The Impact of Crisis on Sustainable European Companies: A Network Approach to Industry-Specific Vulnerabilities

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The Impact of Crisis on Sustainable European Companies: A Network Approach to Industry-Specific Vulnerabilities

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Abstract

This study investigates how religio-sustainable European companies and their industries endured the disruptions of a global crisis, focusing on inter-firm relations and investor sentiment. Grounded in theories of systemic risk and behavioural contagion, we argue that both informational frictions and shifting expectations amplify shocks across markets. Using a novel network-based framework, we integrate stock market dynamics with large-scale sentiment analysis to trace changes during the crisis. The results reveal sharp differences in resilience: while essential consumer goods and energy firms remained relatively stable, consumer-facing companies selling non-essential products proved especially vulnerable to negative sentiment. These firms not only suffered deeper downturns but also displayed heightened sensitivity to investor perceptions.

Keywords: Network analysis, Ethical investing, Sentiment analysis, Market turbulence
JEL: G14, G15, C55, Q56

1. Introduction

The impact of news and social media on economic and financial systems has increased substantially in recent years, reshaping how information is produced, disseminated, and absorbed by market participants (Tetlock, 2007; Aridor et al., 2024; Fujiwara et al., 2024). The COVID-19 pandemic introduced an unprecedented level of economic and financial instability, triggering sharp increases in uncertainty, volatility, and risk aversion across global markets (Baek et al., 2020; Kanamura, 2022). The scale and speed of these disruptions have been widely compared to major historical crises, such as the Great Depression (1929-1941).

While a growing literature documents sharp increases in volatility and financial contagion during the pandemic (Zhang et al., 2020; Akhtaruzzaman et al., 2021; Mazur et al., 2021), comparatively less attention has been paid to the role of non-traditional channels, such as investor sentiment and sustainability attributes, in shaping systemic risk during periods of extreme uncertainty. Recent studies suggest that firms with stronger environmental, social,

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Email addresses: `yassine.essanaani@ntu.ac.uk` (Yassine Essanaani), `o.h.abdelsalam@durham.ac.uk` (Omneya Abdelsalam), `danielfelix.ahelegbey@unipv.it` (Daniel Felix Ahelegbey) and governance (ESG) characteristics exhibited greater downside protection and resilience during the COVID-19 crisis (Albuquerque et al., 2020; Bolton and Kacperczyk, 2021; Pankratz et al., 2023). Parallel evidence indicates that Islamic finance and ethically screened investment universes may dampen shock transmission due to their distinctive screening criteria and risk-sharing principles (Ashraf et al., 2022; Abdelsalam et al., 2024). This paper contributes to this emerging literature by examining how the COVID-19 pandemic reshaped the network structure and systemic interdependencies among leading sustainable firms in Europe, with a particular focus on companies jointly screened using ESG and Islamic finance criteria.

In the age of social networks, information spreads instantaneously, significantly reshaping the behaviour of financial markets (Tetlock, 2007; Bollen et al., 2011). A substantial body of research adopts alternative data sources, particularly news sentiment, to better understand market dynamics (Joshi et al., 2016; Cerchiello et al., 2017; Audrino and Tetereva, 2019). This literature suggests that news not only informs but also shapes investors' expectations and perceptions. As information disseminates rapidly through digital platforms, the accompanying sentiment can evolve and intensify, amplifying its impact on market movements. Studies by Allen et al. (2012) and Caballero and Simsek (2013) support the premise that non-traditional financial channels, such as investor sentiment, limited attention, and selective information processing, can amplify systemic risk, particularly during periods of high uncertainty. During the pandemic, financial markets responded not only to traditional economic indicators but also to shifts in investor sentiment toward risk (Chen et al., 2020; Ahelegbey et al., 2022; Barbaglia et al., 2023; Costola et al., 2023; Ahelegbey et al., 2024).

With the emergence of sentiment data providers, it has become increasingly feasible to incorporate sentiment analysis into conventional financial models. In this context, examining the magnitude and structure of interrelationships among European financial markets during and after the pandemic is crucial to understanding the broader implications of sentiment-driven market behaviour in times of crisis.

