The reputational contagion effects of ransomware attacks

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Abstract

Little research examines investor attention outcomes spreading between firms through partial ownership, without additional business or industry linkages, including the spread of investor attention reactions to firms that are competitors to those firms having ownership stakes in impacted firms. We take advantage of the recent Colonial Pipeline ransomware attack, evidencing reputational contagion from firms impacted directly by reputation events to firms that are competitors of the firms that have significant ownership with the impacted firm, but otherwise no other industrial overlaps. Our results suggest investor attention events have greater breadth of impact than previously realized.

Keywords: Cybercriminality; Reputation; Contagion; Ransomware; Investor Attention; Financial Markets.

1. Introduction

Business research continues to have considerable interest in interconnected firms. Interconnections among firms can be through simple associations such as national markets, common industries, or, alternatively, through more tangible connections such as formal business groups [Khanna and Yafeh, 2007], supply chains, and shared ecosystem platforms [Rietveld et al., 2019]. Concomitantly, the nature of how investor attention influences interconnected firms continues to be of expanding interest to finance scholarship, with recent studies emphasizing the roles of large public events [Gao and Lin, 2015, Gupta-Mukherjee and Pareek, 2020, Huang et al., 2019, Hu et al., 2021, Zhaunerchyk et al., 2020], and social media [Li et al., 2021]. What has so far received insufficient attention is the role of investor attention in spreading between firms through ownership stake alone, without additional business or industry linkages. What is even less investigated is the spread of reputation and attention events to firms that are competitors to those firms having ownership stakes in impacted firms. In this study we take advantage of the recent Colonial Pipeline ransomware attack to investigate what we term *reputational contagion* from firms impacted directly by reputation events to firms that are competitors of the firms that have significant ownership with the impacted firm, but otherwise no industrial overlaps.

Colonial Pipeline operates an oil pipeline system sourced in Houston, Texas that carries fuel products throughout the southern and eastern United States. On 7 May 2021, the company experienced a ransomware cyberattack, thought to have been created by a group called DarkSide[1], characterised as one of the most disruptive digital ransom operations recorded in history froze the supply of fuel throughout many regions in the United States, causing panic buying and sharp price increases for both retail and commercial customers. Further, the attacks exposed a deep-rooted vulnerability within US energy structures, which also have the potential to influence not only broad internal transport, but also both the shipping and airline industry due to the collapse of the approximate 5,500-mile distribution network. To mitigate the attack, the company paid a ransom of 75 Bitcoins, of which 63.7 were recovered by the US Department of Justice one month later. The six-day shut down ended at 5pm on 12 May 2021, however, it took further time to restore supply to gas stations in southern states.

While the cybercrime event had substantiative impacts upon both oil-related share prices and US fuel commodities alike, this research analyses a secondary pathway through which damaging effects occurred, namely social media and negative sentiment associated to companies attached through association, that is, through no direct linkage with Colonial Pipeline. Using TRBC codes, we develop upon GARCH and DCC-GARCH methodologies to specifically investigate the interactions between these companies. Specifically, we test for the presence of significant volatility transfer, indicative of sectoral contagion Although these companies had no direct link to Colonial Pipeline, such inter connectivity would indicate further pathways through which this extraordinary cybercrime event affected financial markets.

Previous works have identified the presence of financial market contagion in the aftermath of major hacking and broad cybercriminality events, with particular susceptibility identified for corporate entities with lower levels of market capitalisation, and lack of regulatory development and enforcement generated a conductive environment through which hackers could operate [Corbet and Gurdgiev, 2019, 2020]. Kamiya et al. [2021] identified that the excess loss experienced by a target company is reduced, should the company pay more attention to risk management before

[1] Elliptic, a company tasked with preventing cybercriminality provided evidence in May 2021 that DarkSide had extracted $90 million from 47 separate victims using a range of attacks.

the attack. Tosun [2021] identified that corporate effects of hacking events were in the short-run centralised on investor attention, but in the long-run, based on policy implications. Lin et al. [2020] found that in the three months before the announcement of a cybersecurity breach, insider traders with knowledge of such events were found to save an average of $35,009 due to timely selling, however, based on single-company analyses, Foecking et al. [2021] identified that data breaches of Facebook are not association with significant abnormal returns. Our analysis of the contagion effects relating to significant short-term idiosyncratic events follows that used by Akyildirim et al. [2020, 2021] and Corbet et al. [2020], while considering theoretical developments provided by Larson and Madura [2003], Benou and Richie [2003], and Zhao and Chen [2021].

