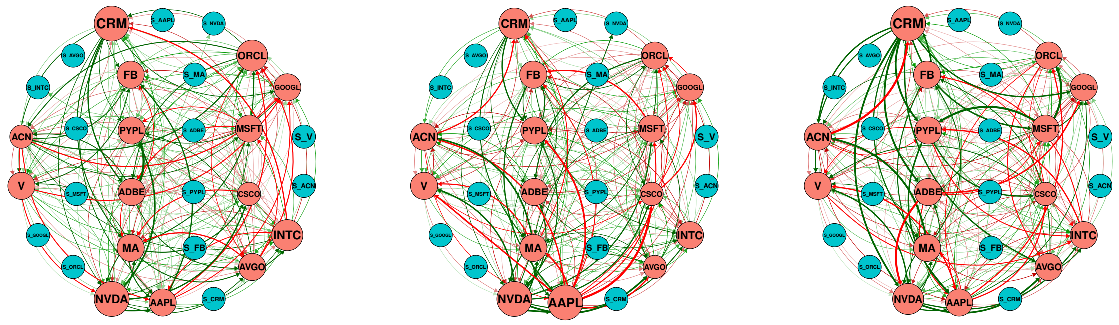
to consumer sub-sector, the links in Figure 8 are mixed and both the hub and the authority indexes in Table 12 tend to change, not only the rankings, but also the relevant companies. This suggest that the pandemic has deeply affected the health care sub-sector, as it is plausible to expect.

	Pre-COVID-19	COVID-19 Wave-1	COVID-19 Wave-2
	Top 5 Hub-Centrality Score		
1	MRK (0.495)	TMO (0.545)	MDT (0.455)
2	ABBV (0.407)	MDT (0.459)	TMO (0.399)
3	JNJ (0.394)	UNH (0.396)	PFE (0.334)
4	TMO (0.361)	MRK (0.266)	MRK (0.327)
5	UNH (0.273)	BMY (0.262)	UNH (0.302)
	Top 5 Authority-Centrality Score		
1	AMGN (0.465)	ABT (0.403)	ABT (0.378)
2	PFE (0.437)	BMY (0.392)	BMY (0.369)
3	BMY (0.356)	JNJ (0.367)	JNJ (0.344)
4	MDT (0.349)	PFE (0.343)	MDT (0.333)
5	MRK (0.276)	ABBV (0.325)	PFE (0.333)

Table 12: Hub and Authority scores of Health-Care sector network before and during COVID-19 period.

Figure 9 and Table 13 reports the network structure and its summary statistics for the Tech sector over the three sub-periods. What immediately emerges is the presence of much more connected networks regardless the period. The indexes are coherent and decrease as the periods pass by. Table 14 confirms the change in the network structure: in particular two new players in the pandemic, namely Apple Inc. and Adobe Inc. for the hub score and Broadcom Inc. and Alphabet Inc. (Google) for the authority score.

The result of the miscellaneous sector which comprises Industrial, Communication and Energy companies are reported in Figure 10, Tables 15 and 16. We observe that similar to the Financial sub-sector, network among the group of companies in the miscellaneous



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 9: Sub-period Tech sub-sector network before and during COVID-19 period

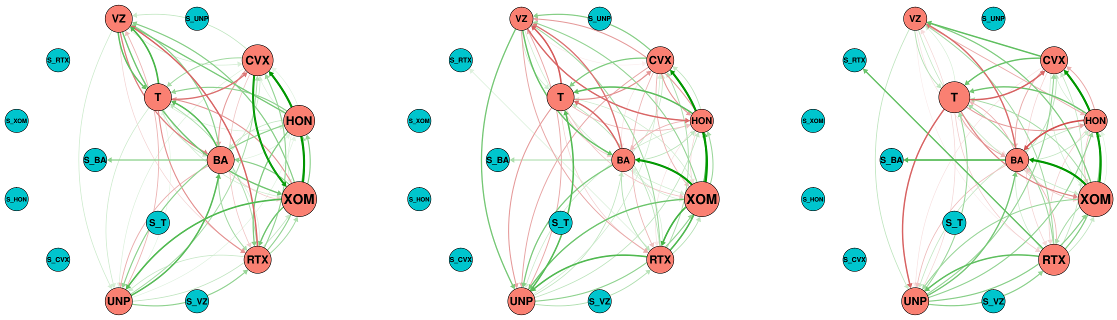
Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	212	24.368	7.067	0.98	1.117
COVID-19 Wave-1	207	23.793	6.900	0.99	1.080
COVID-19 Wave-2	204	23.448	6.800	1.00	1.029

Table 13: Statistics for sub-period Tech sub-sector network before and during COVID-19 period.