Using a Bayesian Graphical Vector Autoregressive (BGVAR) framework following Ahelegbey et al. (2016), we construct dynamic networks that integrate daily stock returns and sentiment scores derived from financial news and blogs. Our focus is to explore two central questions: (i) How did pandemic shocks reshape the structure of financial-sentiment interdependencies among leading sustainable firms? (ii) Did these shocks affect all sectors uniformly, or was the impact heterogeneous across industries? Specifically, we examine which sectors exhibited greater resilience, characterised by lower contagion exposure and weaker sentiment spillovers, and which sectors became more interconnected and vulnerable during the crisis.

The contribution of our study is threefold. First, we contribute to the systemic risk and financial networks literature (Billio et al., 2012; Diebold and Yilmaz, 2014; Akhtaruzzaman et al., 2021; Abdelsalam et al., 2024) by providing a dynamic, network-based perspective on how shocks propagate in ethically screened European markets during a major global crisis. Second, we integrate a BGVAR with sentiment-equity linkages (Allen et al., 2012; Nyman et al., 2021), allowing us to disentangle contemporaneous and lagged transmission channels. Third, we document heterogeneity of contagion channels across ethically screened European sectors. In particular, Consumer Staples, Information Technology, Materials, and Health Care exhibit greater resilience and lower contagion exposure, whereas Consumer Discretionary and Industrials display heightened vulnerability, with stronger spillovers and tighter network connectivity during the crisis.

The rest of the paper is structured as follows. Section 2 outlines the theoretical considerations. Section 3 presents the Bayesian network VAR model. Section 4 describes the data.

Section 5 discusses the empirical results. Section 6 concludes.

2. Theoretical Framework

This study is motivated by theories of systemic risk propagation under uncertainty and the behavioural transmission of shocks through information channels. We integrate elements from network contagion theory (Billio et al., 2012; Acemoglu et al., 2015) and behavioural asset pricing models (Barberis et al., 1998; Allen et al., 2012; Caballero and Simsek, 2013), which collectively suggest that both informational frictions and investor expectations can serve as amplifiers of systemic shocks.

Within this framework, we hypothesise the interaction of two primary forces during crises: (1) financial linkages, where asset returns co-move due to shared economic fundamentals and institutional exposures; and (2) sentiment-driven channels, where correlated beliefs, investor expectations, and media narratives contribute to herding behaviour and price overshooting.

Accordingly, we test the following hypotheses:

H1: COVID-19 amplified systemic links in both financial and sentiment networks.

H2: Sentiment shocks played a stronger role in financial linkages during the pandemic.

H3: Sectoral differences exist in contagion exposure and resilience.

3. Methodology

3.1. Bayesian Graphical VAR (BGVAR) Model

We model the dynamics between stock returns and sentiment using a BGVAR framework, which represents systemic relationships through a network of directed edges. Let $Y_t = (Y_{1,t}, \ldots, Y_{n,t})'$ denote an n-dimensional vector. The structural VAR is given by:

$$Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon), \tag{1}$$

where p is the lag order, B_0 captures contemporaneous relationships, $B_1, \ldots, B_p$ represent lagged effects, and ε_t is a vector of orthogonalized disturbances with covariance matrix Σ_ε.

Direct estimation of (1) is infeasible due to simultaneity in $B_0 Y_t$, multicollinearity from multiple lags, and the need for additional restrictions to identify the structural shocks.

The BGVAR addresses these issues by introducing binary indicators $G_{ij,s} \in \{0, 1\}$ which determine whether each coefficient is active or zero. For each coefficient, we define:

$$B_{ij,s} = \begin{cases} \beta_{ij,s}, & \text{if } G_{ij,s} = 1, \\ 0, & \text{if } G_{ij,s} = 0, \end{cases} \qquad G_{ij,s} = \begin{cases} 1, & \text{if } Y_{j,t-s} \to Y_{i,t}, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where $Y_{j,t-s} \to Y_{i,t}$ indicates a directed effect which many be contemporaneous ($s = 0$) or dynamic ($s \geq 1$). Under this formulation, contemporaneous edges arise from non-zero coefficients in B_0, while dynamic edges arise from non-zero coefficients in $B_1, \ldots, B_p$. This imposes structural zeros, reduces overfitting, and stabilises inference in high-dimensional settings.

