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Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil

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1. Introduction

The impact of public news sentiment on stock returns has received increasing attention in recent years. A growing body of empirical and theoretical studies has focused on understanding whether price movements in financial markets are driven by economic or political news (Smales, 2014; Broadstock and Zhang, 2019; Shi and Ho, 2020). The consensus is that the information arriving from social media channels exerts a significant influence on the stock market dynamic, especially in times of economic or political uncertainty.

Given the COVID-19 pandemic and the considerable amount of related news, stock markets around the world have suffered enormous losses in the first three months of 2020. According to Bloomberg, “through 1 p.m. on March 18, the S&P 500 index was off 27% for the year to date, Germany's DAX was down 38% and Japan's Nikkei was off 29%.” Consequently, the governments around the world have undertaken a series of stimulus packages to offset the damages produced by the pandemic and to regain investor's confidence. Although the major stock market indexes have partially recovered in the middle of April 2020, a great deal of financial uncertainty remains.

While the current literature relating the COVID-19 pandemic to financial markets is limited, the existing studies have provided some very interesting results. For example, Corbet et al. (2020a) reveal a negative knock-on impact from the coronavirus on some companies with similar names. In addition, Akhtaruzzaman et al. (2020), show that listed firms across China and G7 countries have experienced significant increases in the conditional correlations for the market returns. This fact is confirmed by Okorie and Lin (2020) which found considerable fractal contagion on the market return and market volatility. Moreover, Conlon and McGee (2020) and Goodell and Goutte (2020) suggest that cryptocurrencies do not act like safe havens during COVID-19 turmoil.

In this paper, I contribute to the literature by investigating the stock market's reaction to coronavirus news in the top six most affected countries by the pandemic[1]. By employing a panel quantile regression model, I show that the stock markets present asymmetric dependencies with COVID-19 related information. Specifically, the fake news exerts a negative influence on the lower and the middle quantiles throughout the distribution of returns; however, their impact is not statistically significant for the extreme values. Moreover, the media coverage leads to a decrease in returns across middle and upper quantiles and has no effects on the lower ones. Similarly, the financial contagion across companies is detrimental to returns from 50^{th} to 75^{th} quantiles. Furthermore, the estimates show that the gold price dynamic has a nonlinear impact on equity markets, especially during extreme bearish and bullish markets. The rest of the paper has the following structure: Section 2 presents the data, Section 3 discusses the econometric approach, and the results are in Section 4. Section 5 concludes the paper.

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[1] I select the USA, the UK, Germany, France, Spain and Italy, considering the high number of persons infected with COVID-19. On 21 April 2020, the countries mentioned above were the only ones with more than 100.000 total cases according to Worldometer https://www.worldometers.info/coronavirus/ .

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2. The data

To investigate the impact exerted by COVID-19-related news on stock market return, I use a balanced panel covering 50 working days, from 3 February 2020 to 17 April 2020. The dependent variable includes daily returns of DJIA, FTSE 100, DAX, CAC 40, IGBM, and MIB. The choice of this sample displays some disadvantages since the dynamic of stock indexes was influenced by the same global event, i.e., the COVID-19 pandemic, which thereby causes dependence between individual countries in the panel[2]. Zhang et al. (2020) confirm this empirical fact when investigating the correlation across the top 12 major stock markets before and after the World Health Organization declared COVID-19 to be a worldwide pandemic. According to them, “the correlations in February are relatively low, but they increase substantially upon entering March.” Additional details of the correlation matrix during the analyzed period are in Table 1.

The COVID-19 news-related variables come from the RavenPack analytics tool. This platform provides real-time media analytics, which explores announcement describing essential issues linked to the Coronavirus pandemic, such as panic, media hype, and fake news. It covers sources such as Dow Jones Newswire, Wallstreet Journal, or StockTwits, among others (Blitz et al., 2019). For example, Smales (2014) or Shi and Ho (2020) have previously used this news monitor database to investigate the link between news sentiment and implied volatility. Furthermore, to control for the sovereign default risk, I include country CDS spreads among covariates as recommended by Grammatikos and Vermeulen (2012). Additionally, I consider gold price as a benchmark for the common global factor[3]. A detailed data description and its source are presented in Table 2.

