

Journal Pre-proof

What threatens stock markets more - The coronavirus or the hype around it?

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PII: S1059-0560(21)00255-0

DOI: <https://doi.org/10.1016/j.iref.2021.12.007>

Reference: REVECO 2354

To appear in: *International Review of Economics and Finance*

Received Date: 26 October 2020

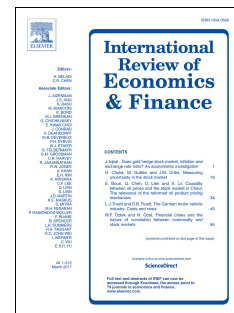
Revised Date: 19 November 2021

Accepted Date: 13 December 2021

Please cite this article as: Nepp A., Okhrin O., Egorova J., Dzhuraeva Z. & Zykov A., What threatens stock markets more - The coronavirus or the hype around it?, *International Review of Economics and Finance* (2022), doi: <https://doi.org/10.1016/j.iref.2021.12.007>.

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Manuscript title: **What Threatens Stock Markets More - the Coronavirus or the Hype Around it?**

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acquisition of data: Zarnigor Dzhuraeva, Alexandr Zykov;

analysis and/or interpretation of data: Julia Egorova.

Category 2

Drafting the manuscript: Alexander Nepp, Ostap Okhrin, Julia Egorova, Zarnigor Dzhuraeva, Alexandr Zykov;

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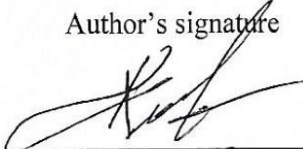
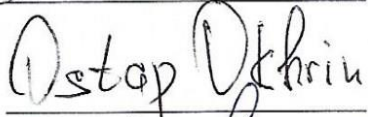

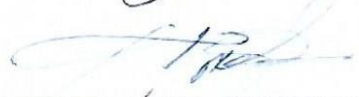

Category 3

Approval of the version of the manuscript to be published (the names of all authors must be listed):

Alexander Nepp, Ostap Okhrin, Julia Egorova, Zarnigor Dzhuraeva, Alexandr Zykov.

Acknowledgments

RFBR, project number 20-04-60158, funded the reported study.

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What Threatens Stock Markets More - the Coronavirus or the Hype Around it?

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June 1, 2021

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Abstract

We use a linear regularised model with structural changes and found that the coronavirus pandemic had a direct and an indirect effect (via media hype) on stock markets. We reveal a correlation between internet search queries, discussions of the pandemic in the press and social media, and changes in stock market indices. We demonstrated that the effect of the pandemic coverage in digital and printed media and the effect of Google queries was comparable to, and sometimes even exceeded, the effect of the pandemic itself. We showed the effect of hype on the volume of Google queries and social media publications.

Keywords: Covid-19, Hype, Social media, Stock Indexes, LASSO.

JEL classification: G41, G32, I1

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*‘Declarations of interest: none’

What Threatens Stock Markets More - the Coronavirus or the Hype Around it?NEPP A.^{1*}, OKHRIN O.², EGOROVA J.^{1,3}, DZHURAEVA Z.¹, ZYKOV A.¹**ABSTRACT**

We use a linear regularised model with structural changes and found that the coronavirus pandemic had a direct and an indirect effect (via media hype) on stock markets. We reveal a correlation between internet search queries, discussions of the pandemic in the press and social media, and changes in stock market indices. We demonstrated that the effect of the pandemic coverage in digital and printed media and the effect of Google queries was comparable to, and sometimes even exceeded, the effect of the pandemic itself. We showed the effect of hype on the volume of Google queries and social media publications.

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1. Introduction

'Financial crisis' (Kawa, 2020), 'panic selling' (Liu, 2020), and 'the biggest loss' (Culp, 2020) are just a few of the headlines describing the situation in the world stock markets in March 2020. Such alarmist rhetoric may seem not entirely unfounded if we consider that the stock market indices of developed countries have fallen by 30% (USA_NDQ) or even 50% (DEU_DAX) since the middle of January 2020: see Cbonds (2020). These indices are very important predictors of economic growth: compare Mauro (2003), Shen and Lee (2006), and Cole, Moshirian, and Wu (2008).

According to classical approaches, the main determinants of financial markets are GDP (Ibbotson and Chen (2003), Chordia and Shivakumar (2006)), inflation and interest rates (Geske and Roll (1983), Fama and Schwert (1977), Lee (1992)), oil prices (Sadorsky (1999), Jones and Kaul (1996), Huang, Masulis, and Stoll (1996)), gold prices (Bouoiyour and Selmi, 2015) and currency exchange rates (Nandha and Hammoudeh, 2007). A number of papers investigating the impact of COVID-19 on financial markets analyse GDP as a control variable (Ashraf, 2020). There is another approach that excludes macroeconomic factors as control variables in the study of the impact of COVID-19 (Baig et al. (2021) Al-Awadhi et al. (2020)). We believe that for our study, the second approach is optimal, as macroeconomic parameters whose analysis is not part of our objectives may, by virtue of their strong effects, shift the effects we are investigating. In the situation of the pandemic, however, it is an open question whether these variables continue to determine the situation in the market.

Bloomberg describes the recent stock market crash using an apt formulation – the 'Coronacrash' - since the shocks were supposedly mainly driven by the pandemic. In Asian countries, stock markets witnessed a fall in the middle of January, when the pandemic started in Wuhan, and began its march across other regions of China (Lee and Qian, 2020). Stock markets in developed countries were shocked at the end of February when it became clear that the virus had 'successfully' reached Europe and America: see Steenhuysen and Hay (2020), Vidalon (2020), Alkousaa (2020).

Is the pandemic solely to blame for these market shocks? Maybe terror simply magnifies objects, and the media coverage of the coronavirus pandemic and the general

hype surrounding this subject rattled the markets? We seek to address these research questions in this study. We aim to shed light on the effects of the pandemic itself, the coverage of this topic in printed and online media, and the public sentiment reflected by Google searches. We sought to determine whether any of these factors resulted in market turmoil by looking at indices such as the DJ (US), S&P 500 (US), NASDAQ (US), FTSE 100 (UK), DAX (DEU), CAC 40 (FRA), Nikkei 225 (JPN), FTSE MIB (IT), and IBEX 35 (SPA). We aim to explain how this outbreak of mass hysteria, fuelled by the media, may raise concerns about the dangers of unlimited media and internet freedom.

There is a vast body of research literature on the economic effects of infectious diseases. Studies of the plague by Maur (1995), Alfani and Percoco (2019), and Mark (2018); typhus by Drali, Brouqui, and Raoult (2014), Watanabe (2002), and Lebrun (1980); tuberculosis by Nor et al. (2015); flu by Johnson and Mueller (2002), and McLafferty (2010); and AIDS by Bloom and Mahal (1997), Cuddington (1993), Dauda (2019), and Cuesta (2010) have showed that these diseases had a negative impact on economic development. Most recent studies of the coronavirus pandemic have demonstrated its negative effects on stock markets (Ozili and Arun (2020), Alber (2020), Schoenfeld (2020)).

In economic development and particularly in market dynamics, unexpected or dramatic events may have effects on markets due to the changes in the behaviour and sentiments of economic actors (De Bondt and Thaler, 1987). In extraordinary situations or shocks, including disease outbreaks, people may be prone to mood swings as the emotional component of decision-making starts to prevail over rational or standard decisions (DellaVigna, 2009). Market participants may be prone to hysteria (Boyer, Kumagai, and Yuan, 2006), which spreads quickly in online communities, following crowd theory. Similar holds for the so-called 'hysterical disease' defined and investigated by Mackay (1841), Le Bon (1896) and Gehlen (1977), or mass fear and panic (Freud and Breuer, 1895). Hysteria among market participants may significantly increase market volatility (Boyer, Kumagai, and Yuan, 2006), and cause severe losses (Kyle and Xiong, 2001).

The study of Cepoi (2020), which is the most relevant to our topic, discusses the impact of coronavirus coverage in the mass media, and the hype and fake news surrounding the Covid-19 pandemic on stock markets. In contrast to Cepoi (2020), however, we develop a theoretical and methodological framework in order to analyse the effects of hype on the stock market; reveal the effects of hype and mass media coverage

by analysing Google queries and unique data on social media publications; determine the structure break for the model for the given period, and explain its relationship to the hype surrounding coronavirus; show the significance of the effects of media coverage and hype, comparing them with the effects of the pandemic itself; and, finally, build unique models for each stock market index to show the effects specific to given countries and stock markets and avoid mixing them.

Our research makes the following contribution to the existing literature. We found that the coronavirus pandemic had a direct and indirect effect (via media hype) on stock markets. We revealed the correlation between internet search queries, discussions of the pandemic in digital and printed media and changes in stock market indices. Thirdly, we demonstrated that the effect of pandemic coverage in the digital and printed media and the effect of Google queries was comparable to, and sometimes even exceeded, the effect of the pandemic itself. Finally, we showed the effect of hype on the number of Google queries and social media discussions of the pandemic.

We used the unique data on coronavirus coverage in social media – Facebook, Instagram, and Twitter – between 30.12.2019 and 30.04.2020. This data was combined with the data on Google queries and the coverage of the pandemic in printed media (Baker et al. (2019), Baker et al. (2020)). LASSO regularisation was used to reduce the dimensionality and solve multicollinearity problem. In Section 2, we describe the theoretical foundation for analysing the impact of the coronavirus pandemic, the influence of the pandemic coverage in printed and digital media and the impact of the media hype. In Section 3, we present our research methodology and hypotheses; we will also explain the choice of the econometric method, and describe the procedure for building our database. In Section 4, we will discuss the results of our study and compare them with previous findings. The final section will present the conclusions of our study.

2. Theoretical framework for analysis of the impact of diseases and their media coverage on stock markets

2.1. Health is the primary duty of life (Oscar Wilde)

The theoretical framework used by studies explaining the impact of health and illnesses on stock markets is the Solow Growth Model (Solow, 1956). Health correlates with economic growth through the determinants included in the Solow model. Health positively correlates with the production function (Hassan, Cooray, and Holmes, 2017) and is an essential factor that affects economic growth via productivity (Kalemli-Ozcan, Ryder, and Weil, 2000). Another health-related determinant in the Solow-Swan model is consumption. Health shocks and major illnesses were found to have a substantially adverse effect on consumption (Gertler and Gruber, 2002). The third way in which public health affects economic growth is via investments and savings. Better health contributes to life expectancy, which, in turn, stimulates people to accumulate savings and invest (Chakraborty, 2004), and may create a conducive environment to attract direct foreign investment (Alsan, Bloom, and Canning, 2006).

There are also some interesting findings related to the effects of Covid-19 on economic development. There is evidence that it had a considerable short-term effect on the GDP of all countries (McKibbin and Fernando, 2020). The coronavirus also had a negative influence on the stock market, as shown by Alber (2020) in their studies of stock market indices.

Diseases as external shocks affect the emotional state of stock market participants. From the perspective of behavioural finance, it may be supposed that the emotional reactions of market participants to external shocks are also an important factor (De Bondt and Thaler, 1985). These emotional reactions may be prompted by the media – television news, the internet, press, and so on (Gupta et al. (2018), Fang and Peress (2009)). We therefore assume that pandemics may affect stock markets not only directly, but also indirectly, via the media.

