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INFLUENCE OF COVID-19 RELATED MEDIA AND NEWS ON THE STOCK AND CRYPTO MARKETS

The entire world was significantly impacted by the COVID-19 pandemic, leading to confusion and turbulence in healthcare systems, as well as to extreme uncertainty in the financial realm. There was a profound distress in stock markets due to the enormously elevated levels of risk instigated by the pandemic, which additionally inflated investors' losses. The contagion was supplemented by a surge of false stories that appear to be news ("fake news") that circulated throughout all media channels, thus additionally amplifying uncertainty. This paper expands the previous literature by investigating media impact on prominent indices of the stock and cryptocurrency markets. RavenPack Panic and Fake News indices were utilized to examine their influence on S&P 500 and crypto (Royalton CRIX) indices' daily movements by employing OLS and quantile regression. The results exhibit that there are noteworthy dependencies over the conditional distribution, but they present only a small influence on observed indices. Fake news influences the cryptocurrencies' daily movements in a bearish market, however the effect is very weak. Furthermore, media-induced panic is significant in both exceptionally bearish and bullish conditions considering S&P 500 daily returns, but is also exhibiting low impact.

Keywords: COVID-19, panic, fake news, S&P500, cryptocurrency index, Quantile regression

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1. INTRODUCTION

The global COVID-19 pandemic was an extreme historical event with tremendous implications and corollaries everywhere, creating an urgent need to extensively scrutinize its course and impact in depth and learn lessons from it. The spring of 2020 brought a shock with the emergence of a (then) unnamed lethal illness caused by a new type of coronavirus. Negative effects of the disease struck the whole world, including investors and financial institutions. Both traditional (equities) and novel (cryptocurrencies) markets showed symptoms of panic and frenzy, driving volatility to new heights. Analysis of intraday oscillations in the financial markets showed that there was a substantial shift in the financial assets' volatility, which peaked during the COVID-19 outbreak (Farid et al., 2021).

Stock markets were heavily impacted by the pandemic; the DJIA dropped 3,000 points, losing 12.9% in a single day, and the New York Stock Exchange had to suspend trading several times during this period (Frazier, 2021). However, among the first that successfully recuperated was the US market, which recaptured more than 85% of the losses caused by the collapse (Ganie et al., 2022). The crypto market also experienced dramatic events. In March 2020, in a single day bitcoin stunningly lost half of its value, although it regained most of it in the following period (Forbes, 2020). Regardless of the mayhem in the crypto market, some researchers implied that bitcoin (as well as US government bonds) could function as safe havens in the periods of elevated volatility within the COVID-19 crisis (Goodell & Goutte, 2021; Le et al., 2021).

Social media platforms have proven to be one of the central and most important points for obtaining information about current events, a phenomenon that gained even more momentum during the pandemic and social (physical) distancing. Under these circumstances, a substantial upsurge in the use of social media was observed, estimated at an increase of 20 to 87% worldwide (Naeem et al., 2021). Online social platforms are the primary channel for spreading rumors, and in this context, the quality of information is an essential issue (De Souza et al., 2020). Evanega et al. (2020) examined more than 38 million articles published in English language globally in online news, blogs, podcasts, TV and radio and found that the majority of COVID-19 misinformation is passed on by the media without questioning or correction. The significance of the COVID-19 "infodemic" should not be taken lightly, as it was found that fear and panic were amplified by the misinformation (e.g., Gabarron et al., 2021).

The purpose of this paper is to explore the influence of panic and fake news related to COVID-19 on a broad stock market index and a cryptocurrency market

index. For this purpose, a quantile regression is applied to the RavenPack Fake News and Panic indices over the S&P 500 and Royalton CRIX indices¹. The novelty of this work is that it attempts to answer the question of the nature of the interconnectedness between the dynamics of fake news dissemination and both traditional as well as progressive financial markets; more specifically, exploring the impact of media and news on the crypto market by using a cryptocurrency index. To the best of our knowledge, there is no previous research which employed this type of data and methodology (quantile regression) in conjunction with COVID 19 related media indices and the crypto indices.

After this introduction, the rest is organized as follows. The second section discusses the literature review, focusing on the most influential and relevant papers. The following section presents the methodology and data. Section 4 presents the main findings, discusses the outcomes, and relates them to previous work. Lastly, conclusions are drawn in section 5.

2. LITERATURE REVIEW

As there has been a huge surge in research due to the substantial impact of COVID-19 on economies worldwide, the influx of articles on these topics has been methodically and systematically reviewed using the VOS Viewer analytical tool. Web of Science, one of the most prominent global scientific databases, was browsed in October 2023 for all publications regarding stock market and COVID-19, yielding a total of 1580 results. The co-occurrence of keywords was examined and 4604 keywords were found. From this population, a subset of 150 keywords with greatest total link strength was selected, which were used at least 10 times in the literature. Excluding "stock market" and "covid-19", as these had already been pre-selected, the ten most frequently used terms are listed in Table 1.

¹ This article is a thoroughly revised, upgraded and amended work stemming from the bachelor thesis of Kuzmić (2022), mentored by Sajter, D.

Table 1.

MOST FREQUENT TERMS IN THE WEB OF SCIENCE LITERATURE CO-OCCURRING WITH STOCK MARKET AND COVID-19, OCTOBER 2023.

