Finance Research Letters 38 (2021) 101591

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic

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ARTICLE INFO

Keywords:
COVID-19
Coronavirus
Contagion
Stock Market
Sentiment

ABSTRACT

In the midst of the 2020 global COVID-19 pandemic and subsequent financial market collapse, corporate entities have to navigate a number of truly unforeseen contagion risks. However, one such group included those who shared their corporate identity with aspects of the rapidly evolving coronavirus. Our results indicate the existence of sharp, dynamic and new correlations between companies related to the term 'corona', outside of pre-existing interrelationships. We provide a number of observations as to why this situation occurred.

1. Introduction

In late 2019, rumours had begun to persist from China that a new virus had started to spread, generating what had been described as symptoms of 'severe pneumonia' which led to an exceptional rate of fatality amongst the elderly and most vulnerable in society. In Q1 2020, through the timeline described in Table 1, COVID-19 (named after "COrona VIrus Disease, 2019") had escalated from a a small marketplace in Wuhan, China, to cause the international social distancing and home isolation of over 1 billion people worldwide, with enormous social, political and economic repercussions to follow (Goodell, 2020; Sharif et al., 2020). The dislocating effects on the economy were expected to be unprecedented since the 1920's depression Baldwin and di Mauro (2020). However, in the middle of this chaos, an abnormality began to manifest. Brands that shared the same name with aspects of the 'coronavirus' began to report abnormal losses and sustained periods of trading volatility. While financial market conditions had deteriorated quite extensively, some companies were experiencing added pressures simply because their name or product base had in some way contained the term 'corona'. This research sets out to establish how this pressure manifested.

While not exclusive to pandemics, there has been some evidence of similar naming abnormalities. A classic in this genre is the renaming of companies to take advantage of the dot.com boom, documented in Cooper et al. (2001). Benos and Jochec (2013) found evidence that US companies whose names contain the words "America" or "USA" earn positive abnormal returns of about 6% per annum during World War II, the Korean War, and recent Middle East conflicts. Kot (2011) investigated similar response in Hong Kong, Biktimirov and Durrani (2017) in Canada, Mase (2009) for companies in the UK and Kadapakkam and Misra (2007) found evidence supporting significant declines in trading volume and prices on dates when tickers were changed for companies. Kashmiri and Mahajan (2014) analysed as to whether pricing abnormalities existed for entities that were founded on historical found family ties. Whereas, Cooper et al. (2005b) investigated the dynamics of this behaviour in falling markets, Cooper et al. (2005a) identified changing dynamics of flows in the markets for mutual funds. In recent works, Jain and Jain (2019) and

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https://doi.org/10.1016/j.frl.2020.101591
Received 17 April 2020; Received in revised form 5 May 2020; Accepted 14 May 2020
Available online 20 May 2020
1544-6123/

Table 1
Key dates in the Chinese COVID-19 outbreak.

Date	Event
December 31, 2019	Cases of pneumonia detected in Wuhan, China, are first reported to the WHO. During this reported period, the virus is unknown. The cases occur between December 12 and December 29, according to Wuhan Municipal Health.
January 1, 2020	Chinese health authorities close the Huanan Seafood Wholesale Market after it is discovered that wild animals sold there may be the source of the virus.
January 5, 2020	China announces that the unknown pneumonia cases in Wuhan are not SARS or MERS
January 7, 2020	Chinese authorities confirm that they have identified the virus as a novel coronavirus, initially named 2019-nCoV by the WHO.
January 11, 2020	The Wuhan Municipal Health Commission announces the first death caused by the coronavirus. A 61-year-old man, exposed to the virus at the seafood market, died on January 9 after respiratory failure caused by severe pneumonia.
January 13, 2020	First cross-border transmission as Thai authorities report a case of infection caused by the coronavirus. The infected individual is a Chinese national who had arrived from Wuhan.

Note: The above table consists of the key events relating to the Chinese epicentre COVID-19 outbreak. The dates represent dummy variables in the associated GARCH and DCC-GARCH estimations.

Sharma et al. (2020) analysed the pricing effects of companies adding the term blockchain to their names. Head et al. (2009) investigates the salience issue further, from the perspective of memorable stock tickers yielding excess returns, further reinforced by Xing et al. (2016). In recent years, naming effects have also been identified to have influential when considering the addition of the terms ‘blockchain’ and ‘cryptocurrency’ into the corporate identity of the company, or through the addition of highly speculative cryptocurrency projects (Corbet et al., 2020b).

