# UTJECAJ VIJESTI O PANDEMIJI COVID-19 NA TRŽIŠTE DIONICA

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# IMPACT OF COVID-19 NEWS ON THE STOCK MARKET

Final paper

Osijek, 2022.

**IZJAVA**
**O AKADEMSKOJ ČESTITOSTI,**
**PRAVU PRIJENOSA INTELEKTUALNOG VLASNIŠTVA,**
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Potpis

## Utjecaj vijesti o pandemiji covid-19 na tržište dionica


## SAŽETAK

Pandemija covid-a 19 imala je negativni utjecaj na svijet, kako u pogledu neizvjesnosti u javnom zdravstvu i zdravstvenim sustavima, tako i nestabilnosti u financijskom sektoru. Burze su značajno zahvaćene iznimno visokom razinom rizika uzrokovanom pandemijom, a što je, u konačnici, ulagačima uzrokovalo značajne gubitke. Pandemija covid-a 19 popraćena je značajnom količinom lažnih vijesti (*eng. fake news*), koje kruže u svim oblicima medija i time uzrokuju nesigurnost u donošenju odluka o ulaganju. Smatra se da medijski kanali na društvenim mrežama prenose informacije koje imaju značajan utjecaj na tržišnu dinamiku u vremenima ekonomske neizvjesnosti. Ovo istraživanje nadopunjuje dostupnu literaturu vezanu za utjecaj covid-19 medijskih indeksa na financijsku imovinu analizirajući pojedinačne burzovne indekse, kao i tržište kriptovaluta. Indeksi lažnih vijesti i panike (*RavenPack Fake news index* i *Panic index*) koristili su se u analizi utjecaja navedenih indeksa na dnevne prinose S&P 500 i indeks kriptovaluta Royalton CRIX pomoću kvantilne i OLS regresije. Rezultati prikazuju da postoje značajne ovisnosti u uvjetnoj distribuciji, no da je utjecaj na tržišne indekse nizak. Lažne vijesti utječu na dnevne prinose Royalton CRIX-a u rastućem tržištu, no snaga utjecaja je gotovo zanemariva. Također, panika u medijima vezana uz S&P 500 dnevne prinose upućuje na značaj u izrazito rastućem i izrazito padajućem tržištu, no također uz prisutan zanemariv utjecaj na prinose.



**Ključne riječi:** kvantilna regresija, covid-19, lažne vijesti, panika, S&P 500, Royalton CRIX

## Impact of COVID-19 news on the stock market

## ABSTRACT

The COVID-19 pandemic has affected the world negatively from uncertainty in healthcare and healthcare systems to turbulence in the financial sector. Stock markets were heavily affected due to the extremely high level of risk caused by the pandemic, which further caused significant losses for investors. The COVID-19 pandemic is accompanied by a lot of fake news that circulates in all forms of media and thus creates uncertainty in the decisions of individuals. Media channels of social networks are considered to deliver information that has a significant impact on market dynamics in times of economic uncertainty. This research complements the previous literature related to the COVID-19 media indices impact on financial assets by analyzing individual market indices of the stock market as well as the cryptocurrency market. RavenPack Fake news index and Panic index were used to analyze their impact on S&P 500 and Royalton CRIX daily returns by implementing a quantile regression approach. The results show that significant dependencies exist through the conditional distribution, but represent a low impact on market indices. Fake news impacts the daily return of Royalton CRIX in a bullish trending market, but the impact is low to non-existent. Also, panic in the media considering S&P 500 daily returns suggest significance in extremely bullish and bearish markets, also measuring a low impact on the returns.

**Keywords:** quantile regression, COVID-19, fake news, panic, S&P 500, Royalton CRIX

# Summary

# 1. Introduction

The beginning of the year 2020 surprised the world with the appearance of a deadly disease COVID-19, caused by a new type of coronavirus known as SARS-CoV-2. As a result of mass hospitalization and strict preventive measures, COVID-19 made a significant impact on world economies, their healthcare systems etc.

On the one hand, it is important to state that the impact of the pandemic led to some positive changes and (a limited) recovery of the environment, and also gave rise to the questions of necessary societal changes and behavior which occurred during the period of uncertainty (Verma & Prakash, 2020). These challenging times could positively affect the importance of corporate social responsibility, consumer, and business ethics.

On the other hand, financial institutions and investors felt the negative consequences of the pandemic and for that reason, the stock and cryptocurrencies markets expressed it also through signs of panic, hysteria, and indecision which might have led to higher levels of volatility in the markets. Analyzing the intraday volatility in financial markets led to the conclusion that there is significant evidence of change in the volatility of financial assets and its peak during the COVID-19 crisis (Farid et al., 2021).

Commodity markets have shown weak robustness and resistance to the COVID-19 crisis. A negative impact was noticed on commodity markets including severe damage to oil markets, industrial materials and the (least affected) agriculture industry. The COVID-19 crisis impact is known to have enduring consequences (Rajput et al., 2021).

Market indices are sets of carefully chosen variables which explain a market or a part of the market. For this reason, market indices values are benchmarks of the market which enable financial economic analysis of the market as a whole, or individual assets of interest (Parameswaran, 2007). Stock markets were heavily impacted by the COVID-19 pandemic; “On March 16 the Dow plummeted nearly 3,000 points to close at 20,188, losing 12.9%. The drop in stock prices was so massive that the New York Stock Exchange suspended trading several times during those days” (Frazier, 2021). COVID-19 had a severe and negative impact on stock markets of countries which had the highest number of confirmed infections by it.

The U.S. market was among the first that successfully recovered and recuperated more than 85% losses caused by the crash (Ganie et al., 2022). To further emphasize the significance of

COVID-19 in financial markets, it is noticed that, in a joint distribution, a wide range of assets have expressed tail dependencies emphasizing the tail contagion increase in equities and commodities markets (Le et al., 2021).

Furthermore, consequences were also noticed in the cryptocurrency market by March 2020. "Bitcoin felt the brunt of a historic week in which the impact of the coronavirus pandemic in the U.S. accelerated at a pace most couldn't have imagined. It lost 50% of its value in a single day Thursday (12th March 2020) and dipped below $4,000 that evening for the first time since last March. By Friday morning, it had recovered some of its losses, rebounding to close to $6,000." (Forbes, 2020). Despite the turmoil in the cryptocurrency market, previous research implies that Bitcoin as well as U.S. Treasury bonds serve as safe-havens during the more pronounced periods of higher volatility during the COVID-19 turmoil (Le et al., 2021; Goodell & Goutte, 2021).

The age of the internet allows for fast access to a large amount of information, encompassing all types of media sources. The fact that anyone can share any kind of information, without prior validation, raises the question of the news being misleading, inaccurate and deceiving, thus being categorized as misinformation, or "fake news". Fake news can be defined as "false stories that appear to be news, spread on the internet or using other media, usually created to influence political views or as a joke." (Cambridge Dictionary, n.d.)