No.	Keyword	Occurrences	Total link strength
1	return	307	1637
2	volatility	289	1388
3	impact	248	1064
4	risk	179	928
5	crude oil	114	809
6	spillover	111	689
7	contagion	111	656
8	prices	109	515
9	time series	106	531
10	volatility spillover	102	649

Source: Authors' calculation

In the "universe" of keywords extracted from the existing literature, crucial topics related to this paper (fake news, panic, etc.) were not found or are very infrequently used, indicating a gap in the field and provides space for the originality and novelty of the research presented here.

The citations were also examined in order to identify the most influential papers. From the total of 1580 documents, 100 documents with the largest number of links were selected, which were cited at least 10 times. The five most cited papers are Baker et al. (2020); Sharif et al. (2020); Al-Awadhi et al. (2020); Ashraf (2020); and Corbet et al. (2020). They are briefly presented here to provide a broader perspective on the findings in this area and to describe the main interests of the most frequently cited researchers.

Baker et al. (2020) used text-based methods to develop the points of large daily stock market movements back to 1900 and in terms of overall stock market volatility back to 1985, and showed that government restrictions on commercial activities and voluntary social distancing are the main reasons why the US stock market has reacted much more violently to COVID-19 than to previous pandemics. Sharif et al. (2020) analyzed the relationship between the spread of COVID-19, the oil price volatility shock, the stock market, geopolitical risk, and economic policy

uncertainty in the US in a time-frequency framework by applying the coherence wavelet method and wavelet-based Granger causality tests to US data. They found that the impact of COVID-19 on geopolitical risk is significantly higher than on economic uncertainty in the US and that COVID-19 risk is perceived differently in the short and long run and could be primarily perceived as an economic crisis. Al-Awadhi et al. (2020) examined the Hang Seng Index and the Shanghai Stock Exchange Composite Index during the COVID-19 outbreak and found, unsurprisingly, that the pandemic negatively affects stock market returns. Specifically, his panel data regression showed that stock returns were significantly negatively related to the daily growth of total confirmed cases and the daily growth of total deaths caused by COVID-19. Ashraf (2020) also used panel data analysis to link daily confirmed COVID-19 cases and deaths and stock market returns of 64 countries in the first quarter of 2020 and found that stock market returns responded quickly to the COVID-19 pandemic and declined as the number of confirmed cases increased. Corbet et al. (2020) showed that the volatility relationship between major Chinese stock markets and bitcoin has evolved during the time of the pandemic, suggesting that these assets do not serve as a hedge in times of severe financial and economic disruption.

Regarding cryptocurrencies and pandemics, research has identified a complex relationship between COVID-19 and bitcoin. Demir (2020) and Nguyen (2022) both suggest that bitcoin can serve as a hedge against the uncertainty caused by the pandemic, with Demir (2020) finding a shift from a negative to a positive relationship between bitcoin and COVID-19 cases and deaths. However, Nguyen (2022) also points to the influence of the stock market on bitcoin in times of high uncertainty, such as the pandemic. Maghyereh (2022) explores this further, noting that the volatility dynamic between bitcoin and traditional financial assets becomes positive during the pandemic, indicating a possible shift in the relationship. Sahoo (2021) confirmed the existence of a unidirectional causal relationship between COVID-19 cases and cryptocurrency price returns, showing that prior knowledge of the growth of the COVID-19 pandemic helps predict cryptocurrency returns. Katsiampa et al. (2021) emphasized the role of ethereum and other altcoins as well as decentralized finance products that gained momentum during the outbreak.

Literature also shows that in countries most influenced by the pandemic there is a connection between stock market returns and COVID-19 related news. Employing panel quantile regression which comprised stock market returns (measured by DJIA, FTSE 100, DAX, CAC 40, IGBM, and MIB indices) and media indices, Cepoi (2020) exhibited that information related to COVID-19 such as media coverage, fake news or contagion are asymmetrically dependent with stock market returns. It was shown that fake news displayed a nonlinear negative U-shaped influence in regular market situations, i.e., from 25th to 75th percentile, highlighting

that fake news in intense bullish and bearish markets are not significantly explicating volatility of the returns in the stock market. Moreover, these findings display a negative impact of media coverage and contagion index on upper percentiles of stock market returns (Cepoi, 2020, p. 4). Likewise, Rahadian and Nurfitriani (2022) explored the influence of COVID-19 related news on five Southeast Asian stock markets², examining different time periods in their analysis. They maintain that different countries present different results depending on the research period; in other words, diverse independent variables have diverse influences contingent on the period and the observed market. Generally, country sentiment and fake news indices are characterized as variables that impact returns of the stock markets in the observed area.

Additionally, Haldar and Sethi (2021) tested the impact of COVID-19 media coverage on the volatility and stock market returns in the countries most struck by the virus. The findings imply that observed countries showed low to negative returns with high volatility only in the early period of COVID-19 crisis, however there was a normalization of returns with the persistence of high volatility in the subsequent period.

Regarding cryptocurrencies as non-classic financial assets, there are findings which suggest that bitcoin could function as a safe-haven during COVID-19 turmoil. Mahdi and Al-Abdulla (2022) state that gold and bitcoin might be effective alternatives when hedging against market turbulence. Employing a quantile-on-quantile regression analysis they found dependencies when using RavenPack media indices. Utilizing a non-parametric approach, they investigated asymmetric dependencies on external shocks vis-à-vis news related to COVID-19 on gold and bitcoin returns, and suggest that the panic index indicates positive relations, thus causing growth of returns for both bitcoin and gold. Asymmetric relations concerning "infodemic" and media indices indicate that these measures might facilitate hedging in market turmoil. Authors infer that a classic quantile regression methodology doesn't elucidate the connection between the observed commodities fittingly because of the shocks in COVID-19 related news.