2.2. Media impact on economic growth and markets

Mass media and the internet have enormous potential to shape our moods and behaviour. The theory of bounded rationality and behavioural economics deal with the role of emotions in economic behaviour, and, therefore, markets and economic growth. People are affected by rational as well as emotional motives when making decisions

(Simon, 1955), Kahneman, Slovic, and Tversky (1982)). Fear and apprehension in the face of the impending disaster may cause a 'shift' in people's behaviour, to emotionally-driven irrational patterns. In these conditions, people (stock market investors being no exception) become more susceptible to manipulation (Day (1971), De Bondt and Thaler (1985)).

The mood of stock market investors affects their willingness to take risks (Yuen and Lee, 2003), which, in its turn, affects the volatility of stock markets (Gupta et al. (2018), Smales (2014)), liquidity of shares (Shyu et al. 2020) and the volume of trading (Sifat and Thaker, 2020). Uncertainty and anxiety, as reflected in an increased number of Google queries, have a negative effect on stock market indices (Škrinjarić (2019), Maneejuk and Yamaka (2019)). Twitter blogs also demonstrate forecast effects (Zhang, Fuehres, and Gloor (2012), De Jong, Elfayoumy, and Schnusenberg (2017)).

The moods of investors are also prone to changes. There is evidence that people's mood swings may be caused by positive or negative content spread by the mass media (Yang, Lin, and Yi (2017), Barber and Odean (2008)). Complimentary publications in social media may improve people's moods (Mayshak, Sharman, and Zinkiewicz, 2016).

The mass media makes fear and other emotions more contagious, and helps them spread, thus creating the effect of 'hype', which can trigger stock market reactions.

2.3. *How hype and hysteria drive the markets*

In this paper, the hype is understood as an effort to fuel the discussion around a situation or event in the media space to attract everyone's interest. The meaning of this term is similar to that of 'hysterical disease': see Kunieda (2014).

Since stock market trading mostly happens online, investors in stock markets can be considered an online community. Online communities have a mindset of their own that can be described as a collective consciousness (Lee, Hosanagar, and Tan, 2015; Dong and Bollen, 2015).

The opinions of internet users may be shaped by what they read in review forums or in social media (Anderson and Magruder, 2012). As information spreads in a crowd, according to Le Bon's theory, it may act as a trigger for mass hysteria (Scales, Zelenev, and Brownstein (2013), Kunieda (2014)). Information online can spread emotions between

countries (Tsai, 2014). It should be noted that fear (Smales and Kininmonth (2016), Smales (2017)), and depression (Griffith, Najand, and Shen, 2020) are important determinants in predicting stock market profitability.

Mass media plays a crucial key role in this process by spreading news about infectious diseases, and thus causing mass psychosis (Auxéméry, 2012), as was the case with the limited Ebola outbreak in the USA, which dominated the news media for a month after the first confirmed case, where the hype was disproportionate to the actual threat (Towers et al. 2015). The 2009 swine influenza pandemic was also accompanied by the spread of mass panic (Meo and Imran (2010), Castledine (2009)). The outbreak of the influenza A virus subtype H1N1 in Malaysia in 2009 also caused widespread fear (Wong and Sam, 2011).

As the fear and paranoia fuelled by the hype around Covid-19 grows, it may lead to outbreaks of mass hysteria and panic. A question that remains unanswered concerning the current Covid-19 pandemic is what effect this pandemic and the surrounding hysteria have had on markets.

3. Research methodology

3.1. Hypotheses

Despite substantial research literature on the effect of health and diseases (including the recent Covid-19 pandemic) on the economy, we have to admit that, to the best of our knowledge, few studies have dealt with the direct and indirect effects of the coronavirus on stock markets. We formulated the following first hypothesis to study the direct effects, and to compare the situation in different countries:

H1: Stock markets responded negatively to the Covid-19 pandemic.

Hypothesis H1 states what we do expect. But we would like to keep it for the sake of completeness of the whole story. It is also the basis for testing further H2-H4 hypotheses.

Publications in the mass media can affect people's moods and emotions: positive news stories enable an audience to experience positive emotions (Barber and Odean,

2008). Quite predictably, exposure to negative news in the mass media means that people experience unpleasant emotions (Paluck, Shafir, and Wu, 2017). There is evidence that coronavirus-related news in the mass media affected the mood and behaviour of the audience (Bursztyn et al. 2020). We have not found any studies comparing the direct and indirect effects of the news about the coronavirus pandemic in the mass media or internet on economic development and stock markets. We have formulated the following hypothesis to address this research gap:

H2: Publications in the printed media had an adverse effect on the stock market compared to the pandemic itself.

External shocks such as the flu pandemic have caused a surge in searches on Google (Ginsberg et al. 2009), and a similar trend is characteristic of social media (Signorini, Segre, and Polgreen, 2011). We formulate the following hypothesis regarding the indirect effect of contagious moods spreading through the internet on stock markets:

H3: The responses of internet users to the pandemic were reflected in their online search behaviour, and had a negative effect on stock markets compared to the pandemic itself.

Publications on social media can also affect people's moods and emotions: see Yang, Lin, and Yi (2017), Mayshak, Sharman, and Zinkiewicz (2016). We formulate the following hypothesis regarding the indirect effect of public reactions spreading through social media on stock markets during the pandemic:

H4: Public reactions in social networks had an adverse effect on stock markets compared to the pandemic itself.

Stock markets are susceptible to uncertainty and external shocks – in these periods, they tend to be more sentiment-driven (Lucey and Dowling, 2005). During a pandemic, free mass media and social media may induce mass panic and hysteria (Auxéméry, 2012). The Cambridge Dictionary (2020) defines hype as a situation in which something is advertised and discussed in the media space to attract everyone's interest. In online communities, hype can become contagious and spread swiftly. Such collective obsessional behaviour can be described with the help of mob theory, or as the 'hysterical disease' (Mackay (1841), Le Bon (1896), Gehlen (1977)). In the context of this study, we can suppose that dramatic events can trigger excessive emotional responses or irrational behaviour among stock market participants (De Bondt and Thaler, 1985).

It should be noted, however, that none of the above studies can explain the impact of the coronavirus pandemic as a source of mass hysteria and hype on stock markets. To fill this gap, we formulate the following hypothesis:

H5: The coronavirus outbreak was surrounded by hype, which had a strong negative effect on stock markets. After interest in the topic receded, this effect became weaker and disappeared.

3.2. Data and model selection

3.2.1. Stock market variables

Stock market indices reflect the state of markets at the national level. These indices are often used by market participants as benchmarks to evaluate the performance of their investment, or to predict market movements. We chose the following financial indices of countries that are major participants in global financial markets as the dependent variables for our models. We focus on countries whose Covid-19 statistics are considered sufficiently reliable: the Dow Jones Industrial Average, USA (*USA_DJ*), Standard and Poor's 500, USA (*USA_SnP*), NASDAQ, USA (*USA_NDQ*), FTSE 100, GBR (*GBR_FTSE 100*), DAX, DEU (*DEU_DAX*), CAC 40, FRA (*FRA_CAC 40*), FTSE MIB, IT (*IT_FTSE MIB*), IBEX 35, SPA (*SPA_IBEX 35*) and Nikkei 225, JPN (*JPN_Nikkei 225*). To address the problem of endogeneity and identify the 'pure' effect, we build on the work of Zhang et al. (2011), Smailović et al. (2013), Bollen, Mao and Zeng (2011), and considered only close-to-open returns (overnight effect) in order to control only for the effect on the prices of the independent variables the day before.

We analysed the behaviour of stock indices between 30 December 2019 to 30 April 2020 – this period was chosen because this was when most of the information about the new pandemic was spreading around the world. The daily financial index data were obtained from Yahoo finance <https://finance.yahoo.com/>.

3.2.2. Variables characterising the Covid-19 pandemic

The vector of the variables characterising the spread of the coronavirus infection contains the data on the daily rates of new cases in the given countries (IV_case_loc) and globally (IV_case_wld). This indicator was chosen for several reasons. In this study, we did not consider the mortality data due to evidence of multiple statistical flaws in coronavirus death figures (see, for example, Paulos, 2020). Moreover, the long-term mortality statistics are incomparable, because even within individual countries, there were changes in the methods applied to calculate Covid-19 mortality rates, as demonstrated by numerous statements made by officials in those countries (see Appendix A, Table A3). Finally, the proportion of Covid-19 deaths in the total number of deaths was relatively small in the period under investigation. Although this figure correlates with the number of confirmed cases, it also depends on various other factors, including the pandemic preparedness of national health care systems, which falls beyond the scope of this study.

We used the statistics published by the European Centre for Disease Prevention and Control (an European Union agency): <https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases>.

The cross-country comparisons of Covid-19 statistics may be misleading as there may be distortions in the Covid-19 case data due to differences in medical standards, funding, and regulations concerning mandatory coronavirus testing. We used only the statistics of each given country for modelling, without comparing it with the statistics of other countries.

3.2.3. Media coverage of the Covid-19 pandemic and reactions of internet users

There is increasing research interest in analysing social media data, as it can be used to monitor public reactions to different events. The most popular social media in the world are Facebook, Instagram and Twitter, and Google is the leading search engine worldwide (Pew Research Center (2021), Statista (2021)).

The vector of the variables reflecting public reaction to the pandemic and its media coverage thus contains the following:

- the number of publications on Facebook (FB_pbls) and reposts on Facebook (FB_repsts), and the number of publications on Instagram (IG_pbls), purchased from <https://popsters.ru/>.

- the number of coronavirus-related Google search queries (Ggle), taken from <https://trends.google.com/trends/>.

- the index of media mentions of Covid-19 for the USA printed media (Press), see Baker et al. (2019), Baker et al. (2020). We used the statistics published by the Economic Policy Uncertainty from <https://www.policyuncertainty.com/>.

Indicators for Facebook were selected using the daily number of publications and post shares on coronavirus-related Facebook pages. For this search, we used keywords such as 'coronavirus', 'Covid19', 'Covid-19', 'Covid 19', 'Sars-Cov-2', 'ncov', and 'quarantine' in combination with the names of countries, ethnonyms (names of specific ethnic groups), and the words 'statistics' or 'data'. We also used isolated search terms related to Covid-19, that is, without the words from the second group denoting countries, nationalities, and so on. The search terms were entered in English and the national languages of the countries of interest. It should be noted that the country-specific figures did not include the data related to those online communities whose home countries were not specified.

Instagram data was analysed according to a similar principle, except for the number of indicators, and we processed only the data on the number of publications on coronavirus-related pages (there is no direct post share function on Instagram). The search for key terms was done in the same way as for Facebook, that is, by looking at the daily number of relevant publications.

Google queries were analysed with the help of Google Trends; more specifically, we looked at the number of coronavirus-related queries for each country. Due to the relative nature of the indices, the number of Google queries for each country, and convenience in calculations, we took the value of the index in Italy as of 23.02.2020 for 100 points. This figure was the relative maximum number of search queries in all the countries in the given period. All the other values for Italy and other countries were calculated relative to this value. We also included a separate indicator of Google queries around the world. Unlike other Google indicators, we did not calculate this one for specific countries, but calculated it using the value of 16.03.2020 taken as 100 points as a separate indicator instead. This

was the day when the number of coronavirus-related queries reached its maximum all over the world. The Google Trends index for each country and the whole world reflects not the absolute value of the number of queries but the number of coronavirus-related queries with the total number of queries in the given period in a given country or the world. In other words, this indicator has a relative nature, and it allows us to take into account that more queries are made in countries with large populations, and that every year, more and more people are using the internet and Google to search for information.