Social media platforms have become one of the main hubs for acquiring information about the ongoing pandemic. During the pandemic, a significant increase in social media usage was noticed, measuring a 20 to 87% increase globally (Naeem et al., 2021). Due to the characteristics of social media validation, misinformation started to spread across media channels (Naeem et al., 2021). "Social media has become the primary source for rumor spreading, and information quality is an increasingly important issue in this context" (de Souza et al., 2020:1). Evanega et al. analyzed over 38 million articles and found that 16.4% percent of misinformation regarding COVID-19 is "fact-checked", thus raising awareness to the impact of fake news (Evanega et al., 2020). The importance of COVID-19 "infodemic" must not be taken lightly, as research reported that consequences of misinformation led to panic and fear (e.g. Gabarron et al., 2021).

The purpose of this paper is to investigate the impact of COVID-19 related news regarding fake news and panic in the U.S. on S&P 500 daily returns, and the impact of news regarding COVID-19 on the cryptocurrency market index Royalton CRIX. The period of research spans from the

5th of February 2020 to the 22nd of April 2022, and OLS and quantile regression were applied. RavenPacks fake news index and panic index are used as a measure of fake news and panic in the media. The hypothesis posits that fake news and panic regarding COVID-19 affect financial markets non-linearly, and that media has stronger impact in a bullish or bearish market trend, than in a non-trending market.

The rest of the paper is structured as follows. Previous research is discussed in Section 2. Section 3 describes the data and methodology. Section 4 shows the results, while Section 5 discusses the findings, and compares them with previous research. Finally, in Section 6, a conclusion is drawn.

## 2. Previous research

Due to the major impact that COVID-19 had on world economies including financial markets, there was a surge in papers published regarding this topic. Some of them are accentuated here.

According to Cepoi (2020), there is evidence of a relationship between COVID-19 related news and stock market returns in countries most impacted by the pandemic. By implementing a panel quantile regression framework consisting of stock market returns and media indices (provided by RavenPack Media Monitor), the results have shown that “the stock markets present asymmetric dependencies with COVID-19 related information such as fake news, media coverage, or contagion.” Cepoi mentions that “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”, emphasizing that fake news in extreme bearish and bullish markets are not significantly explaining the volatility of stock market returns. Furthermore, the results show a negative impact of contagion index and media coverage on higher percentiles of stock market returns (2020: 4).

Similarly, Rahadian and Nurfitriani (2022) researched the impact of COVID-19 news on stock market returns in five Southeast Asian countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand; ASEAN), analyzing different periods in the study. The authors explain that, depending on the research period, different countries present different results, that is, different independent variables have various impacts depending on the time frame and the country of choice. Overall, fake news index and country sentiment index are mentioned as variables that affect stock market returns of ASEAN countries (Rahadian & Nurfitriani, 2022).

Furthermore, Haldar and Sethi (2018) examined how COVID-19 media coverage impacted the stock market returns and volatility of the countries worst hit by the pandemic. The results have shown that only in the early period of COVID-19 those countries exhibited low to negative returns with high volatility, but later there was normalization of returns with the volatility remaining high (Haldar & Sethi, 2018).

As already mentioned, some findings imply that Bitcoin serves as a safe-haven during COVID-19 commotion; according to Mahdi and Al-Abdulla (2022), Bitcoin and gold could be a valid alternative for hedging against market turmoil. They observed Bitcoin and gold returns including RavenPack media indices, and found dependencies utilizing a Quantile-on-Quantile regression analysis. Using a non-parametric approach, they explored asymmetric dependencies on external shocks regarding COVID-19 related news on Bitcoin and gold returns and found that the panic index shows positive dependencies, thus causes an increase in returns for both gold and Bitcoin. Asymmetric dependencies regarding infodemic and media coverage indices imply that they could present a valid hedge against market turmoil. Lastly, fear sentiment is followed by an increase in returns in those assets. Mahdi & Al-Abdulla (2022) imply that a traditional quantile regression approach doesn't explain the relationship between the named commodities correctly, due to shocks in COVID-19 related news.

# 3. Data and methodology

## 3.1. Data

Two different databases were used to explain the relationship between the S&P 500 and Royalton CRIX with the news regarding COVID-19. Each database included a time series spanning from the 5$^{nd}$ of February 2020 to 22$^{th}$ of April 2022. Specificities regarding the data and sources are described here.

### 3.1.1. S&P 500

S&P 500, together with S&P MidCap 400 and S&P SmallCap 600, is the building block of the S&P Composite 1500 index. According to S&P Dow Jones Indices LLC, it is referred to as the best single gauge of large-cap U.S. equities, being the first U.S. market-cap-weighted stock market index created in 1957, and a proxy of the U.S. equity market. Covering roughly 80% of all market capitalization, it consists of the 500 largest American companies covering 11 industries, and is calculated in 11 different currencies including USD, EUR and GBP (S&P Dow Jones Indices, 2022).

The construction of S&P Dow Jones Indices, including S&P 500 takes into account a number of prerequisites. All companies represented in the S&P 500 index must be U.S. companies with an unadjusted market cap of USD 14.6 billion or greater and positive earnings in the last quarter, including last four quarters. Also, there are restrictions on different types of securities like Exchange-Traded Funds (ETF), American Depositary Receipts (ADR) and other types which are ineligible for the indices. Sector representation in also a crucial factor in the selection of eligible companies. Companies must have an investable weight factor (IWF) of at least 0.10 meaning that 10% of the total shares outstanding must be available float shares, which are defined as corrected total shares outstanding for ones that are held by strategic holders. Furthermore, the float-adjusted market cap should be a minimum of 1.00 and at least 250,000 shares traded in the evaluation period (S&P Dow Jones Indices, 2022).

It is necessary to adjust the shares for those which are held long-term and are not available for trading (Equation 1). The adjustment is made in two steps. First, the determination of the investable weight factor for each stock (S&P Dow Jones Indices, 2022).

Equation 1 Calculation of the Investable Weight Factor (IWF) of S&P 500

$$Investable\ Weight\ Factor(IWF) = \frac{Available\ float\ shares}{Total\ shares\ outstanding}$$

Second, summing up the stock price (Pj), total shares outstanding (Sj) and IWF of a stock and dividing it by a index divisor (Equation 2) which is a proprietary value liable to change (S&P Dow Jones Indices, 2022).

Equation 2 Calculation of the S&P 500 Index

$$Index = \frac{\sum_j (PjSjIWFj)}{Divisor}$$

S&P 500 is calculated daily and the IWF and float adjustments are rebalanced annually and quarterly including mandatory and non-mandatory maintenance (S&P Dow Jones Indices, 2022).

S&P 500 historical data was obtained from The Wall Street Journal.

