Global Component of Sentiment in Futures Markets: Evidence from Covid-19 Pandemic

American Business Review
Nov. 2023, Vol.26(2) 355 - 384

ISSN: 2689-8810 (Online)
ISSN: 0743-2348 (Print)

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https://doi.org/10.37625/abr.26.2.355-384

ABSTRACT

We examine the impact of the global component of sentiment on the price return and volatility of 25 major futures market indices across the globe, during the Covid-19 pandemic. The global component of sentiment causes investor overreactions. These overreactions accelerate the fall in prices and contribute to the rising volatility levels. The futures prices revert, though gradually, to their fundamental values as information from more reliable sources becomes available. This leads to price recovery and lower volatility levels.

KEYWORDS

Global Sentiment, Coronavirus, Covid-19, Futures markets

JEL Classification: G12,G14,C33

INTRODUCTION

There seems to be little doubt among academics and practitioners that investor sentiments have a significant impact on security prices (Baker et al., 2012; Tetlock, 2007; Yu & Yuan, 2011). The extant literature documents that investor sentiments cause "overreaction" in prices and an increase in volatility, followed by a reversal in returns (Barberis et al., 1998; Hong & Stein, 1999). Most of these studies provide evidence specific to a market or a country (Antoniou et al., 2015; Baker & Stein, 2004; Baker & Wurgler, 2007). The global component of investor sentiment that systematically affects multiple markets in a similar manner remains less explored (Baker et al., 2012). In their study, Baker et al. (2012) attempt to proxy the global sentiment, and contend that the absence of a precise, unambiguous, and real-time measure of the global component of investor sentiment makes it a difficult proposition.

In this backdrop, the Covid-19 pandemic becomes particularly relevant to this study, owing to its widespread impact on financial markets globally. The International Monetary Fund (IMF) has considered this crisis to be much worse than that of 2008-09, and even compared it to the great depression of 1930s.[1] The spread of this crisis is well-covered globally in popular media and academic circles. These discussions and analyses concerning the future implications of the pandemic on the global economy are made available publicly through various information sources, e.g., conventional

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The authors are extremely grateful to the editor, Prof. Kamal Upadhyaya, and anonymous reviewers for their valuable comments. All the mistakes are our own.

[1] https://www.imf.org/en/News/Articles/2020/03/23/pr2098-imf-managing-director-statement-following-a-g20-ministerial-call-on-the-coronavirus-emergency.

news media, social media, and other internet sources; and thus, contribute to what we call as "*the global component of sentiment*."

To examine this global component of sentiment, we select the 25 important futures indices worldwide, based on turnover. Our choice of index futures as an instrument to examine the broad market-wide retail investor sentiment is driven by the following two important considerations. First, index futures provide a cost-effective and highly leveraged platform to trade a market-wide view. Furthermore, the index futures contracts facilitate a short position in the underlying asset in a cost-effective and convenient way as compared to the spot market route that entails covered shorting.[2] Also, the index futures are less risky, and therefore, require less margin compared to their single stock counterparts. Because of these favorable aspects related to market microstructure coupled with rising financial literacy and investor education, there has been a rise in retail participation in derivative markets in the recent past (Hsiao & Tsai, 2018; Miao et al., 2017; Wang et al., 2018). This claim is further supported by several recent news articles and business reports published by reputable organizations (Financial Times, Economic Times, Credit Suisse, Futures Industry Association (FIA), Bank for International Settlements (BIS), Deloitte)[3]. For example, the Credit Suisse report provides data supporting the rising participation of retail investors in the stock market, particularly in the U.S. context. A similar article published in the Financial Times supports this trend with the data collected from the Bloomberg. Both the studies show that retail participation in financial markets has increased from 14% in the year 2019 to 20% in the year 2020. Similarly, the news article published in Economic Times notes that the retail participation in the Indian derivatives market has been rising, and reports that the retail investors accounted for nearly 39% of trading in the index futures contracts in the year 2021.[4]

Second, in our study, we employ the 25 most heavily traded futures market indices across the world. Arguably, these are some of the most evolved markets in terms of market microstructure and informational efficiency. Therefore, these markets are expected to attract considerable retail investor participation. The literature on market efficiency argues that any systematic deviations from efficient markets need to be tested on the most efficient instruments available (e.g., index futures). Then, with a high probability, such deviations are also expected to hold for other less informationally efficient instruments (Chordia et al., 2008). The index futures markets are highly efficient as the transaction costs per dollar invested remain very low (Dao et al., 2018; De Jong & Nijman, 1997; Frino et al., 2000; Jong & Donders, 1998). In view of the above, we choose index futures to set up our research design.

The extant literature offers various proxies of investor sentiment. These include the closed-end fund discount, first-day IPO returns, option implied volatilities, aggregate market liquidity, number of published newspaper articles, consumer confidence indices, trading volume, advertising expenses, share turnover, and number of financial analysts covering the firm, among others (Chemmanur & Yan, 2019; Fang & Peress, 2009; Gervais et al., 2001; Kurov, 2008; Lee et al., 1991; Ritter, 1991; Schmeling, 2009). However, none of these proxies represents stock market sentiment adequately. The majority

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[2] The market for covered shorting is generally very costly and less liquid, particularly for executing market-wide view that would require shorting an ETF that tracks the market index closely, or the portfolio of assets that constitute the market index. In the falling markets, where a trader (retail or institutional) would need to take a market wide short position, the index futures would serve the purpose to execute this view conveniently and in a cost-effective manner.

[3] (1) https://economictimes.indiatimes.com/markets/stocks/news/is-this-the-era-of-the-retail-investor/articleshow/87236474.cms; (2) https://www.ft.com/content/7a91e3ea-b9ec-4611-9a03-a8dd3b8bddb5; (3) https://www.credit-suisse.com/us/en/investment-banking/ibcm/corporate-insights/the-investor-landscape-four-evolving-themes-and-their-implications.html; (4) https://www.fia.org/marketvoice/articles/viewpoint-rise-retail-derivatives-markets; (5) https://www.bis.org/publ/qtrpdf/r_qt2103v.htm; (6) https://www2.deloitte.com/content/dam/Deloitte/us/Documents/financial-services/us-the-rise-of-newly-empowered-retail-investors-2021.pdf

[4] We are thankful to an anonymous reviewer for suggestions related to a comprehensive development of this paragraph in Introduction, pertaining to the growing role of retail investors in derivative markets.

of these proxies are a result of the equilibrium outcome of many forces, including investor sentiment (Da et al., 2014). This leaves considerable scope for errors in estimation, particularly due to the presence of noise (Engelberg & Parsons, 2011). Moreover, many of these proxies are the U.S. centric, and it is difficult to construct these measures for other countries. More recently, Google has made the user search query data available on its google trends website (https://trends.google.com/trends/: Search volume index: SVI).[5] SVI serves as a more direct measure of information demand by people, and therefore, proxies retail investor sentiment appropriately (Da et al., 2011, 2014). Subsequently, several studies have employed the google search volume index (GSVI) as a proxy of investor attention and sentiments.

In a recent study, Da et al. (2014) build a FEARS index for the U.S. market. The measure proxies investor sentiments using the Google search volume associated with the keywords such as "recession," "unemployment," and "bankruptcy." The study finds that the FEARS index predicts (a) reversals in short-term returns, (b) changes in return volatility, and (c) outflows from equity to bond funds. Similarly, Ding & Hou (2015) examine the stocks listed on S&P500 between January 2004 and December 2009, and support the price pressure hypothesis of Barber & Odean (2007). That is, the demand for information by investors - as captured by the Google search volume measure - affects trading activity and movement of prices. In another study, Goddard et al. (2015) examine the impact of investor attention on seven major currency pairs. They find that information acquisition by investors relates to trading activity, volatility, and variance risk premium in the foreign exchange markets; furthermore, it may be a priced risk factor. Other notable studies that examine the role of SVI measure in trading activity and stock market volatility include Mondria et al. (2010), Smith (2012), Takeda & Wakao (2014), Tantaopas et al. (2016), and Vlastakis & Markellos (2012). Broadly, the literature suggests that investors become sentiment-driven, particularly during crises (such as the Covid-19 pandemic). These investors become anxious about their investments, and therefore, overreact to information. This increased trading activity of sentiment-driven noise traders is also reflected in the relation between the SVI measure and increasing volatility.

More recently, another strand of literature has emerged, suggesting that the response of asset prices to news differs according to the nature of the news source (Fedyk, 2020). For example, Jiao et al. (2020) study the impact of traditional news media and social media on 1,848 stocks from NYSE, AMEX, and NASDAQ, during 2009-14. They find that the news from traditional media sources decreases volatility, whereas the news from social media ("echo chambers") increases volatility. This strand of the literature suggests that systematic and reliable news sources (e.g., traditional news media) create uniform views, and thus, dampen the volatility levels. In contrast, the news from unreliable and nonsystematic sources (such as social media) leads to more disagreement, and therefore, increases volatility levels. These findings related to the response of asset prices to new information are consistent with the postulations of Brenner et al. (2009) and Mullainathan & Shleifer (2005).

During the pandemic, various common headline indicators (HIs, e.g., global daily deaths and active cases, loss of economic activity, etc.) were compiled by the respective state and central authorities, and were verified from multiple credible sources.[6] These HIs were continuously monitored and evaluated by the academic community in the popular media. These analyses were made available to all the market participants (investor community, regulators, and governments) on a real-time basis.

[5] SVI is computed as the number of searches for a given term scaled by the total number of searches on google, over the corresponding period. The measure is further normalized on a scale of 0-100.

[6] For example, the website https://www.worldometers.info/coronavirus/#countries provides a number of Covid-19 related parameters on day-to-day basis. It is important to note that these headline indicators are made available by a number of credible organizations. All of these sources provide accurate, and therefore, largely identical data (such as global death and affliction). This data is continuously monitored and evaluated across the world resulting in similar expectations about the future global macroeconomic conditions.

Leading newspapers, academic journals, and popular television news debates across the world reported similar figures for these HIs. These discussions led to homogenous future expectations about the global economic growth and performance of financial markets. Therefore, we argue that these HIs acted as a proxy of systematic sources of information that contributed to homogenous expectations amongst the various market participants. This may have contributed to the stability and recovery of global financial markets, after the observed downfall during the onslaught of the Covid-19 pandemic (Andersen, 1996; Chae, 2005; Figlewski, 1978, 1981). Our study employs the cumulative daily global deaths and cases related to Covid-19 as the Headline Indicators (HIs). More details about the construction of HI measure is provided in Section 2: Data sample, and variables.

