Covid-19 Media Coverage and Stock Return

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Abstracts: This study empirically investigates the influence of news coverage related to COVID-19 and UK-wide stock market returns. A robust regression model is applied, and demonstrates the asymmetric dependence between stock market data and coverage of COVID-19 including media items, fake news and contagion. The study findings point to the benefits of utilising appropriate communications channels more strongly to minimise financial disruptions related to COVID-19. This particular research appears to be amongst the first research to consider both Covid-19 media coverage and stock return. Our data is limited for only a single country. More clarification for Covid-19 need qualitative understandings into UK market. The control variables fundamentally partial in this topic.

Keywords: Covid-19, Media Coverage, Stock Return, Asymmetric.

1. INTRODUCTION

The current novel coronavirus (COVID-19) pandemic has received intense and prolonged media coverage across broadcasters and publishers worldwide. In general, media news focuses strongly on events with major impacts, including infection outbreaks, and this tendency can cause panic among the general population (Blendon et al., 2004; Mairal, 2011; Young et al., 2013). News coverage of infectious illness may lead to extreme concern and has an impact on the attitude of investors (Tetlock, 2007). The emergence and spread of COVID-19 has caused impacts across the vast majority of states worldwide. The London stock exchange (LSE) declined by almost 25% in quarter 1, 2020, the biggest quarterly contraction in share values since the aftermath of Black Monday in October 1987.

Recently, the influence of representation of news in the media on stock return has increasingly become a focus for researchers. As part of this, theory-based and empirical literature has sought to uncover links between price movement within finance markets and news related to politics and economics (Smales, 2014; Broadstock and Zhang, 2019; Shi and Ho, 2020). Barberis et al. (1998) draw on findings from the field of psychology to point out over-reaction in the financial markets repeated news patterns, despite statistical evidence suggesting that little focus should be placed on such news. While previous research had shown at most a weak-to-moderate connection between news weight/loading and financial market activity in terms of extent, price and fluctuation (Berry and Howe, 1994; Mitchell and Mulherin, 1994), Ederington and Lee’s (1994) study found that fixed-schedule news statements related to macroeconomics are account for a notable proportion of market volatility in finance. Moreover, Klibanoff et al. (1998) found that in relation to closed-ended mutual funds, markets overreacted to news weighting. Other research has found that news sentiment can be linked to the way assets are allocated in managing portfolios (Uhl et al., 2015). There is agreement in the literature that information emerging through social media platforms significantly impacts upon volatility in the dynamics of stock markets, and in particular where the political/economic landscape is volatile.

With the outbreak of COVID-19 pandemic and extensive news space devoted to it, LSE faced significant loss over the first three quarters of 2020. The LSE reports that, “from January 4 to 29- August 2020 the FTSE 100, FTSE 250, FTSE 350, and FTSE all shares were off 24%, 19.5%, 23%, and 23% respectively. Also, markets in the USA and around the globe witnessed almost a 30% drop in the first quarter of 2020. Consequently, government stimulus programmes have been provided in many countries globally to mitigate the harms resulting from COVID-19 and to rebuild confidence in investors. While there was some recovery evident among the primary stock market indexes by mid-April 2020, significant uncertainty in financial markets has continued.

Although there are currently few studies of financial markets in relation to the coronavirus pandemic, initial work has produced intriguing findings. Among this work, Corbet et al. (2021) found that firms with names which have a similarity to the term coronavirus experienced negative impacts during the pandemic. Moreover, Akhtaruzzaman et al. (2021) demonstrate that conditional correlations in market return have risen significantly, in listed companies in the nations of the G7 and in China. Okorie and Lin's (2021) study supports these findings, identifying significant amounts of fractal contagion for market volatility and returns.. In addition, Conlon and McGee's (2020) and Goodell and Goutte's (2021) findings do not support the idea of cryptocurrency providing a refuge from the instability caused by the coronavirus pandemic. Haroon and Rizvi (2020) identify an association between equity market fluctuations and media news, and this effect is more pronounced within industries on which the pandemic is seen to have most impact. Additionally, Cepoi (2020) demonstrate asymmetrical dependence between the stock market and information pertaining to COVID-19, including contagion, news stories in the media and fake news, and suggests that suitable media channels should be utilised more intensively to ameliorate the financial uncertainty flowing from COVID-19.