3.2. Prior Specification

To induce sparsity in both contemporaneous and lagged coefficients, we assign spike-selection priors to each VAR coefficient:

$$[B_{ij,s} \mid G_{ij,s} = 1] \sim \mathcal{N}(0, \eta), \qquad G_{ij,s} \sim \text{Ber}(\pi_{ij}), \qquad \sigma_i^2 \sim \text{InvGamma}(a, b)$$

where η controls shrinkage of coefficients and π_{ij} denotes the prior probability of an edge. When $G_{ij,s} = 1$, the coefficient $B_{ij,s}$ follows a Gaussian prior; when $G_{ij,s} = 0$, the coefficient $B_{ij,s}$ is set to zero. For the structural shocks, we assume mutual independence across equations, implying that Σ_ε is diagonal. We therefore assign independent inverse-Gamma priors to the variances, where a and b are shape and scale parameters, respectively.

3.3. Network Construction

Posterior estimates of the network produce posterior inclusion probabilities (PIPs). Because contemporaneous and lagged effects are associated with distinct coefficient matrices, the BGVAR naturally disentangles instantaneous and dynamic effects. Edges are identified by thresholding the PIPs at level $\alpha = 0.5$, resulting in the estimation of active coefficients:

$$\widehat{B}_{ij,s} = \begin{cases} \beta_{ij,s}, & P(G_{ij,s} = 1 \mid \text{Data}) \geq \alpha, \\ 0, & \text{otherwise.} \end{cases}$$

From these coefficients, we construct two networks: a binary adjacency matrix A and a weighted adjacency matrix W:

$$A_{ij} = \mathbf{1}\left(\sum_{s=0}^{p} \widehat{B}_{ij,s} \neq 0 \right), \qquad W_{ij} = \sum_{s=0}^{p} \widehat{B}_{ij,s}$$

where A_{ij} captures whether there is any contemporaneous or lagged connection from $j \to i$, and W_{ij} aggregates the strength of all active coefficients.

3.4. Network Metrics

To characterise interconnectedness, we compute commonly used systemic-risk network measures (e.g., Acemoglu et al., 2015) on A:

- *Number of links*: Total connections in the network: $L = \sum_{i \neq j} A_{ij}$.
- *Density*: Proportion of observed edges relative to all possible edges: $D = \frac{1}{n(n-1)} L$.
- *Average degree*: Mean number of connections per node: $AD = \frac{1}{n} \sum_{i \neq j} A_{ij}$.
- *Average path length*: Mean shortest-path distance between all node pairs.
- *Clustering coefficient* The proportion of closed triads (triangles) relative to open triads captures local interconnectedness.

4. Data Description

We obtain daily equity prices for 56 companies that were leading constituents of the S&P 350 Europe Islamic Index (S&P Islamic Index) as of January 2020, sourced from Bloomberg, covering the period from January 2, 2019, to September 29, 2021. Fixing the sample to the pre-pandemic index ensures a balanced panel with uninterrupted price and sentiment coverage throughout the period. This enables us to avoid look-ahead bias from subsequent index rebalancing and preserves a stable set of firms for our rolling-window analysis. Companies that entered or exited the index after early 2020 were excluded to prevent unbalanced time series that would compromise comparability across windows.

To capture market sentiment, we use the proprietary sentiment index developed by Brain (`https://braincompany.co`). The index was constructed from financial articles and professional blogs (excluding social media) using natural-language processing (NLP) and machine learning (ML) techniques. For each article, the system generates a sentiment score in the range $[-1, 1]$, which is then aggregated to the company level to produce a daily firm-level sentiment index. Thus, sentiment scores in this study are company-averaged, not article-averaged.

The sentiment extraction pipeline comprises four steps: news collection, entity mapping, sentiment scoring, and firm-level aggregation, summarised in Figure 1.

Figure 1 goes here.

Table 1 goes here.

Table 1 presents the classification of firms into six Global Industry Classification Standard (GICS) sectors represented in our sample: Consumer Discretionary, Consumer Staples, Industrials, Health Care, Information Technology, and Materials. The sector distribution is uneven, with Industrials over-represented relative to Staples, which reflects differences in the index composition.

5. Empirical Application

This section presents the empirical findings from the analysis of equity-sentiment interdependencies among leading European ethical firms. We estimate a BGVAR with one-year (249 trading days) rolling windows, advanced monthly over the period January 2019 to September 2021, yielding 22 overlapping estimation windows. Sub-periods are defined as: Pre-COVID (up to February 2020), Wave-1 (March-June 2020), Wave-2 (July-December 2020), and Wave-3 (January-September 2021).