Similar to our work, some recent studies have also examined the effect of investor sentiments on financial markets during the Covid-19 pandemic. The financial markets literature on the Covid-19 pandemic ascribes considerable significance to the investor sentiment channel (Chundakkadan & Nedumparambil, 2021; Huynh et al., 2021; Smales, 2021; Sun et al., 2021). Most of these studies employ the novel Google search volume index (GSVI) measure as a proxy of retail investor sentiment (Anastasiou et al., 2022; Chundakkadan & Nedumparambil, 2021; Huynh et al., 2021; Smales, 2021). These studies suggest that the most prominent keywords based on the search volume interest include "Coronavirus" and 'Covid-19". These keywords also subsume the search interest associated with other auxiliary derived search terms such as "Coronavirus and stock markets." This is also confirmed by the google trends website (https://trends.google.com/trends/). This recent strand of literature documents some interesting findings. First, the impact of the Covid-19 pandemic across global financial markets follows similar timelines (Smales, 2021; Tripathi & Pandey, 2021). Next, the negative sentiments engendered due to the pandemic resulted in falling prices and high volatility. For example, Corbet et al. (2020) observed the impact of investor behavior on cryptocurrencies during the Covid-19 pandemic. They noted that these digital assets provided safe havens during the pandemic, a role performed by precious metals historically. Huynh et al. (2021) constructed a novel measure of investor sentiment, namely, 'feverish sentiment', and examined the impact of fear sentiments driven by the Covid-19 pandemic on the 17 largest economies. They found that the sentiment shocks to global markets had their epicenter in the U.K., China, the U.S., and Germany. During the onset of the Covid-19 pandemic, this measure of investor sentiment positively (negatively) predicted volatility (returns). Chundakkadan & Nedumparambil (2021) examined the effect of investor sentiment on daily returns in 59 financial markets, during the Covid-19 pandemic. They documented that the Covid-19 crisis generated negative sentiments in the global markets, which led to excess volatility and negative returns. Smales (2021) examined the impact of Covid-19 on G-20 financial markets. The study documented that retail investors' demand for Covid-19 related information sped up the incorporation of pandemic-related negative information in prices. This, in turn, resulted in negative returns and high volatility.

This study contributes to the extant literature by examining the impact of the global component of investor sentiment on the price returns and conditional volatility experienced during the period of Covid-19 pandemic. The study constructs the GSVI measure using the keywords: "Coronavirus," "Corona," and "Covid-19" to measure investor sentiments.[7] The keywords employed in the previous studies are usually based on stock tickers. Therefore, the issue of endogeneity may emerge, i.e., the change in stock price may itself drive the measure of sentiment (Ding & Hou, 2015). In this study, the search terms reflect the shift in attention and information demand corresponding to an exogenous event (Covid-19 pandemic), and are not driven by financial markets themselves. We also contribute to the literature that documents the response of security prices to the news arriving from different sources. To this end, we employ (1) Headline Indicator (HI) measure, based on the reliable information disseminated by reputed organizations, and (2) GSVI measure, which reflects the unsystematic search

[7] We specifically use these keywords as the interest overtime generated for these terms was the highest as indicated by the google trends website.

behavior and information demand of individual users. The study analyses 25 major futures indices across the globe. The results are consistent with our initial hypothesis, that is, the global component of sentiment causes overreaction in security prices, followed by a reversal in returns. We also show that the impact of GSVI and HI measures on the price and volatility is asymmetric. While the GSVI measure relates to falling prices and increasing volatility levels, the HI measure associates with positive returns and decreasing volatility levels. These results indicate that information from reliable sources reduces the disagreement and causes uniformity in expectations, thus lowering the volatility (and recovery in this case). The information that originates from unreliable sources (e.g., nonsystematic Google search by individuals) causes disagreement and high sentiments that lead to price overreactions and higher volatility levels. These findings are consistent with Jiao et al. (2020). Lastly, the application of the quantile regression framework (Koenker & Hallock, 2001) reveals that investor sentiments affect price returns asymmetrically, and the strength of this relationship is relatively high around the extreme-negative returns. This suggests that the effect of investor sentiment on security prices is considerably more during market downturns (Badshah, 2013; Hibbert et al., 2008; Tantaopas et al., 2016). These results have important implications for academics, policymakers, and regulators interested in understanding the arrival and incorporation of news in security prices. These findings may help market regulators and policymakers in managing the impact of crises on financial markets through the dissemination of appropriate information using systematic channels.

The rest of the paper is structured as follows. Section 2 discusses the background literature and hypothesis development. Sections 3 and 4 detail the data sample, variables, and methodology. The empirical analysis of results and robustness tests are presented in Section 5, and Section 6 concludes the study.

RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

There is ample empirical evidence in the "*Behavioral Finance Literature*" that investor sentiment is a contrarian predictor of time series of cross-sectional returns (Andrei & Hasler, 2014; Baker et al., 2012; Stambaugh et al., 2014; Yu & Yuan, 2011). More recently, after the Covid-19 pandemic, this strand of literature has witnessed considerable attention from academics and practitioners (Ali et al., 2020; Anastasiou et al., 2022; Corbet et al., 2020; Huynh et al., 2021). The majority of these studies document market anomalies and security price behavior that does not conform to the postulations of the "*Efficient Market Hypothesis*" of Eugene Fama (Fama, 1970, 1991, 1998). This literature indicates that when the sentiment is high, prices deviate from their fundamental efficient values (Yu & Yuan, 2011). This is ascribed to the mechanism that weakens the risk-return trade-off during high-sentiment periods. Moreover, a considerable volume of this literature focuses on the U.S. data (Barberis et al., 1998; Bondt & Thaler, 1985; De Long et al., 1990). However, as more reliable information from systematic sources arrives, a wide consensus on market prices emerges, and mispricing is revealed (Andersen, 1996; Figlewski, 1978, 1981). Subsequently, prices correct due to pressure from arbitrageurs, correction in noise traders' beliefs, and confirmation from fundamentals (e.g., earnings realizations). This dynamics explains the contrarian return predictability of investor sentiments.

In this backdrop, very few studies examine the impact of the global component of investor sentiment on international stock market returns (Anastasiou et al., 2022; Baker et al., 2012; Fraiberger et al., 2021; Han & Li, 2017; Wu et al., 2017). Most of these studies highlight that measurement of this global component of sentiment is difficult and ascribe this to the unavailability of appropriate international sentiment proxies (Baker et al., 2012; Baker & Wurgler, 2007). In the introduction section, we present the two key measures that are instrumental in price formation, namely, (a) the GSVI measure as the proxy for the global component of investor sentiment, and (b) the headline indicator (HI), which is a more systematic measure of information arrival. In this section, we develop the hypotheses that explore the impact of these measures on security prices. As in the previous literature (e.g., Antoniou et al., 2013; Barber & Odean, 2000; Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999), our hypothesized setting combines two prominent concepts: (a) Overreaction hypothesis, and (b) Underreaction hypothesis. However, unlike the prior literature, we employ more direct and accurate proxies of sentiment and information dissemination.

We argue that investors across the world shared a common negative sentiment about their economy and financial markets during the Covid-19 pandemic (Anastasiou et al., 2022; Huynh et al., 2021; Smales, 2021). This negative sentiment had a similar systematic impact globally. During crises such as the Covid-19 pandemic, a sizable volume of the investor population comprises sentiment-driven, uninformed, noise traders. These investors overreact to the incoming information and therefore cause deviations from efficient prices (Barberis et al., 1998; Daniel et al., 1998). These overreactions lead to falling prices and rising volatility levels. In the early phase of the pandemic, the fear and negative sentiment were further exacerbated by the unavailability of vaccines and uncertainty about the future (e.g., lockdowns, shutting of supply chains), leading to vast heterogeneity in expectations. This kind of market environment - characterized by fear and uncertainty, engenders volatile financial markets as observed during the Covid-19 pandemic. This leads to our first hypothesis, which is as follows:

Hypothesis 1: The GSVI measure - a proxy of the global component of investor sentiment - has a negative (positive) relationship with returns (volatility).

On the other hand, there is an opposite effect that comes into play. As the time passes, more systematic information arrives from reliable sources (e.g., headline indicators). This systematic and credible information leads to more certainty about the future of the global economy and markets, and thus, more homogenous expectations (Andersen, 1996; Figlewski, 1978, 1981). Prices stabilize, and markets become relatively calm. As uncertainty reduces, markets witness more participation from informed arbitrageurs and rational risk-averse traders (Brenner et al., 2009; Fedyk, 2020; Jiao et al., 2020; Mamaysky, 2020). This sets the path to a gradual recovery process with autocorrelated prices. This leads to our second hypothesis, which is as follows:

Hypothesis 2: Headline Indicator (HI) measure - the more direct and systematic measure of reliable information - has a positive (negative) relationship with returns (volatility).

Another strand of the literature shows that markets are more responsive to the arrival of negative news (Badshah, 2013; Hibbert et al., 2008; Tantaopas et al., 2016). That is, the influence of negative sentiment is particularly strong on prices. Different theories provide the conceptual underpinnings to this argument. First, the leverage effect (Black, 1976) suggests that negative shocks increase leverage, making stocks riskier and driving up volatility levels. Next, the volatility feedback hypothesis (Campbell & Hentschel, 1992; Low, 2004; Poterba & Summers, 1984) shows that volatility innovations further drive down the returns, thus leading to an asymmetric and more substantial impact of negative news (than that of positive news) on prices. Lastly, the prospect theory explains this asymmetric relationship through the asymmetric shape of the utility curve around the origin (Barberis, 2013; Odean, 1998). That is, the changes in utility around higher returns may not be as much compared to those around lower returns. While these three theories may differ in the mechanism through which they explain the asymmetric impact of negative news on prices, the final implication is the same as summarized in the following hypothesis:

Hypothesis 3: The relationship between returns and the global component of sentiment is particularly strong for the lower quantiles of return distribution.

The empirical models used for testing the hypotheses are provided in Section 4 (Methodology).

DATA SAMPLE AND VARIABLES

We select daily price data for 25 important index futures from the Bloomberg terminal (Table 1).[8] Our sample includes the largest global financial markets that experienced a major impact of the Covid-19 pandemic. The study analyses the daily closing price data of near-the-month index futures (since they are the most liquid contracts) from January 1, 2020 to October 31, 2020. The natural log differences in closing prices [$r_t = \ln(p_t/p_{t-1})$] are employed as the price return measure. The cumulative global daily cases and deaths related to Covid-19 are employed as headline indicators (HI). We source this data from the European Centre for Disease Prevention and Control.[9] To analyze the spread of Covid-19, these are the two most widely reported and analyzed indicators across the world, and are easily available to the public at large through various sources, including conventional news media, social media, and other internet sources. Since these can be easily verified, a considerable amount of similarity is expected across these HIs available from different sources. The GSVI measure employed in the study uses the keyword "Coronavirus" as a measure of retail investor sentiment, as it exhibits the highest interest over time (Da et al., 2011, 2014). Furthermore, we also compute the GSVI using keywords "Covid-19" and "Corona" to test the robustness of the results. The daily movement of search volume indices for these keywords, provided by the google trends website (https://trends.google.com/trends/), is shown in online Appendix B.