	Pre-COVID-19	COVID-19 Wave-1	COVID-19 Wave-2
	Top 5 Hub-Centrality Score		
1	CRM (0.458)	AAPL (0.542)	CRM (0.511)
2	NVDA (0.453)	NVDA (0.541)	NVDA (0.390)
3	ORCL (0.371)	CRM (0.318)	ADBE (0.290)
4	INTC (0.280)	MSFT (0.236)	MSFT (0.289)
5	MSFT (0.265)	INTC (0.181)	AAPL (0.282)
	Top 5 Authority-Centrality Score		
1	PYPL (0.387)	PYPL (0.357)	AAPL (0.311)
2	ADBE (0.325)	MA (0.346)	PYPL (0.302)
3	MA (0.305)	CSCO (0.344)	V (0.295)
4	V (0.295)	V (0.329)	MA (0.277)
5	AAPL (0.288)	AVGO (0.318)	GOOGL (0.275)

Table 14: Hub and Authority Centrality of Tech sector network before and during COVID-19 period.

sector is centered around the equity market performance, except for a links depicting the reaction of S_BAC (the sentiment associated with Bank of America) to the equity market performance of BAC (Bank of America). The centrality ranking of the companies in this sub-sector shows that despite some slight changes in the top 5 companies, XOM (Exxon Mobile) and CVX (Chevron Corp.) remain the most central in terms of shock transmission and receiving risk, respectively, over the three sub-periods.



(a) Pre-COVID-19 (b) COVID-19 Wave-1 (c) COVID-19 Wave-2

Figure 10: Sub-period network of Miscellaneous sub-sector before and during COVID-19 period

Period	Links	Density	Average Degree	Clustering Coefficient	Average Path Length
Pre-COVID-19	56	23.333	3.500	0.960	1.125
COVID-19 Wave-1	58	24.167	3.625	0.923	1.194
COVID-19 Wave-2	56	23.333	3.500	0.923	1.222

Table 15: Statistics for sub-period Miscellaneous sub-sector network before and during COVID-19 period.

	Pre-COVID-19	COVID-19 Wave-1	COVID-19 Wave-2
	Top 5 Hub-Centrality Score		
1	XOM (0.567)	XOM (0.782)	XOM (0.680)
2	HON (0.377)	RTX (0.419)	T (0.471)
3	CVX (0.36)	T (0.284)	RTX (0.394)
4	UNP (0.354)	CVX (0.235)	UNP (0.289)
5	T (0.294)	UNP (0.194)	CVX (0.203)
	Top 5 Authority-Centrality Score		
1	CVX (0.578)	CVX (0.510)	CVX (0.555)
2	XOM (0.382)	UNP (0.425)	BA (0.459)
3	BA (0.334)	BA (0.422)	UNP (0.404)
4	VZ (0.325)	RTX (0.359)	VZ (0.324)
5	UNP (0.321)	HON (0.340)	HON (0.283)

Table 16: Centrality of Miscellaneous sectors network before and during COVID-19 period.

6. Conclusions

The Covid-19 pandemic has deeply affected the population and all the relative activities. Health impact, social restrictions, economic downturn, overall instability are all direct consequences of the spread of the virus. Researchers worldwide have focused on studying, measuring and assessing such consequences at the different levels. In this paper we cope with the analysis of the economic impact of the pandemic, looking at the US top 50 companies of S&P market. In particular we employ advanced network models able to leverage the temporal-dynamic dimension of the phenomenon through a novel specification of a Bayesian graphical vector autoregressive (BGVAR) approach. Moreover, we do not only rely on market data but emphasize the population perception and opinions by adding to the analysis a sentiment index built upon blogs and regular news. The analysis has revealed several interesting findings. First of all, the American financial market appears rather resilient as the first wave arrives but it is not able to stand the second one. The shock hits the whole system, increasing the interconnections and consequently the associated system risk. However the sub-sectors, which the 50 companies belong to, show different reactions, fully connected with the involved type of business. The Financial sector shows a particular resilience since all the indexes remains exactly the same. The linkage among the financial institutions revolve around their equity market performance with no effect from sentiments. Differently from the financial sector, the consumer one witnesses the strong interconnection between the equity and the sentiment components. Moreover, we notice clear signs of reactions as the pandemic moves on. The Health-Care sector is, as we would expect, affected by the instability induced by the pandemic. There is no a clear common pattern in the evolution of the networks, but it definitely reacts to the turbulence especially if we look at the most important hubs and authorities. Regarding the big Tech we obtain much more connected networks regardless the period. It is interesting to notice two new central players in the pandemic, namely Apple Inc. and Adobe Inc. for the hub score and Broadcom Inc. and Google for the authority score.

Further improvement of this study would consider up to date data, as the pandemic keeps on hitting the whole system. Indeed, the recent start of the vaccination campaign would be a further variable of interest that for sure would impact, not only the virus diffusion, but also the renovate confidence of the economic sectors and the population sentiment. Moreover, an analogous study with comparative purposes would be extremely useful on top 50 European companies.

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