To further emphasise the importance of the COVID-19 crisis on the financial markets, it can be observed that in a joint distribution, a large number of assets have shown tail dependencies that reinforce the increase in tail contagion in commodities and equities (Le et al., 2021). As fear and panic indices and their links to "classical" and "novel" financial markets have not been sufficiently and thoroughly studied overall, this paper aims to fill this gap.

² Indonesia, Malaysia, Philippines, Singapore, and Thailand

3. DATA AND METHODOLOGY

Three different sources were used to gain insight into the relationship between the stock market and the crypto index with the news about COVID-19: S&P500, Royalton CRIX and RavenPack. Each database included a time series covering the period from February 5, 2020 to April 22, 2022. The hypothesis is that panic and fake news about COVID-19 influence both classic and novel financial markets non-linearly and that the media has a greater influence in a bearish or bullish market than in a stagnant situation (without trend).

Wall Street Journal website (2023) was used to obtain S&P 500 index data.

The Royalton CRIX crypto index is a benchmark which upgrades tracking of the overall crypto-market performance by assembling a diversified collection of numerous cryptocurrencies prices. Even though bitcoin is the cryptocurrency with the biggest market capitalization and the most influential in its niche, it is not the only factor that illustrates the trend of the entire crypto-market. As a result of the strong progress of the alternative cryptocurrencies ("altcoins") and their market capitalization, there are numerous diverse influences in this relatively novel market segment. Trimborn & Härdle (2018) noticed the necessity for a crypto-index which will embody the changes of the market in total as a result of varying characteristics and dissimilar price movements of altcoins, thus enabling to answer various economic and financial queries within the cryptomarket. Hence, they developed the cryptocurrency index – CRIX – and later sold the copyrights to it to a commercial company which now holds its name. Its values were obtained from their official website (Royalton CRIX, 2023). The oscillations of Royalton CRIX and S&P 500 indices at the height of the COVID-19 crisis are presented on Graph 1.

Graph 1.

CRIX AND S&P 500 INDICES, RAW VALUES



Source: Authors' calculation

In contrast to the movements of the S&P 500, which seemed to be unscathed by the turmoil and maintained a relatively stable growth trend during the COV-ID-19 crisis (apart from the sharp decline at the onset, in March 2020), the crypto index was subject to greater fluctuations, as evidenced by larger swings in the period observed. This implies higher risk and potential gains, but in the context of this research also indicates a possible higher sensitivity of crypto asset prices to the media and news resulting from the COVID-19 turmoil.

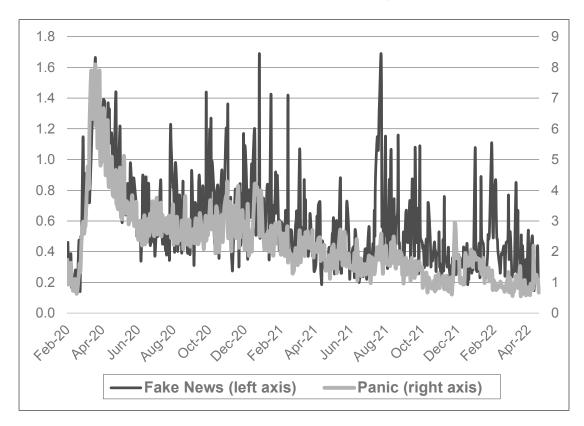
RavenPack media indices are a collection which aim to illuminate media hype, panic and other social and media influences related to COVID-19. They are computed from data provided by RavenPack, Worldometer and Johns Hopkins University (RavenPack, 2022). This data enables breakdown of diverse objects of media interest such as panic, media hype and fake news related to COVID-19 worldwide or per country. This study employs fake news index and panic index, separately for the U.S. only and for the world in general. The rationale to relate U.S. media for analyzing the S&P 500 index and global media for evaluating Roy-

alton CRIX index stems from the premise that COVID 19 related news in the United States is more likely to influence the U.S. market as represented by the S&P 500 index. In contrast, the crypto market is not related to a specific geographical location, leading to the assumption that worldwide news will have a stronger impact on the cryptocurrency market as represented by the observed crypto index.

The Fake News index measures the level of media chatter about the novel coronavirus that refers to misinformation or fake news alongside COVID-19. Values range between 0 and 100, where a value of e.g., 3 indicates that 3 % of all news globally is about fake news and COVID-19. The higher the index value, the more references to fake news are found in the media. Similarly, the Panic index measures the level of news talk that refers to panic or hysteria and coronavirus. Values also range between 0 and 100, where a value of e.g., 6 specifies that 6 % of all news throughout the World is about panic and COVID-19. The higher the index value, the more references to panic are found in the media. The movements of both indices – the Panic and Fake News – across the world during the outbreak of the pandemic are presented on Graph 2.

Graph 2.

PANIC AND FAKE NEWS WORLDWIDE, RAW VALUES



Source: Authors' calculation

Throughout the research period, media induced panic exhibited greater fluctuations in values than fake news, indicating that fake news in the media was fairly more consistent. Furthermore, both fake news and panic in the media demonstrated a declining trend during the COVID-19 crisis.