The nature of how investor attention influences interconnected firms continues to be of great interest to finance scholarship, with recent studies investigating the impact on investor attention of large lottery prizes [Huang et al., 2019, Hu et al., 2021, Zhaunerchyk et al., 2020]; the complementing roles of search engines and social medias such as Twitter in influencing investors [Li et al., 2021]; as well as a host of recent studies highlighting the role of investor sentiment in the much-publicized GameStop short squeeze [Hasso, Müller, Pelster, and Warkulat, 2021, Umar, Yousaf, and Zaremba, 2021, Umar, Gubareva, Yousaf, and Ali, 2021]. Our study, focused on the recent Colonial Pipeline event adds to this ongoing research.

2. Data

We collect data for all companies using Refinitiv Datastream and Eikon for the period 5 January 2015 through 4 August 2021, representing 1,719 observations to be analysed. The period selected is found to represent an adequate sample providing substantial information relating to the selected companies both before and after the analysed events. In Table A1 of the attached Online Appendices, we present both the individual sub-divisions within the Colonial Pipeline Co group, along with the ownership structure of Colonial Pipeline Co, a private company that has five distinct corporate owners, Shell, Koch Industries, Colonial to Caisse de dépôt et placement du Québec, Kohlberg, Kravis Roberts & Co., the South Korean state-run National Pension Service, and IFM Investors. Of this group, both Shell and Kohlberg, Kravis Roberts & Co. have active, liquid share prices upon which we develop a list of TRBC competitors, as presented in Table A2 of the Online Appendices. Companies relating to Shell, such as Nostrum Oil Gas PLC, Franks International NV, Fugro NV, Core Laboratories NV, SBM Offshore NV, and Koninklijke Vopak NV are all directly related in oil-market industries, therefore contagion effects stemming from the Colonial Pipeline cyberattack would be expected. However, competitors of Kohlberg, Kravis Roberts & Co. would not have experience direct effects as a result of the cyberattack due to their sectoral position outside of commodity markets.

3. Empirical Approach and Results

Volatility effects are estimated using a GARCH(1,1) model of the form:

$$R_t = a_0 + \sum_{j=1}^{2} b_j R_{t-j} + b_2 D.hack_t + b_3 D.ransom_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t | \Omega_t \sim i.i.d. \quad N(0, h_t) \tag{2}$$

$$h_t = \omega + \alpha_1 h_{t-1} + \beta_1 u_{t-1}^2 \tag{3}$$

R_{t-j} represents the lagged value of the selected returns, j number of periods before R_t is observed. $b_2 D.hack_t$ represents a dummy variable representing the date 7 May 2021, on which the hacking of the Colonial Pipeline had taken place. $b_3 D.ransom_t$ represents the date on which the ransom was announced to the public to have been paid. The dummy variables are also considered within the variance equation of the GARCH(1,1) methodology to test the specific volatility effects in the dates surrounding the examined events.