For each indicator, HIs and GSVIs, we compute three measures (mean, median, and return based) for analysis purposes (Da et al., 2011, 2014). These are shown below in Equations (1) and (2).

$$GSVI_{mean,t} = \ln(GSVI_t) - \ln(mean(GSVI_{t-1}, \dots, GSVI_{t-7})) \tag{1a}$$

$$GSVI_{median,t} = \ln(GSVI_t) - \ln(median(GSVI_{t-1}, \dots, GSVI_{t-7})) \tag{1b}$$

$$GSVI_{return,t} = \ln(GSVI_t) - \ln(GSVI_{t-1}) \tag{1c}$$

$$HI_{mean,t} = \ln(HI_t) - \ln(mean(HI_{t-1}, \dots, HI_{t-7})) \tag{2a}$$

$$HI_{median,t} = \ln(HI_t) - \ln(median(HI_{t-1}, \dots, HI_{t-7})) \tag{2b}$$

$$HI_{return,t} = \ln(HI_t) - \ln(HI_{t-1}) \tag{2c}$$

Put simply, the measures provided in Equations (1) and (2) compute (a) differences in natural log (ln) of GSVI (and HI) for time '*t*' and that of its median over the last seven days, (b) differences in natural log (ln) of GSVI (and HI) for time '*t*' and that of its mean over the last seven days, and (c) differences in natural log (ln) of GSVI (and HI) for time '*t*' and that of previous day '*t-1*'. Table 2 reports summary statistics. The study employs the cross-sectionally augmented Im, Pesaran, and Shin (IPS)

[8] For selecting these futures markets, we employ two subjective criteria: (1) Turnover of the index, and (2) diversity of the overall sample-set.

[9] The website, https://www.ecdc.europa.eu/en/publications-data provides the Covid-19 related data employed in the study.

unit-root test of stationarity condition for panel models, following Pesaran (2007)[10]. The results provided in Table 2 confirm the stationarity of the measures.

Table 2 shows descriptive statistics for index returns, mean-based HI measure for the cumulative total deaths and cases at the world level, and the GSVI mean-based measure for the global search interest of the keyword "Coronavirus."[11] Since the HI measure at level is a cumulative measure, the minimum value of the return form is 0.00%. In the initial phase, the HI measure rises substantially (maximum values of 131.13% for total cases and 178.34% for total deaths) as the total deaths and cases increase on a lower base (HI >80%, in the February month), gradually stabilizing to lower levels there onwards. The sentiment measure, GSVI, rises sharply from the last week of February till the mid of March and attains the highest value at level. This indicates rising fear across the world and coincides with falling markets (more detailed discussion provided in Section 4, Empirical Results). Due to the low base effect, the return form of GSVI exhibits very large values (GSVI> 50%). From here onwards, there is a gradual decay in the GSVI measure, indicating less feverish sentiment and relative calm. Interesting to note that the GSVI measure is asymmetrically distributed with large positive values compared to the relatively small negative values. This is ascribed to the fact that the transition to high-sentiment and volatile environments is abrupt in nature, while that to more calm and stable periods is relatively gradual.

METHODOLOGY

The following specifications are employed to examine the relationship of return and volatility with the HI and GSVI measures (for all the three variants, namely, mean, median, and return based).

$$r_{cind,t} = \alpha_0' + \sum_{j=0}^{q} c_j' HI_{t-j} + \sum_{k=0}^{r} d_k' GSVI_{t-k} + \varepsilon_{cind,t}' \quad (3a)$$

$$r_{cind,t} = \alpha_0'' + \sum_{i=1}^{p} b_i r_{t-i} + \sum_{j=0}^{q} c_j'' HI_{t-j} + \sum_{k=0}^{r} d_k'' GSVI_{t-k} + \varepsilon_{cind,t}'' \quad (3b)$$

$$h_{cind,t} = \alpha_0''' + \sum_{j=0}^{q} c_j''' HI_{t-j} + \sum_{k=0}^{r} d_k''' GSVI_{t-k} + \varepsilon_{cind,t}''' \quad (4)$$

Here, $r_{cind,t}$ and $h_{cind,t}$ denote daily price return and conditional volatility [AR(4)-EGARCH (1,1) model][12] for day '*t*' and country-index '*cind*.' Equations (3a) & (3b) examine the effect of investor sentiments on returns. The lagged return terms in specification (3b) control for possible autocorrelation in returns. Specification (4) examines the effect of investor sentiments on conditional volatility. The study employs the pooled and fixed-effects panel data regression models, and uses Heteroscedasticity and Autocorrelation consistent (HAC) robust standard errors for computing t-statistics. Using the information criterion BIC, we include four lagged terms (p=4, q=4, r=4)[13] of the return, GSVI, and HI measures in the models.

[10] The individual country returns are also found to be stationary using ADF and PP tests.

[11] In addition to mean based HI and GSVI measures, we also compute median and simple daily measures. For GSVI, we also include global search volume of terms Covid-19 and Corona. These keywords are selected as they exhibit the highest search volume interest over the study period. This selection criterion is in the spirit of prior studies employing the GSVI measure [Anastasiou et al., 2022; Baig et al., 2021; Chundakkadan & Nedumparambil, 2021; Lyócsa et al., 2020; Smales, 2021].

[12] The 'rugarch' package in R has been used for estimating GARCH models. EGARCH (1,1) model offers the best-fit among the Standard-GARCH (1,1), EGARCH (1,1), and GJR-GARCH (1,1) models, as per the information criteria (Akaike, Bayes, Shibata, and Hann-Quinn). These results are not shown here for brevity.

[13] The results are robust to one, two, three, four, and higher lagged returns.

Table 1. Details of the Futures Market Indices Included in the Study

Country	Index	Stock Exchange
American Stock Indices		
U.S.A.	*NASDAQ 100 Futures* *S&P500 Futures* *Dow Jones Futures* *Russell 2000 Futures*	*Chicago Mercantile Exchange (CME)*
Brazil	*IBOVESPA Futures*	*BM&FBOVESPA (B3), CME*
European Stock Indices		
Fifty stocks from Eight Eurozone countries	*EURO STOXX 50 Futures*	*Frankfurt Stock Exchange (Deutsche Börse)*
U.K.	*FTSE 100 Futures*	*Intercontinental Exchange (ICE)*
Germany	*Deutscher Aktienindex (DAX) Futures*	*Eurex Exchange*
France	*Cotation Assistée en Continu (CAC-40) Futures*	*Euronext-Paris*
Sweden	*OMX Stockholm 30 (OMX30) Futures*	*Nasdaq Stockholm AB (Nasdaq Nordic)*
Switzerland	*Swiss Market Index (SMI) Futures*	*Swiss Options and Financial Futures Exchange (SOFEX), Eurex Exchange*
Spain	*IBEX35 Futures*	*Mercado Español de Futuros Financieros (MEFF)*
Austria	*Austrian Traded Index (ATX) Futures*	*Eurex Exchange*
Norway	*OBX 25 Futures*	*Oslo Stock Exchange (OBX)*
Singapore	*SGX MSCI Singapore Futures*	*Singapore Exchange Limited (SGX)*
Italy	*FTSE MIB Futures*	*Borsa Italiana Milan*
Asia-Pacific Region Stock Exchanges		
China	*CSI 300 Futures* *SSE 50 Futures* *Hang Seng Futures*	*China Financial Futures Exchange (CFFEX)*
Japan	*TOPIX Futures*	*Tokyo Stock Exchange (TSE)*
	Nikkei-225 Futures	*Osaka Exchange (OSE) Chicago, SGX, CME*
India	*Nifty-50 Futures*	*National stock exchange (NSE)*
	BSE SENSEX-50 Futures	*Bombay stock exchange (BSE)*
Australia	*S&P/ASX 200 Futures*	*Australian securities exchange (ASX)*
South-Korea	*Korea Composite Stock Price (KOSPI) 200 Futures*	*Korea Exchange (KRX)*

Table 2. Descriptive Statistics

The table provides descriptive statistics for the measures employed in the study for 25 futures indices, over the study period (January 01, 2020, to October 31, 2020). These measures are returns, physical indicators (total daily cases and deaths at the world level), GSVI measure (using the keyword "Coronavirus"). The test statistics for cross-sectionally augmented Im, Pesaran and Shin (IPS) unit-root test for panel models are shown (implemented with "cipstest" command in R package "plm"), indicating the stationarity of the data. For computation purposes, HIs and GSVIs are replicated for all the corresponding return observations.

Variable	N	Mean	Median	Maximum	Minimum	Std. Dev.
Return	5,237	-0.06%	0.04%	13.66%	-16.90%	2.16%
Physical Indicators						
Total Cases	5,237	16.37%	6.99%	131.13%	0.00%	24.59%
Total Deaths	5,237	16.70%	4.18%	178.34%	0.00%	26.52%
GSVI						
Coronavirus	5,237	3.82%	-2.16%	172.28%	-45.20%	29.28%

IPS Unit-Root for Panel Data H0: Non-Stationarity	**Return**	**Total Cases**	**Total Deaths**	**GSVI**
Test-Statistic	-46.12***	-8.68***	-7.43***	-18.439***

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. (4) The GSVI and HI indicators summarized here are mean based. The results for median and return based indicators are available from the authors upon request.

QUANTILE REGRESSION APPROACH

Following (Koenker & Hallock, 2001), the model [Equation (3a)] is further examined in a quantile regression framework to test the robustness of the results. The quantile regression approach can appropriately capture the nonlinear impact of the Covid-19 pandemic on financial market variables. Moreover, the quantile regression approach estimates the tail behavior appropriately in the presence of fat-tails and skewness, which are the stylized facts of the financial time series data. The choice of the quantile regression approach is particularly relevant to this setting (Koenker & Hallock, 2001; Koenker & Xiao, 2006). The estimated quantile regression model is provided in Equation (5).

$$r_{cind,t}[\,Q_{r_{cind,t}}(\tau | HI_{t,} \ldots \ldots, HI_{t-q,}, GSVI_{t,} \ldots \ldots, GSVI_{t-r,}\,)] \;= a_0(\tau) + \sum_{j=0}^{q} b_j(\tau) HI_{t-j} + \sum_{k=0}^{r} c_k(\tau) GSVI_{t-k} \qquad (5)$$

Here, $r_{cind,t}[\,Q_{r_{cind,t}}(\tau | HI_{t,} \ldots \ldots, HI_{t-q,}, GSVI_{t,} \ldots \ldots, GSVI_{t-r,}\,)]$ is the 'τ-th' conditional quantile function (0<τ<1) of the return, and is modeled as a linear function of the contemporaneous and lagged headline indicators (HI_{t-j}) and GSVI's ($GSVI_{t-k}$), for different values of τ (= 0.05, 0.10, 0.15, … 0.95). $a_0(\tau)$ is the quantile-specific constant, and $b_j(\tau)$ and $c_k(\tau)$ represent the quantile-specific coefficients of the contemporaneous and lagged HI and GSVI terms. The quantile regression results are presented in Tables 6 and 7.