Daily returns were used as a substitute for the "raw" prices of assets for the purposes of comparability, detrending and statistical analysis. In addition, due to the requirement of log-normality and raw-log equality, a logarithmic daily return was used for the statistical analysis instead of simple returns. The data of the media indices are accumulated daily, in contrast to the stock market data, which are only collected on working days. Therefore, the stock indices are not available for non-working days and public holidays. For reasons of comparability, the values of the media indices were corrected for non-working days, assuming that the news from the weekend and non-working days influence the stock market prices on the next working day.

Quantile regression is used to estimate the interconnectedness because - since it is not limited to the conditional mean of the regressand – it allows a deeper understanding of the conditional distribution. Its strengths lie in its ability to show changes in scale, location and shape of the conditional distribution of the regressand and to estimate these effects on selected quantiles of the conditional distribution. It has applications in various fields, and one of the main reasons for choosing this method is its unique approach to dealing with heteroscedasticity (Davino et al., 2014). Quantile regression is robust to outliers and does not assume homoscedasticity, making it suitable for data with non-normal and heteroscedastic distributions, while OLS assumes linearity, normality and equal variances, which limits its applicability to certain types of data. Cepoi (2020) and Rahadian and Nurfitriani (2022) both use quantile regression models with panel data to analyze how media indices influence market indices.

The following equation of the quantile regression model estimates stock market returns (Y), panic index (X_1) and fake news index (X_2) (Rahadian & Nurfitriani, 2022, p. 43):

$$Q_{\theta}(X) = \beta_0(\theta) + \beta_1(\theta)X_1 + \beta_2(\theta)X_2$$
 [1]

where $\beta_0(\theta)$ is the intercept of θ -th quantile and $\beta_1(\theta)$ and $\beta_2(\theta)$ are the slopes. Due to the assumption of higher tail dependencies there are nine quantiles tested in this research, and these are q (0.05, 0.10, 0.20, 0.25, 0.5, 0.75, 0.80, 0.90, 0.95).

4. RESULTS AND DISCUSSION

In order to examine if the assumption of multicollinearity of the data is met, Variance Inflation Factor tests were carried out. The data indicates that there is no strong association between the regressors (Table 2).

Table 2.

VARIANCE INFLATION FACTOR RESULTS

Model	VIF	1/VIF
Fake News Index VS Panic Index, S&P500	1.83	0.547
Fake News Index VS Panic Index, Crypto index	1.79	0.557

Source: Authors' calculation

Table 3 and Table 4 present the summary statistics for all dependent and independent variables. Media indices differ due to the different subsets of the underlying data sources; in the case where S&P 500 is the dependent variable (Table 3) media indices are drawn from U.S news only, while in the case where Royalton CRIX is the dependent variable (Table 4) media indices are extrapolated from news worldwide.

Table 3.

DESCRIPTIVE STATISTICS OF S&P 500, PANIC INDEX AND FAKE NEWS

INDEX, LOG DAILY CHANGES, 02/2020 – 04/2022

	S&P500	Panic Index	Fake News Index			
Observations	559	559	559			
Mean	0.000	2.509	0.69			
Std. dev.	0.016	1.415	0.377			
Minimum	-0.128	0.62	0.14			
25 th percentile	-0.608	0.65	0.15			
50 th percentile	0.001	2.27	0.59			
75 th percentile	0.608	8.08	1.893			
Maximum	0.09	9.661	2.217			
Variance	0.000	2.004	0.141			
Skewness	-0.944	1.612	1.094			
Kurtosis	16.642	7.134	3.902			
t-ADF	-29.506*	-10.562*	-12.202*			
* MacKinnon approximate p-value for t < .000, thus statistically significant						

Source: Authors' calculation

The dependent variables in both models exhibit negative skewness and heavy-tailed distributions, whereas all the independent variables display positive skewness and heavy-tailed distributions. Additionally, the variability in the Panic index is further evaluated using variance and standard deviation, which suggests greater oscillations in Panic then in the Fake News index, both for the U.S only and world-wide news. This confirms the earlier observations regarding greater fluctuations in the amount of worldwide media induced panic. Stationarity of all variables is confirmed by the Augmented Dickey-Fuller unit root test, displayed in the descriptive statistics tables.

Table 4.

DESCRIPTIVE STATISTICS OF ROYALTON CRIX INDEX, PANIC INDEX AND FAKE NEWS INDEX, LOG DAILY CHANGES, 02/2020 – 04/2022

	Royalton CRIX	Panic Index	Fake News Index			
Observations	579	579	579			
Mean	0.003	2.221	0.578			
Std. dev.	0.045	1.214	0.299			
Minimum	-0.273	0.56	0.12			
25 th percentile	-0.141	0.59	0.14			
50 th percentile	0.005	2.01	0.5			
75 th percentile	0.12	6.98	1.44			
Maximum	0.186	8.084	1.69			
Variance	0.002	1.475	0.089			
Skewness	-0.65	1.558	1.099			
Kurtosis	6.646	6.762	3.893			
t-ADF	-24.039*	-9.354*	-11.818*			
* MacKinnon approximate p-value for t = 0.000, thus statistically significant						

Source: Authors' calculation

Prior to quantile regression two distinct OLS regression models were conducted both on Royalton CRIX and S&P 500 as regressands. The results show that the Royalton CRIX OLS model explains 1.9% of variance in CRIX daily returns at a significance level of 5% (Table 5). Furthermore, only fake news has a significant impact on CRIX daily returns while considering the conditional mean. According to the Breusch-Pagan/Cook-Weisberg test and the White test, there is no presence of heteroscedasticity. Also, Shapiro-Wilk test results show that the residuals are not normally distributed. The S&P 500 OLS model is not significant at the level of the conditional mean, but there is evidence of heteroscedasticity with absence of normality in residuals. Therefore, further estimation was performed by applying quantile regression.