By employing an OLS regression model, this study demonstrates asymmetrical dependency between stock markets and information on COVID-19. In particular, the Media Hype Index(MHI) significantly influences returns of F250, F350 and FALL; however, its influence on FI00 does not reach statistical significance. Moreover, the Sentiment Index (SEI) shows an impact in reducing returns in the F100 and FALL, an increase in return across F350, and no effects on the F250 index. Similarly, the Infodemic Index (INI) has a significant positive effect on F350 return and a significant negative effect on F100 and FALL returns. The Fake News Index (FNI) and Media Coverage Index (MEI) have no effect on any of the LSE indexes. In addition, estimates reveal a significant effect of fluctuations in the price of gold on all LSE equity indexes except for the F250 index.

This paper extends the literature in adding to the growing body of work considering ways in which markets respond to pandemic events (See: Al-Awadhi et al., 2020; Zhang et al., 2020; Albulescu, 2020; Haroon and Rizvi, 2020; Cepoi 2020). Studies of asset pricing have incorporated variables of mood variables as explanatory factors for the ways in which markets behave (e.g., Tetlock, 2007, Kaplanski and Levy, 2010, Su et al., 2017, etc.). The current study develops this focus consider health crises in particular, through investigating the potential role of media coverage of the pandemic, investor panic, and sentiment globally on unprecedented fluctuations in equity markets. Previous literature in this area points to the disconnection of perceptions of risk versus reality where coverage of a situation is not balanced, and states that this can cause either overreactions or underreactions in terms of sentiment (e.g. Vasterman et al., 2005, Mairal, 2011, Young et al., 2013, etc.). An additional contribution from this paper is to extend the sparse literature focused on examining stock market responses to the current pandemic. The current study also makes a contribution through its assessment of the UK response of financial markets to media communications concerning COVID-19. The remainder of this paper is presented as follows: The data is given in Section 2; a discussion of econometric approaches is given in Section 3, along with the study's findings; and conclusions are discussed in Section 5.

2. THE RELATION BETWEEN MEDIA COVERAGE AND STOCK MARKETS

Recently, many researches have examined the effect of the intensity of media coverage on the financial markets, which includes prices, returns, volatility, and liquidity (Aman & Moriyasu, 2017; Ichev & Marinˇc, 2018; Dang et al., 2020; Shyu et al., 2020; C. H. Wu & Lin, 2017). Aman and Moriyasu (2017) measure the media coverage by using the number of reports in four newspapers and find that high intensity of media reports enhance overreaction reactions in the financial markets. Atri et al. (2021) creates their own COVID-19 media coverage indicator and they conclude that media coverage of COVID-19 related news has a significant positive impact on the prices of oil and gold. In addition, Shyu et al. (2020) use media data from the China Core Newspapers Full-Text Database to point out that firms' earnings dispersion spread by the news is helpful in reducing the liquidity of firms shares. Meanwhile, behavioural finance research shows that investor sentiment affects investors decisions. Afterwards, some researchers assert that media coverage have a significant impact on investor sentiment and then affect investment decisions (Broadstock & Zhang, 2019; Gan et al., 2020; Dang et al., 2020; Haroon & Rizvi, 2020; Wu & Lin, 2017). After collecting sentiment information from Twitter Broadstock and Zhang (2019) find that the stock markets are affected by investors sentiment from media coverage. C. H. Wu and Lin (2017) divide news into ten categories, they find that good or bad media coverage information is significantly associated with abnormal stock returns. Baig et al. (2021) find that negative sentiment that associated with COVID-19-related news reduces financial market stability and liquidity.

Furthermore, many researchers show that there are different media coverage types, such as negative sentiment, media hype, fake news, and panic emotion (Atri et al., 2021; Cepoi, 2020; Shi & Ho, 2021). Smales (2015) collects news sentiment data from Thomson Reuters News Analytics and finds that there is a significant asymmetric effect of news sentiment on the volatility of gold futures. Moreover, some researchers assert that news sentiment may effect on stock markets less than media hype (Haroon & Rizvi, 2020; Biktimirov et al., 2021). Consistent with this view Biktimirov et al. (2021) find that stock market returns are associated with media hype of COVID-19 news than sentiment. Moreover, (Bastick, 2021; Vosoughi et al., 2018) show that individual's unconscious behaviour can be affected by false information. Vosoughi et al. (2018) suggest that fake news has broader audiences hence fake information is outspread faster, and farther than true information. Furthermore, fake news that related to health issues have been documented to lead to public health threats (Hou et al., 2020; Waszak et al., 2018).