Insert Table 1 about here

In Table 1 we present the GARCH(1,1) estimation. Both Shell and KKR present significantly negative pricing effects stemming from the hacking event, indicating that investors appear to have been aware of their investment presence in Colonial Pipeline Co., therefore leading to significant negative associated returns of -0.98% and -1.32% respectively in the period immediately after the hacking. On the day on which the ransom was made public through reputable news sources, significant positive returns are identified of 1.01% and 0.71% respectively. While such results are not unexpected in isolation, through the use of similar dummy variables in the variance equation structure of both models, we observe that there are sharp, significant increases in the share price volatility of both companies. When focusing on the existence of reputational contagion, we observe that in all four significant methodological structures of the competitor companies relating to Shell, all four exhibit sharp, significant declines in their respective share prices in the period surrounding the hack date. Both NOGN and VOPA present significant volatility effects, while only VOPA presents evidence of significant share price movements at the time of which the ransom date was announced to have been paid. Results relating to these oil-related corporations are not unexpected due to the deep-rooted shock that permeated energy companies due to these hacking events. However, competitor companies to KKR, all of which have no explicit inter-connectivity with energy markets, present evidence of significant negative declines on the hacking date examined in almost a quarter of examined cases. However, significant volatility effects are identified in almost half of the randomly selected TRBC competitor institutions. This result indicates that there existed significant simultaneous volatility 'shocks' in these companies on the key dates coinciding with the Colonial Pipeline Co. hacking event.

The next stage of our analysis specifically measures the estimated time-varying connectivity between these identified significant relationships. Sectoral contagion effects stemming from the Colonial Pipeline cybercrime events are measured using a dynamic conditional correlation methodology (DCC-GARCH) similar to that developed by Engle [2002], who decomposed the conditional covariance matrix as:

$$H_t = D_t R_t D_t \tag{4}$$

$$R_t = \text{diag}(Q_t)^{-\frac{1}{2}}.Q_t.\text{diag}(Q_t)^{-\frac{1}{2}} \tag{5}$$

$$Q_t = \Omega + \alpha\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1} \tag{6}$$

R_t is defined as the conditional correlation matrix, while D_t is a diagonal matrix with time-varying standard deviations $\sqrt{h_{i,t}}$ on the main diagonal. Next, Q_t is identified as the approximation of the conditional correlation matrix, where the positive semi-definiteness of Q_t is assured if both α and β are both positive, while the sum of both α and β is less than one while the initial matrix (Q_1) being positive. $\Omega = (1-\alpha-\beta)\bar{R}$, where $\bar{R}$ representing the unconditional average correlation.

Insert Figures 1 and 2 about here

Results are presented for corporate relationships relating to Shell in Figure 1, and for those relationships relating to KKR in Figure 2. In almost all circumstances examined, the effects of the COVID-19 pandemic[2] are evident in the periods surrounding March and April 2020. However, it

[2]The COVID-19 pandemic is included in our analysis to remove ambiguity surrounding influence upon the hypotheses under investigation. Much academic research has already identified the sharp negative impacts that have

must be noted that such effects are found to be in isolation of the Colonial Pipeline Co. hacking event which takes place twelve months later. Only results where dynamic correlation movements above 5% during the time of the hacking event. Results verify those identified in the GARCH(1,1) methodology, where not only do we identify that there existed significant movements in both share price and volatility, we observe that during the same period of time, there were significant, and in some cases, long-term changes in the dynamic conditional correlation relationships of competitor companies. This result indicates that both Shell and KKR's investment in Colonial Pipeline Co. generated volatility pass-through effects to sectoral competitors.

Insert Tables 2 and 3 about here

Summary statistics relating to the returns of sectoral competitors are presented in Table 2 for Shell, and Table 3 for Kohlberg, Kravis Roberts & Co., where data is separated as before, during, and after the analysed hacking events. Presented results further demonstrate significant differentials between the analysed companies in the periods before, during, and after the analysed hacking event in terms of both returns and estimated conditional correlations. Overall, our results clearly evidence that the investor attention generated by the Colonial Pipeline ransomware attack led to reputational contagion that extended even to companies without direct linkages to Colonial.