2. Data and methodology

We investigate if there is evidence of a connection between the onset of the COVID-19 pandemic and any negative effects on companies with similarities in identity with the virus. To begin we conducted a thorough search using both Thomson Reuters Eikon and Bloomberg to search for all corporate entities, with active, liquid listed shares and market capitalisation values above $10 million as of February 2020 where Corona was a substantial component of business or the business name. The results are presented in Table 2, with evidence of the associated share price behaviour and volatility presented in Fig. 1. We can observe in the shaded regions of these graphs quite a strong variation in share price performance, with Constellation Brands, as owner and importer of the beer brand, Corona in the United States (STZ) and Corona Corp (5909.JP) presenting evidence of sharp declines during the pandemic period, while Coronation Fund Managers (CML), a South African company, presenting evidence of a fall in share price, but noticeably less than the other analysed companies. However, visual inspection presents evidence of sharp, elevated and sustained pricing volatility for both STZ and CML in comparison to that of 5909.JP.

In this study, we use hourly, and for robustness, daily returns to analyse the dynamic correlations between companies unfortunate to share their name with ‘corona’ and a range of financial assets including Chinese financial markets, denoted as the epicentre of the COVID-19 pandemic, the Dow Jones Industrial Average as a measure of international financial performance (Ekinci et al., 2019), gold as a measure of the international flight to safety (Akyildirim et al., 2020) and Bitcoin, which has presented evidence of inverse correlations with some international stock exchanges, thereby providing strong diversification benefits (Akhtaruzzaman et al., 2019; Akyildirim et al., 2019a). Our hourly returns are calculated as:

$$r_{t,h} = (\ln r_{t,h} - \ln r_{t,h-1})\text{x}100 \tag{1}$$

where $r_{t,m}$ is the return for hour h on trading day t. Time periods with no trading activity are determined to be best represented by the last traded price. Hourly data 11 March 2019 to 10 March 2020 (5,701 observations), where the period denoted as both pre- and post-COVID-19 pandemic (4,580 and 1,122 observations respectively) is denoted to be before and after 31 December 2019. Data is sourced through Thomson Reuters Eikon. Evidence of sharp declines are evident in the period thereafter through exceptionally changes

Table 2
Selected companies under observation.

Name	Ticker	Exchange	Industry
Constellation Brands Inc	STZ	New York Stock Exchange	Fortune 500 company, is an international producer and marketer of beer, wine and spirits. Constellation is the largest beer import company in the US, measured by sales, and has the third-largest market share of all major beer suppliers.
Corona Corp	5909:JP	Tokyo Stock Exchange	Manufactures and sells air-conditioners, heaters, and household equipment. The products include oil-heating units, air purifiers, humidifiers, and water heaters.
Coronation Fund Managers Ltd	CML	Johannesburg Stock Exchange	Coronation Fund Managers is a South-African third-party fund management company, headquartered in Cape Town. The company has locations in all South African major centres and offices in, Ireland, United Kingdom and in Namibia where it is represented by Namibia Asset Management a strategic partner.

Note: The above companies represent a sample that possesses the term ‘Corona’ as a substantial component of the corporate brand. In the case of Constellation Brands Inc, the company owns the beer branded ‘Corona’.