Thus, on the one hand, few research papers examined the effect of covid-19 media coverage on the stock markets, but the impact of media coverage on the financial markets should never be ignored from the behaviour finance perspective. On the other hand, different COVID-19-related news indices, such as media hype, panic, sentiment and fake news, may have different impacts on the stock market. This paper attempt to fill these gaps in the literature.

3. METHOD

In this section, balanced panel data covering 50 working days (3 Feb. 2020 to 17 Apr. 2020) were used to examine impacts from news about COVID-19 upon stock market returns in the UK. F100 daily return is the dependent variable, while F250, F350, FALL, independent and control variables include PAI, NHI, FNI, SEI, INI, MEI, GR and LOK (see Table 1). The sample faced limitations such as the fact that stock index fluctuations were all impacted by

COVID-19 as a ubiquitous event worldwide, meaning that the separate individual variables were interdependent.

The variables selected in relation to COVID-19 news are provided by the platform RavenPack, which offers media analytics tools in real time, including on announcements of information which relates to COVID-19 and responses (Blitz et al., 2019). Previous studies (e.g., Smales, 2014, and Shi and Ho, 2021) utilise RavenPack to explore associations connecting news sentiment to volatility. Moreover, in controlling for sovereign default risk the platform includes CDS spread across covariates by country, in line with the recommendations of Grammmatikos and Vermeulen (2012). Moreover, gold price is used to benchmark the common global factor. Zhang et al. (2020) indicate that their empirical findings support a statistically significant connection linking twelve major stock markets to COVID-19 as a pandemic across the world. However, the authors find a weak relationship for the early pandemic compared to the periods that followed it.

Table 1. Variable definitions and measurements.

Group	Variable	Code	Measurement
Dependent variables	FTSE 100	F100	Firms code 100
	FTSE 250	F250	Firms code 250
	FTSE 350	F350	Firms code 350
	FTSE ALL	FALL	Firms code All

Independent variables	Panic Index	PAI	It measures the level of news chatter that makes reference to panic or hysteria and coronavirus. Values range between 0 and 100. The higher the index value, the more references to panic found in the media. Source: RavenPack https://coronavirus.ravenpack.com/
	Media Hype Index	MHI	It measures the percentage of news talking about the novel coronavirus. Values range between 0 and 100. Source: RavenPack https://coronavirus.ravenpack.com/
	Fake News Index	FNI	It measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19. Values range between 0 and 100 where a value of 2.00 indicates that 2 percent of all news globally is talking about fake news and COVID-19. Source: RavenPack https://coronavirus.ravenpack.com/
	Sentiment Index	SEI	It measures the level of sentiment across all entities mentioned in the news alongside the coronavirus. The index ranges between -100 (most negative) and 100 (most positive) sentiment while 0 is neutral. Source: RavenPack https://coronavirus.ravenpack.com/
	Infodemic Index	INI	It calculates the percentage of all entities (places, companies, etc.) that are somehow linked to COVID-19. Values range between 0 and 100.
	Media Coverage	MEI	It calculates the percentage of all news sources covering the topic of the novel coronavirus. Values range between 0 and 100. Source: RavenPack https://coronavirus.ravenpack.com/
	Gold Return	GR	Daily spot closing price of Gold. Source: Thomson Reuters.
Control variables	LOCKED	LOK	Growth is the annual growth rate of assets for the firm.

4. EMPIRICAL ANALYSIS

4.1. Descriptive Statistics and Discussion

This section provides the results of descriptive statistical analysis and univariate analysis applied to the variables in the study, estimating the effects of COVID-19 news for stock market returns of UK companies. Table 2 below presents findings of mean, median, maximum, minimum and standard deviation across each of the seven independent variables of performance, four variables for dependent earnings management, and the control variable. The findings support expectations in that mean F350 (0.001) is greater than mean F100 (0.000), F250, while FALL have the same means (-0.001).