3. Methodology

Considering the excessive market volatility during the COVID-19 financial turmoil, I employ a panel quantile regression framework. Unlike other econometric approaches that only focus on the mean effects, the quantile regression model is a more powerful tool for handling fat tails or extreme values throughout the asset return distributions (du Plooy, 2019). Generally, at any level (τ) across the distribution of y given a set of variables x, the conditional quantile shows $Q_y(\tau|x) = \inf\{k\!: F(k|x) \geq \tau\}$ where $F(\bullet|x)$ is the conditional distribution function. Thereby, the panel quantile regression is illustrated by the following specification:

$$Q_{y_{i,t}}(\tau|x_{i,t}) = \alpha_i + x_{i,t}^T\beta(\tau). \tag{1}$$

In Eq. (1) $i = \overline{1, N}$ and $t = \overline{1, T}$, denote the number of countries and days, respectively, $y_{i,t}$ is the stock market return, $x_{i,t}$ denotes the set of covariates, $\beta(\tau)$ is the common slope coefficient while α_i is individual-specific fixed effect coefficient. To account for the unobserved country heterogeneity, I follow Koenker (2004), which treats the fixed effects as nuisance parameters. The ingenuity of this approach comes from the introduction of a penalty term in the minimization problem leading to the following algorithm:

$$\min_{(\alpha,\beta)} \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{i=1}^{N} w_k \rho_{\tau_k}(y_{i,t} - \alpha_i - x_{i,t}^T\beta(\tau_k)) + \lambda \sum_{i}^{N} |\alpha_i|. \tag{2}$$

In Eq. (2) $K$is the quantiles’ index, ρ_{τ_k} is the quantile loss function while w_k is the relative weight given to the k^{th} quantile. The penalty term λ is diminishing the impact of individual effects on achieving higher efficiency for the global slope coefficients.

The quantile regression represents an important class of nonlinear data models (Galvao et al., 2020) and has become a successful tool in economics and finance due to its ability to draw inferences about observations that rank below or above the population conditional mean. In some cases, the quantile-varying estimates reveal that OLS methods provide an incomplete picture regarding the link between variables, especially for extreme events. However, by estimating the entire quantile processes one can capture the presence of some potential nonlinear relationships between the dependent variable and the covariates which could not be brought to light by other linear approaches. Recent findings have extended the basic method of Koenker (2004) for panel data by accounting for the presence of nonlinear conditional quantile functions (Mizera, 2018; Geraci, 2018). All in all, the quantile regression enjoys a number of features such as robustness to outliers and equivalence to monotone transformations (Gilchrist, 2000) making it a useful tool when it comes to capturing some stylized facts, especially when the assumption of linearity may not be appropriate.

The characteristics of the panel necessitate two additional comments. First of all, the existence of cross-sectional dependence is likely to bias the estimated standard errors. To overcome this problem, Gaibulloev and Sandler (2014) suggest the usage of a standard factor-augmented regression. However, in a quantile framework, this issue is less investigated[4], which leads us to use a proxy for common global factor[5] such as gold or oil prices. Second, Baur et al. (2012) bring strong empirical evidence indicating that current returns exhibit a positive autoregressive behavior on lower quantiles and a negative one across higher ones. For this reason, I include one day lagged returns among covariates. Details regarding the correlation matrix of covariates are presented in Appendix 1.

[2] **Breusch and Pagan (1980)** test which account for large T, and small N reject the null hypothesis of no cross-section dependence at the 1% level.

[3] **Hood and Malik (2013)** show that gold serves as a “hedge and a weak safe haven for US stock market." This hypothesis is confirmed by **Wu et al. (2019)** during both extreme bearish and bullish markets.

[4] Even though **Harding and Lamarche (2014)** and **Harding et al. (2020)** propose estimators robust to cross-sectional dependence in a quantile regression framework, they are applicable when both T and N are large, which is not the case here.

[5] Based on pairwise **Dumitrescu and Hurlin's (2012)** panel causality test, gold return homogeneously causes stock market returns but not otherwise. When considering the crude oil price as a proxy for the common global factor no significant evidence of causality comes to light.

Table 1
Correlation coefficients of stock market returns.