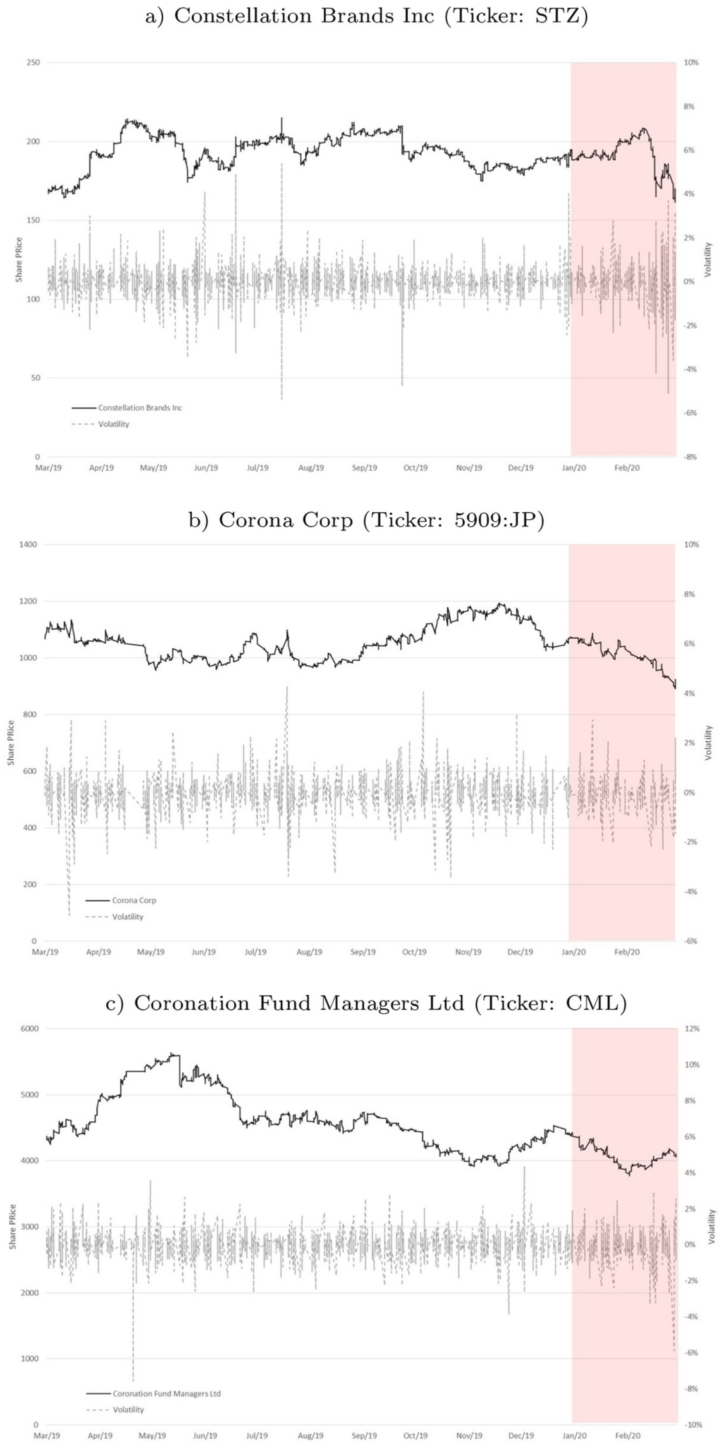

Fig. 1. Price and volatility behaviour of the selected companies. Note: The above figure represents the price (left-hand axis) and volatility (right-hand axis) behaviour of the selected companies. The shaded area to the right represents the period inclusive of the outbreak of the COVID-19 pandemic.

evident in the minima, skewness and kurtosis of these short-term returns. The summary statistics of the selected variables are presented in Table 3. Times are adjusted to Greenwich Mean Time to allow for comparability across the selected geographical regions. For the purpose of exchange comparison out-of-session, daily returns are used to measure dynamic correlations (similarly to the methods used by Akyildirim et al. (2019b), Katsiampa et al. (2019a,b). The time period also allows us to disaggreagate the effects

Table 3
Summary statistics of selected financial market variables.

Total Period Analysed (5701 observations)									
	STZ	5909:JP	CML	Shanghai	Shenzhen	DJIA	WTI	Gold	Bitcoin
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Std Dev	0.0045	0.0035	0.0044	0.0023	0.0028	0.0023	0.0047	0.0018	0.0092
Minimum	−0.0537	−0.0496	−0.0755	−0.0718	−0.0750	−0.0615	−0.0666	−0.0225	−0.0886
Maximum	0.0539	0.0429	0.0435	0.0252	0.0304	0.0295	0.0724	0.0175	0.0865
Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Skewness	−0.4122	−0.4904	−1.2390	−5.9042	−3.4336	−4.3918	−0.0317	−0.6658	−0.2070
Kurtosis	27.9622	33.7866	32.4863	196.9949	113.1889	140.2742	35.0332	17.6908	8.9373
Before Coronavirus (4580 observations)									
	STZ	5909:JP	CML	Shanghai	Shenzhen	DJIA	WTI	Gold	Bitcoin
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Std Dev	0.0041	0.0036	0.0043	0.0020	0.0025	0.0016	0.0039	0.0016	0.0097
Minimum	−0.0537	−0.0496	−0.0755	−0.0337	−0.0371	−0.0189	−0.0410	−0.0225	−0.0886
Maximum	0.0539	0.0429	0.0435	0.0252	0.0304	0.0175	0.0337	0.0138	0.0865
Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
Skewness	−0.1666	−0.5357	−0.9621	−0.5488	−0.2841	−1.0825	−0.5360	−0.4233	−0.2010
Kurtosis	34.1575	34.1932	33.7251	41.2553	33.4127	34.5759	10.4541	16.9029	8.3757
After Coronavirus (1122 observations)									
	STZ	5909:JP	CML	Shanghai	Shenzhen	DJIA	WTI	Gold	Bitcoin
Mean	−0.0001	−0.0001	0.0000	0.0000	0.0001	−0.0001	−0.0002	0.0000	0.0002
Std Dev	0.0060	0.0030	0.0049	0.0031	0.0037	0.0040	0.0072	0.0022	0.0067
Minimum	−0.0511	−0.0228	−0.0588	−0.0718	−0.0750	−0.0615	−0.0666	−0.0209	−0.0530
Maximum	0.0402	0.0294	0.0294	0.0129	0.0248	0.0295	0.0724	0.0175	0.0428
Variance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
Skewness	−0.6542	−0.1889	−1.9568	−11.6273	−6.9313	−3.8890	0.3583	−0.9857	−0.1866
Kurtosis	15.3899	25.5440	27.9893	271.3470	151.0273	72.4226	28.6361	14.7752	7.6318