EMPIRICAL RESULTS

We visually examine the movement of prices and conditional volatility (Appendix A), and SVI measure (Appendix B) for the futures indices, over the study period.[14] The impact of the pandemic on index futures prices appears to manifest itself from the third week of February 2020, as the prices continue to fall up until the third week of March 2020. The fall in prices, the rise in conditional volatility, and also the increase in SVI measure move in sync. The rise in queries about Covid-19, as indicated by the rising SVI measure, reflects the increasing fear sentiment; which, in turn, causes the increase in volatility levels. Interestingly, while the physical and economic impact of the Covid-19 pandemic across different countries has different timelines[15], the impact on financial markets appears to be synchronous, suggesting that the prices are driven by a common force. This commonality in global markets can arguably be a manifestation of the global component of sentiment. As the information about the pandemic disseminated rapidly through the internet and other news media, the global component of sentiment - about the impact of the pandemic and future uncertainty - started forming. Subsequently, the prices started rising, and recovery began from the last week of March 2020 and continued up till July 2020. Again, this period coincides with the decline in values of conditional volatility and the SVI measure.

The study further confirms the relationship between price returns and global component of investor sentiment [Equation (3)] by employing the pooled and panel regression models. Tables (3) and (4) provide these results. The results suggest a negative relationship between the GSVI measure and returns [mean-based, Equations (1a) & 2(a)][16]. This is consistent with our hypothesis that the global component of investor sentiment precipitates the fall in prices. In contrast, we find that the HI measure, which is a proxy of systematic information from reliable sources, exhibits a positive relationship with returns. This suggests that the systematic information from reliable sources may have contributed to the recovery of prices.

To further test this argument, we examine the relationship of the GSVI and HI measures with conditional volatility. The results corresponding to the mean based measures of GSVI and HI are presented in Table 5.[17] The GSVI measure exhibits a positive relationship with conditional volatility. The lags of HI measure exhibit a negative relationship with conditional volatility. These results confirm our earlier postulations that the global component of sentiment may have precipitated the fall in prices and the increase in volatility levels. However, as the more systematic information from reliable sources becomes available, the prices recover gradually, and volatility levels decline. These results appear to be consistent with the overreaction hypothesis.

Overall, the evidence provided by the study appears to be a manifestation of investors' overreaction driven by a negative sentiment (Barberis et al., 1998; Hong & Stein, 1999). Crises events, such as Covid-19, and their subsequent spread through various information sources lead to high investor sentiments. These sentiment-driven investors overreact to new information. For example, during high negative sentiments, prices witness a sharp fall as investors overreact to the crisis event. Moreover, there is considerable disagreement among investors about the future worldview and

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[14] The price and conditional volatility graphs (Appendix A) are provided only for the six markets [S&P/ASX 200 Futures (Australia), CAC-40 Futures (France), EURO STOXX 50 Futures (Eurozone countries), FTSE 100 Futures (the U.K.), Nifty-50 Futures (India), S&P500 Futures (the U.S.)] for brevity. The price movement and behaviour of conditional volatiltiy is similar across the remaining 19 markets and can be provided upon reasonable request.

[15] For example, the spread and implications of the pandemic materialized in the U.S. and European countries much earlier than that in the Asian countries (e.g., India).

[16] The results from the other two measures (median and return based) are provided in online Appendix C. The results are qualitatively similar.

[17] The results from the other two measures (median and return based) are provided in online Appendix C. The results are qualitatively similar.

Table 3. Pooled Regressions of Returns on Headline Indicator (HI) and GSVI

Panels A and B present the results from the pooled method [following Equations (3a) & (3b)]. The measures of GSVI and HI are mean-based [following Equations (1a) & (2a)]. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	*5,237*	*-0.003*	*0.019****	*0.001*	*-0.009****	*0.001*	*-0.019****	*0.007****	*-0.003*	*-0.005****	*-0.002***	*4.80%*	*188.431****
		-1.145	*9.709*	*0.492*	*-3.974*	*0.571*	*-11.645*	*4.365*	*-1.042*	*-3.156*	*-2.333*		
TD	*5,237*	*-0.001*	*0.009****	*0.009****	*-0.014****	*0.005****	*-0.016****	*0.007****	*-0.008****	*-0.003*	*-0.000*	*4.56%*	*200.819****
		-0.413	*3.257*	*2.814*	*-5.675*	*4.012*	*-8.825*	*5.009*	*-3.625*	*-1.632*	*-0.017*		
Panel B: with controls Equation (3b)													
TC	*5,237*	*-0.002*	*0.018****	*0.005***	*-0.010****	*-0.001*	*-0.020****	*0.006****	*0.000*	*-0.006****	*-0.003***	*9.80%*	*388.331****
		-0.896	*10.864*	*2.288*	*-5.168*	*-0.589*	*-10.961*	*3.366*	*0.023*	*-5.245*	*-2.363*		
TD	*5,237*	*0.000*	*0.006****	*0.013****	*-0.014****	*0.004****	*-0.017****	*0.007****	*-0.006****	*-0.005****	*0.001*	*9.48%*	*512.685****
		0.166	*2.839*	*5.416*	*-7.168*	*2.678*	*-8.662*	*4.400*	*-2.624*	*-4.485*	*0.376*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table 4. Panel Fixed-Effects Regressions of Returns on Headline Indicator (HI) and GSVI

Panels A and B present the results from the panel fixed-effects method [following Equations (3a) & (3b)]. The measures of GSVI and HI are mean based [following Equations (1a) & (2a)]. We report the coefficients of headline indicator [HI: Total cases(TC)/Total deaths (TD)] and GSVI measure [Keyword ("Coronavirus")], t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	*5,237*	*-0.003*	*0.019****	*0.001*	*-0.009****	*0.001*	*-0.019****	*0.007****	*-0.003*	*-0.005****	*-0.002***	*4.36%*	*189.382****
		-1.168	*9.733*	*0.500*	*-3.996*	*0.695*	*-11.630*	*4.370*	*-1.040*	*-3.154*	*-2.335*		
TD	*5,237*	*-0.001*	*0.009****	*0.009****	*-0.014****	*0.005****	*-0.016****	*0.007****	*-0.008****	*-0.003*	*-0.000*	*4.12%*	*204.202****
		-0.451	*3.262*	*2.823*	*-5.666*	*4.094*	*-8.829*	*5.032*	*-3.632*	*-1.634*	*-0.044*		
Panel B: with controls Equation (3b)													
TC	*5,237*	*-0.002*	*0.018****	*0.005***	*-0.010****	*-0.000*	*-0.020****	*0.006****	*0.000*	*-0.006****	*-0.003***	*9.41%*	*390.23****
		-0.913	*10.916*	*2.311*	*-5.188*	*-0.435*	*-10.950*	*3.357*	*0.020*	*-5.235*	*-2.420*		
TD	*5,237*	*0.000*	*0.006****	*0.013****	*-0.014****	*0.004****	*-0.017****	*0.007****	*-0.006****	*-0.005****	*0.000*	*9.08%*	*523.252****
		0.166	*2.839*	*5.416*	*-7.168*	*2.678*	*-8.662*	*4.400*	*-2.624*	*-4.485*	*0.308*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

market prices. This gives rise to high volatility levels. In these uncertain times, arbitraging away anomalies becomes highly risky, and therefore, the pricing inefficiency prevails in the short-term (one to three weeks). In the medium term, as further information from more reliable sources (HIs from news media) becomes available, a broad consensus emerges among the vast majority about the future worldview and market prices. Subsequently, more rational and informed investors enter that market and carry out arbitrage activities. This causes the reversal in price returns and decline in volatility levels, as witnessed from the third week of March 2020. We also observe that the sentiment levels (GSVI measure) exhibit a declining trend during this period. Notably, unlike the sharp fall in prices, the reversal is more gradual, as the rational investors are more cautious and tend to underreact to new information.

QUANTILE REGRESSION APPROACH

We further test the robustness of our results by examining the relationship between the returns and global component of sentiment [Equation (3a)][18], using the quantile regression approach of Koenker & Hallock (2001). Tables (6) and (7) present the results corresponding to the mean-based measures of global sentiment [Equations (1a) and (2a)][19]. First, these results confirm our hypothesis that the global component of sentiment contributes to falling prices. Second, the information from reliable sources, proxied by the HI measure, exhibits a positive relationship with returns and appears to have contributed to the price recovery. Lastly, the strength of this relationship (as measured by the goodness-of-fit measure) appears to be particularly strong around extreme negative returns. This kind of asymmetric relationship between returns and investor sentiment (and other measures of information such as volume) has been previously reported in the literature (Badshah, 2013; Hibbert et al., 2008; Tantaopas et al., 2016). This suggests that the impact of negative sentiment on prices is particularly significant.

In summary, we employ two contrasting measures of information dissemination in this study. First, the GSVI measure is a more direct measure of information demand by retail investors globally (Da et al., 2011, 2014). During the Covid-19 period, these retail investors often acted on the basis of sentiment and contributed to noise in prices. Therefore, this measure aims to capture the impact of the global component of sentiment on prices during the pandemic. This dynamics in trading activity is captured by the relationship of the GSVI measure with returns and volatility. More specifically, these retail investors often acquire information from less reliable but easily accessible sources, such as nonsystematic Google searches or viral topics from social media. This information has contradictory implications and creates disagreement among investors. In such an uncertain environment with heterogenous expectations, sentiment-driven investors are anxious about their investments and overreact to any new information that does not conform to their current view about the market conditions. Therefore, the trading activity of these sentiment-driven retail investors led to falling prices and high volatility levels observed during the onslaught of the pandemic. The impact of this trading dynamics on prices is captured by the observed negative relationship between the GSVI measure and returns, and the positive relationship between the GSVI measure and conditional volatility. Moreover, the results from quantile regression show that the strength of the relationship between GSVI and returns is particularly strong around the lower return quantiles. This suggests that during falling markets, the impact of sentiment on prices was relatively more.

[18] The results corresponding to Equation (3b) are qualitatively similar, and not reported for brevity. These results can be obtained from the authors upon request.

[19] The results from the other two measures (mean- and return-based) are provided in online Appendix C. The results are qualitatively similar.