The index of media mentions of Covid-19 for the USA press was adopted from Baker et al. (2020) and Baker et al. (2019). It is calculated in two stages. In the first stage, we computed the share of articles containing economic terms, including articles in the American press. This indicator was then normalised for the USA stock market volatility index. In the second stage, we found the proportion of articles which mentioned coronavirus related terms from this indicator.

3.2.4. Control variables

The control variables in our models were the commonly accepted classical determinants of stock market performance: volatility (Naifar (2016), Billio and Pelizzon (2003)); oil prices (Jones and Kaul (1996), Sadorsky (1999), Park and Ratti (2008)); and gold prices (Bouoiyour and Selmi, 2015).

The vector of control variables characterising other financial markets contains the following variables – Brent crude oil price (*Oil*), gold price (*Gold*), and the volatility of stock market indices (*Vlty*) in the given countries. In our study volatility is the bipower variation known to be an estimator of integrated volatility that is robust to noise and jumps: see Barndorff-Nielsen and Shephard (2004). The data for Brent oil and gold prices was obtained from Yahoo finance, <https://finance.yahoo.com/>, and from the Heber et al. (2009), Oxford-Man Institute of Quantitative Finance <https://realized.oxford-man.ox.ac.uk/data> for the volatility of stock market indices.

We also considered a much broader list of variables in the preliminary study, including other indices, cryptocurrencies, and so on, but they did not show any extra importance for the model.

3.3. *Model selection*

3.3.1. *Specification of the model*

Studies which focus on the effect of direct and indirect determinants of stock markets and aim to identify predictor variables often use panel data models (for example, Bhargava et al. 2001) and quantile regression models (Swamy, Dharani, and Takeda, 2019), however, these models cannot reflect the dynamic nature of our data, which means that it will be impossible to demonstrate the key hypotheses discussed in this paper.

Dynamic panels, usually estimated as ARDL models, which include lags of dependent as well as independent variables, are used in studies of the relationship between financial development and economic growth (Samargandi, Fidrmuc, and Ghosh, 2015), or between Google trends and the predictability of the most traded precious metals (Salisu, Ogbonna, and Adewuyi, 2020). Some studies use capital asset pricing models (CAPM) to describe the behaviour of financial resources, which helps estimate the returns on financial resources (Del Giudice and Paltrinieri, 2017).

The basic model in our setup is linear. Classic approaches to detecting different effects for different time intervals (before and after hype) would contain dummy variables. Under conditions of a short observation period this, however, might lead to challenges in searching the structural break, and dummy variables will increase the overall number of independent variables. The models will then be overfitted. We therefore assume structural change in our data, such that one model is effective before the break and another afterwards. If the data possesses several structural breaks, we will consider only the time points which lead to the biggest difference in the quality of the fit of the two separate models compared to only one model over the whole-time interval.

Since the number of observations we have at hand is very small in comparison to the number of variables, we apply LASSO regularisation, which allows us to automatically determine the optimal composition of variables, and also eliminates the risk of multicollinearity, as well as taking into account the optimal number of lags of the determinants to increase the descriptive power of the models.

When working with the data, our model should control for a list of different characteristics. In the beginning, we perform some data preprocessing, as all the data on social networks and pandemic is available every day (including holidays and weekends), while stock indices are traded only on the weekdays, excluding holidays and weekends. So as not to lose more data, we decided to impute the stock indices' missing data for the non-trading days using the ARIMA process, thus keeping the autocorrelation dependency with the imputed observations on the same level as the original data: see Figure 1. The structure of the raw data is clearly non-stationary, which is solved by the first differences. The resulting data possesses almost no autocorrelation, see Appendix C.

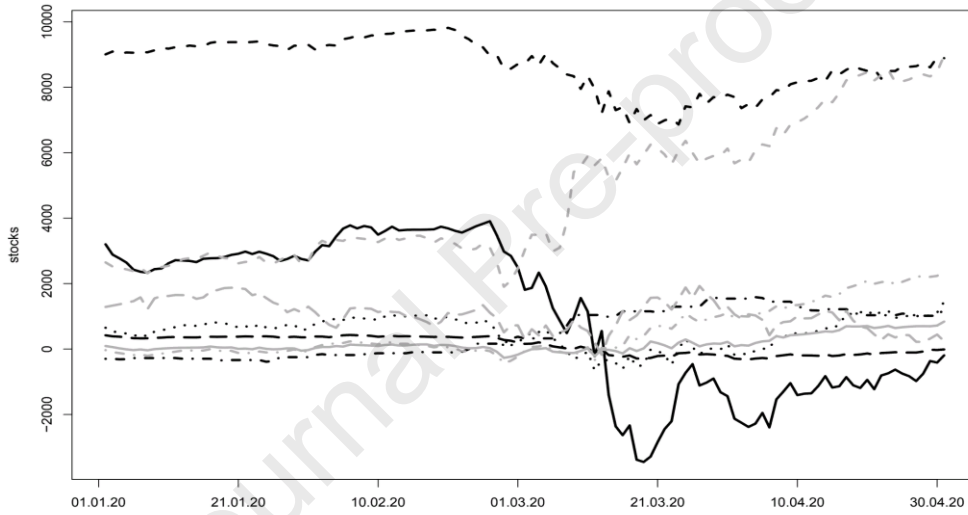


Fig. 1. The dynamics of selected stock indices from 30.12.19 to 30.04.20, index points.

The dynamics of the nine stock market indices: USA_DJ (solid black line), USA_SnP (long dash black line), USA_NDQ (dashed black line), GBR_FTSE 100 (dot and dash black line), DEU_DAX (dotted black line), FRA_CAC 40 (solid grey line), JPN_Nikkei 225 (long dash grey line), IT_FTSE MIB (dashed grey line) and SPA_IBEX 35 (dot and dash grey line).

The overall model is thus linear with no conditional heteroscedasticity assumed:

$$\Delta index_t^k = b_0^k + \sum_{i=1}^3 b_i^k \Delta x_{t-i}^k + \sum_{j=1}^3 \gamma_j^k \Delta z_{j,t} + \varepsilon_t^k, \quad (1)$$

$$\text{where } \Delta index_t^k = index_{opened_t}^k - index_{closed_{t-1}}^k, \quad (2)$$

where the constituents of the index, namely $index_{opened_t}^k$ and $index_{closed_{t-1}}^k$ are the value of the k -th stock index at the opening of the exchange at day t and closing at day

$t-1$ respectively. Changes in the independent variable with the regression coefficients being b_i^k are denoted by $\Delta x_t = x_t - x_{t-1}$. The independent COVID-variables are those explained in Section 3.2.2: *IV_case_loc* – the total number of cases in the country; *IV_case_wld* – the total number of cases in the world (used in one model together with *IV_case_loc*). From Section 3.2.3 the independent media variables: *Fb_pbls* – the number of publications in Facebook in communities on coronavirus by country; *Fb_repsts* – the number of reposts in Facebook in communities on coronavirus by country; *IG_pbls* – the number of publications in Instagram accounts about coronavirus by country; *Twtr* – the number of publications in Twitter accounts about coronavirus by country; *Press* – the proportion of notes on economic topics in which coronavirus is mentioned, or the total number of notes in USA print media, normalised to the stock exchange volatility of the USA stock exchange; *Ggle* – Google Trends index on the term ‘Coronavirus_name of country’. Changes of the j -th control variable respectively at time point t with the regression coefficients being γ_j^k we denoted by $\Delta z_{j,t} = z_{j,t} - z_{j,t-1}$. There are three control variables, as discussed in Section 3.2.4: *Gold* – average daily USD gold price; *Oil* – Brent Crude Oil Price; *Vlty* – stock market estimator of the index integrated volatility through the bipower variation by country. Finally, the error term of the model is denoted by ε_t^k . These combinations of dependent variables and determinants allows us to partially avoid the problem of endogeneity.

Since the model will be estimated via OLS, no distributional assumptions of the residuals are needed. As we are interested not only in the correlations, but also in the causal effects of the independent variables on the dependent variable, we add to all the independent variables lags up to order three. Higher lag orders make the model extremely unstable, and therefore we concentrate only on three-lag models. Past observations were also used in other studies on the impact of Covid-19 on stock market returns Al-Awadhi et al. (2020), Yousfi et al. (2021), and on stock market liquidity and stability (Baig et al. (2021), Ashraf (2020)). Bollen, Mao, and Zeng (2011) analysed the effect of public sentiment, measured from a large-scale collection of tweets posted on twitter.com, on the DJ stock index values, and used up to 7 lags.

3.3.2. Structural breaks

Using Model (1)-(2), we can find the structural break and elaborate on the causes. We expect a structural break in our model to occur at the end of the hype period (a state of dramatic increase in attention to an issue (see also Cambridge Dictionary, 2020) and a substantial change in the effects of social media, Google, and the press, which in our study act as measures of attention to an issue. Wherever the breakpoint t^* is located on our time domain $(t_{min}; T - t_{min})$ there are often not enough observations to estimate the model properly on the observations before or after the t^* . Initially, we aimed at computing the usual F -statistics over the whole interval $(1; T)$ and two subintervals $(1; t)$ and $(t + 1; T)$ for all $t \in (t_{min}; T - t_{min})$ to search for t^* . If the overall data was long enough, we could choose large enough t_{min} and obtain satisfactory and robust results. Unfortunately, the data is too short for this, and the model is precarious at the smallest possible intervals $(1; t_{min})$ and $(T - t_{min}; T)$. The size of the model (number of independent variables) should therefore be reduced before searching for structural breaks.

To determine the size of models, we took into account the problem of statistical significance discussed in recent years. Given the prevalent misuses of, and misconceptions concerning p -values, the ASA Statement on Statistical Significance and p -values mentions other approaches that emphasise estimation over testing, such as Bayesian methods: see Wasserstein and Lazar (2016). For this reason, instead of estimating the complete linear model via OLS on each of the subintervals and selecting significant variables via p -values, we perform model selection via adaptive LASSO (adaLASSO) regularisation, Zou (2006) which is based on the minimisation of the penalised least squares as:

$$\hat{\beta}^{*(n)} = \arg \min_{\beta} \|y - \sum_{j=1}^p x_j \beta_j\|^2 + \lambda_n \sum_{j=1}^p \hat{w}_j |\beta_j|, \quad (3)$$

where λ_n is the regularisation parameter, \hat{w}_j is the weight vector. Together with the selection of the ‘significant’ variables, the regularisation solves the problem of multicollinearity.

The advantage of using these methods is in the reduction of the variance of the forecast due to the slight increase in the bias. Model interpretability is thus improved by excluding variables with no significant impact on the given feature from the predictor sets. Such procedures are highly effective for estimating conditional expectations, both computationally and theoretically, and sufficient for estimating optimal instruments: see

Belloni, Chernozhukov, and Hansen (2011). After selecting the model via LASSO regularisation, we re-estimate it via OLS to diminish the bias, following Belloni and Chernozhukov (2013). In autoregressive modelling, some LASSO procedure features become especially advantageous, as both the AR order and the corresponding AR coefficients can be estimated simultaneously, as noted by Nardi and Rinaldo (2011). The interpretation of LASSO regression coefficients (and, therefore, non-zero parameters) depends on the chosen parameter of regularisation. Since no autocorrelation was present in the data, and temporal dependency was diminished through the first differences the regularisation parameter could be found via cross-validation for each of the submodels separately.