Table 2. Descriptive statistics

Variables	Mean	Std. dev.	Median	Max.	Min.
F100	0.000	0.022	0.001	0.091	-0.109
F250	-0.001	0.023	0.001	0.084	-0.094
F350	0.001	0.022	-0.002	0.119	-0.082
FALL	-0.001	0.022	0.002	0.089	-0.105
PAI	4.933	2.428	4.325	15.580	0.990
MHI	44.932	15.462	47.010	73.010	9.010
FNI	0.996	0.605	0.825	2.750	0.140
SEI	-10.809	17.230	-9.685	28.790	-53.930
INI	55.241	16.399	61.975	70.750	13.970
MEI	65.417	14.730	69.140	83.520	27.530
GR	0.000	0.015	0.001	0.044	-0.053
LOK	0.000	0.022	0.001	0.091	-0.109

The MEI variable gives the highest mean, of 65.417, with the INI, MHI, PAI, FNI, GR, LOK then SEI variables giving respective values of 55.241, 44.932, 4.933, 0.996, 0.000, 0.000 and -10.809. Scales for stock market return factors and COVID-19 news are generally in line with comparable studies around the world, such as those of Cepoi (2020) and Umar and Gubareva (2021).

In terms of COVID-19 news, the findings generally point to a strong impact of UK companies on stock market returns in developed countries, and particularly in the UK. In addition, stock market return values vary significantly, and this might imply that findings would therefore vary also, supporting the hypothesis put forward here, that variations in COVID-19 news can influence the extent of stock market returns for UK companies.

4.2. Correlation Matrix

Restricted testing for potential multicollinearity issues was conducted within the regression analysis, as well as examining the associations with statistical significance found between variables. Table 3 presents the Pearson correlation coefficients for COVID-19 news proxy variables, stock price return estimations and controls. The FTSE proxy variables show the predicted statistically significant correlation with F100, F250, F350 and FALL, and these results were expected, in which all of these variables overlapped with each other. As all stock price return proxy variables were predicted to relate to firms' investments and effective behaviours, with the result that each proxy showed a significant relationship with each of the other factors. Finally, only PAI and MHI are associated with 0.642, MHI and MEI are 0.974 and INI and MEI, LOK is 0.945 and 0.689 respectively.

Table 3. Correlation coefficients

Variables	F100	F250	F350	FALL	PAI	MHI	FNI	SEI	INI	MEI	GR	LOK
F100	1.000											
F250	0.872	1.000										
F350	-0.995	-0.908	1.000									
FALL	0.995	0.917	-0.998	1.000								
PAI	0.115	-0.036	-0.076	0.085	1.000							
MHI	0.174	0.145	-0.165	0.171	0.642	1.000						
FNI	0.080	0.067	-0.072	0.079	0.559	0.568	1.000					
SEI	-0.078	-0.003	0.053	-0.064	-0.311	-0.251	-0.316	1.000				
INI	0.131	0.155	-0.137	0.139	0.400	0.916	0.391	-0.015	1.000			
MEI	0.163	0.147	-0.156	0.163	0.587	0.974	0.539	-0.151	0.945	1.000		
GR	0.213	0.207	-0.221	0.217	-0.147	-0.032	-0.063	0.147	0.013	0.004	1.000	
LOK	0.114	0.173	-0.138	0.130	-0.033	0.430	0.003	0.517	0.689	0.531	0.110	1.000

4.3. Normality Test

Normality is defined as the apportionment of residuals within a normal distribution, in order to employ the parametric assessment, Hair's (2006) assumption that data must have a normal distribution to examine hypotheses. Notably, the standardised normal probability plot/P-P normal probability plot, histograms, the quartile of a normal distribution plot/Q-Q normal probability plot, and a kernel density estimate plot are all variations of graphs that can be utilised to showcase the distribution of each variable. Therefore, this study sample reveals that the data was not normally distributed, which indicated that the other regression such as robust should be used rather than OLS (see Table 4).

Table 4. Normality Tests

	Panel A		Panel B (Shapiro-Wilk test)	
	Skewness	Kurtosis	Z. Stat	Sig. P.
F100	-2.082	9.001	4.465	0.000
F250	-0.504	11.283	6.897	0.001
F350	1.258	13.658	5.563	0.010
FALL	1.817	4.558	4.159	0.020
PAI	4.500	16.528	7.357	0.000
MHI	0.660	7.963	2.956	0.030
FNI	2.968	10.584	9.628	0.000
SEI	0.102	4.517	0.859	0.241
INI	6.852	99.254	8.458	0.000
MEI	0.998	3.819	4.662	0.045
GR	0.322	9.385	3.002	0.007
LOK	0.517	9.352	4.251	0.000

4.4. Autocorrelation

Autocorrelation is deemed one of the underlying assumptions for the OLS model, which is stated that there is no correlation in terms of the conditional x between different time periods (Corr , lx] = 0 or Corr[,] = 0, for all t ≠ s). Certainly, the characteristic assumption here is that what is possible to happen in time t + 1 can be prediction based on what happens in time t. Drukker (2003) documented that 'when it comes to the exact situation of autocorrelation, the results tend to be less consistent, since the standard error is usually underestimated and yet the coefficient estimates are not biased.