4. Conclusions

We investigate *reputational contagion* ensuing from the recent Colonial Pipeline ransomware attack. This attack and its aftermath will certainly be the focus of policy makers and security officials because it exposed a deep-rooted vulnerability within US energy structures. However, this widely publicized event also provides an opportunity to for finance researchers to investigate new aspects of investor attention. While this cybercrime event had significant impacts upon both oil-related share prices and US fuel commodities alike, we evidence that damaging effects to firms also occurred through social media and negative sentiment associated with companies attached through association, but with no direct industry linkage with Colonial Pipeline. Using GARCH and DCC-GARCH methodologies, we investigate the interactions between these companies, finding significant volatility transfer, indicative of sectoral contagion. More generally, such interconnectivity among companies that have no direct link to Colonial Pipeline suggests that investor attention events have

been sourced within the COVID-19 pandemic [Ashraf and Goodell, 2021, Goodell, 2020, Corbet et al., 2020, 2021, 2022].

potential far greater breadth than previously considered. Researchers and policy makers concerned with the impact of large media events on investor attention will likely find these new findings of particular interest.

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Table 1: GARCH methodology statistics

		Mean Eq.		Variance Eq.				
	Mean Eq	Hack Date	Ransom Date	Hack Date	Ransom Date	Log-L	Wald chi2(2)	Prob >chi2
RDSa.AS	Coef.	-0.0098***	0.0101***	0.2406**	0.2445**	4,865.40	131.68	0.0000***
	Std. Err.	(0.0054)	(0.0053)	(0.1187)	(0.1185)			
KKR	Coef.	-0.0132***	0.0071***	0.4354***	0.2664***	4,886.32	94.39	0.0000***
	Std. Err.	(0.0029)	(0.0016)	(0.1400)	(0.0730)			
RDSa.AS Competitor Companies								
NOGN.L	Coef.	0.0196***	-0.0137***	0.3900*	0.1651	3,110.53	5.82	0.1206
	Std. Err.	(0.0053)	(0.0026)	(0.2031)	(0.1870)			
CLB	Coef.	-0.0121***	0.0013	0.2291	0.1203	3,706.82	48.04	0.0000***
	Std. Err.	(0.0114)	(0.0086)	(0.3974)	(0.4362)			
SBMO.AS	Coef.	-0.0190***	-0.0035	0.0327	-0.1885	4,293.54	1,196.48	0.0000***