Combining the classical F -test with the LASSO regularisation, the overall procedure can be summed up in the following algorithm:

1. Fix the dependent variable, f.e. DJ and the set of independent variables, f.e. IV_case_wld , IV_case_loc together with control variables: *Oil*, *Gold* and *Vlty*. Therefore, the model (1) has the form:

$$\begin{aligned} \Delta DJ_t = & b_0 + b_1 \Delta IV_case_wld_{t-1} + b_2 \Delta IV_case_wld_{t-2} + b_3 \Delta IV_case_wld_{t-3} + \\ & b_4 \Delta IV_case_loc_{t-1} + b_5 \Delta IV_case_loc_{t-2} + b_6 \Delta IV_case_loc_{t-3} + \gamma_1 \Delta Oil_{t-1} + \\ & \gamma_2 \Delta Oil_{t-2} + \gamma_3 \Delta Oil_{t-3} + \gamma_4 \Delta Gold_{t-1} + \gamma_5 \Delta Gold_{t-2} + \gamma_6 \Delta Gold_{t-3} + \gamma_7 \Delta Vlty_{t-1} + \\ & \gamma_8 \Delta Vlty_{t-2} + \gamma_9 \Delta Vlty_{t-3} + \varepsilon_t^k, \end{aligned} \quad (4)$$

on the interval $t \in (1; T)$. At this stage we have sixteen parameters to estimate, and if only two months of data are available, the estimators become extremely unstable.

2. Standardise the data to have the same mean and variance to fulfil the adaptive LASSO assumptions.
3. For the fixed $t^* \in (t_{min}; T - t_{min})$ estimate the model from Step 1 on the interval $t \in (1; t^*)$ via adaLASSO and denote it by $M^-(t^*)$. Then estimate again with adaLASSO two models $M^+(t^*)$ and $M(t^*)$ on the intervals $t \in (t^* + 1; T)$ and $t \in (1; T)$ respectively. The regularisation parameter is estimated separately on each interval via cross-validation, as mentioned above.
4. Find the estimated errors $\varepsilon^-(t^*)$, $\varepsilon^+(t^*)$ and $\varepsilon(t^*)$ from the models on the corresponding intervals. With $\varepsilon^-(t)$ being a vector of length $t - 3$, $\varepsilon^+(t)$ of length $T - t - 4$, and $\varepsilon(t)$ of length $T - 3$. Constants are due to the lags used.

5. Compute the sum of squared errors of the corresponding intervals: $S^-(t^*) = \boldsymbol{\varepsilon}^-(t^*)' \boldsymbol{\varepsilon}^-(t^*)$, $S^+(t^*) = \boldsymbol{\varepsilon}^+(t^*)' \boldsymbol{\varepsilon}^+(t^*)$, and $S(t^*) = \boldsymbol{\varepsilon}(t^*)' \boldsymbol{\varepsilon}(t^*)$, where the prime operator stands for transpose.
6. Compute the penalised '*F-statistics*' as $F(t^*) = \frac{S^-(t^*) + S^+(t^*)}{S(t^*)}$. It should be noted that these are not the real *F-statistics* since the regularisation varies over the intervals, and models are not nested. There is currently no statistical theory of the behaviour of these models in the finite sample. For this reason, we are not performing the formal test, but rather a selection of the break with the most substantial changes in the explanation of the data at the three intervals.
7. Repeat Steps 3-7 for all $t^* \in (t_{min}; T - t_{min})$.
8. Select the \hat{t} for which $F(\hat{t}) \geq F(t)$, $t \in [t_{min}, T - t_{min}]$ will be the largest one, and define this as the date of the structural break. This point splits the whole interval $[t_{min}, T - t_{min}]$ into two subintervals, over which the models differ most.
9. Having found the structural break \hat{t} , estimate the model on the non-standardised data at the intervals $(1; \hat{t})$ and $(\hat{t} + 1; T)$ using usual OLS, omitting the variables that were excluded by the adaLASSO.

This procedure is performed for each of the sets of the independent and dependent variables, simultaneously delivering the date of the break (\hat{t}), and the models before ($M^-(\hat{t})$) and after ($M^+(\hat{t})$) the break. The model is thus built for each index, resulting in nine different models for each target variable. The results of modelling and their graphic interpretations are shown in Figures 2-8 and explained in detail in the succeeding sections.

We built six different models for each index to test our hypotheses. The first model comprises variables from the number of confirmed cases for each country and the world in general as target variables. Next, five models use one variable from the five target variables reflecting the public reaction to the pandemic – *Fb_pbls*, *Fb_repsts*, *IG_pbls*, *Press* and *Ggle*.

We tested each model for structural breaks, located the date of the structural break, and then tested Hypothesis H5 by comparing the regression coefficients of models built by using the data samples before and after the date of the structural change.

It should be noted that in order to test Hypotheses H2-H5, the input data for the models were standardised to ensure the comparability of the coefficients (Hypotheses H2-

H4). This was also done to trace the changes in the coefficient calculated for the samples before and after the structural change (Hypothesis H5). Non-standardised data was used for the correct interpretation of the results obtained.

3.4. *Robustness checks*

To check the robustness of the models containing variables that reflect public responses to the pandemic in social media, we used a model built similarly, and containing the number of coronavirus-related terms found on Twitter as an experimental variable. Twitter is available in all of the analysed countries. This social media site is used by less than 5% of the population, making it suitable for robustness testing.

4. **Results**

4.1. *General results*

In this section, we present the results obtained through the procedure described above, as we modelled the effect of the pandemic and the hype surrounding it in the press and social media on stock markets. Before discussing the results, we focus on the structural changes in models. We applied our algorithm to identify the dates (see Appendix D) on which structural breaks occurred in our models. As illustrated in the table in Appendix D, the structural changes in all the models occurred between the middle of February and the middle of March. This may be linked to the changes in the given variables corresponding to the number of Covid-19 cases, the media coverage of the pandemic, and the number of Google queries. We expect that our model results will demonstrate that these changes occurred due to the hype surrounding the pandemic in mass media and the internet.

The cause-and-effect relationships and correlation dependencies will be given particular attention. The significance of the lags of the factors in our models shows a causal relationship between the preceding (in the lag level) change in the factor, and the following (in the level of the dependent variable itself) change in the stock market index. When we examine the significance in the factor level, however, we see this situation as correlation

dependence with a dependent variable – the stock market index – and do not interpret it as a cause-and-effect relationship.

For the sake of brevity, we limit ourselves to discussing the factors considered statistically significant. If the $p\text{-value} < 0.001$, the variable was considered highly significant. If the $p\text{-value} > 0.001$ and < 0.05 , then the variable was considered significant. Finally, if the $p\text{-value} > 0.05$ and < 0.1 , then the variable had low significance. Variables with a $p\text{-value} > 0.1$ were considered insignificant. Figures 2-8 show only significant variables. We have included the complete modelling results in Internet Appendix E (non-standardised data) and Internet Appendix F (standardised data).

Let us now consider the results of the analysis of the control variables - volatility, oil, and gold - and describe the results of the identification of structural changes in our models. When the LASSO was applied, the Volatility variable had either the strongest effect, or one of the most significant effects, on stock market indices - this effect was observed for all countries before and after the structural change in the model. These results are in agreement with those of previous studies, which showed the interdependence between volatility and financial indices: see Naifar (2016); Billio and Pelizzon (2003), Lyócsa et al. (2020) and Lyócsa and Molnár (2020).

Our study has shown that in the majority of cases, changes in oil prices have a non-stable effect in a state of hype, after which the correlation became steadily constant, which is not consistent with the results of Jones and Kaul (1996), Sadorsky (1999), Park and Ratti (2008), and may be related to the effect of Covid-19, and its discussion in the mass media. Our models, however, did not suggest that gold prices had any effect. In this respect, our results agree with those of the previous studies, which showed that when the stock markets are highly volatile, there is a weak correlation between gold prices and stock markets, and thus, the role of gold is that of a haven (e.g., Hood and Malik (2013), Baur and Lucey (2010)).

The main aim of our study is to show the effect of the coronavirus pandemic and its coverage in the different media on stock markets. Let us now look at these results in more detail and systematise them following our hypotheses.

4.2. Coronavirus: Frightening or not?

Applying the regularisation, we found that the increase in Covid-19 cases in a country was significant for stock indices in most countries (see Figure 2), however, the effect was not stable: the DEU_DAX, USA_DJ, FRA_CAC 40 and USA_NDQ experienced a negative impact, the IT_FTSE MIB, USA_SnP and GBR_FTSE 100 experienced a positive one, and the SPA_IBEX 35 was mixed. The JPN_Nikkei 225 showed no correlation at either the lag or factor level. We did not observe any effects after the structural change. The only exception was USA_SnP, which demonstrated a significant correlation at the factor level.

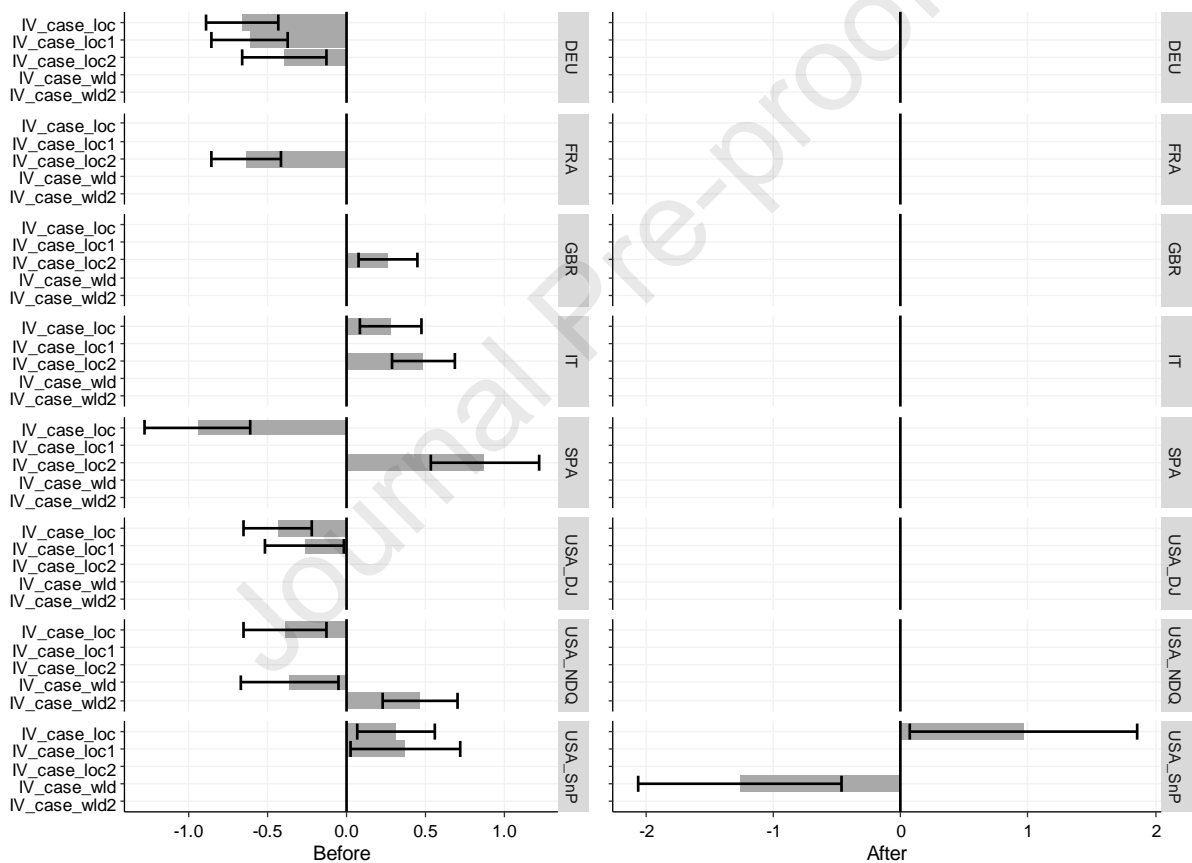


Fig. 2. Model of the impact of coronavirus, standardised data. The model includes the number of COVID-19 cases in the corresponding country and control variables (oil and gold prices, and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the COVID-19 effect (coronavirus cases) and only when they are significant:

the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

Having studied the effect of the spread of Covid-19 in the world, we cannot identify the presence of even unstable effects for stock markets: we found correlations before the structural break only for USA_NDQ, and after the structural break only for USA_SnP at the factor level.