Note: Hourly data is presented to the period 11 March 2019 and 10 March 2020, where the period denoted as both pre- and post-COVID-19 pandemic is denoted to be before and after 31 December 2019.

of the coronavirus pandemic from the generalised equity market rout that was occasioned by the widespread arrival of the virus to the USA and European countries (on Feb 27 new cases outside China exceeded those within China for the first time, as presented in Fig. 2) and the "oil price war" which began on 9-10 March. The changing correlations between the identified companies susceptible to the 'corona' naming shock and these financial assets are presented in Table 4. Comparing the periods both before and after the COVID-19

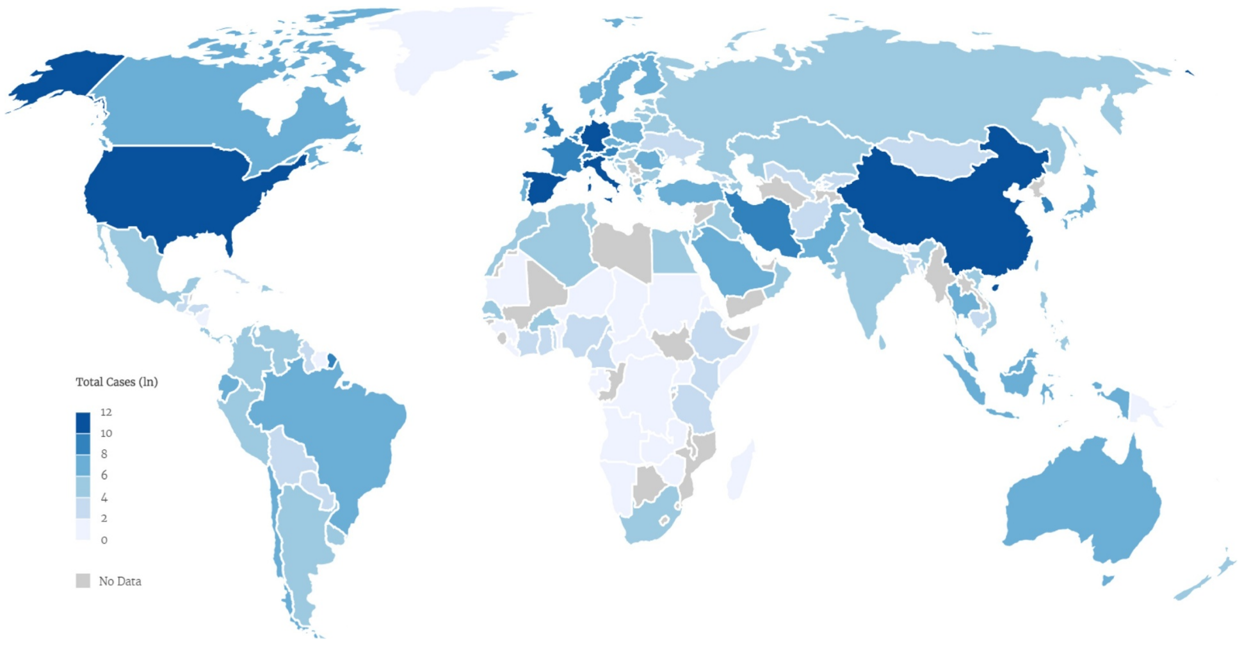

Fig. 2. Total number of announced COVID-19 cases worldwide. Note: The above figure represents the log of total calculated cases as of 27 February 2020 during the outbreak of the COVID-19 pandemic. Data is sourced from WHO estimates as available through Thomson Reuters Eikon.