### 3.1.2. Royalton CRIX Crypto Index

The Royalton CRIX Crypto Index is a diversified collection of various cryptocurrencies representing the market through a benchmark, thus improving market performance tracking. Research has shown that Bitcoin, which is the currency with the biggest market capitalization in the market, is not the only factor that shows the direction of the cryptocurrency market. Due to the fast-paced growth of the alternative cryptocurrencies ("altcoins") and market capitalization, there are many different cryptocurrencies. As a result of changing characteristics and different market directions of altcoins, Trimborn & Härdle (2018) found the need for a cryptocurrency market index which will represent the movement of the market as a whole, hence making it possible to answer financial and economic questions in the cryptocurrency market.

Like other price indices which compensate for the effect of individual market change, company bankruptcy, changes in outstanding share numbers etc., Royalton CRIX uses the adjusted Laspeyres formula whose purpose is to weight asset prices by their quantity and compare it against a base period adjusting for the effect of constituent change. The Laspeyres index (Equation 3) in the case of cryptocurrency is defined as

*Equation 3 Calculation of the Royalton CRIX Crypto Index using the Laspeyres definition.*

$$CRIX_t = \frac{\sum_i P_{it} Q_{i0}}{\sum_i P_{i0} Q_{i0}}$$

Source: *https://www.royalton-crix.com/methodology*

with the price (P) of crypto *i* at *t* point in time and Q as the amount of crypto *i* at *t* point in time. An adjustment is required to account for the effect of change of a single constituent in the index, thus only represent the change in price based on a starting date value (Equation 4). This is done by implementing an index divisor

*Equation 4 Calculation of the Royalton CRIX Crypto Index divisor*

$$Divisor(k, \beta)_0 = \frac{\sum_{i=1}^{k} \beta_{i0} P_{i0} Q_{i0}}{starting\ value}$$

Source: *Trimborn & Härdl, 2018*

with β representing the adjustment factor of asset *i*. Inserting the index in the denumerator, the adjusted Laspeyres index for Royalton CRIX (Equation 5) is defined

*Equation 5 Calculation of the Royalton CRIX Crypto Index*

$$CRIX_t(k, \beta) = \frac{\sum_{i=1}^{k} \beta_{i,t_l^-} P_{i0} Q_{it_l^-}}{Divisor(k)_{t_l^-}}$$

*Source: Trimborn & Härdl, 2018*

with $\beta_{i,t_l^-}$ representing the adjustment factor of asset *i* at point in time $t_l^-$, *l* representing *l*th adjustment factor. Adjustments revisions and rebalances are done quarterly (Trimborn & Härdl, 2018).

Royalton CRIX historical data was obtained from Royalton CRIX.

### 3.1.3. RavenPack media indices

RavenPacks media indices are a collection of indices explaining panic, media hype and other social and media factors regarding the novel coronavirus COVID-19. They are calculated by RavenPack from COVID-19 and market data provided by RavenPack, Johns Hopkins University (CSSE) and Worldometer (RavenPack, 2022). This media dataset allows for analysis of different parameters like panic, media hype, fake news regarding COVID-19 per country or worldwide. Indices used in this research include panic index and fake news index (RavenPack, 2022).

Panic index quantifies the amount of panic or hysteria in news regarding COVID-19. Values are in the range of 0 to 100 representing the percentage of global news talking about panic and hysteria (RavenPack, 2022).

Fake news index quantifies the amount of media spreading fake news about COVID-19. Values are in the range of 0 to 100 representing the percentage of news being misinformation (RavenPack, 2022).

RavenPack media indices database was obtained from RavenPack, Coronavirus Media Monitor.

### 3.2. Methodology

For the purpose of detrending, comparability and statistical evaluation, daily returns were used instead of prices of assets. Due to the need of log-normality and raw-log equality for statistical analysis, a logarithmic return was chosen instead of simple returns.

Daily returns were calculated by the Equation 6.

*Equation 6 Calculation of the logarithmic daily returns*

$$Daily\ returns_t = \ln \frac{P_t}{P_{t-1}}$$

where $P_t$ is the price of an asset at *t* point in time, and $P_{t-1}$ the price of the asset in the period $t$-*1*, representing the day before *t*.

First, media index data is collected on an everyday basis, unlike stock index data which is collected five days a week due to stock exchanges which are working five days a week. Hence, values of stock indices are not available for non-working days like holidays and other. For this reason, media index values had to be corrected for non-working days. This was made under the presumption that news from the weekends and non-working days would reflect on stock market prices on the next working day. The correction was done by calculating the weighted average from the non-working days and the next working day, thus explaining that non-working days news is going to take effect on the price the next working day.

Prior to the quantile regression analysis, all variables were subjected to a unit root test for stationarity with the Augmented Dickey-Fuller test (Uribe & Guillen, 2020). Furthermore, a OLS regression was performed for comparison with quantile regression. Moreover, the Pearson's correlation between the variables is tested.

First, a classical OLS regression is run to acquire the coefficients of OLS considering the conditional mean of the distribution. Furthermore, due to multicollinearity, a Variance Inflation Factor (VIF) test is required for determination of multicollinearity and selection of valid regressors. A VIF factor of 10 and above considers the presence of collinearity (Garcia et al., 2015). Further, post-estimation tests regarding heteroscedasticity and normality of the residuals are reported for a statistically significant OLS regression. The tests include the Cameron & Trivendi IM test and Bareusch-Pagan/Cook-Weisberg test for heteroscedasticity.

The quantile regression model includes stock market returns *(Y)*, panic index *($X_1$)* and fake news index *($X_2$)* compiled into the following equation:

*Equation 7 Calculation of the quantile regression*

$$Q_\theta(Y|X) = \beta_0(\theta) + \beta_1(\theta)X_1 + \beta_2(\theta)X_2$$

where $\beta_0(\theta)$ is the intercept of $\theta$-th quantile and $\beta_1(\theta)$and $\beta_2(\theta)$ being the slopes. The quantiles that are tested are q(0.05, 0.10, 0.20, 0.25, 0.5, 0.75, 0.80, 0.90, 0.95) because of the assumption of greater tail dependencies.

Unlike OLS regression, quantile regression allows for a deeper understanding of the conditional distribution, not limiting itself only on the conditional mean of the response (dependent, outcome) variable. Its strengths lay in the ability to present information about the location, scale and shape shift of the conditional distribution of the dependent variable, analyzing those effects on different quantiles of the conditional distribution. Quantile regression has many different applications and purposes, and one of the main factors for choosing this approach is the unique way that it handles heteroskedasticity (Davino et al., 2013).

Unlike classical regression which defines the mean by the minimization of the squared sum of deviations (Equation 8), quantile regression defines the median as the center of the distribution by minimizing the absolute sum of deviations (Equation 9)

*Equation 8 Minimization of the squared sum of deviations*

$$\mu = argmin\, E(Y - c)^2$$

*where c* represents the mean or the center of the distribution (*argmin* = the input to the function that yields the minimum).