	USA	UK	Germany	France	Spain	Italy
USA	**1.0000**					
UK	0.6082	**1.0000**				
Germany	0.5314	0.7567	**1.0000**			
France	0.5673	0.8122	0.8531	**1.0000**		
Spain	0.4971	0.7224	0.7600	0.7731	**1.0000**	
Italy	0.4465	0.6751	0.7290	0.7322	0.7633	**1.0000**

Table 2
The data.

Variables	Description and source
Stock market return (RET)	Daily returns are calculated as: $R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1$, where $P_{i,t}$ is the value of the market index in day t for country i. Source: Thomson Reuters.
The panic Index (PI)	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/
The Media Hype Index (HY)	It measures the percentage of news talking about the novel coronavirus. Values range between 0 and 100. Source: RavenPack https://coronavirus.ravenpack.com/
The 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/
The Country Sentiment Index (CSI)	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/
The Contagion Index (CTI)	It calculates the percentage of all entities (places, companies, etc.) that are reported in the media alongside COVID-19. Values range between 0 and 100. Source: RavenPack https://coronavirus.ravenpack.com/
The media coverage Index (MCI)	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/
Sovereign CDS	Credit Default Swap (CDS) rate on 5-year bonds issued by the national government. Source: Thomson Reuters.
Gold Price	Daily spot closing price of Gold. Source: Thomson Reuters.

4. Results

Tables 3 provide the estimated coefficients for a representative selection of quantiles. To assess robustness for the results, I additionally report the estimates of a Seemingly Unrelated Regression (SUR), which is recommended for handling cross-sectional

Table 3
Estimation results (p-values in pharenthesis).

Variables	Quantiles 5th	10th	25th	50th	75th	90th	95th	Panel SUR
Intercept	**-0.0563**	**-0.0431**	**-0.0180**	0.0006	**0.0150**	**0.0331**	**0.0435**	**-0.0038**
	(0.0000)	**(0.0000)**	**(0.0000)**	(0.6326)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
Lagged Returns	-0.0540	-0.0255	-0.1220	-0.1018	**-0.2398**	**-0.3452**	**-0.4079**	**-0.2250**
	(0.5366)	(0.6540)	(0.1566)	(0.2791)	**(0.0165)**	**(0.0002)**	**(0.0002)**	**(0.0000)**
Panic Index	-0.0004	-0.0058	-0.0010	-0.0035	-0.0030	0.0058	0.0024	-0.0012
	(0.9694)	(0.5596)	(0.8207)	(0.2179)	(0.3893)	(0.4257)	(0.7802)	(0.7487)
Media Hype Index	-0.0679	-0.0401	0.0144	0.0179	0.0154	0.0108	0.0255	**0.02196**
	(0.2095)	(0.4601)	(0.7517)	(0.2051)	(0.1712)	(0.5383)	(0.1847)	**(0.0774)**
Fake News Index	0.0061	**0.0040**	**-0.0024**	**-0.0051**	**-0.0041**	-0.0021	-0.0001	**-0.0035**
	(0.1334)	**(0.0740)**	**(0.0956)**	**(0.0000)**	**(0.0003)**	(0.5605)	(0.9865)	**(0.0270)**
Sentiment Index	-0.0013	-0.0007	0.0005	0.0006	0.0018	0.0024	0.0028	0.0004
	(0.4354)	(0.6186)	(0.7209)	(0.3883)	(0.1714)	(0.1583)	(0.1933)	(0.5431)
Contagion Index	0.0136	-0.0085	-0.0092	**-0.0129**	**-0.0184**	-0.0075	-0.0133	**-0.0170**
	(0.4354)	(0.6754)	(0.4280)	**(0.0511)**	**(0.0016)**	(0.6808)	(0.3699)	**(0.0333)**
Media Coverage	-0.0847	-0.0758	**-0.0769**	**-0.0367**	-0.0367	**-0.1109**	**-0.1412**	**-0.0815**
	(0.1068)	(0.1645)	**(0.0833)**	**(0.0163)**	(0.1173)	**(0.0375)**	**(0.0221)**	**(0.0016)**
Sovereign CDS	-0.0047	0.0095	-0.0104	-0.0139	**-0.0283**	-0.0138	-0.0160	-0.0091
	(0.8993)	(0.7663)	(0.6980)	(0.1768)	**(0.0017)**	(0.3737)	(0.4532)	(0.4397)
Gold Returns	**0.5554**	**0.4286**	**0.3030**	0.1941	**0.3008**	**0.5698**	**0.7541**	**0.4556**
	(0.0000)	**(0.0121)**	**(0.0096)**	(0.2245)	**(0.0443)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
Observations	**300**	300	300	300	300	300	300	300