Table 4
Correlations between identified companies and traditional financial markets, both before and after the COVID-19 outbreak.

Constellation Brands Inc

	Before COVID-19								*After COVID-19*						
	Constell.	Shang.	Shenz.	DJIA	WTI	Gold	BTC		Constell.	Shang.	Shenz.	DJIA	WTI	Gold	BTC
Constell.	1.000							Constell.	1.000						
Shang.	0.032	1.000						Shang.	0.286	1.000					
Shenz.	0.025	0.889	1.0000					Shenz.	0.315	0.967	1.000				
DJIA	0.394	0.165	0.1454	1.000				DJIA	0.813	0.243	0.263	1.000			
WTI	0.098	0.091	0.0802	0.302	1.000			WTI	0.552	0.484	0.488	0.601	1.000		
Gold	−0.065	−0.009	−0.0141	−0.180	0.013	1.000		Gold	0.285	0.335	0.347	−0.116	0.014	1.000	
BTC	0.012	0.0188	0.020	0.036	−0.007	0.039	1.000	BTC	0.650	0.343	0.385	0.429	0.279	0.468	1.000

Corona Corp

	Before COVID-19								*After COVID-19*						
	Cor C.	Shang.	Shenz.	DJIA	WTI	Gold	BTC		Cor C.	Shang.	Shenz.	DJIA	WTI	Gold	BTC
Cor C.	1.000							Cor C.	1.00						
Shang.	0.106	1.000						Shang.	0.502	1.000					
Shenz.	0.097	0.889	1.000					Shenz.	0.517	0.967	1.000				
DJIA	0.082	0.145	0.145	1.000				DJIA	0.263	0.243	0.263	1.000			
WTI	0.000	0.091	0.080	0.302	1.000			WTI	0.363	0.484	0.488	0.601	1.000		
Gold	−0.058	−0.009	−0.014	−0.182	0.013	1.000		Gold	0.334	0.335	0.347	−0.116	0.014	1.000	
BTC	−0.032	0.018	0.020	0.036	−0.007	0.039	1.000	BTC	0.363	0.343	0.385	0.429	0.279	0.468	1.000

Coronation Fund Managers Ltd

	Before COVID-19								*After COVID-19*						
	CFM	Shang.	Shenz.	DJIA	WTI	Gold	BTC		CFM	Shang.	Shenz.	DJIA	WTI	Gold	BTC
CFM	1.000							CFM	1.000						
Shang.	0.155	1.000						Shang.	0.383	1.000					
Shenz.	0.126	0.889	1.000					Shenz.	0.365	0.967	1.000				
DJIA	0.159	0.165	0.145	1.000				DJIA	0.702	0.243	0.263	1.000			
WTI	0.145	0.091	0.080	0.302	1.000			WTI	0.611	0.484	0.488	0.601	1.000		
Gold	−0.062	−0.009	−0.014	−0.180	0.013	1.000		Gold	0.293	0.335	0.347	−0.116	0.014	1.000	
BTC	0.044	0.018	0.020	0.036	−0.007	0.039	1.000	BTC	0.516	0.343	0.385	0.429	0.279	0.468	1.000

Note: In the above table, the changing correlations between the identified companies susceptible to the ‘corona’ naming shock and these financial assets. The date indicating the start of the pandemic is that of 31 December 2019, when cases of pneumonia detected in Wuhan, China, are first reported to the WHO.

pandemic for each of our selected companies. In the case of each analysed company, there is evidence of sharp elevated positive correlations between each and the selected analysed assets. However, for companies such as Constellation Brands Inc, the owner of the beer branded Corona, while possessing a correlation of 0.032 and 0.025 respectively with both of the Shanghai and Shenzhen stock exchanges, both correlations increase sharply to 0.286 and 0.315 respectively. All companies, investigated present evidence of sharp elevations in correlation, however, this interaction between STZ, CML and Asian markets is particularly interesting as domestic correlations do not follow the same trend. This evidence suggests a sharp decoupling of the market performance of each company with their domestic exchange with simultaneous evidence of interactions where none existed before.