Table 5.

OLS RESULTS FOR ROYALTON CRIX AND S&P 500 MODELS

	Dependen	t variables
	Royalton CRIX	S&P 500
Intercept	-0.007 (0.004)*	-0.002 (0.002)*
Panic Index	-0.003 (0.002)*	-0.000 (0.001)*
Fake News Index	0.029* (0.008)*	0.004 (0.002)*
R ² _{adjusted}	0.019**	0.003
Breusch-Pagan/Cook-Weisberg test (χ²)	0.19	30.67**
White test (χ^2)	10.52	247.46**
Shapiro-Wilk test (W)	0.962**	0.834**
* Standard errors in brackets. ** Statistical significance at p < .05	,	

Source: Authors' calculation

Looking at the results of the S&P 500 model (Table 6 and Figure 1), the fake news index shows that fake news has a positive asymmetric U-shaped effect depending on the market movement, decreasing from the lower quantiles towards the middle of the distribution and then shifting in an increasing direction in the higher quantiles. This suggests that the largest impact of misinformation on daily returns is mainly found in a moving market (either bearish or bullish), rather than in a stagnant situation. However, the quantile regression results also show that fake news did not have a statistically significant impact on the conditional distribution of daily returns of the S&P 500 during the observed period.

Table 6.

DESCRIPTIVE RESULTS OF QUANTILE REGRESSION

OF THE S&P 500 MODEL

Quantile and	Regressors	Coeff.	Std. err.	t	P>t	95% conf.	
Pseudo R ²	Regressors	Cocii.				inte	rval
	Intercept	012	.004	-2.95	.003*	021	004
q05; 0.103	Panic Index	007	.003	-2.16	.031*	013	001
	Fake News Index	.008	.005	1.65	.100	002	.017
	Intercept	008	.003	-2.82	.005*	013	002
q10; 0.044	Panic Index	004	.002	-2.25	.025*	007	000
	Fake News Index	.002	.004	0.44	.662	006	.01
	Intercept	004	.002	-2.11	.035*	008	000
q20; 0.011	Panic Index	003	.001	-3.48	.001*	004	001
	Fake News Index	.003	.002	1.89	.060	000	.007
	Intercept	003	.002	-1.76	.079	007	.000
q25; 0.007	Panic Index	002	.001	-1.47	.143	004	.001
	Fake News Index	.003	.002	1.45	.148	001	.007
	Intercept	001	.002	-0.59	.557	005	.002
q50; 0.005	Panic Index	.001	.001	0.92	.358	001	.002
	Fake News Index	.001	.002	0.48	.629	003	.006
	Intercept	.001	.001	0.50	.618	002	.004
q75; 0.037	Panic Index	.003	.001	3.48	.001*	.001	.004
	Fake News Index	.002	.003	0.72	.472	003	.007
	Intercept	.002	.002	0.89	.374	002	.005
q80; 0.048	Panic Index	.003	.001	2.39	.001*	.001	.004
	Fake News Index	.003	.003	0.99	.322	003	.008
	Intercept	.004	.002	1.72	.087	001	.008
q90; 0.077	Panic Index	.003	.001	2.39	.017*	.001	.006
	Fake News Index	.004	.003	1.26	.208	002	.011
	Intercept	.005	.004	1.25	.213	003	.012
q95; 0.145	Panic Index	.006	.003	2.24	.025*	.001	.011
	Fake News Index	.005	.007	0.63	.529	01	.019
* statistical significance at p < .05							

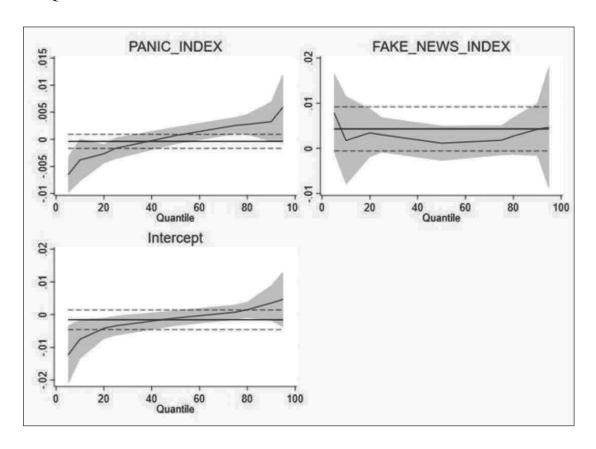
Source: Authors' calculation

As for the Panic index, the daily returns of the S&P 500 daily returns have reacted both negatively and positively to the panic in the US media. The lower quantiles up to the median and near the median (from the entire distribution of

daily changes) have shown a non-linear negative impact due to the magnitude of the panic. Moreover, the upper quantiles from the 75th to 95th percentile show a non-linear positive impact of panic on the daily returns of the S&P 500. Statistically significant results are found from the 5th to the 25th percentile and from the 75th to the 95th percentile. These results suggest that panic related to COVID-19 in a bearish market negatively affects stock market returns in a non-linear manner, contingent on how much returns have stagnated. Conversely, panic in the media showed a positive, upward influence in a bullish market.