*Equation 9 Minimization of the absolute sum of deviations*

$$Me = argmin\ E|Y - c|$$

Least squares linear regression model relies on the minimization function for estimation of the conditional mean function (Equation 10).

*Equation 10 Minimization function of the conditional mean*

$$\hat{\mu}(x_i, \beta) = argmin\ E[Y - \mu(x_i, \beta)]^2$$

where $\mu(x_i, \beta)$ = E[Y | X = $x_i$] is the function of the conditional mean.

For the linear mean function $\mu(x_i, \beta) = x_i^T \beta$ the least squares linear regression estimator is explained as in Equation 11.

*Equation 11 Calculation of the linear regression estimator*

$$\hat{\beta} = argmin\ E[Y - x_i^T \beta]^2$$

After applying the same approach to different quantiles of the conditional distribution, the minimization function for estimation of the conditional quantile function is defined as in Equation 12.

*Equation 12 Minimization function of the conditional quantile function*

$$\hat{q}_Y(\theta, X) = argmin\ E[\rho_\theta(Y - Q_Y(\theta, X))]$$

where $Q_Y(\theta, X) = Q_\theta[Y \mid X = x]$ is the conditional quantile function, and $\rho_\theta$ is the absolute loss function.

Thus, the linear model estimator can be defined as in Equation 13.

*Equation 13 Linear estimator for the conditional quantile function*

$$\hat{\beta}(\theta) = argmin\ E[\rho_\theta(Y - X\beta)]$$

The linear regression line based on the estimators is defined as in Equation 14.

*Equation 14 Calculation of the linear regression line of the conditional quantile distribution*

$$\hat{Y}_\theta = \hat{\beta}_0(\theta) + \hat{\beta}_1(\theta) X_\theta$$

where $\theta$ represents the $\theta$-th quantile of the conditional distribution (Davino et al., 2013).

Data preparation is done using Microsoft Excel 2019. All tests, modeling and graphics are created using Stata/BE 17.

# 4. Results

The following section shows the summary statistics of all variables, results of quantile regressions and OLS regressions. Both OLS and quantile regression use the panic index and fake news index as independent variables, and Royalton CRIX and S&P 500 daily returns as dependent variables.

## 4.1. Fake news and S&P 500

The summary statistic is reported in the Table 1. The distribution of S&P 500 (*Skewness = -0.944, Kurtosis = 16.642*) is negatively moderately skewed, with heavy tails. On the other hand, both the distributions of the panic index (*Skewness = 1.612, Kurtosis = 7.134*) and fake news index (*Skewness = 1.094, Kurtosis = 3.902*) are positively heavily skewed, both having heavy tails. The results of the Augmented Dickey-Fuller unit root test show that all variables are stationary.

*Table 1* Summary statistics of S&P 500, panic index and fake news index

| | S&P 500 | 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 being statistically significant.*

Source: Author's calculation.

Figure 1 shows that the S&P 500 daily returns, arranged from the lowest to the highest values, are peaking in the extremely low and extremely high quantiles of the distribution, confirming the fact of the presence of fat tails and outlier values.

Furthermore, the correlation matrix (Table 2) shows that both panic index *($r_{(557)} = .034$, $p = .418$)*, and fake news index *($r_{(557)} = .073$, $p = .069$)* suggest a weakly positive correlation with S&P 500 daily returns, but not being statistically significant at a 5% level. Moreover, the correlation between panic index and fake news index *($r_{(557)} = 0.673$, $p < .000$)* is positive which is statistically significant at a 5% level. Further testing for multicollinearity is required and presented in post-estimation after the initial OLS regression.

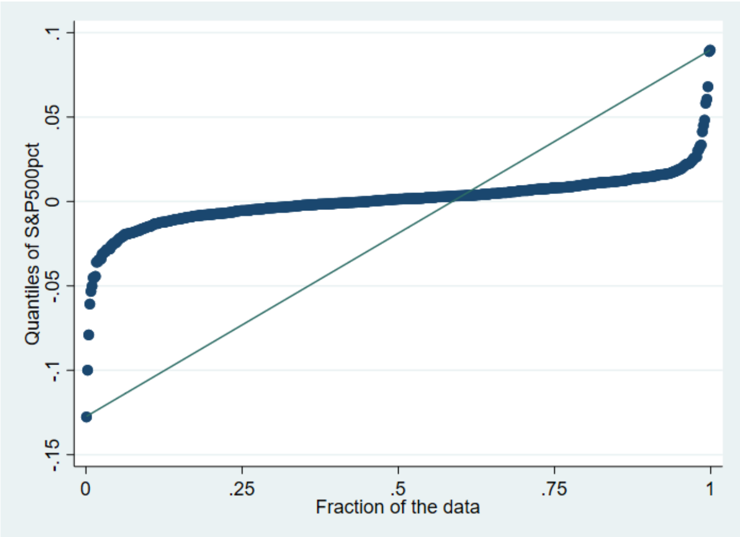


*Figure 1* Quantile plot of the distribution of S&P 500.

Source: Author's calculation.

*Table 2* Pearson's correlation matrix for S&P 500, panic index and fake news index

| | S&P 500 | Panic Index | Fake News Index |
|---|---|---|---|
| S&P 500 | 1 | | |
| Panic Index | 0.034 ($p = .418$) | 1 | |
| Fake News Index | 0.077 ($p = .068$) | 0.673 ($p = .000$)* | 1 |

** statistical significance at $p < .05$.*

Source: Author's calculation.

OLS regression results (Table 3) show that the model explains less than 1% of the relationship between the independent variables and the dependent variable *($F_{(2, 556)} = 1.83$, $p = .161$, $R^2 =.007$, $R^2_{adjusted} = .003$)*. Not being statistically significant, the conditional mean is not viable for the explanation of the relationship, hence normality of residuals is not reported.

*Table 3* Ordinary least squares regression results of the S&P 500 model

| | Coefficient | Std.Err | t | P>t | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| Intercept | -.002 | .002 | -1.03 | .305 | -.005 | .001 |
| Panic Index | -.000 | .001 | -0.57 | .572 | -.002 | .001 |
| Fake News Index | .004 | .002 | 1.73 | .084 | -.001 | .009 |

** statistical significance at p < .05.*

Source: Author's calculation.

Further, a Variance Inflation Factor (Table 4) test is performed to test if the data meets the assumption of multicollinearity. There is no strong relationship between the regression exploratory variables (Table 4).

*Table 4* Variance Inflation Factor results of S&P 500 model

| | VIF | 1/VIF |
|---|---|---|
| Fake News Index VS Panic Index | 1.83 | 0.547 |

Source: Author's calculation.