Dufour and Dagenais (1985) stated that the Durbin-Watson value of 2.0 (on a scale ranging from 0 to 4) indicates no autocorrelation within the study sample, despite the fact that the transformed model's error term is serially independent because it needs to be transformed if it has an autocorrelation issue. Therefore, this study used robust regression because we found our sample model challenged by autocorrelation (see Table 5).

Table 4. Durbin-Watson Test (Autocorrelation)

	F100	F250	F350	FALL
Durbin-Watson	1.748	0.984	1.587	1.480

4.5. Multicollinearity and Heteroscedasticity

In order to assess the higher possibility of multicollinearity issues, estimations were made of variance inflation factors (VIFs) as well as tolerances, as provided in Table 4. Based on accepted statistical findings, VIFs of over 10, and tolerances of under 0.2 point to significant multicollinearity. Table 4 demonstrates that this standard was met for each variable in the study, which includes the control and independent variables. Based on this, it is suggested that there is serious multicollinearity in three variables in model samples MHI, INI and MEI.

Heteroscedasticity is an issue which emerges with the use of the datasets selected for the study, and in particular in linking cross-sectional data, as here. The Breusch–Pagan/Cook–, Weisberg method was applied in evaluating heteroscedasticity, with □2 values (with bracketed p-values). For the F100 sample model, heteroscedasticity is insignificant, at 1.240 (0.256), while with the F250 sample model, it presents as significant, at 5.750 (0.016), as for the F350 sample model, at 7.750 (0.001). Finally, using the FALL sample model, heteroscedasticity is not significant, at 1.880 (0.170). On the basis of these findings, a nonparametric regression is appropriate, and robust regression is chosen for the analysis.

Table 6. VIF and Tolerance.

Variable	VIF	Tolerance
PAI	3.030	0.330
MHI	35.530	0.028
FNI	1.830	0.548
SEI	2.290	0.436
INI	28.170	0.036
MEI	32.930	0.030
GR	1.070	0.936
LOK	5.210	0.192
MEAN VIF	13.76	

Table 7. Heteroscedasticity Tests.

	F100	F250	F350	FALL
□2(1)	1.240	5.750	7.750	1.880
Prob > □2	0.256	0.016	0.001	0.170

4.6. Multivariate Analysis

Table 8 provides t-statistic and coefficient data from the assessment for robust regression models for COVID-19 news and stock price return. Regarding incorporated determinations and consideration, when robust regression is applied, the findings shown in Tables 4 and 5 reveal multicollinearity and heteroscedasticity problems for particular variables and regressions. Therefore, these regressions provide strong results compared with ordinary least squares regression estimates, despite the absence of a heteroscedasticity issue. It is seen in Table 6 that each model shown has strong overall significance, with the null hypotheses- slope coefficients =0 at .01- being rejected in each case. Based on model strength, they are explanatory for 12.7% (F100), 11.1% (F250), 12.4% (F350) and 12.3% (FALL). Thus, when comparing each model, F100 is found to be more explanatory than the others, as shown in Table 6.

Considering firstly t-statistic estimates for COVID-19 news variables, it is clear in the FTSE 100 (F100) data that the findings have statistical significance and are negative for SEI and INI for the 10% level, while being significant and positive for GR and LOK at 10% and 5%, respectively. As for the F250 model sample, it is noted that only two news variables have significantly affected stock price returns in the UK: PAI shows a negative effect, with -1.800 at a 10% level, and LOK a positive effect, with 1.690 at 10%. However, F350 shows more effect compared to prior models, wherein three COVID-19 news variables, namely MHI (- 1.660), GR (-1.660) and LOK (-2.350), have negatively affected stock price return, in addition to two COVID-19 news variables, SEI and INI that have positively affected stock price return, with 1.650 and 1.860, respectively. The findings here support those found in previous works (Allcott and Gentzkow, 2017; Zhang and Ghorbani, 2020; Corbet et al., 2020).