Figure 1.

QUANTILE REGRESSION COMPONENTS IN THE S&P 500 MODEL



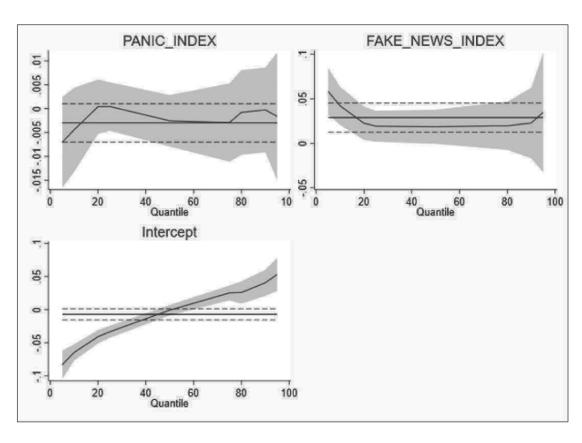
Source: Authors' calculation

When observing the cryptocurrency market (Table 7 and Figure 2), the impact of the Fake News index on the crypto index is analogous to the S&P 500, with a positive, non-linear, U-shaped impact showing up in the low quantiles and weakening in the high quantiles of the return distribution, suggesting that it has

an impact in both strongly bullish and bearish markets. Within the center of the distribution, it remains relatively constant, suggesting less impact in a stagnant market. The findings suggest that worldwide misinformation has a statistically significant impact in the lower quantiles to the median.

Figure 2.

QUANTILE REGRESSION COMPONENTS
IN THE CRYPTO INDEX MODEL



Source: Authors' calculation

Focusing on the co-movements of the panic index and cryptocurrency index, throughout the conditional distribution of daily returns asymmetrical dependencies could be observed. A negative impact is visible in the low 5th and 10th percentile of the distribution, suggesting that in bearish market conditions panic in the media negatively impacts the daily returns of the crypto index. From the 20th to the 50th percentile, panic has a positive impact on the returns, as well as a negative nonlinear impact through the 50th to 95th percentile. That implies that in a bullish trading mar-

ket, daily returns will be decreased by the amount of panic in the media. However, none of the quantiles regarding the panic index is found to be statistically significant.

Table 7.