H1: COVID-19 amplified systemic links in both financial and sentiment networks

We assess whether interconnectedness intensified during the pandemic. Figure 2 displays the evolution of network density across rolling windows and highlights the distinct behaviour across sub-periods. Density rises sharply from its pre-pandemic minimum of 13.8%, surges during Wave-1, remains elevated in Wave-2 with values approaching 20.3%, and then stabilises at somewhat lower levels during Wave-3 before easing in the recovery period. This temporal pattern is summarised in Table 2, which reports descriptive statistics for each sub-period.

Figure 2 goes here.

The pattern in Table 2 confirms that interconnectedness increased substantially relative to the pre-pandemic period. Both Wave-1 and Wave-2 exhibit higher levels of density and lower dispersion, indicating strong and sustained spillovers during the early pandemic phases. Wave-3, by contrast, exhibits higher variability across rolling windows, indicating a period of more volatile and less uniform connectivity compared with the earlier waves.

Table 2 goes here.

Table 3 goes here.

Table 3 reports summary metrics for the sub-period networks. Relative to the Pre-COVID period, the number of links, network density, and average degree increase in Wave-1 and remain elevated through Wave-3. For example, network density rises from 18.89% to 25.43%, while average degree increases from 20.96 to 28.23. The clustering coefficient peaks at 0.949 in Wave-1, whereas the average path length reaches its minimum, suggesting a small-world structure conducive to rapid shock transmission.

These findings corroborate (Ahelegbey et al., 2022; Costola et al., 2023) and support H1: systemic interconnectedness intensified during the pandemic, with sustained increases in Wave-1 and 2, followed by a structural transition in Wave-3. This amplification reflects the joint role of financial and sentiment-driven spillovers during periods of heightened uncertainty.

H2: Sentiment shocks played a stronger role in financial linkages during the pandemic

To evaluate the role of sentiment in driving financial spillovers, we decompose the network into directional layers: *Equity→Sentiment* and *Sentiment→Equity*. Figure 3 visualises these layers across sub-periods, while Table 4 reports associated metrics. Sentiment-to-Equity connections increase from 24 in the Pre-COVID period to a peak of 42 in Wave-2, before easing to 36 in Wave-3. Both network density and average degree follow a similar pattern. In contrast, Equity-to-Sentiment links rise more steadily from 24 in Pre-COVID and remain elevated across subsequent phases, reaching 65 by Wave-3.

Table 4 goes here.

These results suggest that Sentiment-to-Equity spillovers peaking in Wave-2 coincide with heightened behavioural uncertainty, intense media coverage, and policy ambiguity. Renewed lockdowns and shifting policy signals during this phase amplified investor attention, making sentiment shocks more influential on equity prices. In contrast, Wave-3 reflects a period of market adaptation, with stabilising uncertainty and more updated expectations, reducing the marginal impact of sentiment on equity dynamics. This explains the weaker Sentiment-to-Equity effects observed in Wave-3 relative to Wave-2.

This pattern is consistent with behavioural asset pricing theory (Barberis et al., 1998), which suggests that investor expectations amplify systemic volatility. This supports H2: sentiment shocks played an influential role in financial interconnections during the pandemic.

H3: Sectoral differences in contagion exposure and resilience

We next assess sectoral heterogeneity. Figure 4 shows sector-level networks, and Table 5 reports associated metrics by sub-period.

Table 5 goes here.

Consumer Discretionary and Industrials display the most pronounced increases in connectivity across pandemic phases, with higher numbers of links, greater density, and shorter path lengths in the early waves. These patterns indicate heightened vulnerability to demand contractions, supply-chain disruptions, and sentiment-driven uncertainty. Technology remains predominantly equity-driven with limited sentiment spillovers; although connectivity rises moderately during the crisis, the sector shows relative resilience to behavioural shocks. Materials and Consumer Staples exhibit modest structural changes, with networks that are largely equity-based and only minor sentiment influence. Health Care emerges as the most stable sector, showing minimal variation in connectivity and a consistently weak sentiment component, consistent with its defensive characteristics during periods of macroeconomic stress.