dependence across a panel with small N and large T (Sarafidis and Wansbeek, 2012). According to the estimation results, several interesting facts come to light. First of all, fake news appears to exhibit a negative nonlinear U-shaped impact during normal market conditions, i.e., from 25th to 75th, throughout the distribution of returns. This empirical fact is illustrating the growing importance of online fake news in the globalized financial markets and its implications for stock trading (Allcott and Gentzkow, 2017; Zhang and Ghorbani, 2020). However, it is worth mentioning that fake news is not affecting stock market returns at the times of extreme bearish (5th quantile and lower) and bullish markets (95th quantile and upper) and appears to influence the stock dynamic in a positive manner during periods of harshly decline (around the 10th quantile).

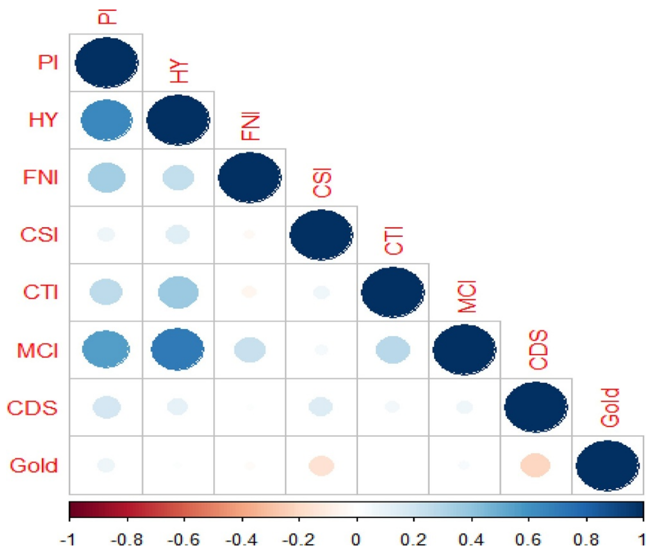
Second, the media coverage has a negative and monotonically decreasing impact from the middle to superior quantiles. This result is in line with the previous findings reported in the literature by Fang and Peress (2009), arguing that "the breadth of information dissemination affects stock returns." A slightly similar effect is noticeable for the contagion index, indicating that the higher the numbers of entities related to COVID-19 news, the lower the expected stock market returns, especially during recovering periods.

Third, the superior quantiles of returns distribution exhibit negative dependence on past performances, while smaller and middle quantiles are not affected by this phenomenon. This empirical fact confirms the previous findings reported in Baur et al. (2012), which suggests that the stock market underreacts to macroeconomic news if they are in a bad state. Furthermore, the gold return has a nonlinear positive correlation with the stock markets, which amplifies during extreme bearish and bullish periods indicating that it does not behave as a "Safe Havens" asset. This intersting result confirms the findings reported by Corbet et al. (2020b). All relevant estimates retain their signs and statistical significance under SUR specification illustrating in this way their robustness.

5. Conclusions

This study offers novel empirical evidence on the relationship between COVID-19 related news and stock market returns across the top six most affected countries by the pandemic. By employing a panel quantile regression model, I show that the stock markets present asymmetric dependencies with COVID-19 related information such as fake news, media coverage, or contagion. The result suggests the need for more intensive use of proper communication channels to mitigate COVID-19 related financial turmoil.

Appendix 1. The correlation matrix of covariates



Credit authorship contribution statement

Cosmin-Octavian Cepoi: Conceptualization, Methodology, Data curation, Software, Writing - original draft, Writing - review & editing.

CRediT authorship contribution statement

Cosmin-Octavian Cepoi: Conceptualization, Methodology, Data curation, Software, Writing - original draft, Writing - review & editing.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101658.

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