DESCRIPTIVE RESULTS OF QUANTILE REGRESSION
OF THE CRYPTO INDEX MODEL

Pseudo R	Quantile and	Regressors	Coeff.	Std.	t	P>t	95% conf.	
Q05; 0.026 Panic Index 007 .005 -1.46 .145 017 .002 Fake News Index .058 .013 4.35 .000* .032 .085 .006 .10.25 .000* .077 .052 .006 .10.25 .000* .007 .052 .006 .10.25 .000* .007 .005 .006 .10.25 .000* .001 .004 .004 .009 .323 .013 .004 .004 .009 .021 .064 .006 .006 .006 .001 .006 .001 .006 .001 .006 .001 .006 .001 .001 .006 .001 .0	Pseudo R ²	Regressors	Cociii	err.	·	171	inte	rval
Fake News Index		Intercept	083	.011	-7.65	.000*	105	062
Intercept	q05; 0.026	Panic Index	007	.005	-1.46	.145	017	.002
Q10; 0.027 Panic Index 004 .004 -0.99 .323 013 .004 Fake News Index .042 .011 3.86 .000* .021 .064 .020; 0.016 Panic Index .000 .003 0.14 .886 005 .006 .006 Fake News Index .023 .01 2.36 .019* .004 .041 .041 .042 .024 .023 .01 .033 .005 .7.18 .000* .042 .024 .024 .024 .025 .006 .005 .006 .005 .006 .006 .005 .006 .006 .005 .006 .005 .006 .006 .005 .006 .006 .005 .006 .006 .005 .006 .006 .005 .006 .006 .006 .006 .006 .007 .	*	Fake News Index	.058	.013	4.35	.000*	.032	.085
Fake News Index .042 .011 3.86 .000* .021 .064		Intercept	065	.006	-10.25	.000*	077	052
Panic Index 041 .005 -7.90 .000* 051 031 .006 .007 .006 .007 .007 .007 .007 .007 .007 .007 .007 .007 .007 .007 .008 .0	q10; 0.027	Panic Index	004	.004	-0.99	.323	013	.004
q20; 0.016 Panic Index Fake News Index .000 .003 0.14 .886 005 .006 Fake News Index .023 .01 2.36 .019* .004 .041 q25; 0.013 Intercept 033 .005 -7.18 .000* 042 024 Panic Index .000 .003 0.17 .866 005 .006 Fake News Index .019 .009 2.17 .031* .002 .037 Intercept 001 .004 -0.18 .855 009 .007 Panic Index 003 .003 -0.93 .354 008 .003 Fake News Index .019 .01 1.90 .057 001 .038 Intercept .025 .006 4.39 .000* .014 .037 q80; 0.005 Panic Index .003 .004 -0.70 .487 011 .005 q80; 0.007 Panic Index .001 .005		Fake News Index	.042	.011	3.86	.000*	.021	.064
Fake News Index .023 .01 2.36 .019* .004 .041		Intercept	041	.005	-7.90	.000*	051	031
Intercept 033 .005 -7.18 .000* 042 024 Panic Index .000 .003 0.17 .866 005 .006 Fake News Index .019 .009 2.17 .031* .002 .037 Intercept 001 .004 -0.18 .855 009 .007 Panic Index 003 .003 -0.93 .354 008 .003 Fake News Index .019 .01 1.90 .057 001 .038 Intercept .025 .006 4.39 .000* .014 .037 q75; 0.005 Panic Index 003 .004 -0.70 .487 011 .005 Fake News Index .02 .013 1.49 .137 006 .045 q80; 0.007 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 q90; 0.015 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 q95; 0.020 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102 Fake News Index .035 .034 1.01 .311 033 .102 Fake News Index .035 .034 1.01 .311 033 .102 Contact 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102 Contact 002 .007 -0.24 .007 .028 .078 Contact 002 .007 -0.24 .007 .028 .007 Contact 002 .007 -0.24 .007 .028 .007 Contact 002 .007 -0.24 .007 .007 .007 .007 Contact 002 .007 -0.24 .007	q20; 0.016	Panic Index	.000	.003	0.14	.886	005	.006
q25; 0.013 Panic Index Fake News Index .000 .003 0.17 .866 005 .006 Fake News Index .019 .009 2.17 .031* .002 .037 q50; 0.006 Intercept 001 .004 -0.18 .855 009 .007 Panic Index 003 .003 -0.93 .354 008 .003 Fake News Index .019 .01 1.90 .057 001 .038 Intercept .025 .006 4.39 .000* .014 .037 Panic Index 003 .004 -0.70 .487 011 .005 Fake News Index .02 .013 1.49 .137 006 .045 Intercept .026 .009 2.99 .003* .009 .043 q80; 0.007 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156		Fake News Index	.023	.01	2.36	.019*	.004	.041
Fake News Index .019 .009 2.17 .031* .002 .037 Intercept 001 .004 -0.18 .855 009 .007 Panic Index 003 .003 -0.93 .354 008 .003 Fake News Index .019 .01 1.90 .057 001 .038 Intercept .025 .006 4.39 .000* .014 .037 Panic Index 003 .004 -0.70 .487 011 .005 Fake News Index .02 .013 1.49 .137 006 .045 Intercept .026 .009 2.99 .003* .009 .043 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 Intercept .041 .010 4.04 .000* .021 .060 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102 Fake News Index .035 .034 1.01 .311 033 .102 Fake News Index .035 .034 1.01 .311 033 .102 Contact .000 .000 .000 .000 Contact .000 .000 .000 Contact .000 .000 .000 Contact .000		Intercept	033	.005	-7.18	.000*	042	024
Intercept	q25; 0.013	Panic Index	.000	.003	0.17	.866	005	.006
q50; 0.006 Panic Index 003 .003 -0.93 .354 008 .003 Fake News Index .019 .01 1.90 .057 001 .038 Intercept .025 .006 4.39 .000* .014 .037 Panic Index 003 .004 -0.70 .487 011 .005 Fake News Index .02 .013 1.49 .137 006 .045 Intercept .026 .009 2.99 .003* .009 .045 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 q90; 0.015 Panic Index 000 .005 -0.06 .954 009 .009 q95; 0.020 Panic Index .023 .020 1.13 .260 017 .063 q95; 0.020 Panic Index 002 .007 -0.24		Fake News Index	.019	.009	2.17	.031*	.002	.037
Fake News Index .019 .01 1.90 .057 001 .038		Intercept	001	.004	-0.18	.855	009	.007
Intercept .025 .006 4.39 .000* .014 .037 Panic Index 003 .004 -0.70 .487 011 .005 Fake News Index .02 .013 1.49 .137 006 .045 Intercept .026 .009 2.99 .003* .009 .043 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 Intercept .041 .010 4.04 .000* .021 .060 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102 Fake News Index .035 .034 1.01 .311 033 .102 Contact .000 .005 .006 .000* .005 .006 Contact .000 .005 .006 .006 .006 .006 Contact .000 .005 .006 .006 .006 Contact .000 .000* .006 Contact .000 .000* .006 Contact .000 .000* .006 Contact .000 .000* .006 Contact .000 .006 .006 Contact .000 .00	q50; 0.006	Panic Index	003	.003	-0.93	.354	008	.003
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Fake News Index	.019	.01	1.90	.057	001	.038
Fake News Index .02 .013 1.49 .137 006 .045		Intercept	.025	.006	4.39	.000*	.014	.037
q80; 0.007 Intercept .026 .009 2.99 .003* .009 .043 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 Intercept .041 .010 4.04 .000* .021 .060 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 q95; 0.020 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102	q75; 0.005	Panic Index	003	.004	-0.70	.487	011	.005
q80; 0.007 Panic Index 001 .005 -0.17 .861 01 .008 Fake News Index .02 .014 1.42 .156 007 .047 Intercept .041 .010 4.04 .000* .021 .060 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 q95; 0.020 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102		Fake News Index	.02	.013	1.49	.137	006	.045
Fake News Index .02 .014 1.42 .156 007 .047		Intercept	.026	.009	2.99	.003*	.009	.043
q90; 0.015 Intercept .041 .010 4.04 .000* .021 .060 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102	q80; 0.007	Panic Index	001	.005	-0.17	.861	01	.008
q90; 0.015 Panic Index 000 .005 -0.06 .954 009 .009 Fake News Index .023 .020 1.13 .260 017 .063 Intercept .053 .013 4.19 .000* .028 .078 Panic Index 002 .007 -0.24 .812 015 .012 Fake News Index .035 .034 1.01 .311 033 .102		Fake News Index	.02	.014	1.42	.156	007	.047
Fake News Index .023 .020 1.13 .260 017 .063		Intercept	.041	.010	4.04	.000*	.021	.060
q95; 0.020	q90; 0.015	Panic Index	000	.005	-0.06	.954	009	.009
q95; 0.020		Fake News Index	.023	.020	1.13	.260	017	.063
Fake News Index .035 .034 1.01 .311 033 .102		Intercept	.053	.013	4.19	.000*	.028	.078
	q95; 0.020	Panic Index	002	.007	-0.24	.812	015	.012
* statistical significance at n < 05		Fake News Index	.035	.034	1.01	.311	033	.102
* statistical significance at p < .05								