In conclusion, it should be noticed that the combination of all sample models as one sample leads to results that differ from the prior samples. PAI was only positive and significant in F250, but not in F100 and F350, and in the full sample (FALL) was insignificant (-0.440). MHI is found to be positive in F100 and negative in F350, whereas FALL shows a positive relationship, at 1.690. In addition, SEI and INI were only negative and significant in F100 and positive and significant in F350, but in the full sample were dominated by a negative and significant relationship, as previously discussed.

Table 8. Regression Estimates.

			F100			F250			F350			FALL	
		Coef.	Std. Err.	T.stat /Sig	Coef.	Std. Err.	T.sta t/Sig	Coef.	Std. Err.	T.sta t/Sig	Coef.	Std. Err.	T.stat/Sig
	PAI	0.000	0.001	-0.080	-0.002	0.001	-1.730*	0.001	0.001	0.420	-0.001	0.001	-0.430
Ordinary least squaresregression	MHI	0.001	0.001	1.680*	0.001	0.001	1.600	-0.001	0.001	-1.770*	0.001	0.001	1.700*
	FNI	-0.002	0.004	-0.530	0.001	0.004	0.300	0.001	0.004	0.340	-0.001	0.004	-0.360
	SEI	0.000	0.000	-1.440	0.000	0.000	-0.780	0.000	0.000	1.340	0.000	0.000	-1.360
	INI	-0.001	0.001	-1.930*	-0.001	0.001	-1.460	0.001	0.001	1.860*	-0.001	0.001	-1.880*
	MEI	0.000	0.001	-0.140	0.000	0.001	-0.180	0.000	0.001	0.280	0.000	0.001	-0.150
	GR	0.326	0.123	2.660**	0.281	0.130	2.160**	-0.330	0.124	-2.660***	0.315	0.121	2.620***
	LOK	0.012	0.005	2.370***	0.010	0.005	1.820*	-0.012	0.005	-2.420**	0.012	0.005	2.330**
	Constant	0.001	0.016	0.050	0.002	0.017	0.100	-0.003	0.016	-0.170	0.001	0.016	0.060
	F–stat/R^2	2.410**	0.127		2.070**	0.111		2.350**	0.124		2.320**	0.123	
	PAI	0.000	0.001	-0.080	-0.002	0.001	-1.800*	0.001	0.001	0.420	-0.001	0.001	-0.440
	MHI	0.001	0.001	1.600	0.001	0.001	1.520	-0.001	0.001	-1.660*	0.001	0.001	1.690*
Robust regression	FNI	-0.002	0.004	-0.590	0.001	0.004	0.340	0.001	0.004	0.390	-0.001	0.003	-0.400
	SEI	0.000	0.000	-1.700*	0.000	0.000	-0.800	0.000	0.000	1.650*	0.000	0.000	-1.870*
	INI	-0.001	0.001	-1.960*	-0.001	0.001	-1.470	0.001	0.001	1.860*	-0.001	0.001	-1.880*
	MEI	0.000	0.001	-0.150	0.000	0.001	-0.180	0.000	0.001	0.300	0.000	0.001	-0.160
	GR	0.326	0.199	1.650*	0.281	0.213	1.320	-0.330	0.199	-1.660*	0.315	0.197	1.680*
	LOK	0.012	0.005	2.350**	0.010	0.006	1.690*	-0.012	0.005	-2.350**	0.012	0.005	2.330**
	Constant	0.001	0.014	0.050	0.002	0.015	0.110	-0.003	0.014	-0.200	0.001	0.013	0.070
	F–stat/R^2	F–stat/R^2	1.760*	0.127		1.850*	0.111		1.650*	0.124		1.670*	0.123

Note: Asterisks denote significance at the *** – 0.01, ** – 0.05, and * – 0.10 level.

5. CONCLUSION

This paper contributes new, empirically-based findings regarding the association between news about COVID-19 and UK stock market returns. Through the use of a robust regression model, the findings reveal asymmetric dependence between stock market performance and information on COVID-19, including media news, contagion and fake news. The study findings point to the need to target appropriate communications channels more intensively to minimise the financial disruption stemming from the COVID-19 pandemic.

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DOI: https://doi.org/10.15379/ijmst.v10i2.1255