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Impact of Covid-19 cases on Global Stock Market

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Abstract: The current research tries to analyze the impact of the Covid-19 event and related deaths on the GLOBAL equity market (Dow Jones and the S&P500 indices), which compensate for trading volume and predictions of volatility, as well as the results on the weekday. Based on the GARCH(1) model and data from 8 April 2019 to 9 April 2020, the findings indicate that most affected countries with covid-19 crisis did not affect the stock market income. Nonetheless, the conditional heteroscedasticity of the Dow Jones and S&P500 returns in certain countries is having a positive effect. VAR models say that in Italy and France the number of deaths registered has a positive effect on the VIX returns. Finally, Markov-Stitching models show that the scale of VIX's negative effect on stock market prices increased threefold by the end of February 2020.

Keywords: Covid-19 Cases, Global Stock Market, Financial volatility

INTRODUCTION

How do Covid-19 related cases and deaths affect the GLOBAL stock market?

The study investigates on how Covid 19 cases and deaths have affected global stock markets using a GARCH(1,1) model. This is a time series data statistical model, that defines the variance of the present error term or novelty as a function of the real sizes of the error terms of the previous time frame. The model explains the effect of changes in recorded cases and deaths due to COVID-19 and mean in both conditional heteroscedastic tacitly (in logs). It identifies nonconstant volatility when future periods of high and low volatility cannot be identified. The results suggest that, while there seems to be little evidence of an impact on the returns on the Dow Jones and S&P500 indices, conditional heteroscedasticity tends to be affected, especially by deaths and cases in Italy and Spain. Further tests with VAR and Markov-Switching models are also provided to support the findings.

There is little but quickly growing literature on the impact of Covid-19 on the stock market (e.g., Gormsen & Koijen (2020), Yilmazkuday (2020), and Baker et al. (2020)). Yilmazkuday (2020) studies the impact of the number of deaths related to Covid-19 on the S&P500. Baker et al. (2020) quantifies the impact of news related to Covid-19 on stock market volatility using textual analysis and report that Covid-19 has had a much larger impact on stock market volatility than other similar diseases, such as Ebola. However, this is the first paper that estimates the impact of daily reported Covid-19 cases and deaths on both the conditional mean and the conditional volatility of the returns of the Dow Jones index. The results reported are based on data up to 9th April 2020, and considers the impact of reported cases and deaths in the US, as well as in China, France, Iran, Italy, Spain, and the UK. In additional tests, we also examine whether the Covid-19 crisis has caused a change in the relationship between volatility expectations and stock market returns. The research question addressed in this paper is of paramount importance to investors and policy makers alike. A recent article in the Wall Street Journal points out that a drop in the Dow Jones Industrial Average on 16th March 2020, “the second-worst day in its 124-year history was over 12 percent. But the remarkable volatility is not fully explained by the reasons.” Typically, high-volatility periods are associated with economic and political instability. In March 2020, the US government implemented a series of measures aiming at calming down the market. Gormsen & Koijen (2020) argue that economic relief programs released on 13th March did not improve expectations about short-term growth, and neither did a fiscal stimulus package announced on 24th March, 2020.

Implied Volatility and VIX

The nature of stock return is associated with the underlying market asset established performance indices around the world. While there is substantial research on these subjects for US capital markets, the literature on these subjects is fairly scarce for foreign stocks and other asset groups. By analyzing implied volatility values on foreign share index, individual securities, has broadened the current return-volatility relation and the knowledge quality of implied volatility over ex-post measurements of actual volatility. In 1993, the Chicago Board Options Exchange (CBOE) launched the initial CBOE Volatility Index (VIX) based on pioneering research by Whaley (1993). Before that year, Gastineau (1977) had actually introduced the volatility index as an empirical term.