Source: Authors' calculation

While the significant results regarding the influence of media-induced panic on the S&P 500 and the impact of fake news on the cryptocurrency market are consistent with our assumption of nonlinearity, the unexpected positive impact of panic in the media and fake news on returns seems rather counterintuitive and would require further investigation. Furthermore, the results suggest that different markets are affected differently by different forms of news. However, a more indepth investigation of these issues is beyond the scope and resources of this study. Additionally, the results are consistent with initial expectations that the impact of news is greater in moving markets than in stagnant markets.

The presented findings are somewhat similar to the previous research. Cepoi (2020) reported that the panic index doesn't have any statistically significant impact on the stock market. He also noted a nonlinear U-shaped impact of fake news in a "normal" market in the 25th to 75th percentiles of the market, highlighting the significance of fact-checked, sound news. Slight variances in results could have occurred due to different time spans and markets that were examined. Conversely, Rahadian & Nurfitriani (2022) state that the panic index shows a positive impact in the 80th to 85th percentile, and a negative impact in a bearish market within the 5th to 20th percentile. Besides, Rahadian & Nurfitriani (2022) observed a positive and increasing impact of fake news on different stock markets considering the upper 90th to 95th quantile in one of three periods of their research. Having in mind the inference made by Mahdi & Al-Abdulla (2022) who perceive bitcoin as a safehaven against media-driven panic in the COVID-19 outbreak, in this research bitcoin is indirectly observed as a central component of Royalton CRIX index. Panic index displayed mostly low negative influence on daily returns in the crypto index, which suggests that cryptocurrencies are not a hedging solution for media-induced panic, but the results are statistically insignificant.

5. CONCLUSION

Every type of media source plays a role in the investors'decision-making process. The influence of the media on investor decisions in both the stock and crypto-currency markets can be much stronger for a retail investor than for a professional – an investment fund or a large corporation. With this in mind, media sources should be verified and fact-checked for the accuracy of the news they disseminate.

The investigation performed in this paper shows that fake news has a positive directional impact on the daily return of cryptocurrencies globally in a bearish trending market, but its influence is small to non-existent. The association of the daily return of the S&P 500 with panic in the US media is significant, especially

in bearish and bullish trending markets, but also has a small impact on returns. Furthermore, there is no statistically significant evidence that cryptocurrencies are a viable hedging solution for media-driven panic.

The specific and original contribution of this study to the current literature stems from novel insights on the diverse and nonlinear effects of media on financial markets gained from the features and possibilities of quantile regression. The focus of this study is on the influence of COVID-19 news in US media and its impact on the US stock market and the influence of COVID-19 news in world-wide media and its impact on the cryptocurrency market. However, the findings of this research may not be generalizable to other markets, countries or regions. To complement the understanding of this research topic further, we recommend investigating the differences between the impact of COVID-19 news in emerging and mature markets and a panel data approach to gain a broader perspective regarding its implications.

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UTJECAJ MEDIJA I VIJESTI O BOLESTI COVID-19 NA BURZE I KRIPTO TRŽIŠTA

Sažetak

Pandemija COVID-19 značajno je utjecala na cijeli svijet, što je dovelo do konfuzije i turbulencija u zdravstvenim sustavima, kao i do izrazite neizvjesnosti u financijskom području. Tržišta dionica bila su duboko uzdrmana zbog enormno povišenih razina rizika potaknutih pandemijom, što je dodatno povećalo gubitke investitora. Pandemiju je pratio val lažnih priča koje se doimaju kao vijesti ("fake news") koje su kružile svim medijskim kanalima, dodatno pojačavajući neizvjesnost. Ovaj rad proširuje prethodnu literaturu istražujući utjecaj medija na istaknute indekse tržišta dionica i kriptovaluta. Indeksi RavenPack Panic i Fake News korišteni su za ispitivanje njihovog utjecaja na dnevna kretanja S&P 500 i kripto-indeksa (Royalton CRIX) primjenom OLS-a i kvantilne regresije. Rezultati pokazuju da postoje značajne ovisnosti kroz uvjetnu distribuciju, ali pokazuju mali utjecaj na promatrane indekse. Lažne vijesti utječu na dnevni prinos kriptovaluta na medvjeđem tržištu, no učinak je vrlo slab. Nadalje, panika u medijima je značajna i na izrazito medvjeđim kao i bikovskim tržištima s obzirom na dnevne prinose S&P 500, ali također pokazuje slab utjecaj.

Ključne riječi: COVID-19, panika, lažne vijesti, S&P500, indeks kriptovaluta, kvantilna regresija