We attribute the instability of the results to the fact that during the pandemic the stock indices, whose decline during this period we can clearly see from the figures in Appendix B, were not primarily affected by the development of the epidemic itself, under the impact of which we would observe stable negative effects (e.g., Alber (2020); Yilmazkuday 2020)). We believe that the main reason lies in the side effects associated with the Covid-19 hype, and fear of it, manifested among other things in media discussions. We plan to demonstrate these assumptions in the discussion of Hypotheses 2-4. We also explain the disappearance of the effects after the structural break, which we will discuss in detail during the discussion of Hypothesis 5, by hype and mass hysteria, or rather their short duration and cessation.

Our results thus partially confirmed Hypothesis H1. We complement the findings of Alber (2020) and Yilmazkuday (2020) on the negative impact of the pandemic on stock markets by concluding that this effect is unstable as a result of the presence of mass media exposure. Our findings are also consistent with those of Schoenfeld (2020), who showed an increase in risks in a pandemic.

Hysteria and panic triggered by a shocking event may spread in ways similar to that of infectious disease, and provoke reactions disproportionate to the actual threat (see Section 2.3). Let us look at the influence of mass media and the internet on stock markets in the light of Hypotheses H2-H4.

4.3. Press

To analyse the effects of the Covid-19 discussion in the press, let us transform specification (1), which will take the form

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta press_{t-1}^k + b_2^k \Delta press_{t-2}^k + b_3^k \Delta press_{t-3}^k + \gamma_1^k \Delta Oil_{t-1}^k + \\ & \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \gamma_6^k \Delta Gold_{t-3}^k + \\ & \gamma_7^k \Delta Vltty_{t-1}^k + \gamma_8^k \Delta Vltty_{t-2}^k + \gamma_9^k \Delta Vltty_{t-3}^k + \varepsilon_t^k \quad (5) \end{aligned}$$

As our study has shown, the changes in the number of publications in printed media usually had a long-lasting negative effect on financial indices before the structural change (see Figure 3).

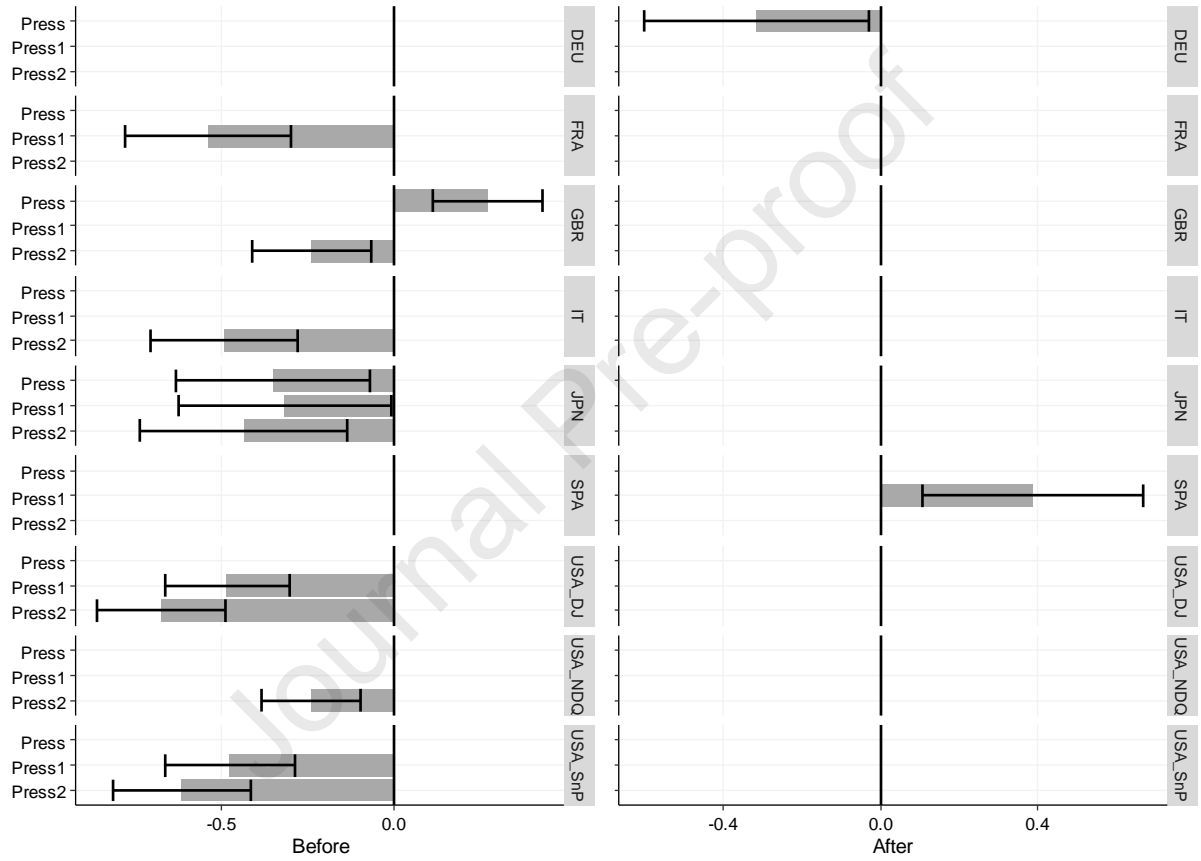


Fig. 3. Model of the impact of coronavirus mentions in the press, standardised data. The model includes the index of press attention towards COVID-19 in the corresponding country and control variables (oil and gold prices, and the volatility of the corresponding stock index) as the explanatory variables and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with media attention (Press indices) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

Our results agree with the findings of the previous studies on the effect of mass media on people's anxiety and fear (Bursztyn et al. 2020) and on the impact of investor moods on financial indices (Smales (2014), Gupta et al. (2018)).

We observed a significant negative effect from the Press variable and its lags for most of the given indices, even though the Press index is determined through analysis of the US press. The strongest effect was observed for the USA_DJ, while GBR_FTSE 100 and SPA_IBEX 35 were exceptions, showing positive effects on the factor or lag side of Press (see Figure 3, Appendices E and F).

As noted above, we separated the variables under study into different models to eliminate multicollinearity. We will therefore make the comparison through an analysis of the stability of the effect in the models. The comparison will be done via Sargan's J-test (Sargan, 1958) to compare the descriptive power of the two models. Of the two models in the J-test, one will be the 'benchmark' model for all comparisons, containing the Covid-19 incidence variables and the control variables, and the other will be the model included in one of the independent variables under study.

Comparing the effects of Covid-19 and Press, we observe that Press has a more stable effect for five indices, USA_SnP, USA_DJ, IT_FTSE MIB, FRA_CAC 40 and JPN_Nikkei; 225 experienced negative effects, and GBR_FTSE 100 experienced mixed effects. We see no effect before the break, and a negative effect after for the DEU_DAX, while the effect for the SPA_IBEX 35 is positive. If we look at the effects on the Covid-19 side, we see very unstable results: DEU_DAX, USA_DJ and FRA_CAC 40 are negative; SPA_IBEX 35 and

USA_NDQ and USA_SnP are mixed, and IT_FTSE MIB, and GBR_FTSE 100 are positive; JPN_Nikkei 225 showed no correlation at either lag or factor level. Comparing the results of the J-test for the reference model with Covid-19 and models with mass-media, we observe a slight, but still an advantage for models with mass-media.

These results confirm that Covid-19 mentions in the media had a more significant or comparable effect on the stock markets than the direct impact of Covid-19. This also supports Hypothesis H2, and agrees with Lucey and Dowling (2005), who showed the role of feelings in investor decision-making under conditions of risk and uncertainty.

After the structural change, we observed virtually no effects of the coronavirus pandemic coverage in the press. We observe an effect only for SPA_IBEX 35 at the level of the first lag, and for DEU_DAX at the factor level. This was because the structural change in the models was caused by the hype and hysteria around the pandemic in online media, whose impact exceeded that of the mass media. We discuss in more detail the effect of the coronavirus hype as regards Hypothesis H5, and in particular the effect of mass media coverage before and after the structural change.

4.4. Search engines

We used the following specification while modelling the effect of search activity:

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta Ggle_{t-1}^k + b_2^k \Delta Ggle_{t-2}^k + b_3^k \Delta Ggle_{t-3}^k + \gamma_1^k \Delta Oil_{t-1}^k + \\ & \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \gamma_6^k \Delta Gold_{t-3}^k + \\ & \gamma_7^k \Delta Vlty_{t-1}^k + \gamma_8^k \Delta Vlty_{t-2}^k + \gamma_9^k \Delta Vlty_{t-3}^k + \varepsilon_t^k \end{aligned} \quad (6)$$

We found (see Figure 4) that the increased volume of coronavirus-related Google queries in the period before the structural change had a negative effect on the USA_SnP, USA_DJ, DEU_DAX and FRA_CAC 40 through the level of the factor or its lags. We observe the strongest impact for IT_FTSE MIB. When Google queries increased by a point at the second lag level, the IT_FTSE MIB index decreased by 130.3 points. In the weakest significant effect in SPA_IBEX 35 a 1-point increase in Google at the factor level was accompanied by a 7.3-point increase in the stock index, see Appendix E. These results confirm H3 and support the findings of other studies which showed the relationship between Google queries and prices on the market for precious metals (Salisu, Ogbonna,

and Adewuyi, 2020) and the real estate market (Venkataraman, Panchapagesan, and Jalan, 2018). However, we note that the H3 hypothesis was partially confirmed for USA_NDQ, IT_FTSE MIB and SPA_IBEX 35: we observed alternating negative and positive effects. Hypothesis H3 did not hold for GBR_FTSE 100 and JPN_Nikkei 225: we could not find any correlation.

The correlation between Google queries and stock market indices before the structural break in models was more stable than the correlation with Covid-19. The results of the J-test confirm these conclusions: for five indices out of nine, the models with Google had a higher descriptive power than the models with Covid-19. The concern of internet users about Covid-19, which manifested itself in an increase in the number of queries about Covid-19 on Google, has an effect on the stock indices comparable in effect to the direct effect of Covid-19. This confirms Hypothesis H3.