The VIX index soon became an indicator for U.S. instability in the stock sector. Currently, we have 68 implied volatility indices that include both stocks and a large asset class base. For a fact, derivative sector liquidity is improved by volatility indices because uncertainty is an integral component of increasing derivative quality. Volatility Index often strengthens control practice; for this an implied Value-at- Risk (VAR) estimation index may be used as an input variable (Slime et al,2019). Finally, volatility index may be seen as a tool in derivatives. The growing amount of related literature indicates the popularity of implied volatility indices (primarily VIX) in quantitative studies. A thorough overview of the primary uses on financial literature in the VIX Index was given by Gonzalez-Perez in 2015. In brief, quantitative work has concentrated on perceived volatility by analyzing mathematically the properties of the volatility indices (Alexander et al, 2015). In other experiments, volatility is implied. Further researches analyze specifically the volatility knowledge, quality of potential volatility experienced and its capacity to forecast in future; the predictive volatility literature is examined extensively by these researchers (Figlewski,1993), (Poon et al,2003), (Gonzalez-Perez 2015) and brought out a report. The relation of volatility indices and actual stock returns has been examined in various research areas (Fleming et al . 1995; Low, 2004; Giot, 2005; Hibbertet al . 2008; Whaley, 1999). Ultimately, the studies on the transition of inferred volatility through foreign markets and various asset groups give an overall statistical graph of stock markets (Siriopoulos et al, 2013);(Kenourgios 2014); (Maghyereh et al, 2016); (Bouri et al , 2019); (Ji et al , 2018). This is the most detailed attempt in literature, as per records, 68 implied volatility indices are available in public worldwide with 25 indices suggested in an academic sense, based on established studies (Alexander et al, 2015; Datta et al, 2017; Velev et al, 2018) which include a review of the publicly accessible volatility.

This paper encourages an interest in different world indices and asset classes with a broader understanding of the confidence indices available. The study adds in two respects to the current literature: firstly it studies earlier tests on two well-known subjects; the relationship between the return to volatility and the quality of volatility predictions with respect to the forward volatility.

Given, extensive research on these subjects, the current literature still includes without addressing few key points. In fact, VIX, S&P500 index and stock prices are the main subject in this analytical report. Within this analysis, all the involved volatility indices widely accessible from 20 developed and developing stock markets are analyzed. Therefore, through examining non-equity tools, we expand the reach of previous research. A broad dataset allows one to analyze asymmetric relationship between return and volatility and volatility of information quality across diverse markets. Although VIX is commonly known as a "fear gage" for large-scale investors (Whaley, 2000), other volatility indices cannot automatically be assumed to be used as indicators of investor sentiment and market uncertainty. So our analysis strengthens the established details and demonstrates the position of the implicit volatility indices that are currently accessible. Furthermore, the Quantile Regression approach(Quantile regression is an extension of linear regression that is used when the conditions of linear regression are not met (i.e., linearity, homoscedasticity, independence, or normality), more acceptable though often sporadically utilized, is a more reliable way for the analysis of the risk- return relationship though it needs distributional assumptions as it is optimal for distorted distributions, and as implied adjustments in volatility and returns are expected (Badshah et al, 2018). Furthermore, the study offers analytical data on the efficacy of the markets for ETF options by examining and contrasting the effects of four commodities (S&P 500, Gold, Gas, and EUR USD) via two volatility indices (one focused on ETF options and the other on futures on potential stocks). The remaining part of the paper is structured as follows: the next section is to analyze the methods of the estimation for the implied volatility indices and provides a detailed taxonomy with regard to it around the world. The fourth part explores the connection between Volatility Indices and the underlying asset returns, and the fifth part explores the association between implied Volatility Indices and achieved volatility. Finally, a detailed summary of our analytical findings, comparison of Global VIX, INDIA VIX, VXAPL (Apple), VXAZN (Amazon), VXGS (Goldman Sachs), VXGOG (Google) and VXIBM (IBM),NIFTY, SENSEX. Section 7 offers the final conclusion.

U.S Stock Market Scenario during COVID-19

Investors face a dilemma in their reading of capital markets. Should they be guided by the rising cases of coronavirus in the U.S. and minimize risk, or do they take on risk in the expectation that the Federal Reserve will be there to support markets once more. The resultant uncertainty can be seen in the VIX, which measures investor’s expectations for volatility on the S&P 500 index. The so-called Fear Index remains at historically elevated levels even after falling significantly from the record highs it reached at the beginning of the pandemic's arrival on U.S. shores in March.

The VIX reached a record 82.69 on March 16 but was back down to 33.29 by April 27 as the combined forces of the U.S (CBOE, 2020). Treasury and Federal Reserve committed trillions of dollars to support the economy. That support has continued to ease other key measurements of risk in financial markets, yet the VIX has remained stubbornly high. It was 33.84 at the close of June 24, it remains more than double the 16.6 average from the first two months of the year." Though equity volatility will further normalize with a better macro context, it is likely to stay elevated in the coming months relative to long-term history," Goldman Sachs strategists led by Christian Mueller-Glissmann wrote in a research report. The number of coronavirus cases rose by over 36,000 on June 23 causing the S&P 500 to drop 2.6% on June 24, and with the June 24 infection rate rising by a further 38,386 — the second-highest daily increase — more turbulence seems likely. Still, the benchmark U.S. equity index has rallied more than 36% since touching this year's low on March 23 and is less than 10% below the record high it reached on Feb. 19 (CBOE,2020).