To specifically analyse the dynamic correlations between the corporate entities exposed to reputational exposure due to naming similarity from the COVID-19 pandemic, we employ a standard GARCH (1,1) methodology of Bollerslev (1986) and extract dynamic conditional correlations (of Engle, 2002) that takes the form:

$$r_t = \alpha_t + \sum_{j=1}^{t} \sigma r_{t-j} + \sum_{j=1}^{t} \eta b_{t-j} + \sum_{j=1}^{t} \gamma v_{t-j} + u_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

where r_t, e_t and h_t are the returns of the investigated lagged corporate returns, international exchanges (Shanghai SE, Shenzhen SE and DJIA) and hedging alternatives (WTI, gold and BTC) at time t respectively. σ, η and γ represent the effects of lagged returns of each selected variable on the returns of the company’s hourly price volatility. The variance equation includes the long-term average volatility α_0. Similar methodological structures were utilised by Corbet et al. (2015) and Corbet et al. (2020a). We explore the dynamic co-movements via the dynamic conditional correlations of Engle (2002). The GARCH (1,1) specification requires that in the conditional variance equation, parameters α_0, α_1 and β should be positive for a non-negativity condition and the sum of α_1 and β should be less than one to secure the covariance stationarity of the conditional variance. Moreover, the sum of the coefficients α_1 and β must be less than or equal to unity for stability to hold. The GARCH (1,1) methodology used in this study has the following form:

$$R_t = a_0 + \sum_{j=1}^{3} b_j R_{t-j} + b_2 Sg_t + b_3 Sz_t + b_4 DJIA_t + b_5 WTI_t + b_6 G_t + b_7 BTC_t + D_t + \varepsilon_t \tag{4}$$

$$\varepsilon_t | \Omega_t \sim i.\ i.\ d. \quad N(0,\ h_t) \tag{5}$$

$$h_t = \omega + \alpha_1 h_{t-1} + \beta_1 u_{t-1}^2 + \sum_{i=1}^{10} D_{COVID} \tag{6}$$

R_{t-j} represents the lagged value of the selected companies, j number of hourly periods before R_t is observed. b_2Sg_t represents the interaction between the selected company and the Shanghai Stock Exchange, while b_3Sz_t and b_4DJIA_t represents the interactions with the Shenzhen Stock Exchange and DJIA respectively. Finally, b_5WTI_t, b_6G_t and b_7BTC represent the relationship between the selected companies and the returns of WTI, gold and Bitcoin respectively. D_t and $\sum_{i=1}^{t} D_v$ are included in both the mean and variance equations to provide estimates of the corporate pricing and volatility estimates relating directly to the COVID-19 pandemic. Bollerslev (1986) argued for restrictions on the parameters for positivity, $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$, and the wide-sense stationarity condition, $\alpha + \beta < 1$. While the GARCH (1,1) process is uniquely stationary if $E[log(\beta + \alpha\epsilon_t^2)] < 0$, Bollerslev (1986) also proved that if the fourth order moment exists, then the model can handle leptokurtosis. Bonferroni adjusted results are presented in this analysis. To cater the multiple hypothesis problem, we adjust the significance level using the Bonferroni correction, which leads to a significance level of 1%. The generalised Bonferroni method adjusts the significance level such that hypothesis $H_{0,(i)}$, $i = 1, \ ..., s$, is deemed rejected if and only if:

$$\hat{p}_{(i)} \leq \alpha_{(i)} \equiv k{\cdot}\alpha/s.$$

This procedure has the advantage of being robust to the dependence structure of the hypothesis tests.

3. Empirical results

In Table 5, we present the results of our DCC-GARCH methodology. We clearly observe that both STZ and 5909.JP have had no correlation with Chinese financial markets. However, this is not the case for CML. Each company analysed had strong positive

Table 5
DCC-GARCH estimates.