The pseudo $R^2$ results of the quantile regression (Table 5) show that the regressors explain the variance of the dependent variable between 0.49% and 14.48%, depending on the quantile of the distribution. Extremely low (q05) and extremely high quantiles (q95) were most impacted by the regressors, and the median explains little to none of the variance with a pseudo $R^2$ value of less than 1%.

Furthermore, Table 5 shows that the panic index is statistically significant through the distribution except from the 25$^{th}$ to the 50$^{th}$ quantile of the distribution. Fake news index appears not to be statistically significant in the entire conditional distribution.

Figure 2 shows a graphical interpretation of the quantile regression results for further explanation. The graphic shows a negative to positive growing trend from the lower to the higher quantiles, peaking in the extremely low and extremely high quantiles. Furthermore, fake news exhibits a non-linear asymmetric relationship through the distribution of quantiles, but is not statistically significant.

*Table 5* Results of quantile regression of S&P 500 model

| | ***Pseudo $R^2$*** | ***Coefficient*** | ***Std. err.*** | ***t*** | ***P>t*** | ***[95% conf. interval]*** | |
|---|---|---|---|---|---|---|---|
| **q05** | 0.103 | | | | | | |
| *Intercept* | | -.012 | .004 | -2.95 | .003* | -.021 | -.004 |
| *Panic Index* | | -.007 | .003 | -2.16 | .031* | -.013 | -.001 |
| *Fake News Index* | | .008 | .005 | 1.65 | .100 | -.002 | .017 |
| **q10** | 0.044 | | | | | | |
| *Intercept* | | -.008 | .003 | -2.82 | .005* | -.013 | -.002 |
| *Panic Index* | | -.004 | .002 | -2.25 | .025* | -.007 | -.000 |
| *Fake News Index* | | .002 | .004 | 0.44 | .662 | -.006 | .01 |
| **q20** | 0.011 | | | | | | |
| *Intercept* | | -.004 | .002 | -2.11 | .035* | -.008 | -.000 |
| *Panic Index* | | -.003 | .001 | -3.48 | .001* | -.004 | -.001 |
| *Fake News Index* | | .003 | .002 | 1.89 | .060 | -.000 | .007 |
| **q25** | 0.007 | | | | | | |
| *Intercept* | | -.003 | .002 | -1.76 | .079 | -.007 | .000 |
| *Panic Index* | | -.002 | .001 | -1.47 | .143 | -.004 | .001 |
| *Fake News Index* | | .003 | .002 | 1.45 | .148 | -.001 | .007 |
| **q50** | 0.005 | | | | | | |
| *Intercept* | | -.001 | .002 | -0.59 | .557 | -.005 | .002 |
| *Panic Index* | | .001 | .001 | 0.92 | .358 | -.001 | .002 |
| *Fake News Index* | | .001 | .002 | 0.48 | .629 | -.003 | .006 |
| **q75** | 0.037 | | | | | | |
| *Intercept* | | .001 | .001 | 0.50 | .618 | -.002 | .004 |
| *Panic Index* | | .003 | .001 | 3.48 | .001* | .001 | .004 |
| *Fake News Index* | | .002 | .003 | 0.72 | .472 | -.003 | .007 |
| **q80** | 0.048 | | | | | | |
| *Intercept* | | .002 | .002 | 0.89 | .374 | -.002 | .005 |
| *Panic Index* | | .003 | .001 | 2.39 | .001* | .001 | .004 |
| *Fake News Index* | | .003 | .003 | 0.99 | .322 | -.003 | .008 |
| **q90** | 0.077 | | | | | | |
| *Intercept* | | .004 | .002 | 1.72 | .087 | -.001 | .008 |
| *Panic Index* | | .003 | .001 | 2.39 | .017* | .001 | .006 |
| *Fake News Index* | | .004 | .003 | 1.26 | .208 | -.002 | .011 |
| **q95** | 0.145 | | | | | | |
| *Intercept* | | .005 | .004 | 1.25 | .213 | -.003 | .012 |
| *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: Author's calculation.

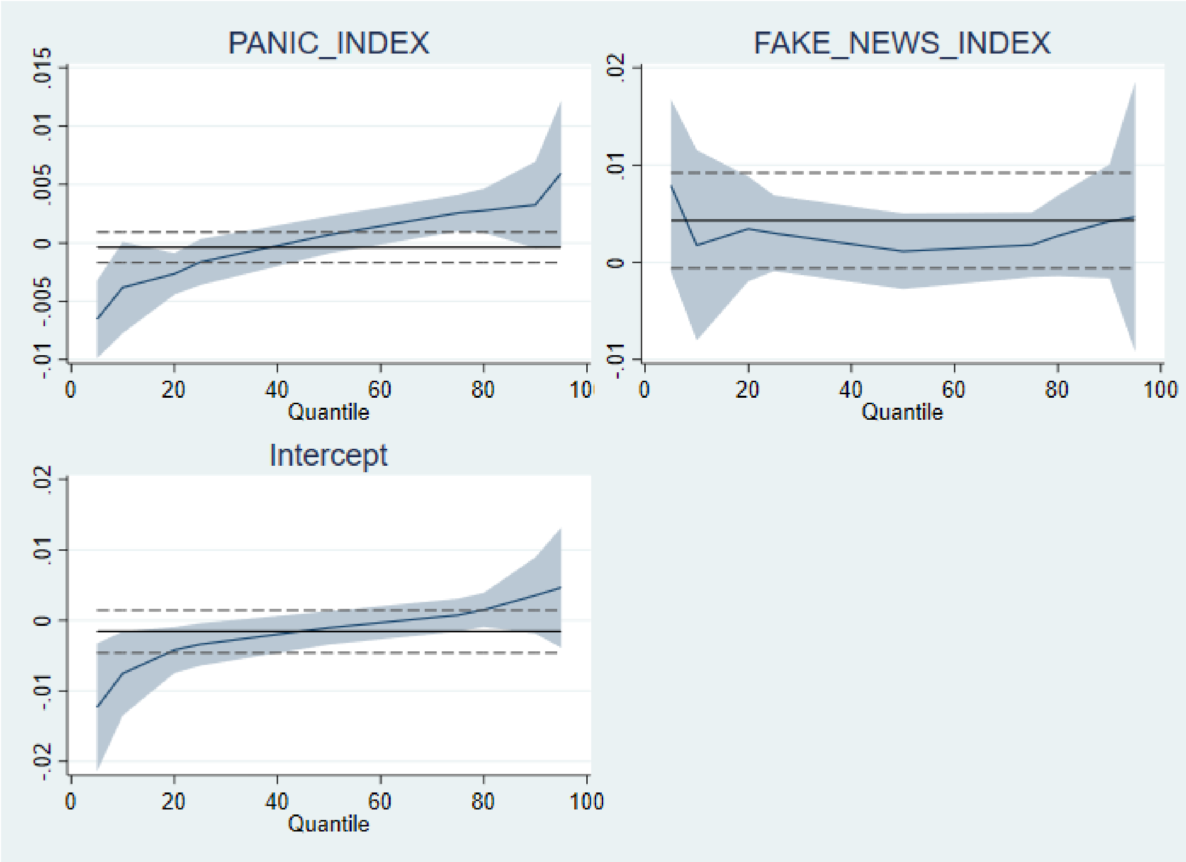


*Figure 2* Graphical representation of quantile regression coefficients of the S&P 500 model.