	Std. Err.	(0.0047)	(0.0029)	(0.1254)	(0.1692)			
VOPA.AS	Coef.	-0.0210***	0.0033	0.1003***	-0.2195*	4,837.75	11.38	0.0098***
	Std. Err.	(0.0035)	(0.0030)	(0.0268)	(0.1172)			
KKR Competitor Companies								
BX	Coef.	-0.0019	0.0051	0.0151	-0.1976	4,990.77	1,371.09	0.0000***
	Std. Err.	(0.0033)	(0.0034)	(0.2104)	(0.2941)			
BEN	Coef.	0.0004	-0.0033	0.1246***	0.0339	5,016.18	834.06	0.0000***
	Std. Err.	(0.0056)	(0.0045)	(0.0464)	(0.1172)			
ARES.K	Coef.	-0.0041	0.0053***	0.1355***	-0.1231	4,601.96	6,112.45	0.0000***
	Std. Err.	(0.0031)	(0.0001)	(0.0294)	(0.2894)			
CG.O	Coef.	-0.0063**	0.0021	0.2773***	0.1073	4,729.95	587.26	0.0000***
	Std. Err.	(0.0027)	(0.0020)	(0.0967)	(0.1315)			
IVZ	Coef.	-0.0046	0.0019	0.2257**	0.2846***	4,886.94	1,189.04	0.0000***
	Std. Err.	(0.0054)	(0.0053)	(0.0875)	(0.0965)			
AB	Coef.	-0.0155***	0.0041	0.1548	-0.2209	4,938.50	7,787.71	0.0000***
	Std. Err.	(0.0070)	(0.0065)	(0.1747)	(0.1445)			
APAM.K	Coef.	-0.0005	-0.0051	-0.0036	-0.1474	4,799.17	883.75	0.0000***
	Std. Err.	(0.0053)	(0.0045)	(0.1713)	(0.1773)			
CNS	Coef.	0.0003	0.0001	0.0084	-0.2156	4,966.34	468.00	0.0000***
	Std. Err.	(0.0034)	(0.0027)	(0.1720)	(0.1601)			
FHI	Coef.	-0.0005	-0.0030	0.0876	-0.2132	4,791.37	346.75	0.0000***
	Std. Err.	(0.0063)	(0.0032)	(0.1070)	(0.1547)			
BSIG.K	Coef.	0.0037	-0.0047*	0.3915***	0.3118***	4,520.68	328.43	0.0000***
	Std. Err.	(0.0031)	(0.0028)	(0.0908)	(0.1069)			
WETF.O	Coef.	-0.0138***	0.0118	-0.0790	0.1377	3,934.09	243.54	0.0000***
	Std. Err.	(0.0053)	(0.0128)	(0.1961)	(0.2145)			
TCPC.O	Coef.	0.0000	0.0003	0.1978***	-0.2007	5,490.73	108.93	0.0000***
	Std. Err.	(0.0048)	(0.0037)	(0.0201)	(0.2095)			
PZN	Coef.	-0.0132***	0.0024	0.2352*	0.1877	3,970.52	239.44	0.0000***
	Std. Err.	(0.0060)	(0.0064)	(0.1434)	(0.1572)			
TPVG.K	Coef.	-0.0096	0.0054	0.2402***	-0.3730*	4,764.45	78.88	0.0000***
	Std. Err.	(0.0127)	(0.0054)	(0.249)	(0.1922)			
MN	Coef.	0.0022	0.0011	0.1520***	-0.2084*	3,522.86	26.48	0.0000***
	Std. Err.	(0.0050)	(0.0074)	(0.0239)	(0.1216)			
MMAC.O	Coef.	0.0012	0.0108	-0.1901	1.0374	4,836.49	28.60	0.0000***
	Std. Err.	(0.0046)	(0.0194)	(0.6671)	(0.7543)			
GROW.O	Coef.	-0.0119	0.0050	0.0076	-0.1875	2,864.09	13.63	0.0035***
	Std. Err.	(0.0181)	(0.0177)	(0.1498)	(0.1530)			