Dependent Variable	Constellation B.	Corona C.	Coronation F.M.
1st lag	0.0863***	−0.0306	0.0013**
	(0.0253)	(0.0270)	(0.0450)
2nd lag	0.0847**	−0.0663*	−0.0155
	(0.0394)	(0.0384)	(0.0390)
3rd lag	0.0052	−0.0076	−0.0002***
	(0.0463)	(0.0372)	(0.0411)
Shanghai SE	0.0472	0.0499	0.3666***
	(0.1062)	(0.0665)	(0.1355)
Shenzhen SE	0.0190	0.0429	−0.1959*
	(0.0863)	(0.0516)	(0.1173)
DJIA	0.7543***	0.1303***	0.3213***
	(0.0708)	(0.0361)	(0.0947)
WTI	0.0111	−0.0177	0.0861**
	(0.0258)	(0.0140)	(0.0359)
Gold	0.0517	−0.1317***	0.0004
	(0.0723)	(0.0417)	(0.0894)
Bitcoin	0.0042	0.0019	0.0188
	(0.0092)	(0.0081)	(0.0174)
COVID-19, Mean eq.	−0.0016***	−0.0011***	−0.0008***
	(0.0003)	(0.0004)	(0.0001)
Constant	0.0003***	0.0023***	0.0002***
	(0.0001)	(0.0004)	(0.0001)
COVID-19, Var eq.	0.0056***	0.0016*	0.0012***
	(0.0000)	(0.0000)	(0.0000)
ARCH	0.0240***	0.0760**	0.0993*
	(0.0070)	(0.0309)	(0.0517)
GARCH	0.8619***	0.8596***	0.7763***
	(0.0694)	(0.0692)	(0.2269)
Log likelihood	1719.07	3823.18	1518.22
Wald chi2(10)	194.72	60.20	60.32
Prob >chi2	0.0000	0.0000	0.0000

Note: The presented analysis was conducted using hourly data between the period 11 March 2019 and 10 March 2020 (5,701 observations), where the period denoted as both pre- and post-COVID-19 pandemic (4,580 and 1,122 observations respectively) is denoted to be before and after 31 December 2019.. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels respectively.