From Figure 4, Consumer Discretionary and Industrials exhibit the strongest sensitivity to sentiment shocks. Consumer Discretionary firms are particularly exposed to shifts in consumer confidence and news-driven demand expectations, making their returns particularly responsive to sentiment dynamics during crises. Industrial firms also display heightened vulnerability, reflecting the sector's reliance on global supply chains, sensitivity to operational disruptions, and exposure to broader macroeconomic cyclicality during the crisis. By contrast, Islamic-screened firms generally operate with lower leverage and more conservative balance-sheet structures, which may dampen certain contagion channels and contribute to the greater resilience observed in sectors such as Health Care and Consumer Staples. Overall, these patterns support H3 and indicate that the pandemic amplified sector-level interconnectedness in uneven ways, with more cyclical sectors exhibiting pronounced spillovers and more defensive sectors remaining comparatively insulated.

6. Conclusion

This study investigates how religio-sustainable European companies navigated the systemic disruptions of the COVID-19 pandemic by combining a Bayesian Graphical VAR framework with measures of equity and sentiment interdependencies. By integrating structural spillover modelling with a sentiment-aware financial network, the analysis contributes to the literature on systemic risk, behavioural contagion, and crisis transmission in ethically screened markets. The results highlight the central role of dynamic inter-firm linkages and sentiment amplification in shaping shock propagation during periods of extreme uncertainty.

Our findings show increased system-wide interconnectedness during the pandemic (Ahelegbey et al., 2022; Costola et al., 2023), with the strongest and most persistent rise occurring in Wave-1 and Wave-2, followed by a structural shift in Wave-3. This reflects heightened systemic fragility driven by the joint intensification of financial and behavioural transmission channels. Although equity-based spillovers remained the dominant transmission mechanism, sentiment-equity linkages strengthened significantly during periods of elevated uncertainty. These results are consistent with behavioural theories of market co-movement and narrative contagion, which emphasise the role of investor sentiment in amplifying volatility and accelerating shock transmission under stress (Barberis et al., 1998; Nyman et al., 2021).

We further uncover substantial sectoral heterogeneity in contagion dynamics. Consumer Discretionary and Industrials emerge as the most vulnerable sectors, with sharper increases in network density, stronger bidirectional spillovers, and greater sensitivity to sentiment fluctuations. In contrast, Consumer Staples, Information Technology, Materials, and Health Care display more stable network structures and weaker sentiment amplification, indicating greater resilience to pandemic-induced disruptions. These findings indicate that while ethical and sustainability screening may mitigate certain dimensions of risk, it does not eliminate sector-specific exposure to behavioural shocks and supply-demand imbalances during crises.

The findings carry important implications for investors, regulators, and policymakers. From an investment perspective, they suggest that sustainability and religious screening alone may be insufficient as risk-mitigation tools during systemic crises unless complemented by active monitoring of sentiment-driven interconnectedness. For regulators and policymakers, the results highlight the need to account for behavioural transmission channels when assessing systemic risk, particularly in markets characterised by high information intensity and rapid news diffusion. Incorporating sentiment indicators into macroprudential surveillance frameworks may help improve early-warning signals and crisis preparedness.

Finally, future research could extend this framework by examining global ESG and Islamic indices, exploring cross-market and cross-asset network spillovers, or incorporating real-time sentiment derived from social media and alternative data sources. Such extensions would further enhance our understanding of how behavioural and sustainability-related factors interact with financial networks in shaping systemic risk.

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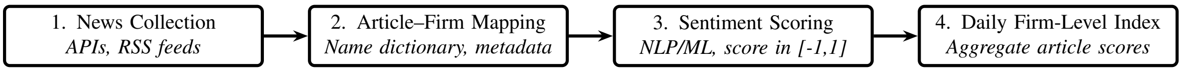


Figure 1: Sentiment extraction pipeline: news collection, article, firm mapping, sentiment scoring, and daily firm-level aggregation.

Figure 2: Evolution of network density over time (rolling-window estimates, summarised by sub-periods). *Notes:* Density (in percentage) is the fraction of active directed edges relative to all possible edges in the (equity, sentiment) network. Edges are identified using a PIP threshold $\alpha = 0.5$. Shaded bands indicate sub-periods: Pre-COVID, Wave-1 (Mar-Jun 2020), Wave-2 (Jul-Dec 2020), Wave-3 (Jan-Sep 2021).