Note: Volatility effects are estimated using: $R_t = a_0 + \sum_{j=1}^{2} b_j R_{t-j} + b_2 D.hack_t + b_3 D.ransom_t + \varepsilon_t$. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. For brevity, only significant methodological structures are presented. Further results, including methodologically supporting pre- and post-estimation testing are available from the authors upon request.

Table 2: Return summary statistics of sectoral competitors

	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
			Before Hack			
	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
NOGN.L	0.2360	0.0005	1.5030	37.65	0.0212	0.4545
VOPA.AS	0.2599	0.0030	-1.0625	5.12	-0.0051	0.4390
ARES.K	0.2844	0.0005	-8.2212	77.30	0.0143	0.3203
CG.O	0.4138	0.0000	-11.1951	416.06	0.3676	0.4346
IVZ	0.3994	0.0000	-8.6134	280.55	0.3548	0.4225
AB	0.3733	0.0000	-2.8397	254.46	0.3316	0.4005
BSIG.K	0.2264	0.0172	0.7930	0.12	0.0000	0.5424
TCPC.O	0.2227	0.0050	-1.4403	1.27	0.0007	0.3353
PZN	0.2588	0.0071	-1.3005	0.92	0.0008	0.3565
TPVG.K	0.1578	0.0027	-1.3273	0.92	0.0005	0.2443
MN	0.1406	0.0001	-6.7010	74.17	0.0169	0.1834
MMAC.O	0.2215	0.0001	-6.8877	102.80	0.0267	0.3026
GROW.O	0.0623	0.0000	-2.9394	30.88	0.0075	0.0959
			During Hack			
	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
NOGN.L	0.1971	0.0001	-0.3994	-1.10	0.1768	0.2151
VOPA.AS	0.2560	0.0001	-0.2716	-1.98	0.2423	0.2695
ARES.K	0.2872	0.0000	-0.7899	0.28	0.2866	0.2876
CG.O	0.4136	0.0000	-2.5317	7.03	0.4099	0.4148
IVZ	0.3993	0.0000	-1.8656	3.69	0.3967	0.4006
AB	0.3730	0.0000	-1.8637	3.47	0.3697	0.3746
BSIG.K	0.4103	0.0000	0.6910	-1.57	0.4070	0.4148
TCPC.O	0.2754	0.0000	0.7029	-1.61	0.2744	0.2772
PZN	0.3449	0.0000	0.4400	-1.73	0.3440	0.3462
TPVG.K	0.2005	0.0000	0.7756	-1.51	0.2000	0.2013
MN	0.1421	0.0000	1.3352	0.96	0.1414	0.1433
MMAC.O	0.2135	0.0003	-2.3804	4.32	0.1669	0.2227
GROW.O	0.0618	0.0000	-0.9435	1.52	0.0582	0.0634
			After Hack			
	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
NOGN.L	0.2301	0.0000	-0.7451	-0.46	0.2171	0.2374
VOPA.AS	0.2721	0.0005	-2.3548	5.30	0.2029	0.2941
ARES.K	0.2873	0.0000	1.0131	0.74	0.2867	0.2882
CG.O	0.4138	0.0000	1.0801	9.14	0.4119	0.4162
IVZ	0.3993	0.0000	-2.4194	10.78	0.3965	0.4006
AB	0.3734	0.0000	0.3980	5.70	0.3718	0.3749
BSIG.K	0.4072	0.0000	0.1387	-1.66	0.4052	0.4095
TCPC.O	0.2737	0.0000	0.1191	-1.33	0.2727	0.2748
PZN	0.3451	0.0000	0.2969	-0.59	0.3439	0.3466
TPVG.K	0.1992	0.0000	0.3147	-1.53	0.1983	0.2003
MN	0.1402	0.0000	-1.3954	0.85	0.1361	0.1424
MMAC.O	0.2118	0.0001	-1.6166	1.66	0.1751	0.2208
GROW.O	0.0640	0.0000	1.3433	0.80	0.0623	0.0686

Note: For brevity, only significant relationships are presented. Further results are available from the authors upon request. Further results, including methodologically supporting pre- and post-estimation testing are available from the authors upon request.

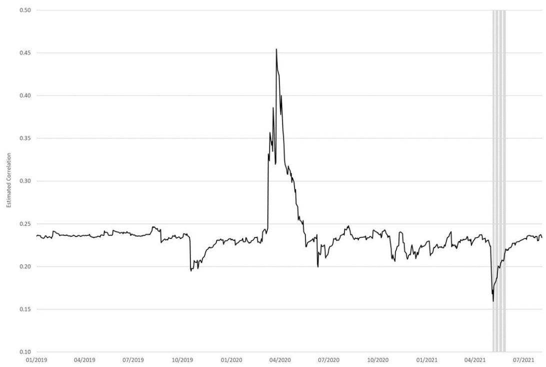
Table 3: Conditional correlation summary statistics of sectoral competitors