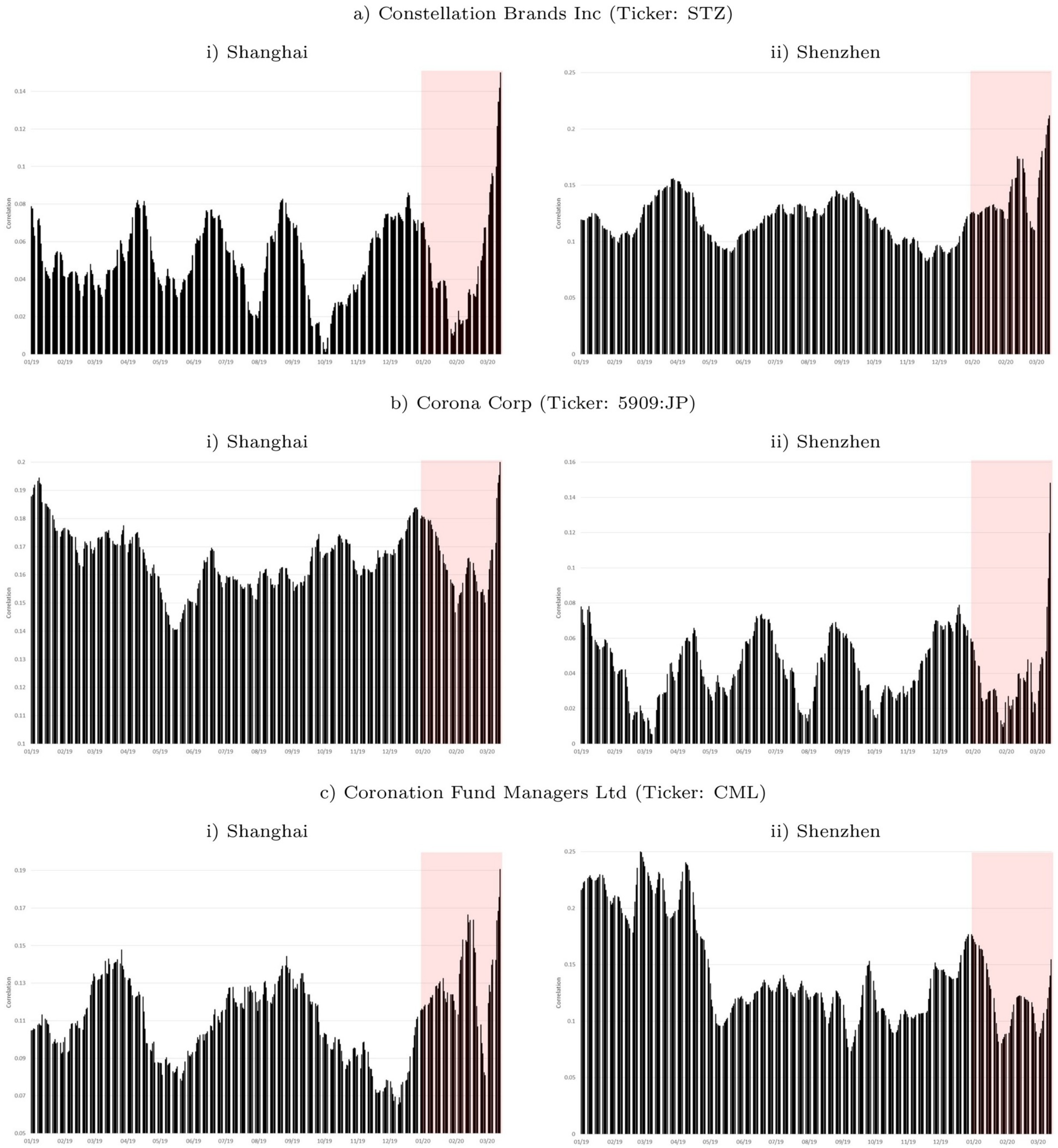

Fig. 3. Dynamic correlations between denoted company and the Shanghai & Shenzhen Stock Exchanges. Note: The above figure represents the estimated dynamic correlations between the selected companies and the Chinese stock exchange. The selected time periods presented no similar increases and decreases in correlation with domestic indices, indicated significant behavioural shift.

interactions with the DJIA, with STZ being the most positively related (+0.7543) as it is an American company traded on the NYSE. However, without any direct exposure outside of un-diversifiable risk, all of the analysed companies exhibit strong negative hourly returns in the period after the announcement of the existence of the COVID-19 pandemic. Further, there is an exceptionally large significant increase in hourly volatility for each of the analysed companies. While in Fig. 3, we observe the time-varying dynamic conditional correlations between each exposed company and the two key Chinese markets, the Shanghai and Shenzhen stock exchanges. In each case, after mitigating international effects, there is evidence of a sharp increase in dynamic correlations between the companies and Chinese markets with the exception of CML in South Africa. There is clear evidence that Constellation Brands (STZ) and Corona Corp (5909:JP) experienced a sharp and sustained deterioration in share prices outside of that expected through market-

Fig. 4. Dynamic correlations between non-Corona related companies and the Shanghai & Shenzhen Stock Exchanges. Note: The above figure represents the estimated dynamic correlations between the selected non-Corona named companies and the Chinese stock exchange as a robustness test of the provided results.

driven forces. The reasons for so would be deemed somewhat irrational, but mostly very unfortunately driven by name association. In general, all three considered companies have no interactions with hedging alternatives with two exceptions. 5909.JP has negative interactions with gold while CML has positive interactions with WTI. For robustness, a similar methodology was applied in Fig. 4 for comparable companies such as Anheuser-Busch InBev SA/NV, Ambev SA and United Breweries Co. Inc. We observe that similar sharp elevations in dynamic correlations with both the Shanghai and Shenzhen stock exchanges are not observed.

The source of this unwarranted reputational damage can be identified through a number of social media memes linking the beer 'Corona' which is owned by Constellation Brands (STZ) and the coronavirus, known as the COVID-19 pandemic. The intention to buy Corona beer in the United States among adults has fallen to its lowest level in the past two years, while the perception of the brand has also collapsed. In a 27 February 2020 release, 5W conducted phone surveys with 737 American beer drinkers, identifying that 38% of respondents would not buy Corona under any circumstances since the beginning of the coronavirus. Further, 16% of respondents stated confusion as to whether Corona beer was actually related to the coronavirus. A measure of how likely consumers are to buy the beer has fallen to a two-year low (according to YouGov, a market research firm). Corona's rating according to the firm had fallen to 51 from 75 at the start of the 2020, indicating a strong decline in sentiment towards the brand.

Further, the trading volumes in the investigated companies increased sharply during this time, indicating a potential role for AI and algorithmic trading strategies in the sharp decline in share price in line with the collapse of corporate sentiment. Overall, it is very much evident that companies such as STZ experienced a sharp and sustained deterioration on the fair valuation of their corporations during this time due to the unfortunate coincidence of sharing their names with an international pandemic.

4. Concluding comments

There is a significant body of research, to which we add, which suggests that name and brand salience is an important pricing element for companies. We document negative knock-on effects from the coronavirus pandemic on some companies with related names, over and above the actual economic effects. While such companies have not in any way been connected or responsible for the COVID-19 outbreak, they appear to have unfortunately been the target of sustained reputational damage. The role of algorithmic trading cannot be ruled out, as evident in the elevated traded volumes during these times.

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