Table 5. Regressions of Conditional Volatility on Headline Indicator (HI) and GSVI

Panels A and B present the results from pooled and panel fixed-effects methods [following Equation (4)]. The measures of GSVI and HI are mean-based [following Equations (1a) & (2a)]. The conditional volatility is obtained using AR(4)-EGARCH (1,1) model on time-series of returns. The model is selected using information criteria (AIC/BIC/SIC). The results from other GARCH models (standard GARCH and GJR-GARCH) are qualitatively similar and not reported for brevity. We report the coefficients of headline indicator [HI: Total cases(TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. For better presentation, the coefficients of HI and GSVI measures are multiplied by 100. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: Pooled model													
TC	*5,237*	*0.055****	*-0.051****	*-0.021****	*0.004*	*0.019**	*0.037***	*0.008*	*0.013**	*0.001*	*0.018****	*1.39%*	*52.337****
		2.938	*-3.416*	*-2.914*	*0.465*	*1.836*	*2.146*	*0.593*	*1.693*	*0.208*	*2.894*		
TD	*5,237*	*0.063****	*-0.025*	*-0.027****	*0.024****	*-0.019**	*0.028*	*-0.008*	*0.031****	*0.004*	*0.014**	*1.47%*	*50.397****
		2.841	*-1.263*	*-3.048*	*3.379*	*-1.770*	*1.523*	*-0.575*	*3.106*	*0.496*	*1.807*		
Panel B: Panel fixed-effects model													
TC	*5,237*	*0.055****	*-0.050****	*-0.021****	*0.003*	*0.019**	*0.037***	*0.008*	*0.014**	*0.001*	*0.017****	*0.92%*	*51.04****
		2.952	*-3.387*	*-2.890*	*0.350*	*1.719*	*2.145*	*0.572*	*1.760*	*0.133*	*2.758*		
TD	*5,237*	*0.062****	*-0.025*	*-0.028****	*0.024****	*-0.018**	*0.028*	*-0.008*	*0.031****	*0.003*	*0.013**	*1.00%*	*50.2****
		2.841	*-1.266*	*-3.144*	*3.432*	*-1.656*	*1.536*	*-0.586*	*3.169*	*0.429*	*1.681*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table 6. Quantile Regression of Returns on Total Cases (TC: Headline Indicator) and GSVI

The table presents the results from the quantile regression framework [following Equation (5)], using Total Cases (TC: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are mean-based [following Equations (1a) & (2a)]. We report the coefficients of headline indicator [HI: Total Cases (TC)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisk *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*	*5,237*
HI_C	*0.082****	*0.043****	*0.032****	*0.020****	*0.016****	*0.017****	*0.022****	*0.026****	*0.028***	*0.053****
	6.248	*6.941*	*6.783*	*4.647*	*3.581*	*3.313*	*3.188*	*3.067*	*2.448*	*4.243*
HI_lag1	*-0.037*	*0.026***	*0.023****	*0.015****	*0.006*	*0.003*	*0.001*	*-0.002*	*0.002*	*0.012*
	-0.447	*2.193*	*4.365*	*3.458*	*1.412*	*0.693*	*0.143*	*-0.315*	*0.122*	*0.374*
HI_lag2	*0.107****	*0.049****	*0.027****	*0.010***	*0.003*	*0.004*	*-0.001*	*-0.003*	*-0.011*	*-0.016*
	11.338	*8.094*	*5.946*	*2.440*	*0.846*	*0.938*	*-0.198*	*-0.617*	*-1.443*	*-0.530*
HI_lag3	*0.058*	*-0.031*	*-0.013*	*-0.004*	*-0.004*	*-0.003*	*-0.005*	*0.001*	*0.025*	*0.004*
	1.279	*-1.449*	*-1.010*	*-0.864*	*-0.903*	*-0.908*	*-1.346*	*0.071*	*1.538*	*0.102*
HI_Lag4	*-0.088**	*0.030*	*0.007*	*0.002*	*0.001*	*0.002*	*-0.001*	*-0.005*	*-0.021****	*-0.046****
	-1.860	*1.427*	*0.493*	*0.350*	*0.227*	*0.520*	*-0.257*	*-1.234*	*-4.098*	*-5.307*
GSVI_C	*-0.101****	*-0.067****	*-0.032****	*-0.022****	*-0.020****	*-0.022****	*-0.029****	*-0.033****	*-0.044****	*-0.087****
	-3.531	*-2.801*	*-3.405*	*-4.770*	*-5.616*	*-6.811*	*-8.524*	*-9.439*	*-9.620*	*-11.232*
GSVI_lag1	*0.043***	*0.000*	*-0.018****	*-0.016****	*-0.014****	*-0.008*	*0.000*	*0.002*	*0.004*	*0.014*
	2.430	*0.007*	*-3.160*	*-2.907*	*-2.639*	*-1.537*	*-0.077*	*0.377*	*0.473*	*1.006*
GSVI_lag2	*-0.046*	*-0.015*	*0.000*	*0.002*	*0.004*	*0.005*	*0.005*	*0.000*	*-0.005*	*-0.023*
	-1.400	*-1.377*	*-0.071*	*0.442*	*0.773*	*0.915*	*1.056*	*0.031*	*-0.847*	*-1.490*
GSVI_lag3	*-0.087**	*-0.004*	*-0.002*	*-0.003*	*-0.006*	*-0.012****	*-0.015****	*-0.010***	*-0.009*	*0.017*
	-1.864	*-0.375*	*-0.239*	*-0.587*	*-1.512*	*-3.021*	*-4.165*	*-2.377*	*-1.350*	*0.956*
GSVI_lag4	*-0.012*	*-0.036****	*-0.035****	*-0.024****	*-0.015****	*-0.013****	*-0.006*	*-0.007*	*-0.003*	*-0.005*
	-0.515	*-3.955*	*-6.102*	*-4.125*	*-2.729*	*-2.597*	*-1.217*	*-1.374*	*-0.483*	*-0.278*
Goodness-of-fit	*15.00%*	*8.77%*	*6.35%*	*4.08%*	*3.61%*	*3.35%*	*3.56%*	*4.24%*	*5.17%*	*7.30%*

Table 7. Quantile Regression of Returns on Total Deaths (TD: Headline Indicator) and GSVI

The table presents the results from the quantile regression framework [following Equation (5)] using Total Deaths (TD: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are mean-based [following Equations (1a) & (2a)]. We report the coefficients of headline indicator [HI: Total Deaths (TD)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisk *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237
HI_C	-0.269**	-0.011	0.003	0.004*	0.004**	0.002	0.001	0.002	-0.007	-0.014***
	-2.164	-0.888	0.887	1.924	2.189	1.073	0.423	0.454	-1.566	-3.866
HI_lag1	0.175*	0.024***	0.009**	0.004	0.001	0.003	0.002	0.002	0.015*	0.129***
	1.939	2.642	2.435	1.252	0.230	0.899	0.618	0.306	1.741	2.879
HI_lag2	0.023	-0.010	0.000	0.004	0.008**	0.008***	0.008***	0.013*	0.017**	-0.062
	0.197	-1.270	0.093	1.168	2.505	3.050	2.609	1.883	2.015	-1.378
HI_lag3	0.032	0.004	-0.009**	-0.010***	-0.013***	-0.013***	-0.013***	-0.016*	-0.021*	-0.016
	0.386	0.760	-2.392	-3.923	-5.751	-5.423	-4.434	-1.938	-1.718	-0.194
HI_Lag4	-0.012	-0.008	0.000	-0.001	0.001	0.003	0.006***	0.006**	0.005	0.012
	-0.351	-1.259	-0.013	-0.222	0.704	1.575	3.307	2.056	1.488	0.196
GSVI_C	-0.066***	-0.036***	-0.017***	-0.012***	-0.010***	-0.009***	-0.010***	-0.011***	-0.008***	-0.004**
	-4.176	-4.558	-4.443	-4.812	-5.294	-5.688	-5.757	-3.909	-3.562	-2.015
GSVI_lag1	0.052***	0.023***	0.005	0.002	0.003	0.003	0.004**	0.002	0.003	0.006
	4.010	2.812	1.128	0.681	1.348	1.543	2.232	1.176	1.281	0.989
GSVI_lag2	-0.014	-0.006	0.000	-0.001	-0.003	-0.003	-0.002	-0.001	-0.008***	-0.017***
	-0.960	-0.963	0.023	-0.336	-1.445	-1.403	-0.837	-0.236	-3.595	-4.430
GSVI_lag3	-0.027	-0.017**	-0.008**	-0.006**	-0.005**	-0.005**	-0.006***	-0.005*	-0.002	0.001
	-1.305	-2.418	-2.028	-2.231	-2.180	-2.196	-2.732	-1.857	-0.764	0.155
GSVI_lag4	0.009	0.003	0.002	0.004	0.005***	0.004**	0.004**	0.001	0.000	0.004
	0.443	0.456	0.718	1.583	2.672	2.559	2.332	0.394	0.115	0.652
Goodness-of-fit	11.97%	3.87%	2.50%	2.02%	1.83%	1.70%	1.61%	1.71%	2.06%	6.66%

Next, we employed the HI measure as the proxy of more reliable information obtained in a systematic manner (e.g., traditional news media, news vendors such as Bloomberg and Thomson Reuters). This information is expected to create uniformity of views and homogenous expectations about the future world view of the economy and financial markets (Andersen, 1996; Chae, 2005; Figlewski, 1978, 1981). Thus, it is expected to reduce volatility levels, and contribute to more stable prices and market recovery post sentiment engendered overreactions. This dynamics is in contrast to that of the GSVI measure, and it is captured in the form of a positive relationship between the HI measure and returns and a negative relationship between the lagged HI measure and conditional volatility measure.

Overall, the results from this study confirm the "noise trader" hypothesis of retail investors (Gemmill & Thomas, 2002). These results show that investors can safeguard their interests by investing their resources in acquiring information from reliable sources of news and not putting excessive faith in prevailing sentiments. These results also suggest that market regulators can improve the reliability of prices by taking measures that contribute to the informational efficiency of prices and making them less vulnerable to sentiment-driven shocks.

CONCLUSION

This study provides evidence on the impact of the global component of investor sentiment on the price return and volatility of 25 major futures indices globally. We find that this global component of investor sentiment – proxied with the GSVI measure – contributes to the falling prices and increase in conditional volatility levels. We also examine the impact of information from systematic and reliable sources, proxied with the HI measure. The impact of GSVI and HI measures on the price return and volatility is asymmetric. While the GSVI measure relates to falling prices and increasing volatility levels, the HI measure associates with positive returns and decreasing volatility levels. These results indicate that information from reliable sources corrects price overreactions, whereas the information from unreliable sources (e.g., unsystematic Google searches by individuals) causes price overreactions. Our findings are consistent with Jiao et al. (2020). Overall, our results support the overreaction hypothesis of investor behavior. The findings of this study have important implications for academics, practitioners, and market regulators. Market regulators and policymakers may like to disseminate appropriate information from reliable sources to alleviate the impact of crises on financial markets. Moreover, our results contribute to the behavioral finance literature, suggesting that investor sentiment may indeed be a priced factor, and may be employed to augment the conventional asset pricing models.

FUNDING ACKNOWLEDGMENT

The authors received no financial support for the research, authorship, and publication of this article.

CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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APPENDICES

APPENDIX A

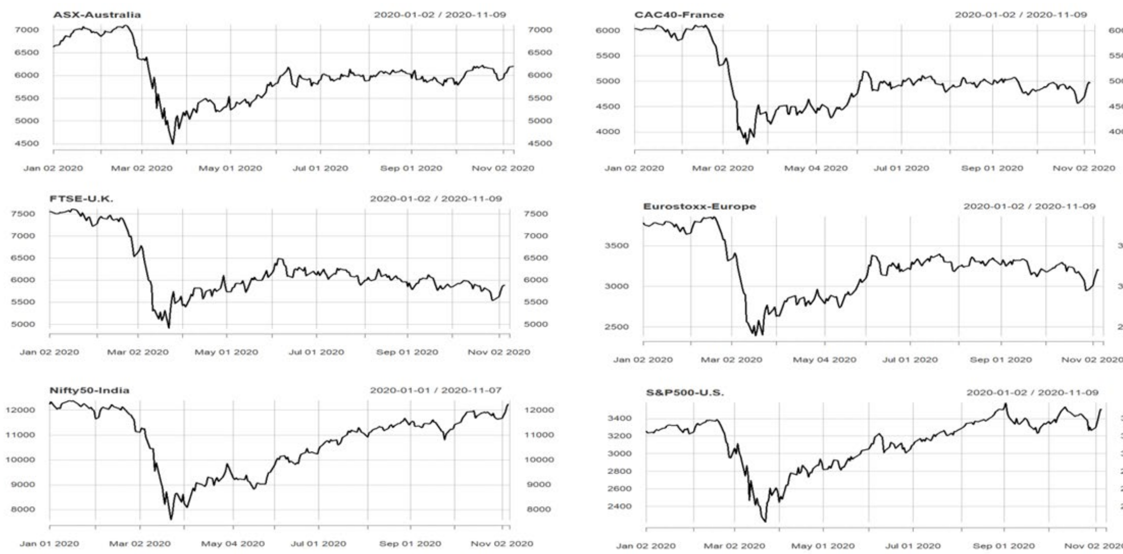

Figure A1. Price movement provided for six futures indices [S&P/ASX 200 Futures (Australia), CAC-40 Futures (France), EURO STOXX 50 Futures (Eurozone countries), FTSE 100 Futures (the U.K.), Nifty-50 Futures (India), S&P500 Futures (the U.S.)] in the sample set for the period Jan-October, 2020. Price movements for the remaining 19 indices are qualitatively similar, and can be provided upon reasonable request.

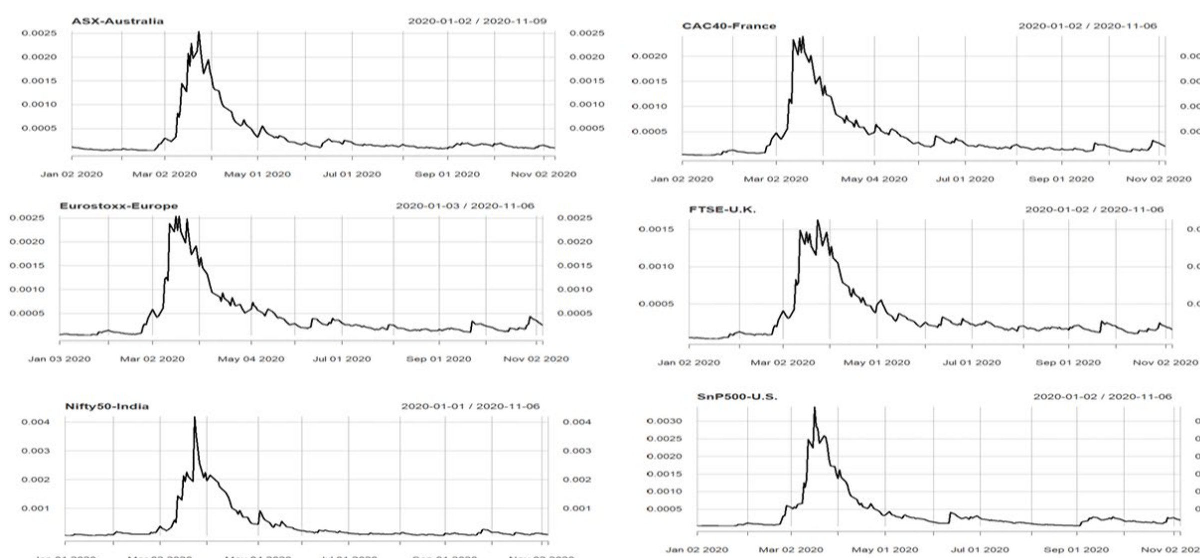

Figure A2. Conditional volatility (CV) is shown for the six futures indices [S&P/ASX 200 Futures (Australia), CAC-40 Futures (France), EURO STOXX 50 Futures (Eurozone countries), FTSE 100 Futures (the U.K.), Nifty-50 Futures (India), S&P500 Futures (the U.S.)] in the sample set for the period Jan-October, 2020. CV is obtained by modeling the returns using AR(4)/EGARCH(1,1) model. The behavior of conditional volatility for the remaining 19 indices is qualitatively similar, and can be provided upon reasonable request.

APPENDIX B

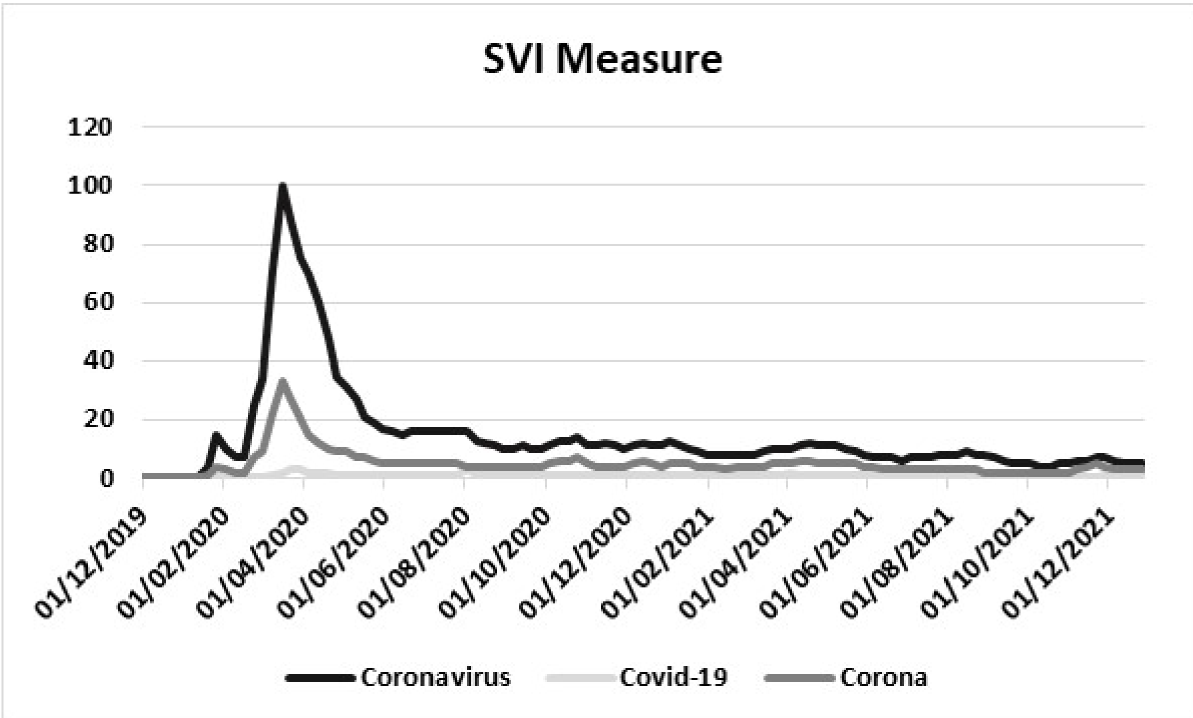

Figure B1. Movement of Search Volume Index (for the keywords: Coronavirus, Covid19, Corona) Over the Period Jan-Oct 2020.

APPENDIX C

Table C1. Pool Regressions of Returns on Headline Indicator (HI) and GSVI (median-based)

Panels A and B present the results from the pooling method [following Equations (3a) & (3b)]. The measures of GSVI and HI are median-based [following Equations (1b) & (2b)]. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	5,237	-0.002*	0.007***	0.010***	-0.010***	0.004***	-0.009***	0.001**	-0.003**	-0.003***	-0.003***	3.33%	191.367***
		-1.719	4.421	4.637	-7.173	3.814	-12.531	1.998	-2.395	-3.758	-5.342		
TD	5,237	0.000	0.007***	0.008***	-0.008***	0.001	-0.008***	0.001	-0.004***	-0.002***	-0.001*	3.16%	126.347***
		-0.181	3.897	3.242	-3.604	0.565	-9.148	1.121	-4.551	-2.852	-1.732		
Panel B: with controls Equation (3b)													
TC	5,237	-0.002	0.006***	0.012***	-0.009***	0.002*	-0.009***	0.001*	-0.002**	-0.003***	-0.003***	8.15%	344.513***
		-1.210	3.879	7.287	-7.765	1.728	-12.093	1.816	-2.117	-5.278	-4.423		
TD	5,237	0.000	0.007***	0.010***	-0.008***	0.000	-0.009***	0.001	-0.004***	-0.003***	-0.001	8.01%	353.841***
		-0.223	4.511	5.927	-4.367	-0.046	-9.152	1.257	-4.629	-3.807	-1.325		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C2. Pool Regressions of Returns on Headline Indicator (HI) and GSVI (return-based)

Panels A and B present the results from the pooling method [following Equations (3a) & (3b)]. The measures of GSVI and HI are return-based [following Equations (1c) & (2c)]. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	5,237	0.031***	-0.003	0.027***	-0.006***	-0.007**	-0.028***	0.001	-0.018***	-0.008***	-0.010***	5.01%	125.37***
		5.240	-0.842	8.993	-2.725	-2.194	-9.182	0.298	-8.122	-5.905	-7.721		
TD	5,237	0.012***	0.009***	0.026***	-0.010***	0.010***	-0.028***	-0.004	-0.022***	-0.009***	-0.008***	5.59%	178.881***
		3.816	6.784	17.889	-3.957	3.998	-9.065	-1.590	-9.944	-5.489	-4.379		
Panel B: with controls Equation (3b)													
TC	5,237	0.031***	0.000	0.024***	-0.002	-0.010***	-0.028***	-0.003	-0.015***	-0.009***	-0.010***	9.53%	414.341***
		5.162	-0.044	10.232	-0.995	-3.326	-9.472	-1.434	-8.169	-8.349	-7.191		
TD	5,237	0.016***	0.01***	0.026***	-0.006***	0.005**	-0.028***	-0.009***	-0.019***	-0.012***	-0.007***	10.15%	846.959***
		4.571	7.698	20.934	-3.148	2.363	-8.917	-3.887	-10.820	-8.724	-3.859		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C3. Panel Fixed-Effects Regressions of Returns on Headline Indicator (HI) and GSVI (median-based)