No.	Stock	ID
	Consumer Discretionary	
1	Kering	KER
2	Adidas AG	ADS
3	EssilorLuxottica	EL
4	Ferrari NV	RAC
5	Compass Group	CPG
6	Delivery Hero AG	DHR
7	Continental AG	CON
8	Zalando SE	ZAL
9	PUMA SE	PUM
10	Moncler SpA	MON
11	Persimmon	PSN
12	Burberry Group	BRB
13	Barratt Dev.	BDV
14	Berkeley Group	BKG
15	Taylor Wimpey	TWL
	Consumer Staples	
16	L'Oreal	OR
17	Unilever	ULV
18	Reckitt Benckiser	RKT
19	Beiersdorf AG	BEI
20	Ass. British Foods	ABF
21	Tate and Lyle	TAT
22	Nestle SA	NES

No.	Stock	ID
	Industrials	
23	Airbus SE	AIR
24	Schneider Electric	SU
25	Safran SA	SAF
26	RELX Plc	REL
27	Experian Plc	EXP
28	Teleperformance	TEP
29	Alstom	ALO
30	MTU Aero Engines	MTX
31	Intertek Group	ITK
32	Smiths Group	SMN
33	IMI	IMI
34	ABB Ltd	ABB
35	SGS SA	SGS
	Health Care	
36	AstraZeneca Plc	AZN
37	Sanofi	SAN
38	Smith & Nephew	SNL
39	Lonza AG	LON
40	Novartis AG	NOV
41	Roche Holding AG	ROG

No.	Stock	ID
	Information Technology	
42	SAP SE	SAP
43	Dassault Systemes	DSY
44	Infineon Tech.	IFX
45	STMicroelectronics	STM
46	Worldline SA	WLN
47	Halma	HLM
48	Sage Group	SGE
49	Logitech Intl.	LGN
	Materials	
50	Rio Tinto Plc	RIO
51	BHP Group Plc	BHP
52	Symrise AG	SY1
53	Croda Intl.	CRD
54	Covestro AG	COV
55	Mondi Plc	MND
56	Johnson Matthey	JMT

Table 1: List of selected companies categorised by sector.

Period	Mean	SDev	Median	Min	Max	Q0.25	Q0.75
Full Sample	17.86	2.42	18.79	13.8	20.29	15.55	20.02
Pre-COVID	13.93	0.16	13.88	13.80	14.10	13.84	13.99
Wave-1	19.44	0.83	19.60	18.39	20.18	18.99	20.06
Wave-2	19.98	0.22	20.00	19.59	20.21	19.92	20.12
Wave-3	17.06	1.99	16.29	15.19	20.29	15.51	18.28

Table 2: Summary statistics of network density over the full sample and sub-periods.

Period	**Links**	**Density**	**Avg. Degree**	**Clust. Coef.**	**Avg. Path**
Pre-COVID	2,348	18.89%	20.96	0.859	1.796
Wave-1	2,968	23.87%	26.50	**0.949**	**1.730**
Wave-2	3,058	24.60%	27.30	0.942	1.853
Wave-3	**3,162**	**25.43%**	**28.23**	0.936	2.014

Table 3: System-wide network metrics by sub-periods. *Notes:* Density is the fraction of active edges; average degree is the mean number of connections per node; clustering coefficient is the proportion of closed triads relative to open triads; average path is the mean shortest path length. Networks are constructed from rolling-window adjacency matrices using PIP threshold $\alpha = 0.5$.

	Equity→Sentiment			**Sentiment→Equity**		
Period	**Links**	**Density**	**Avg. Degree**	**Links**	**Density**	**Avg. Degree**
Pre-COVID	24	0.193	0.214	24	0.193	1.214
Wave-1	37	0.298	0.330	25	0.201	0.223
Wave-2	45	0.362	0.402	42	0.338	0.375
Wave-3	65	0.523	0.580	36	0.289	0.321

Table 4: Directional network metrics by sub-periods. *Notes:* Layers isolate directed effects from equities to sentiment and from sentiment to equities. Density is the fraction of active directed edges; average degree is the mean number of links per node within each layer.