	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
			Before Hack			
NOGN.L	0.1917	0.0006	2.9041	31.79	0.0130	0.4231
CLB	0.3296	0.0182	-0.6469	-0.38	0.0000	0.6138
BX	0.7120	0.0000	-40.1138	1,621.73	0.6426	0.7121
ARES.K	0.5328	0.0004	-4.9485	143.94	0.1371	0.7142
APAM.K	0.6879	0.0000	11.9738	301.41	0.6838	0.7009
FHI	0.5479	0.0214	-1.9410	2.97	0.0025	0.6575
TCPC.O	0.4045	0.0032	0.1370	9.92	0.0204	0.7854
TPVG.K	0.2439	0.0023	3.4967	28.28	0.0246	0.7851
MN	0.1787	0.0001	-10.2585	143.04	0.0406	0.2172
MMAC.O	0.3375	0.0048	1.2543	8.15	0.0080	0.6537
			During Hack			
	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
NOGN.L	0.1759	0.0000	0.3554	-1.40	0.1664	0.1856
CLB	0.4361	0.0000	0.4750	-1.43	0.4332	0.4401
BX	0.7121	0.0000	1.1147	-2.33	0.7121	0.7121
ARES.K	0.5342	0.0000	-0.8201	-0.41	0.5240	0.5402
APAM.K	0.6879	0.0000	0.8543	3.37	0.6875	0.6884
FHI	0.6441	0.0000	0.6294	-1.30	0.6437	0.6447
TCPC.O	0.4704	0.0024	-0.3600	-0.97	0.3860	0.5420
TPVG.K	0.2381	0.0020	-0.9673	-0.42	0.1539	0.2904
MN	0.1778	0.0000	-0.4474	-0.42	0.1750	0.1799
MMAC.O	0.2830	0.0010	-2.3376	4.15	0.2053	0.3008
			After Hack			
	Mean	Variance	Skewness	Kurtosis	Minimum	Maximum
NOGN.L	0.1850	0.0000	-0.8774	-0.36	0.1738	0.1917
CLB	0.4292	0.0000	0.0022	-0.55	0.4247	0.4338
BX	0.7121	0.0000	1.0312	-2.09	0.7121	0.7121
ARES.K	0.5342	0.0000	0.2170	0.07	0.5285	0.5399
APAM.K	0.6879	0.0000	-0.7866	3.70	0.6874	0.6882
FHI	0.6430	0.0000	0.7493	-1.14	0.6426	0.6437
TCPC.O	0.4354	0.0011	0.2857	-0.07	0.3699	0.5098
TPVG.K	0.2432	0.0002	0.7267	1.99	0.2181	0.2900
MN	0.1783	0.0000	-1.3601	1.70	0.1755	0.1799
MMAC.O	0.2350	0.0003	0.0383	-1.25	0.2075	0.2629

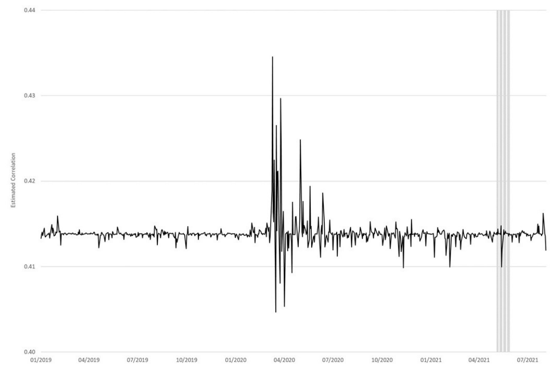
Note: For brevity, only significant relationships are presented. Further results are available from the authors upon request. Further results, including methodologically supporting pre- and post-estimation testing are available from the authors upon request.

Figure 1: DCC-GARCH relationships of sectoral competitors of Shell (RDSa.AS)