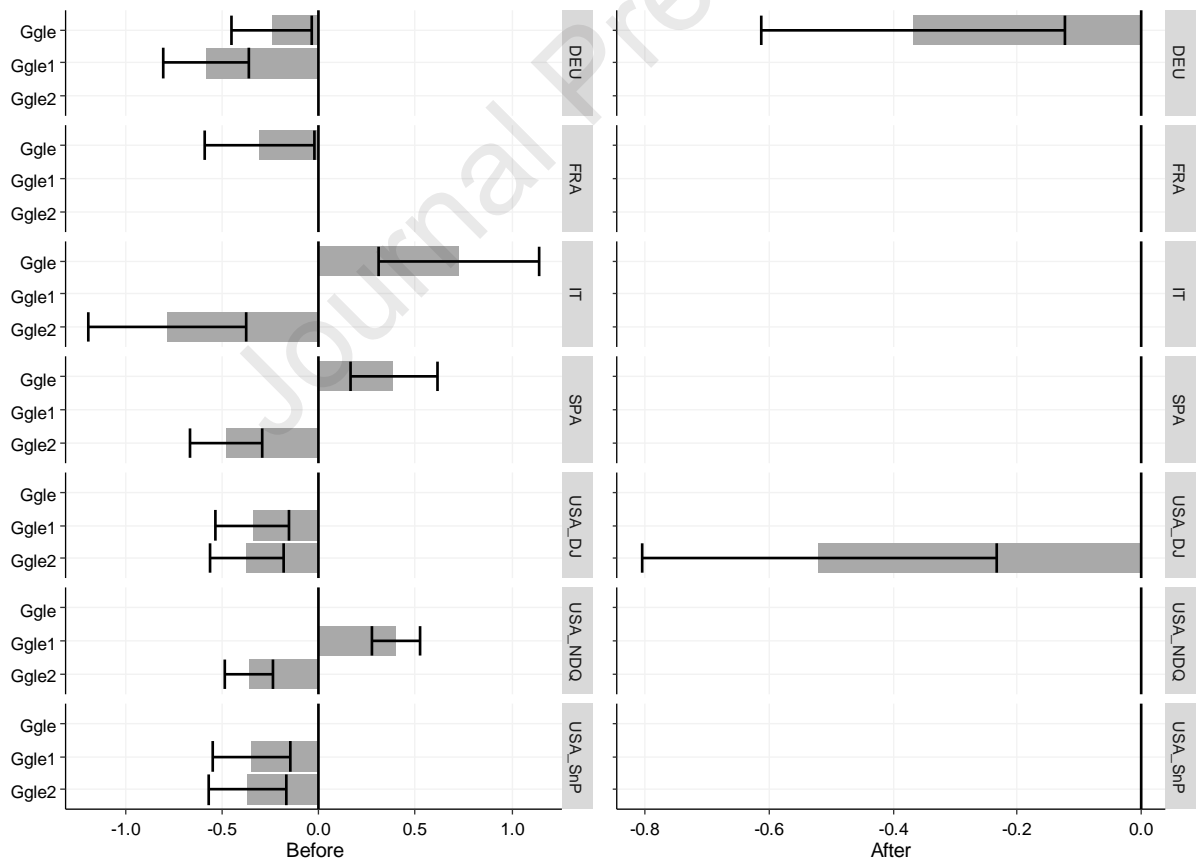


Fig. 4. Model of the impact of Google Trends, standardised data. The model includes the index of Google search activity on COVID-19 in the corresponding country and control variables (oil and gold prices and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with search activity (Google search activity indices) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

The effect almost disappeared after the structural change, and the impact of Google queries started to be observed only in the level of the factor for the DEU_DAX and in the second lag for the USA_DJ. The fact that the effect of Google queries is more pronounced than that of the pandemic itself can be explained the same way as for the printed media: the spike in coronavirus-related searches reflects the increasing anxiety of internet users. The effect was so strong that it persisted even after the structural change, when the effect of the pandemic disappeared. We will discuss in more detail the effect of the coronavirus hype as regards Hypothesis H5, and in particular, the effect of Google queries before and after the structural change.

4.5. Social media

First of the variables related to social media that we used is the number of publications on Instagram accounts. The following model was used for this case:

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta IG_pbls_{t-1}^k + b_2^k \Delta IG_pbls_{t-2}^k + b_3^k \Delta IG_pbls_{t-3}^k + \gamma_1^k \Delta Oil_{t-1}^k + \\ & \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \gamma_6^k \Delta Gold_{t-3}^k + \\ & \gamma_7^k \Delta Vlty_{t-1}^k + \gamma_8^k \Delta Vlty_{t-2}^k + \gamma_9^k \Delta Vlty_{t-3}^k + \varepsilon_t^k \quad (7) \end{aligned}$$

As our study has shown, before the structural break the negative effect of coronavirus-related discussions on Instagram (see Figure 5) was observed for DEU_DAX in the level of the factor and its lags. We observe a positive correlation before the break for the GBR_FTSE 100, USA_SnP, JPN_Nikkei 225, FRA_CAC 40 and USA_NDQ while USA_DJ

shows mixed effects. After the structural change, we observe a negative correlation with Instagram USA_SnP, USA_DJ and USA_NDQ lags. We thus note the inconsistency with the H4 hypothesis of the effects detected both in terms of direct effects on stock indices and in terms of comparisons with Covid-19 effects. We attribute such results to the fact that Instagram is more prevalent among young people, and not popular among the middle-aged generation (Pew Research Center (2021), Statista (2021)), which includes stock market participants. Instagram is also less prevalent in the countries whose stock markets we studied (Vincos Blog, 2021).

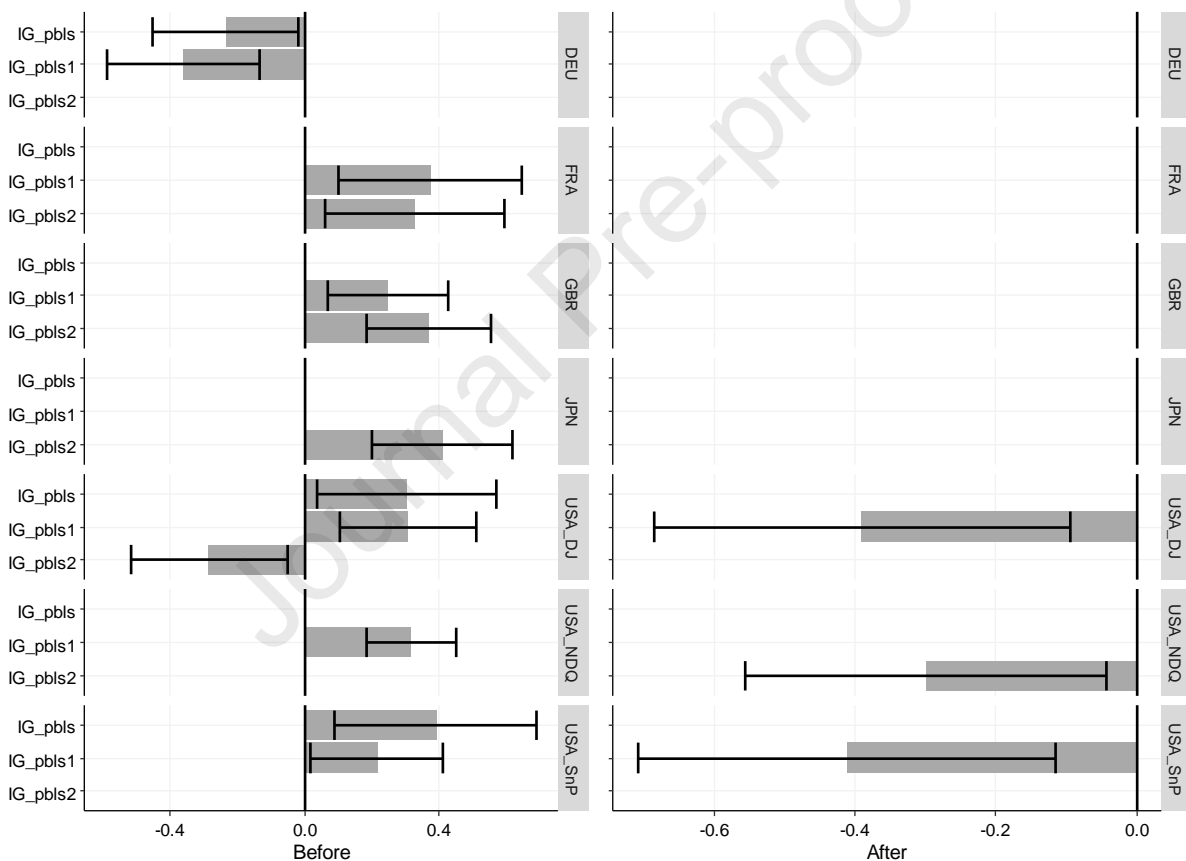


Fig. 5. Model of the impact of the number of publications on Instagram, standardised data. The model includes the number of publications in Instagram accounts about COVID-19 in the corresponding country and control variables (oil and gold prices and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with social networks (number of publications on Instagram) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

The next set of models include Facebook publications on coronavirus in related accounts and can be described as follows:

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta FB_pbls_{t-1}^k + b_2^k \Delta FB_pbls_{t-2}^k + b_3^k \Delta FB_pbls_{t-3}^k + \\ & \gamma_1^k \Delta Oil_{t-1}^k + \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \\ & \gamma_6^k \Delta Gold_{t-3}^k + \gamma_7^k \Delta Vlt y_{t-1}^k + \gamma_8^k \Delta Vlt y_{t-2}^k + \gamma_9^k \Delta Vlt y_{t-3}^k + \varepsilon_t^k \quad (8) \end{aligned}$$

Facebook posts show a mixed effect. We note a stable negative effect only for the JPN_Nikkei 225 and SPA_IBEX 35. Furthermore, we observe alternating negative and positive correlations and partial consistency with the H4 hypothesis at different lags for USA_DJ, USA_SnP, and USA_NDQ. There is a positive effect for FRA_CAC 40 on the first lag, with no significant effects on the second lag and the factor. We do not observe a negative correlation after the structural break (see Figure 6). Comparing these results to the mixed effects of Covid-19 on stock indices (see Figure 2), we conclude that these results are comparable. When examining the effects of Facebook publications, we record the partial fulfilment of Hypothesis H4 when expecting a negative effect from Facebook publications, and we note the complete fulfilment of Hypothesis H4 when comparing the effects of Hypothesis H4 with the effects of Covid-19.