Panels A and B present the results from the panel fixed-effects method [following Equations (3a) & (3b)]. The measures of GSVI and HI are median-based [following Equations (1b) & (2b)]. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI measure [Keyword ("Coronavirus")], t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	*5,237*	*-0.003**	*0.007****	*0.010****	*-0.010****	*0.004****	*-0.009****	*0.001***	*-0.003***	*-0.003****	*-0.003****	*2.89%*	*194.646****
		-1.748	*4.442*	*4.657*	*-7.194*	*3.845*	*-12.507*	*2.001*	*-2.403*	*-3.750*	*-5.340*		
TD	*5,237*	*0.000*	*0.007****	*0.008****	*-0.008****	*0.001*	*-0.008****	*0.001*	*-0.004****	*-0.002****	*-0.001**	*2.72%*	*128.751****
		-0.220	*3.905*	*3.261*	*-3.593*	*0.612*	*-9.154*	*1.139*	*-4.558*	*-2.851*	*-1.767*		
Panel B: with controls Equation (3b)													
TC	*5,237*	*-0.002*	*0.006****	*0.012****	*-0.009****	*0.002**	*-0.010****	*0.001**	*-0.002***	*-0.003****	*-0.003****	*7.75%*	*383.699****
		-1.231	*3.911*	*7.332*	*-7.765*	*1.794*	*-12.080*	*1.802*	*-2.144*	*-5.270*	*-4.509*		
TD	*5,237*	*-0.001*	*0.007****	*0.010****	*-0.008****	*0.000*	*-0.009****	*0.001*	*-0.004****	*-0.003****	*-0.001*	*7.61%*	*408.207****
		-0.223	*4.511*	*5.927*	*-4.367*	*-0.046*	*-9.152*	*1.257*	*-4.629*	*-3.807*	*-1.414*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C4. Panel Fixed-Effects Regressions of Returns on Headline Indicator (HI) and GSVI (return-based)

Panels A and B present the results from the panel fixed-effects method [following Equations (3a) & (3b)]. The measures of GSVI and HI are return-based [following Equations (1c) & (2c)]. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI measure [Keyword ("Coronavirus")], t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: without controls Equation (3a)													
TC	*5,237*	*0.031****	*-0.003*	*0.027****	*-0.006****	*-0.007***	*-0.028****	*0.001*	*-0.018****	*-0.008****	*-0.010****	*4.58%*	*127.591****
		5.236	*-0.846*	*8.990*	*-2.666*	*-2.131*	*-9.183*	*0.298*	*-8.123*	*-5.915*	*-7.733*		
TD	*5,237*	*0.012****	*0.009****	*0.026****	*-0.010****	*0.010****	*-0.028****	*-0.004*	*-0.022****	*-0.009****	*-0.008****	*5.16%*	*182.036****
		3.804	*6.744*	*17.997*	*-3.934*	*4.076*	*-9.081*	*-1.571*	*-9.954*	*-5.551*	*-4.462*		
Panel B: with controls Equation (3b)													
TC	*5,237*	*0.031****	*0.000*	*0.025****	*-0.001*	*-0.010****	*-0.028****	*-0.003*	*-0.015****	*-0.009****	*-0.010****	*9.13%*	*419.372****
		5.155	*-0.032*	*10.229*	*-0.878*	*-3.243*	*-9.471*	*-1.459*	*-8.203*	*-8.366*	*-7.222*		
TD	*5,237*	*0.016****	*0.010****	*0.026****	*-0.006****	*0.005***	*-0.028****	*-0.009****	*-0.020****	*-0.012****	*-0.007****	*9.76%*	*834.637****
		4.571	*7.698*	*20.934*	*-3.148*	*2.363*	*-8.917*	*-3.887*	*-10.820*	*-8.724*	*-3.998*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C5. Regressions of Conditional Volatility on Headline Indicator (HI) and GSVI (median-based)

Panels A and B present the results from pool and panel fixed-effects methods [following Equation (4)]. The measures of GSVI and HI are median-based [following Equations (1b) & (2b)]. The conditional volatility is obtained using AR(4)-EGARCH (1,1) model on time-series of returns. The model is selected using information criteria (AIC/BIC/SIC). The results from other GARCH models (standard GARCH and GJR-GARCH) are qualitatively similar and not reported for brevity. We report the coefficients of headline indicator [HI: Total cases (TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: Pool Model													
TC	*5,237*	*0.030****	*-0.015*	*-0.027****	*0.003*	*0.006*	*0.015**	*0.017***	*0.001*	*0.012****	*0.000*	*0.77%*	*48.963****
		2.580	*-1.570*	*-3.985*	*0.380*	*0.780*	*1.690*	*2.201*	*0.204*	*3.296*	*-0.082*		
TD	*5,237*	*0.045****	*-0.022*	*-0.023****	*0.006*	*0.004*	*0.006*	*0.015*	*0.004*	*0.015****	*-0.003*	*0.80%*	*73.138****
		2.980	*-1.636*	*-2.704*	*0.658*	*0.471*	*0.588*	*1.546*	*1.002*	*3.026*	*-0.734*		
Panel B: Panel Fixed-Effects Model													
TC	*5,237*	*0.030****	*-0.015*	*-0.027****	*0.003*	*0.005*	*0.015**	*0.017***	*0.001*	*0.012****	*-0.001*	*0.30%*	*51.763****
		2.598	*-1.563*	*-3.975*	*0.319*	*0.677*	*1.689*	*2.186*	*0.231*	*3.276*	*-0.240*		
TD	*5,237*	*0.044****	*-0.021*	*-0.023****	*0.006*	*0.005*	*0.006*	*0.015*	*0.004*	*0.015****	*-0.004*	*0.33%*	*72.716****
		2.969	*-1.629*	*-2.792*	*0.634*	*0.532*	*0.615*	*1.525*	*1.001*	*3.007*	*-0.873*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C6. Regressions of Conditional Volatility on Headline Indicator (HI) and GSVI (return-based)

Panels A and B present the results from pool and panel fixed-effects methods [following Equation (4)]. The measures of GSVI and HI are return-based [following Equations (1c) & (2c)]. The conditional volatility is obtained using AR(4)-EGARCH (1,1) model on time-series of returns. The model is selected using information criteria (AIC/BIC/SIC). The results from other GARCH models (standard GARCH and GJR-GARCH) are qualitatively similar and not reported for brevity. We report the coefficients of headline indicator [HI: Total cases(TC)/Total deaths (TD)] and GSVI [Keyword ("Coronavirus")] measure, t-statistics (below), adjusted-R^2, and F-values. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Information criteria are employed for the selection of lags.

	N	HI_C	HI_lag1	HI_lag2	HI_lag3	HI_Lag4	GSVI_C	GSVI_lag1	GSVI_lag2	GSVI_lag3	GSVI_lag4	Adj. R^2	F-value
Panel A: Pool Model													
TC	*5237*	*0.062***	*0.010*	*-0.056****	*0.025****	*0.007*	*0.026*	*-0.024**	*0.090****	*0.064****	*0.019*	*1.12%*	*45.339****
		2.418	*0.994*	*-5.318*	*4.036*	*1.004*	*1.139*	*-1.739*	*4.201*	*3.874*	*1.349*		
TD	*5237*	*0.057***	*0.006*	*-0.071****	*0.022**	*-0.008*	*0.026*	*-0.019*	*0.097****	*0.056****	*0.008*	*1.12%*	*39.663****
		2.322	*0.442*	*-4.650*	*1.827*	*-0.653*	*1.125*	*-1.249*	*4.707*	*3.727*	*0.538*		
Panel B: Panel Fixed-Effects Model													
TC	*5237*	*0.019*	*0.046***	*-0.062****	*-0.035****	*0.068****	*0.041**	*-0.009*	*0.076****	*0.05****	*0.004*	*0.57%*	*36.474****
		0.552	*2.394*	*-4.645*	*-4.469*	*4.522*	*1.923*	*-0.799*	*4.982*	*4.053*	*0.299*		
TD	*5237*	*0.057***	*0.005*	*-0.072****	*0.023**	*-0.008*	*0.026*	*-0.019*	*0.097****	*0.055****	*0.005*	*0.66%*	*39.332****
		2.304	*0.398*	*-4.696*	*1.892*	*-0.585*	*1.146*	*-1.215*	*4.708*	*3.661*	*0.374*		

Note: (1) 'N' denotes the number of observations. (2) *, **, and *** denote statistical significance at 10%, 5%, and 1% levels. (3) The GSVI ("Coronavirus") is selected as it exhibits the highest interest over time. Results with other GSVIs ("Corona" and "Covid-19") are qualitatively similar and not reported for brevity.

Table C7. Quantile Regression of Returns on Total Cases (TC: headline indicator) and GSVI (median-based)

The table presents the results from the quantile regression framework [following Equation (3a)], using Total Cases (TC: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are median-based [following Equations (1b) & (2b)]. We report the coefficients of headline indicator [HI: Total Cases (TC)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisks *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237
HI_C	-0.099***	-0.004	0.001	0.001	0.001	0.000	-0.001	-0.003**	-0.006***	-0.009***
	-4.426	-1.077	0.407	0.781	0.664	-0.036	-0.871	-2.568	-4.416	-3.806
HI_lag1	0.067	0.020***	0.009**	0.006*	0.004	0.002	0.002	0.003	0.007**	0.098
	0.260	2.944	2.026	1.887	1.331	0.916	1.154	1.526	2.058	1.574
HI_lag1	0.022	0.002	0.006**	0.006**	0.007***	0.008***	0.008***	0.008***	0.005	-0.024
	0.085	0.322	2.180	2.434	3.215	3.526	3.397	2.958	0.692	-0.386
HI_lag3	-0.021**	-0.010*	-0.011***	-0.008***	-0.007***	-0.008***	-0.009***	-0.008***	-0.005	-0.024
	-1.997	-1.900	-3.879	-4.049	-3.924	-4.021	-3.849	-2.732	-0.914	-0.322
HI_Lag4	0.001	-0.003	-0.001	-0.002	-0.003*	0.000	0.004**	0.008***	0.009***	0.006
	0.034	-0.597	-0.277	-1.366	-1.828	0.088	1.967	3.944	2.899	0.096
GSVI_C	-0.03***	-0.018***	-0.011***	-0.01***	-0.008***	-0.007***	-0.005***	-0.004***	-0.003***	-0.004***
	-3.576	-6.566	-5.246	-5.787	-5.398	-4.628	-3.703	-2.972	-2.789	-3.418
GSVI_lag1	0.028*	0.009	0.001	0.000	0.000	0.001	0.000	0.000	-0.001	0.003*
	1.724	1.634	0.478	0.201	0.201	0.618	-0.006	0.021	-0.495	1.649
GSVI_lag2	-0.017	-0.002	0.002	0.003	0.001	-0.001	0.000	-0.001	-0.002	-0.009***
	-0.986	-0.367	1.056	1.576	0.421	-0.597	0.066	-0.912	-1.323	-4.352
GSVI_lag3	-0.027	-0.012***	-0.005**	-0.005***	-0.003**	-0.002**	-0.002**	-0.003**	-0.002**	0.001
	-0.723	-3.491	-2.066	-3.221	-2.389	-2.021	-2.176	-2.313	-2.244	0.566
GSVI_lag4	0.008	0.001	-0.001	0.001	0.001	0.001	0.000	-0.002*	-0.004***	-0.005**
	0.248	0.559	-1.006	0.740	1.209	0.734	-0.128	-1.933	-3.977	-2.244
Goodness-of-fit	7.25%	3.13%	2.08%	1.69%	1.45%	1.14%	1.01%	1.30%	1.60%	4.99%