*Note* Black lines represents the OLS coefficient and the black dotted lines present the 95% confidence interval of OLS coefficients. The blue line represents the quantile regression coefficient and the blue boundaries represent the 95% confidence interval of quantile regression coefficients.

Source: Author's calculation.

### 4.2. Fake news and Royalton CRIX

Table 6 reports the summary statistics of the variables Royalton CRIX, panic index and fake news index. Unlike the distribution of daily returns on Royalton CRIX (*Skewness = -0.65, Kurtosis = 6.646*), which is fairly symmetrical with heavy tails, distributions of the panic index (*Skewness = 1.558, Kurtosis = 6.762*) and fake news index (*Skewness = 1.099, Kurtosis = 3.893*) again appear highly positively skewed with heavy tails. The Augmented Dickey-Fuller unit root test shows that all variables are stationary.

Furthermore, Figure 3 shows the daily return quantiles plotted against the corresponding fraction of the data, which allow for further explanation of the distribution of Royalton CRIX daily returns. The graphical representation confirms the presence of heavy tails, as the lower and upper quantiles manifest peaking values, thus implying the presence of outlier values.

*Table 6* Summary statistics of Royalton CRIX index, panic index and fake news index

| | *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 |
| *25th percentile* | -0.141 | 0.59 | 0.14 |
| *50th percentile* | 0.005 | 2.01 | 0.5 |
| *75th 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 being statistically significant.*

Source: Author's calculation.

Table 7 shows the correlation matrix to determine the correlation between the dependent variable and the regressors, also considering the correlation between the independent variables. Both the panic index $(r_{(577)} = .047, p = .262)$ and fake news index $(r_{(577)} = .138, p = .001)$ exhibit weakly positive correlation with Royalton CRIX daily returns. Further, the regressors express a moderately to high positive correlation $(r_{(557)} = .665, p < .000)$. Thus, there is a requirement for testing for multicollinearity after the initial OLS regression.

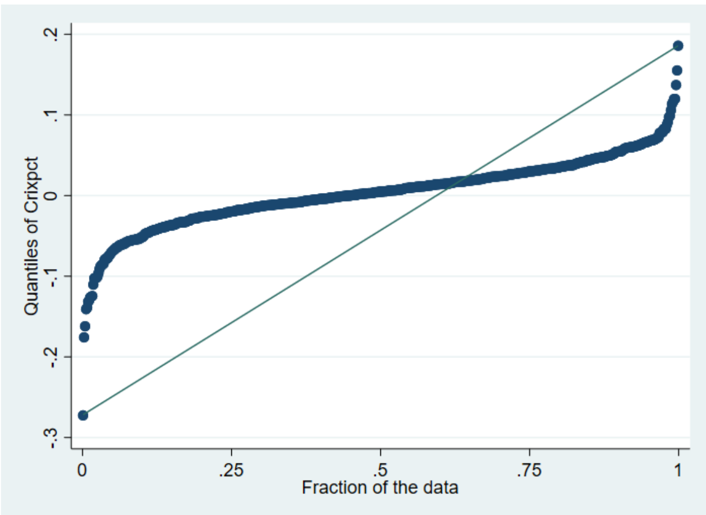


*Figure 3* Quantile plot of the distribution of Royalton CRIX.

Source: Author's calculation.

*Table 7* Pearson's correlation matrix for Royalton CRIX, panic index and fake news index

| | *Royalton CRIX* | *Panic Index* | *Fake News Index* |
|---|---|---|---|
| *Royalton CRIX* | 1 | | |
| *Panic Index* | 0.047 | 1 | |
| *Fake News Index* | 0.138* | 0.665* | 1 |

** statistical significance at p<0.05.*

Source: Author's calculation.

By analyzing the results of the OLS regression (Table 8), it can be concluded that the model explains 1.9% of variation in the Royalton CRIX daily returns ($F_{(2, 576)} = 6.65, p = .001, R^2 = .023, R^2_{adjusted} = .019$). Fake news index ($t = 3.47, p = .001$) is the only statistically significant regressor at a 5% significance level measuring 0.029%, meaning that for a 1% change in the fake news index (*ceteris paribus*), Royalton CRIX daily returns will change by 0.029%. The impact of the panic index ($t = -1.46, p = .114$) is not significant.

*Table 8* Ordinary least squares regression results of the Royalton CRIX model

| | **COEFFICIENT** | **STD.ERR** | **t** | **P>t** | **[95% CONF. INTERVAL]** | |
|---|---|---|---|---|---|---|
| Intercept | -.007 | .004 | -1.67 | .095 | -.016 | .001 |
| Panic Index | -.003 | .002 | -1.46 | .144 | -.007 | .001 |
| Fake News Index | .029 | .008 | 3.47 | .001* | -.013 | .045 |

** statistical significance at p<0.05.*

Source: Author's calculation.

Post-estimation analysis suggests that there is no presence of multicollinearity. Variance Inflation Factor test results show that both fake news index and panic index ($VIF = 1.79, 1/VIF = .557$) do not show signs of concern regarding collinearity.

Furthermore, both the Cameron & Trivendi IM test ($chi2 = 10.52, p_{(5)} = .619$) and Bareusch-Pagan/Cook-Weisberg test ($chi2_{(1)} = .19, p = .666$) suggest that there is no evidence of heteroscedasticity in the model, meaning that the residuals have a constant standard deviation. Figure 4 shows the distribution of the residuals.