Period	**Links**	**Density**	**Avg. Degree**	**Clust. Coef.**	**Avg. Path**
			Consumer Discretionary		
Pre-COVID	185	21.26%	6.167	0.871	1.447
Wave-1	211	24.25%	7.033	0.942	1.341
Wave-2	213	24.48%	7.100	**0.954**	**1.280**
Wave-3	**226**	**25.98%**	**7.533**	0.882	1.559
			Consumer Staples		
Pre-COVID	36	19.78%	2.572	0.815	1.509
Wave-1	40	21.98%	2.857	0.891	1.184
Wave-2	42	23.08%	3.000	0.946	1.143
Wave-3	42	23.08%	3.000	1.000	1.000
			Information Technology		
Pre-COVID	49	20.42%	3.063	0.962	1.140
Wave-1	54	22.50%	3.375	**1.000**	**1.036**
Wave-2	59	24.58%	3.688	0.889	1.305
Wave-3	**60**	**25.00%**	**3.750**	0.891	1.478
			Industrials		
Pre-COVID	115	17.69%	4.423	0.859	1.341
Wave-1	153	23.54%	5.885	**0.962**	**1.175**
Wave-2	**161**	**24.77%**	**6.192**	0.957	1.214
Wave-3	161	24.77%	6.192	0.946	1.266
			Materials		
Pre-COVID	39	21.43%	2.786	0.882	1.456
Wave-1	41	22.53%	2.929	1.000	1.024
Wave-2	42	23.08%	3.000	0.946	1.143
Wave-3	41	22.53%	2.929	1.000	1.024
			Health Care		
Pre-COVID	29	21.97%	2.417	0.909	1.216
Wave-1	28	21.21%	2.333	0.857	1.250
Wave-2	29	21.97%	2.417	1.000	1.033
Wave-3	**31**	**23.49%**	**2.583**	**1.000**	**1.000**

Table 5: Sector-level network metrics by sub-periods. *Notes:* Density, clustering coefficient, and average path length are scale-free measures and thus comparable across sectors of different sizes. The raw number of links reflects sector size directly. Average degree depends on both connectivity and sector size and should be interpreted alongside density. Networks constructed using PIP threshold $\alpha = 0.5$.

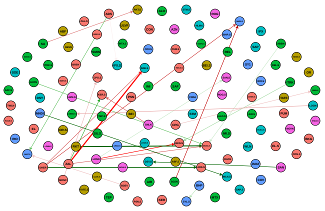
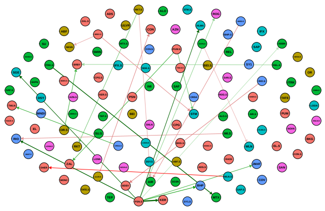
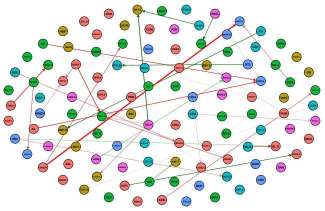
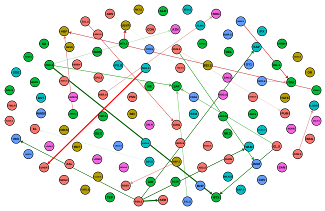
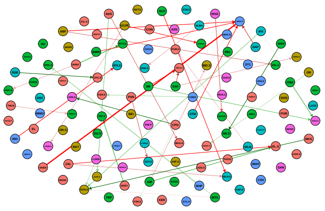
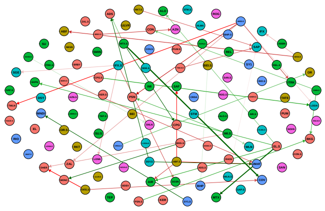
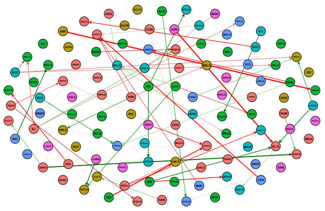
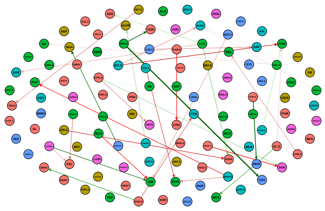
	Equity→Sentiment	**Sentiment→Equity**
Pre-COVID		
Wave-1		
Wave-2		
Wave-3		

Figure 3: Equity→Sentiment and Sentiment→Equity networks by sub-period. *Notes:* Networks are based on PIP threshold $\alpha = 0.5$. Nodes represent companies and are coloured by sectors: Consumer Discretionary, Consumer Staples, Industrials, Information Technology, Materials, Health Care. Edges: green (red) indicates positive (negative) causal effects.