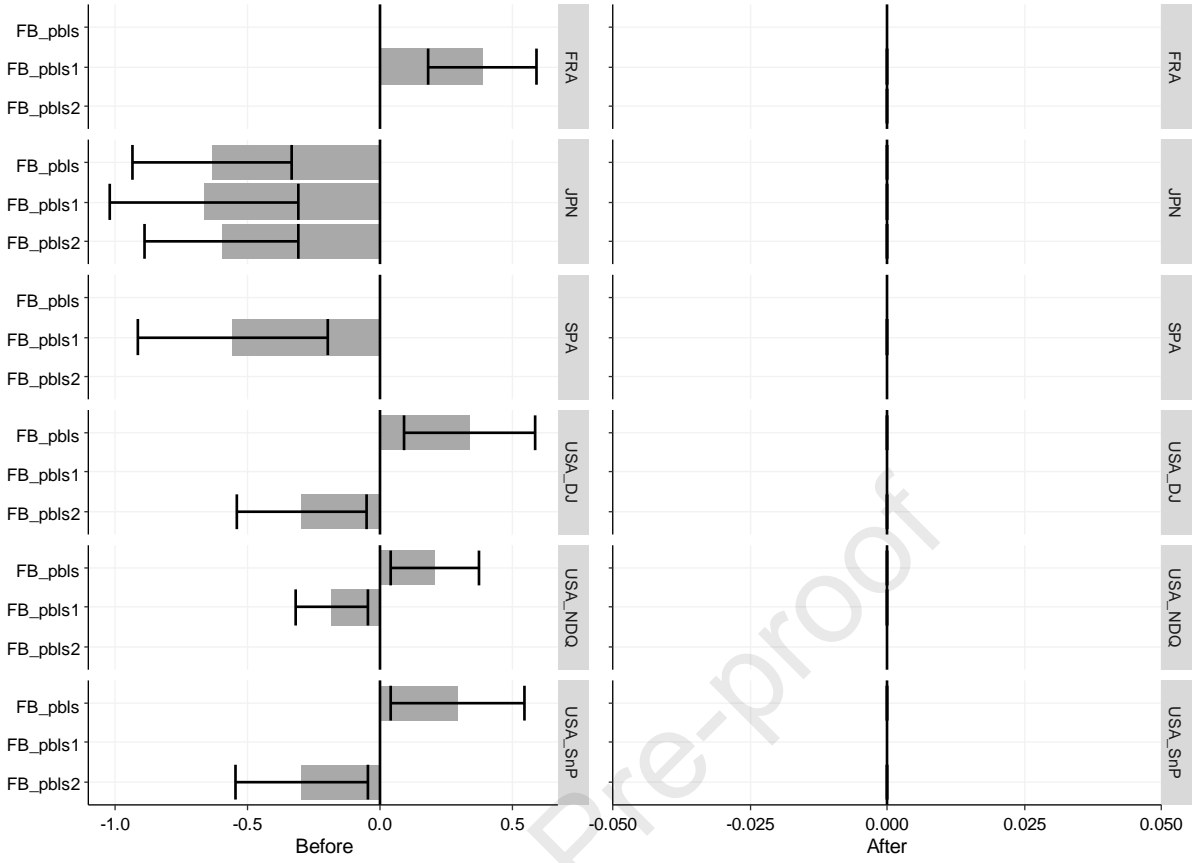


Fig. 6. Model of the impact of the number of publications on Facebook, standardised data. The model shown included the number of publications in Facebook accounts about COVID-19 in the corresponding country and control variables (oil and gold prices and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with social networks (number of publications on Facebook) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

Another variable that was included is the number of Facebook reposts on the topic of coronavirus in the corresponding communities. The set of such models can be described as follows:

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta FB_repsts_{t-1}^k + b_2^k \Delta FB_repsts_{t-2}^k + b_3^k \Delta FB_repsts_{t-3}^k + \\ & \gamma_1^k \Delta Oil_{t-1}^k + \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \gamma_6^k \Delta Gold_{t-3}^k + \\ & \gamma_7^k \Delta Vlty_{t-1}^k + \gamma_8^k \Delta Vlty_{t-2}^k + \gamma_9^k \Delta Vlty_{t-3}^k + \varepsilon_t^k \end{aligned} \quad (9)$$

When examining the impact of reposts about Covid-19 on Facebook on stock markets, we note a steady and consistent negative effect. There is a negative correlation to be found at the lag and factor levels for the DEU_DAX, FRA_CAC 40, JPN_Nikkei 225, IT_FTSE MIB and USA_NDQ. We observed a negative impact for USA_DJ, at the second lag, and a positive impact at the factor level. There are positive effects for USA_SnP and SPA_IBEX 35. After a structural break, we observe a positive correlation at the second lag level for IT_FTSE MIB (see Figure 7). Comparing these results with the effects of Covid-19 (see Fig. 2), we note a more stable negative effect on stock markets from shared posts on Facebook about Covid-19 compared to the impact of the pandemic itself. These findings are also supported by the results of the J-test: the descriptive power of the models with Facebook reposts was stronger than with Covid-19. Such results support Hypothesis H4. Note the discrepancy in the results of the study of the influence of Facebook publications and reposts, despite the fact that Hypothesis H4 is generally confirmed in both cases. Such results, in our opinion, are due to the fact that it is the reposts, which do not require substantial time and labour input, that are to a greater extent a characteristic of spontaneous reaction to an event. Publications that require time, labour, and thinking about the event are reactions to the event, but not spontaneous reactions.

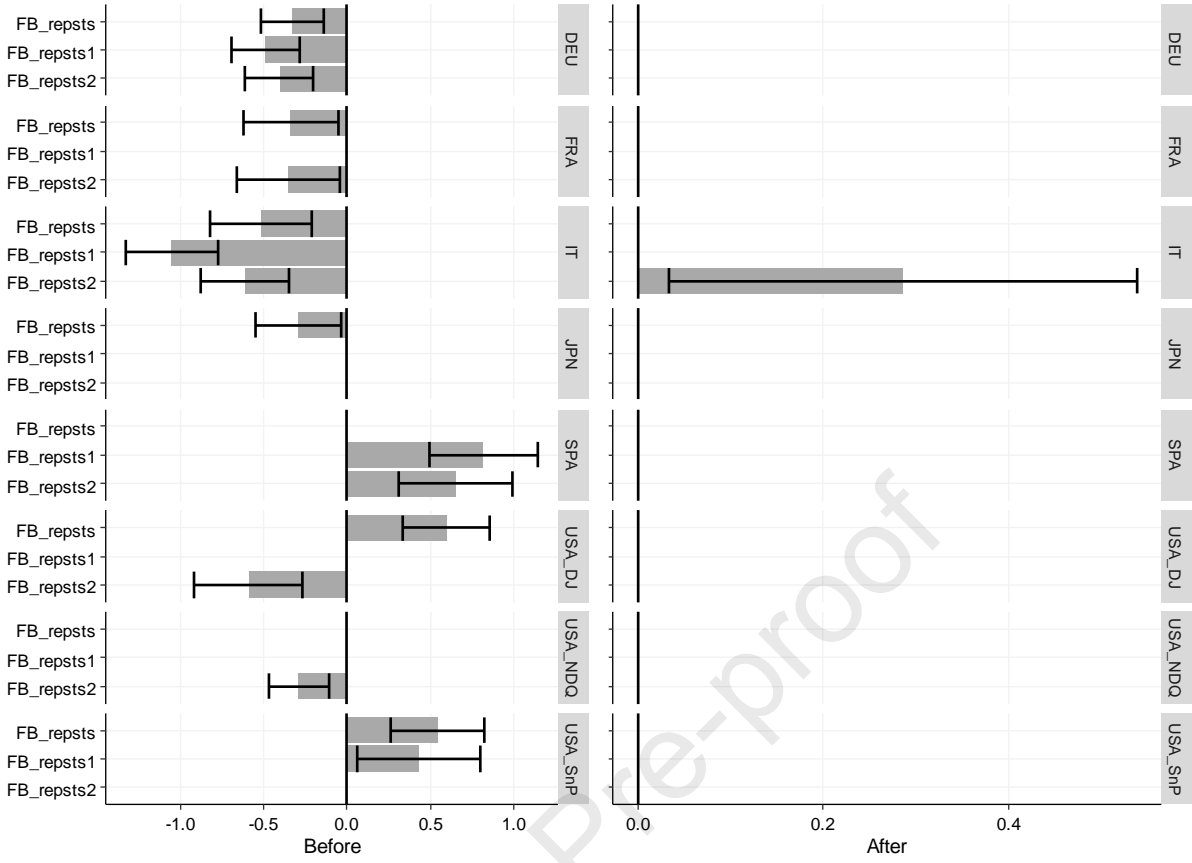


Fig. 7. Model of the impact of the number of Facebook reposts, standardised data. The model includes the number of reposts in Facebook accounts about COVID-19 in the corresponding country and control variables (oil and gold prices and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with social networks (number of reposts on Facebook) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

We tested our results by building a robust model of Twitter effects (see Figure 8) for stock markets:

$$\begin{aligned} \Delta index_t^k = & b_0^k + b_1^k \Delta Twtr_{t-1}^k + b_2^k \Delta Twtr_{t-2}^k + b_3^k \Delta Twtr_{t-3}^k + \gamma_1^k \Delta Oil_{t-1}^k + \\ & \gamma_2^k \Delta Oil_{t-2}^k + \gamma_3^k \Delta Oil_{t-3}^k + \gamma_4^k \Delta Gold_{t-1}^k + \gamma_5^k \Delta Gold_{t-2}^k + \gamma_6^k \Delta Gold_{t-3}^k + \\ & \gamma_7^k \Delta Vlty_{t-1}^k + \gamma_8^k \Delta Vlty_{t-2}^k + \gamma_9^k \Delta Vlty_{t-3}^k + \varepsilon_t^k \end{aligned} \quad (10)$$

While testing, we arrived at similar conclusions: a negative effect was observed for DEU_DAX, USA_SnP, USA_DJ, IT_FTSE MIB, FRA_CAC 40 and USA_NDQ in the level of the factor and its lags before the structural change. These results support previous findings, which showed the negative effect of reposts in social media. After the structural shift, the effect virtually disappears: we observe a negative correlation only at the level of the first lag for the GBR_FTSE 100 (see Figure 8). Comparing these results to the effects of Covid-19, we see that Twitter publications about Covid-19 have a more stable effect on stock markets than Covid itself. The J-test confirms these conclusions: for eight out of nine indices considered, the inclusion of Twitter instead of Covid in the model led to an increase in the descriptive power of the model, which confirms Hypothesis H4.

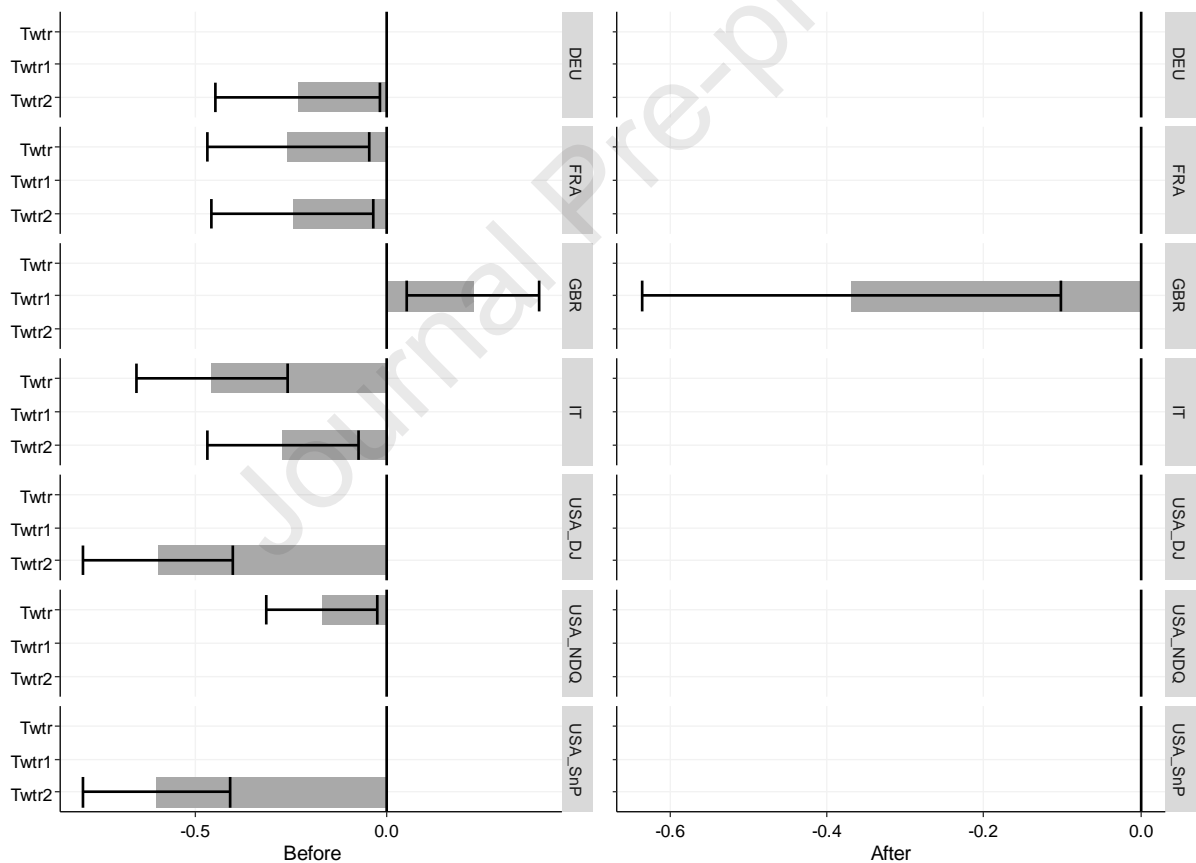


Fig. 8. Model of the impact of coronavirus and the number of publications on Twitter, standardised data. The model includes the number of Twitter publications about COVID-19 in the corresponding country and control variables (oil and gold prices and the volatility of the corresponding stock index) as the explanatory variables, and the country's stock index as the dependent variable. For the sake of brevity and comparability, the figure shows only the variables of interest in line with our research hypotheses of the indirect effects of COVID-19 connected with social networks (number of publications on Twitter) and only when they are significant: the grey bar presents the coefficient itself, while the black line depicts the 95% confidence interval for the coefficient.