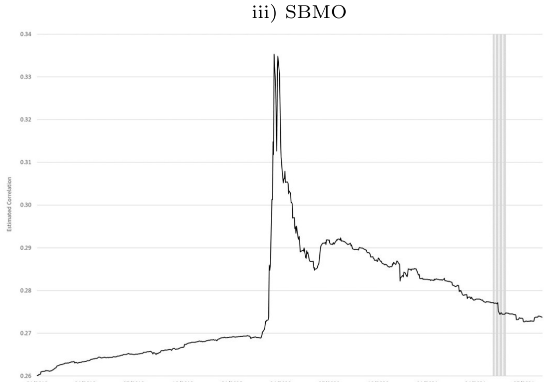
i) NOGN.L



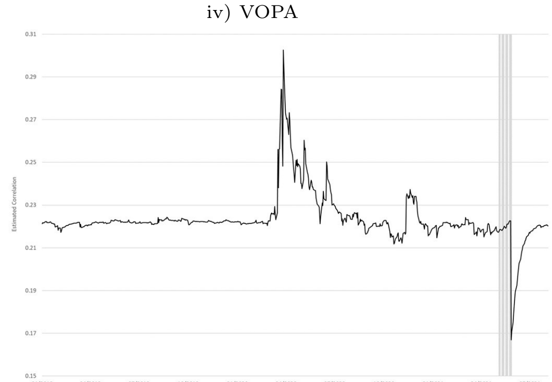
ii) CLB



iii) SBMO



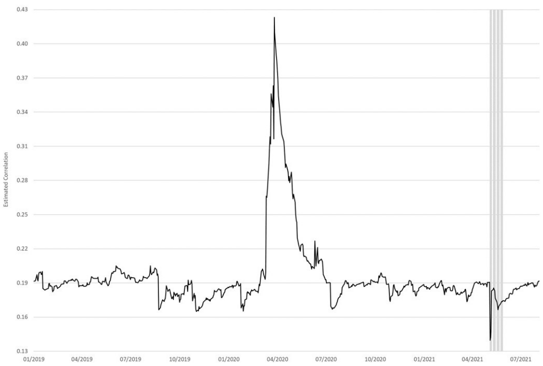
iv) VOPA



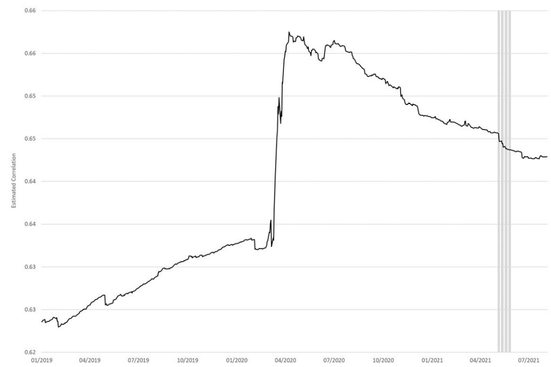
Note: Sectoral contagion effects stemming from the Colonial Pipeline cybercrime events are measured using a dynamic conditional correlation methodology (DCC-GARCH). Further results, including methodologically supporting pre- and post-estimation testing are available from the authors upon request.

Figure 2: DCC-GARCH relationships of sectoral competitors of Kohlberg, Kravis Roberts Co. (KKR)

i) BEN

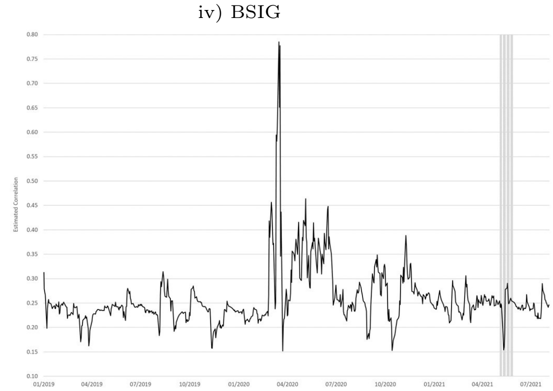


ii) CG

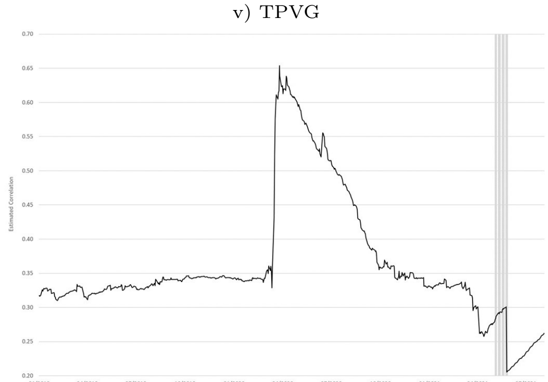


iii) IVZ

iv) BSIG



v) TPVG



Note: Sectoral contagion effects stemming from the Colonial Pipeline cybercrime events are measured using a dynamic conditional correlation methodology (DCC-GARCH). Further results, including methodologically supporting pre- and post-estimation testing are available from the authors upon request.