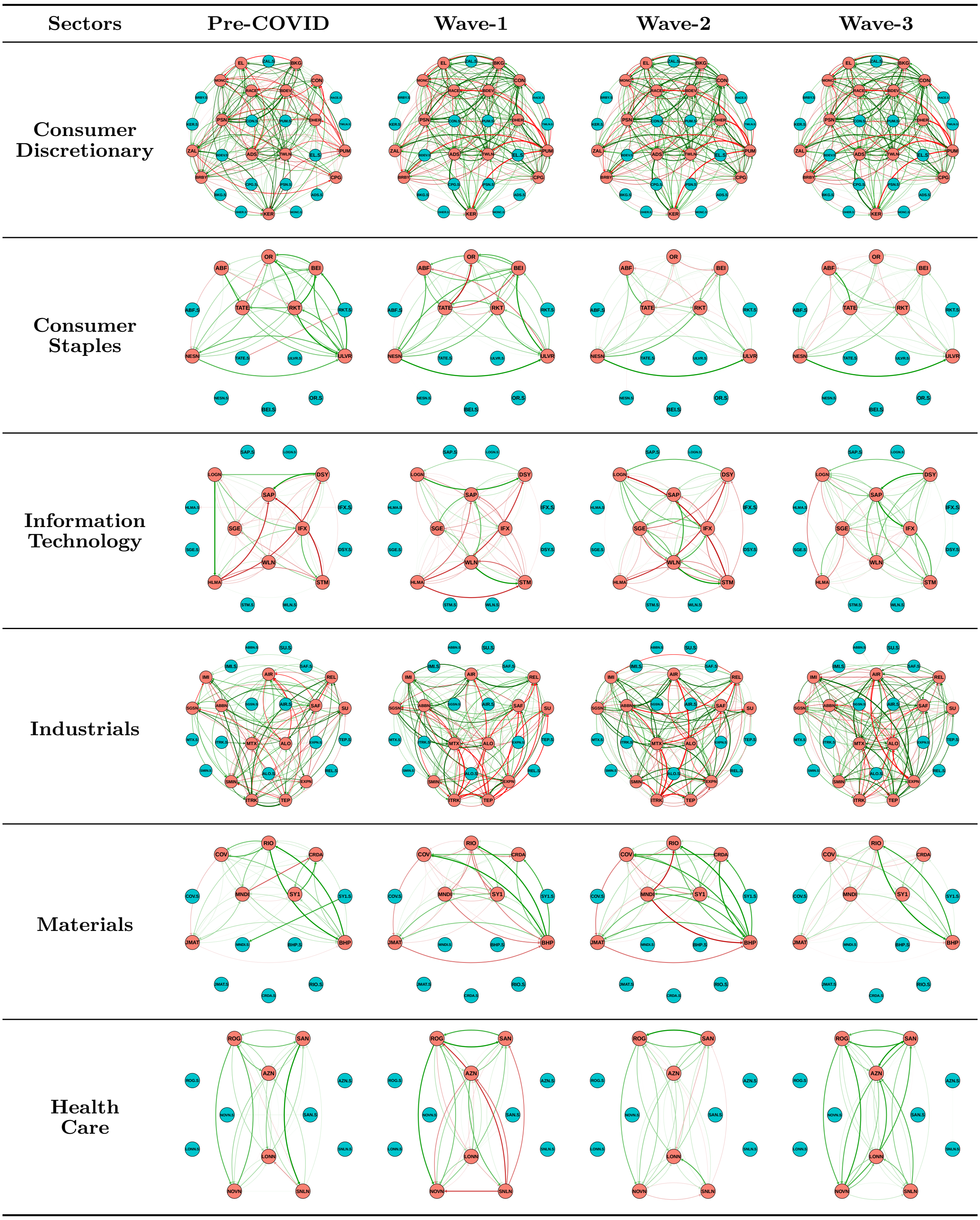


Figure 4: Sector-level networks by sub-period. *Notes:* Networks are based on PIP threshold $\alpha = 0.5$. Nodes: red (blue) = equity (sentiment). Edges: green (red) indicates positive (negative) causal effects.