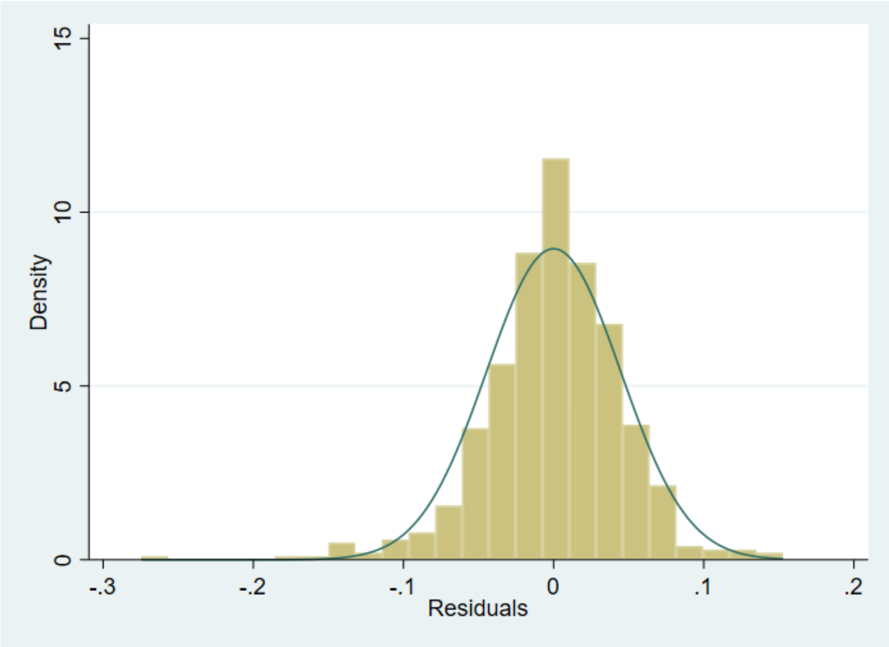


*Figure 4* Distribution of residuals in the Royalton CRIX model.

Source: Author's calculation.

Figure 4 suggest that the OLS residuals are not normally distributed, thus not fulfilling the normality assumption of OLS regression. To confirm this, results of the Shapiro-Wilk test *($W = .962$, $p < 0.000$)*, imply that there is no evidence of the normality of residuals, which questions the stability and reliability of the model.

Quantile regression results (Table 9) show that the model explains between 2.7% and 0.5% of the variance in the dependent variable asymmetrically, depending on the quantile.

For the lower quantiles q(0.05 – 0.25) and higher quantiles q(0.90 – 0.95), fake news gives greater insight in the relationship with daily returns, unlike the middle part of the conditional distribution. Furthermore, fake news index has a significant impact on daily returns considering the lower quantiles of the conditional distribution with emphasis of extreme low quantiles q(0.05 and 0.10). Moreover, the panic index doesn't have a significant impact on daily returns considering the tested quantiles.

Considering OLS regression as a benchmark (Figure 5), slopes regarding the panic index, acquired analyzing OLS and quantile regression, do not appear to be different because the OLS coefficient lies inside the 95% confidence interval of the quantiles. Furthermore, the estimator of fake news which lies at lower quantiles of the distribution appears to have significantly different impact on returns considering OLS regression, showing asymmetric dependencies through the distribution.

*Table 9* Results of quantile regression of the Royalton CRIX model

| | Pseudo $R^2$ | Coefficient | Std. err. | t | P>t | [95% conf. interval] | |
|---|---|---|---|---|---|---|---|
| **q05** | .026 | | | | | | |
| *Intercept* | | -.083 | .011 | -7.65 | .000* | -.105 | -.062 |
| *Panic Index* | | -.007 | .005 | -1.46 | .145 | -.017 | .002 |
| *Fake News Index* | | .058 | .013 | 4.35 | .000* | .032 | .085 |
| **q10** | .027 | | | | | | |
| *Intercept* | | -.065 | .006 | -10.25 | .000* | -.077 | -.052 |
| *Panic Index* | | -.004 | .004 | -0.99 | .323 | -.013 | .004 |
| *Fake News Index* | | .042 | .011 | 3.86 | .000* | .021 | .064 |
| **q20** | .016 | | | | | | |
| *Intercept* | | -.041 | .005 | -7.90 | .000* | -.051 | -.031 |
| *Panic Index* | | .000 | .003 | 0.14 | .886 | -.005 | .006 |
| *Fake News Index* | | .023 | .01 | 2.36 | .019* | .004 | .041 |
| **q25** | .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 |
| **q50** | .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 |
| **q75** | .005 | | | | | | |
| *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 |
| **q80** | .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 |
| **q90** | .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 |
| **q95** | .02 | | | | | | |
| *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 |

** statistical significance at p<0.05.*

Source: Author's calculation.

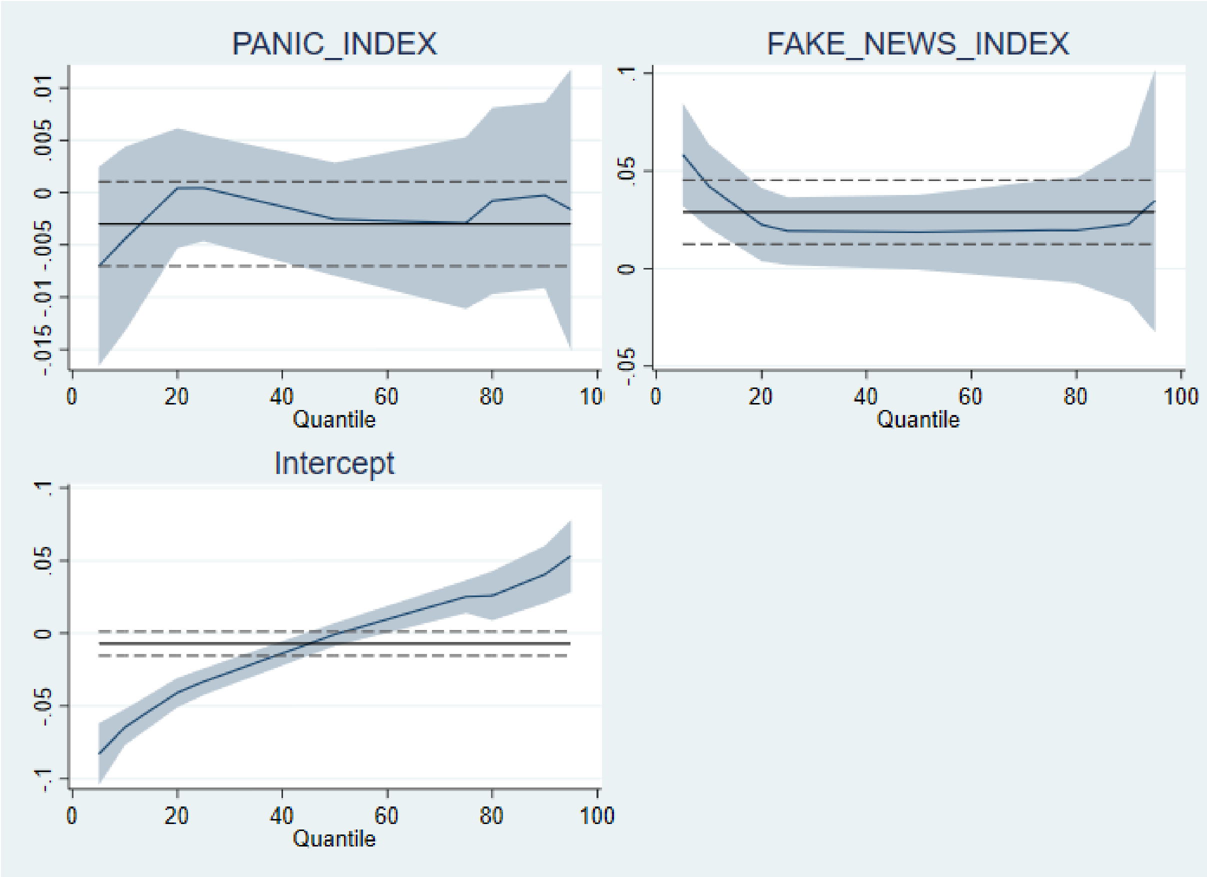


*Figure 5* Graphical representation of quantile regression coefficients of the Royalton CRIX model.
*Note* Black lines represents the OLS coefficient and the black dotted lines present the 95% confidence interval of OLS coefficients. The blue line represents the quantile regression coefficient and the blue boundaries represent the 95% confidence interval of quantile regression coefficients.