Table C8. Quantile Regression of Returns on Total Deaths (TD: headline indicator) and GSVI (median-based)

The table presents the results from the quantile regression framework [following Equation (3a)] using Total Deaths (TD: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are median-based [following Equations (1b) & (2b)]. We report the coefficients of headline indicator [HI: Total Deaths (TD)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisks *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237
HI_C	-0.230***	-0.005	0.006**	0.005***	0.006***	0.003**	0.001	-0.003	-0.008**	-0.015***
	-3.402	-0.824	2.197	2.691	3.535	1.994	0.423	-1.069	-2.081	-3.371
HI_lag1	0.203***	0.018***	0.005	0.002	0.000	0.001	0.001	0.004	0.014*	0.131***
	3.100	2.907	1.453	1.050	-0.183	0.474	0.511	1.118	1.671	2.910
HI_lag1	-0.022	-0.001	0.003	0.005	0.005*	0.005**	0.008***	0.007***	0.004	-0.08*
	-0.349	-0.153	0.660	1.559	1.947	2.102	3.490	2.735	1.167	-1.953
HI_lag3	-0.032	-0.007	-0.005*	-0.006***	-0.007***	-0.007**	-0.006**	-0.003	-0.005	-0.019
	-1.044	-1.171	-1.913	-2.626	-3.064	-2.558	-2.093	-0.635	-0.737	-0.660
HI_Lag4	0.043	-0.002	-0.005**	-0.004**	-0.002	-0.001	0.001	0.001	0.003	0.025*
	1.510	-0.545	-2.154	-2.351	-0.949	-0.258	0.312	0.342	0.784	1.725
GSVI_C	-0.029***	-0.018***	-0.009***	-0.007***	-0.006***	-0.007***	-0.006***	-0.004***	-0.003**	-0.004***
	-3.442	-5.640	-4.101	-4.734	-4.664	-4.947	-3.910	-2.803	-2.451	-2.998
GSVI_lag1	0.025**	0.007	-0.002	-0.002	0.000	0.002	0.002	0.001	-0.001	0.003
	1.980	1.073	-0.391	-1.157	-0.102	1.029	1.056	0.309	-0.525	1.631
GSVI_lag2	-0.014	-0.001	0.002	0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.008***
	-1.080	-0.138	0.431	0.805	-0.463	-1.558	-1.336	-1.207	-1.491	-3.786
GSVI_lag3	-0.028***	-0.015***	-0.008**	-0.005**	-0.003**	-0.002	-0.002**	-0.003**	-0.003**	0.001
	-3.141	-4.180	-2.427	-2.344	-2.037	-1.445	-2.000	-2.356	-2.189	0.447
GSVI_lag4	0.014***	0.005*	0.002	0.002**	0.002**	0.001	0.000	-0.001	-0.004***	-0.004***
	4.095	1.867	1.215	2.401	2.361	1.353	0.295	-1.113	-3.801	-2.897
Goodness-of-fit	9.24%	2.86%	2.02%	1.59%	1.33%	1.13%	1.03%	1.20%	1.63%	6.33%

Table C9. Quantile Regression of Returns on Total Cases (TC: headline indicator) and GSVI (return-based)

The table presents the results from the quantile regression framework [following Equation (5)], using Total Cases (TC: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are return-based [following Equations (1c) & (2c)]. We report the coefficients of headline indicator [HI: Total Cases (TC)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisks *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237
HI_C	-0.099***	-0.004	0.001	0.001	0.001	0.000	-0.001	-0.003**	-0.006***	-0.009***
	-4.426	-1.077	0.407	0.781	0.664	-0.036	-0.871	-2.568	-4.416	-3.806
HI_lag1	0.067	0.020***	0.009**	0.006*	0.004	0.002	0.002	0.003	0.007**	0.098
	0.260	2.944	2.026	1.887	1.331	0.916	1.154	1.526	2.058	1.574
HI_lag1	0.022	0.002	0.006**	0.006**	0.007***	0.008***	0.008***	0.008***	0.005	-0.024
	0.085	0.322	2.180	2.434	3.215	3.526	3.397	2.958	0.692	-0.386
HI_lag3	-0.021**	-0.010*	-0.011***	-0.008***	-0.007***	-0.008***	-0.009***	-0.008***	-0.005	-0.024
	-1.997	-1.900	-3.879	-4.049	-3.924	-4.021	-3.849	-2.732	-0.914	-0.322
HI_Lag4	0.001	-0.003	-0.001	-0.002	-0.003*	0.000	0.004**	0.008***	0.009***	0.006
	0.034	-0.597	-0.277	-1.366	-1.828	0.088	1.967	3.944	2.899	0.096
GSVI_C	-0.030***	-0.018***	-0.011***	-0.01***	-0.008***	-0.007***	-0.005***	-0.004***	-0.003***	-0.004***
	-3.576	-6.566	-5.246	-5.787	-5.398	-4.628	-3.703	-2.972	-2.789	-3.418
GSVI_lag1	0.028*	0.009	0.001	0.000	0.000	0.001	0.000	0.000	-0.001	0.003*
	1.724	1.634	0.478	0.201	0.201	0.618	-0.006	0.021	-0.495	1.649
GSVI_lag2	-0.017	-0.002	0.002	0.003	0.001	-0.001	0.000	-0.001	-0.002	-0.009***
	-0.986	-0.367	1.056	1.576	0.421	-0.597	0.066	-0.912	-1.323	-4.352
GSVI_lag3	-0.027	-0.012***	-0.005**	-0.005***	-0.003**	-0.002**	-0.002**	-0.003**	-0.002**	0.001
	-0.723	-3.491	-2.066	-3.221	-2.389	-2.021	-2.176	-2.313	-2.244	0.566
GSVI_lag4	0.008	0.001	-0.001	0.001	0.001	0.001	0.000	-0.002*	-0.004***	-0.005**
	0.248	0.559	-1.006	0.740	1.209	0.734	-0.128	-1.933	-3.977	-2.244
Goodness-of-fit	7.25%	3.13%	2.08%	1.69%	1.45%	1.14%	1.01%	1.30%	1.60%	4.99%

Table C10. Quantile Regression of Returns on Total Deaths (TD: headline indicator) and GSVI (return-based)

The table presents the results from the quantile regression framework [following Equation (5)] using Total Deaths (TD: headline indicator) and GSVI measure [Keyword ("Coronavirus")], across the conditional quantiles of the return distribution. The measures of GSVI and HI are return-based [following Equations (1c) & (2c)]. We report the coefficients of headline indicator [HI: Total Deaths (TD)] and GSVI measure, corresponding t-statistics (below), and Goodness-of-fit measure for the regression. The coefficients are reported for the contemporaneous (C), and four lag (lag1, lag2, lag3, and lag4) terms. Asterisks *, **, and *** indicate the significance of the relevant test-statistic at 10%, 5%, and 1% levels, respectively. For the implementation of the method, the 'Quantreg R package' developed by Koenker (Koenker, 2012; Koenker et al., 2018) is employed. The goodness-of-fit (GoF) measure in the quantile regression framework is provided in the 'WRTDStidal' package in R. The function follows conventional R^2 measure. It is computed as one minus the ratio between the appropriately weighted sum of absolute errors (deviations) from the conditional model and that from the unconditional model (Koenker & Machado, 1999).

Quantiles	t=0.05	t=0.15	t=0.25	t=0.35	t=0.45	t=0.55	t=0.65	t=0.75	t=0.85	t=0.95
N	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237	5,237
HI_C	-0.272*	0.007	0.010***	0.009***	0.008***	0.010**	0.017***	0.024***	0.028***	0.063*
	-1.837	0.754	4.284	3.807	2.900	2.323	2.723	3.701	3.901	1.758
HI_lag1	0.029***	0.018***	0.012***	0.008***	0.003	0.000	-0.002	0.000	0.005	0.081
	4.112	3.958	4.049	2.932	1.197	-0.106	-0.744	0.131	0.888	1.025
HI_lag1	0.031***	0.018***	0.015***	0.013***	0.014***	0.017***	0.018***	0.025***	0.034***	-0.01
	5.132	2.605	5.259	4.539	5.641	5.473	3.890	4.276	5.194	-1.251
HI_lag3	-0.079	-0.005	-0.009	-0.008**	-0.006**	-0.009***	-0.009***	-0.009***	-0.011***	0.038
	-0.107	-0.065	-1.267	-1.991	-1.991	-3.196	-3.511	-3.413	-3.743	0.918
HI_Lag4	0.092	0.003	-0.001	0.000	-0.001	0.008**	0.006*	0.002	0.004	0.006
	0.130	0.035	-0.126	0.041	-0.167	2.225	1.791	0.641	0.878	0.390
GSVI_C	-0.068***	-0.044***	-0.022***	-0.015***	-0.014***	-0.017***	-0.02***	-0.023***	-0.028***	-0.049***
	-3.614	-3.793	-4.169	-5.442	-6.159	-7.769	-7.548	-8.025	-8.441	-2.927
GSVI_lag1	-0.013	-0.015*	-0.004	-0.005*	-0.003	-0.001	-0.004	-0.009***	-0.012***	-0.009
	-0.536	-1.846	-1.215	-1.938	-1.335	-0.274	-1.108	-2.785	-3.416	-0.895
GSVI_lag2	-0.037	-0.019***	-0.012***	-0.01***	-0.010***	-0.010***	-0.008**	-0.011***	-0.019***	-0.041***
	-1.471	-3.572	-4.438	-4.481	-4.528	-3.915	-2.301	-2.746	-3.859	-3.932
GSVI_lag3	-0.007	-0.018**	-0.008	-0.009**	-0.008***	-0.009***	-0.009***	-0.009***	-0.011***	0.001
	-0.215	-1.986	-1.457	-2.069	-3.228	-3.596	-3.133	-3.212	-3.389	0.155
GSVI_lag4	-0.022	-0.006	-0.003	-0.003	-0.002	-0.004	-0.004	-0.005	-0.006*	-0.010
	-1.625	-0.808	-0.849	-0.936	-0.857	-1.386	-1.431	-1.537	-1.862	-0.834
Goodness-of-fit	9.86%	2.84%	2.16%	1.87%	1.86%	1.98%	2.17%	2.81%	3.66%	8.00%