Our research into the effects of Covid-19 discussion on social networks demonstrates that the identified influence of Instagram did not support Hypothesis H4, which we attribute to the age structure of Instagram users (Pew Research Center (2021), Statista (2021)) and the spread of Instagram in the countries studied (Vincos Blog, 2021). At the same time, the effects of Facebook posts and reposts, as well as Twitter postings in general, confirmed Hypothesis H4, and are consistent with the findings of Mayshak, Sharman, and Zinkiewicz (2016) on the effect of negative publications on people's emotions.

4.6. Is Covid-19 really hyped too much?

We applied the algorithm proposed in Section 3.3.2 to reveal the structural changes in our models and show the effect of hype on stock markets (see Appendix D). We suppose that structural changes in our models are caused primarily by radical transformations in the given factors characterising the spread of the new coronavirus disease and its coverage in printed and digital media, as well as the volume of coronavirus-related Google queries. The volume of this media coverage began a steady upward climb from the beginning of the pandemic. After the hype reached its peak, the issue of Covid-19 gradually receded from the headlines. In our view, structural changes may show the period between the increasing and then abating public attention to the topic, and the corresponding decline in the effect of this factor on stock markets. Following this line of reasoning, we will compare

the effects before and after the structural break. To this end, we will demonstrate the strong and significant influence of the press, Google queries and social media on stock market indices before the structural change (that is, in the period when the hype was at its most intense), and a dramatic reduction in this influence after the structural change. As we compare the effects before and after the structural change in the models built on non-standardised data, we may face a comparability problem due to the differences in the dispersion of the indicator. We will therefore rely on standardised data models.

If we compare the dates of structural changes in the models (Appendix D) with the dynamics of the indicators related to Google queries and social media (Appendix B), it becomes evident that in all the models for GBR_FTSE 100, FRA_CAC 40, IT_FTSE MIB, SPA_IBEX 35 and the majority of the models for USA_DJ, USA_SnP, USA_NDQ, DEU_DAX and JPN_Nikkei 225, the structural changes fall in the period between end of February and middle of March, and entirely or partially coincide with the time when publications in the media, the volume of Google queries, and publications in some social media, reached a peak, followed by a steady decline. The graphic representations of these indicators have an inverted U-shape, with a pronounced peak point. Interestingly, the number of Covid-19 cases was also proliferating, but a similar peak in this indicator occurred a little later, at the end of March. This delayed effect can be explained by the fact that the growth in the number of shared posts follows that of the original publications. We thus suppose that, on the one hand, the hype surrounding the pandemic in search engines and social media mostly coincided with the period before the structural change, and afterward, the interest in this topic subsided. On the other hand, public attention was at its most intense before the number of cases hit the highest levels, which means that public interest in this topic may have already started to decline while the pandemic was at its peak.

A study of the impact of media publications showed that before the structural break, eight indices out of nine were significantly affected by the press either at the lag or factor level. Only DEU_DAX was not found to be significantly correlated. After structural breaks, the effect was found for SPA_IBEX 35 and DEU_DAX. Hypothesis H5 was thus generally confirmed. For seven indices, USA_SnP, USA_DJ, IT_FTSE MIB, FRA_CAC 40 and JPN_Nikkei 225, GBR_FTSE 100 and USA_NDQ, the effects disappeared after the hype disappeared (see Figure 3).

Our analysis of the effect of Google queries showed that for eight indices out of the nine considered, the effects during the rush peak were stronger than after the decline of the hype: the effects either disappeared (IT_FTSE MIB, FRA_CAC 40, JPN_Nikkei 225, USA_NDQ, USA_SnP and SPA_IBEX 35), or became weaker (USA_DJ, DEU_DAX). The H5 hypothesis was only not confirmed for GBR_FTSE 100 (see Figure 4).

The effect of the hype is also evident in the effects that Instagram had on the stock markets. The H5 hypothesis was confirmed for seven indexes out of nine. For the USA_SnP, USA_NDQ and USA_DJ indices, the disappearance of the hype led to a weakening effect of Instagram publications. The effect of Instagram on DEU_DAX, GBR_FTSE 100, JPN_Nikkei 225 and FRA_CAC 40 disappeared with the passing of the hype, and the hypothesis was not confirmed for IT_FTSE MIB and SPA_IBEX 35, see Figure 5.

The decrease in hype around Covid-19 led to the disappearance of the effect from Facebook publications for JPN_Nikkei 225, USA_DJ, USA_SnP, USA_NDQ and SPA_IBEX 35. For the FRA_CAC 40 such results support Hypothesis H5. The hypothesis is not supported for IT_FTSE MIB, DEU_DAX and GBR_FTSE 100, for which there were no significant correlations either before or after the structural break (see Figure 6).

The effect of Facebook reposts during the coronacrash was significant for DEU_DAX, FRA_CAC 40, JPN_Nikkei 225, IT_FTSE MIB and USA_NDQ, USA_DJ, USA_SnP and SPA_IBEX 35. After the structural break, the effect weakens for IT_FTSE MIB, and disappears for the other indices (see Figure 7). Only the GBR_FTSE 100 did not reflect the effect of the hype, the effect of reposts on which was insignificant both during and after the rush.

We also trace the effect of the hype when examining Twitter posts (see Figure 8), at the end of which the influence of tweets for DEU_DAX, USA_SnP, USA_DJ, IT_FTSE MIB, FRA_CAC 40 and USA_NDQ becomes insignificant. We note an increasing effect for GBR_FTSE 100, however. The JPN_Nikkei 225 and SPA_IBEX 35 were not significantly affected by the Covid-19 discussion in Twitter publications, either during or after the high.

Our analysis thus confirmed Hypothesis H5 about the effect of coronavirus-related Google queries and publications in the mass media and social media. These results agree with previous findings, which demonstrated the effect of investor sentiments such as stress (Griffith, Najand, and Shen, 2020) and fear (Smales and Kininmonth (2016), Smales

(2017)) on stock markets. Our results confirm the findings of Cepoi (2020), who showed the impact of hype surrounding the coronavirus on stock markets. Our results also support the previous findings that these sentiments can spread across countries (e.g., Tsai, 2014).

The results of the models that did not confirm the effect of social media hype may be explained by the low quality of statistics on Google queries related to a particular topic. We believe that a study based on higher-quality statistical data on social media is needed to show the effect of hype on stock markets. Another possible reason lies in the dates of structural change that occurred before the hype reached its peak. In these cases, the hypothesis was also not confirmed. It is likely that the peak of hype occurred after the structural change.

5. Conclusion

From February to March 2020, stock markets reacted strongly to global shocks caused by the Covid-19 pandemic: the fall in financial indices was from 30% (USA_NDQ) to over 50% (DEU_DAX) (Cbonds, 2020). Bloomberg aptly named this situation 'Coronacrash'.

Was the Covid-19 pandemic the main reason for the crash of stock markets? From the perspective of behaviour finance (Curatola et al. 2016), it may be supposed that this situation primarily results from the emotional reactions of market participants (De Bondt and Thaler, 1985) rather than the pandemic itself. Their reactions, in turn, may result from the information coming from television news, the internet, press, and so on, (Gupta et al. (2018), Fang and Peress (2009)). It may thus be concluded that the behaviour of stock markets can be shaped by public moods and sentiments (indirect effects of the pandemic) as much as by an event itself (direct effects).

In this article, we focused on the indirect effects of the pandemic and sought to determine the impact of public moods (reflected in coronavirus-related Google queries and publications in social media) on stock market indices – USA_DJ; USA_SnP; USA_NDQ; GBR_FTSE 100; DEU_DAX; FRA_CAC 40; JPN_Nikkei 225; SPA_IBEX 35; and IT_FTSE MIB. We were testing hypotheses about the impact of the pandemic (H1), coronavirus-related Google queries (H3), the coverage of the pandemic in mass media (H2), and in social media (H4) on stock markets. We also tested Hypothesis H5 on the dramatic increase in the

impact of coverage in digital and printed media (hype) on stock markets, as they were slammed by shocks.

To test these effects, in addition to the factors characterising Google queries, mass media coverage, and social media discussions, we followed the prior research and integrated characterising trade market conditions (gold and oil prices) into our model control variables, and a variable characterising the level of risk on stock markets (Volatility). To test these hypotheses, we analysed the stock market data for the period between 30.12.2019 and 30.04.2020. We also used the data for the same period characterising the volume of coronavirus-related Google queries, publications in the press, and social media.

We believe that LASSO models are optimal for this task as they reveal the structural changes in the models linked to the disappearance of hype, and help eliminate the variables that cause multicollinearity.

Our analysis has led us to the following conclusions. First, the pandemic was observed to have a direct impact on stock markets for the phase that preceded the structural change in the model, that is, during the peak of hype. Second, the effects of Google queries, publications in printed and digital media, were comparable to or even exceeded that of the pandemic itself. Third, the hype surrounding the pandemic intensified the effect of Google queries and social media discussions on stock markets. Interestingly, the effect of hype occurred before the peak of the pandemic. This may signify that the public interest in the new topic surged and receded quickly while the problem was still unsolved.

We believe that our findings may be of use to stock market investors and regulators, as well as to specialists in crowd psychology and behavioural economics, as they provide us with a better understanding of stock market reactions to specific events and their coverage in mass and digital media.

In the course of our research, we identified some problems that were beyond our immediate concerns, but might present interest in further studies, such as studies of hype in the social media and countries where this effect was not detected.

Declaration of competing interest

None.

Acknowledgements

We would like to thank our colleague Fedor Karpeko for his engaging discussions, excellent collaboration, and advice throughout this research. RFBR, project number 20-04-60158, funded the reported study.

We would like to thank reviewers for time and effort in our research. Thanks to reviewer's contribution, this research has improved in quality

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Highlights:

- The pandemic's direct impact on stock markets was observed during the phase of the hype in the media
- The structural breaks were searched through the modified F-test for the LASSO regularized regression of the influence of hype on stock markets
- The number of COVID-19 cases didn't change its growth significantly during the hype period
- The effects of the interest to the pandemic in social media and through Google search on stock indices are often of the same size or even larger than of the coronavirus itself
- The hype around COVID-19 intensified the effect of Google queries and social media on stock markets