Source: Author's calculation.

Moreover, quantile regression gives a more in-depth insight in the intercept values, showing non-linear growing dependencies on the conditional distribution.

## 5. Discussion

Considering S&P 500 index, the results regarding the fake news index suggest that depending on the state of the market, fake news exhibits a positive asymmetrical U-shaped impact declining from lower quantiles to the middle of the distribution, and then change to a growing direction to the upper quantiles. This implies that the greatest impact of misinformation on daily returns lies primarily in a stagnating market and growing market, rather than in a non-trending market. As for the period of that was researched, fake news did not exhibit a statistically significant impact on the conditional distribution of S&P 500 daily returns, both in OLS and quantile regression.

The impact of the fake news index on the Royalton CRIX shows similar results, comparable to the S&P 500. A positive non-linear U-shaped impact is visible in the low quantiles and weaker in the high quantiles of the return distribution, implying its effect in very bullish and very bearish markets. Through the middle of the distribution, it remains relatively constant, suggesting a lower impact in a non-trending market. The results show that misinformation has a statistically significant impact, considering the lower quantiles to the median of the distribution. Regarding the conditional mean in OLS regression, fake news suggest a positive statistically significant impact on the Royalton CRIX daily returns.

Previous research conducted by Cepoi (2020) suggests similar results. Cepoi noticed a nonlinear U-shaped impact in a normal market in the $25^{th}$ to $75^{th}$ percentiles of the market, emphasizing the importance of valid news (2020). Minor differences in results might be due to different markets and time spans that were researched.

Furthermore, Rahadian & Nurfitriani (2022) noticed a positive and increasing impact on various stock markets considering the upper $90^{th}$ to $95^{th}$ quantile in three different periods of research. As for the results, it is interesting to see that fake news have a positive impact on stock market daily returns of five ASEAN countries (Indonesia, Singapore, Malaysia, the Philippines, and Thailand), considering that it could be expected for them to have a negative impact on various markets.

As for the panic index, daily returns on the S&P 500 index have shown both a positive and negative impact resulting from the amount of panic in the media. Lower quantiles up to and around the median (of the returns distribution) have shown a non-linear negative impact resulting from the amount of panic. Additionally, upper quantiles from $75^{th}$ to $95^{th}$ percentile exhibit a nonlinear positive impact of panic on the daily returns of S&P 500. The analysis has shown that the results lasting from the 5th to the 25th percentile and 75th to 95th percentile are statistically significant.

On the one hand, these results imply that in a bullish market panic regarding COVID-19 is going to impact the daily stock market returns in a negative nonlinear way, depending on how much the returns have stagnated. On the other hand, panic in media has a positive growing impact in the bullish market.

Considering daily returns of the cryptocurrency index, the panic index shows asymmetrical dependencies through the conditional distribution of daily returns. 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 Royalton CRIX. From the 20th to the 95th percentile, panic has a positive nonlinear impact on the returns, including a positive, slightly stagnating, impact through the 50th to 75th percentile. That implies that in a bullish trading market, daily returns will be increased by the amount of panic in the media. However, none of the quantiles regarding the panic index appear statistically significant.

The above results are also similar to the research of Cepoi (2020). According to Cepoi, the panic index doesn't show any statistically significant impact. Rahadian & Nurfitriani (2022) report that the panic index exhibits a positive impact in the 80th to 85th percentile, and a negative impact in a down trending market regarding the 5th to 20th percentile.

Considering the conclusion made by Mahdi & Al-Abdulla (2022), who suggest Bitcoin and gold as safe-havens against media-induced panic during the pandemic, Bitcoin is also discussed in this research as a main constituent of Royalton CRIX index. Panic index showed a positive impact on daily returns in the Royalton CRIX index from the 20th to 95th percentile, which suggests that cryptocurrency is a hedging solution for media-induced panic, except in a strongly bearish trending market (5th to 20th percentile). However, the results are statistically insignificant., Gold seems to be a poor choice of a safe-haven according to Cepoi (2020), who found prominent nonlinear positive correlation with gold in extreme bearish and bullish periods.

Bringing together all the results and previous research, it is evident that media indices regarding COVID-19 news impact daily returns of stock and cryptocurrency in a non-linear way. Despite the impact being low in the observed sample, further research and a larger sample size could yield different results.

Considering the possibility that social media allows for information dissemination, many small investors use it in their decision-making process. This can be observed in media channels such as YouTube, Twitter, Telegram and others, which play a large part in information sharing for cryptocurrency investors. Thus, this raises the question are information from these channels valid. It can be reasonably assumed that social media news have an impact on the volatility of cryptocurrencies, thus making it important to validate the information that is being shared.

Further research is required to explain this impact, since research conducted in this field yields opposing results. Considering the sample size of the research performed here and the observed market, a panel quantile regression on market indices might be the way forward. Quantile regression proved to be a more detailed approach to explaining the relationship between media indices and stock market indices, by considering not only the conditional mean of returns, but also the entire conditional distribution.

# 6. Conclusion

According to previous research, it is evident that fake news and panic regarding COVID-19 in the media have an impact on the daily returns of stock market indices. The analysis performed here shows that fake news worldwide has some impact on the daily return of Royalton CRIX in a bullish trending market, however the impact is low to non-existent.

S&P 500 daily return relationship with the panic in the U.S. media is significant in extremely bullish and bearish markets, but also with a low impact on the returns. All types of media play a role in the investors' decision-making process. To a retail investor, the impact of media on the decisions that investor makes in the stock and cryptocurrency market might be a lot stronger than it would be for large companies and investment funds. That said, media has to be fact-checked and verified for the validity of the news that they provide.

Further research regarding media implications in the stock and cryptocurrency market could be conducted using quantile regression, as it is capable of interpreting the underlying data in a way that is not possible with OLS regression. As results differ from period to period, all the media indices provided by RavenPack could be analyzed in a panel quantile regression approach, including different stock indices and cryptocurrencies, and also considering different lags of the independent variable.

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## Summary of tables



## Summary of figures



## Summary of equations