"Over the past three months, markets have struggled to reconcile the sharpest ever quarter-over-quarter decline in the economic activity with the announcement of the largest economic stimulus packages in history," wrote Frederique Carrier, head of investment strategy at RBC Wealth Management. "The result has been high volatility, and we believe this will likely continue."

High quality credit spreads have been relatively unaffected by the recent increase in U.S. coronavirus cases, aided by the Federal Reserve's June 15 announcement that it would go ahead with purchases of corporate bonds. The spreads on investment grade U.S. corporate bonds barely moved, decreasing from 158 basis points(bps) to 156 basis points between June 16 and June 23(Federal Reserve Bank St. Louis,2020). Similarly the spread on emerging market corporate bonds ticked down from 409 bps to 404 bps by June 23(Federal Reserve Bank St. Louis,2020). In the words of Polina Kurdyavko, head of emerging markets at BlueBay Asset Management "While the growth slowdown has been sharp, defaults and debt restructurings shouldn't indiscriminately wash across the emerging-market landscape". However, heightened investor nervousness is revealing itself in the high yield market.

Having fallen back to 578 bps by June 16, the spread was up to 602 bps at the close of June 23. It was the second such spike in June after the spread widened from 550 bps on June 5 to 640 bps on June 11 (Federal Reserve Bank St. Louis, 2020).

Money markets have stayed calm during the pandemic period. (The Libor-OIS spread, 2020) — a primary U.S. banking sector risk tracker that calculates the gap between the three- month dollar London Interbank offered rate, the average cost of funding from each other for banks, and the overnight indexed swap rate — continued to contract, falling from 23.2 on June 18 to 21.3 on June 25. The leveraged loan market also continued to grind lower, with the percentage of the S&P Global-rated U.S. loan index priced below 80 — a closely watched indicator of stress — falling slightly from 9.2% on June 16 to 8.1% on June 23.

Index Volatility Calculation

The calculation of an index volatility is typically in two ways: the first is based on Black Sholes' expected volatility, and the second approach uses a formula from Orlando and Taglialatela(2016). The approximate prices for the underlying product derived from the field are both closely related in their methodologies. Nevertheless, the normal implied volatility of Black & Scholes represents actual (monetary strike) demand (powerful) future variability, whereas the variance swaps are representative of business size variance industry forecasts. The key precondition of the variance-driven calculations is that there are fully liquid choices (from zero to infinity) for each exercise size. The calculation does not require less cash out-of- the-money accumulation to ensure that the measured volatility indicator is correct. Thus, the approach utilized by Whaley (1993) focused on volatility-dependent market option formulation employed from the VIX, it is a model-free technique centered on the reasonable value of a swap of variance is somewhat different, but it typically fits CBOE's two requirements. In Whaley (1993, 2000) and Fleming et al,(1995) the initial VIX technique is further established. On 22nd September 2003, the CBOE introduced a new VIX focused on the concept of reasonable value of uncertainty to calculate Hang Seng's Volatility Index (VHSI) that chooses options with strike prices ranging between 80 & 120 percent across the monetary strike point. The current VIX is calculated directly from market observables (e.g. call and spot price and interest rate). A description of the latest VIX approach is given in the Chicago Options Exchange article. The element behind the S&P100 has shifted to an S&P500. Provided that the metric is based on unsafety, the square root of variance of VIX is sometimes referred to as the tacit uncertainty of such choices. Throughout 2014, the VIX index was improved by the CBOE by introducing SPX Weekly number, which is more reliable in the expected 30-day fixed index era. The study evaluate all implied volatility indices by asset class and are publicly accessible on the following sections.

Volatility Indices in Companies

CBOE frequently measures and disseminates volatility indices extracted from the holdings of existing securities and share, ETF options in comparison with the key S&P 500, DJIA, Nasdaq 100, and Russell 2000 market volatility indices. The Equity VIX indices of five US companies are determined on the basis of option values for VXGS (Goldman Sachs), VXGOG (Google), VXAPL (Apple), VXAZN (Amazon) and VXIBM (IBM). In addition, CBOE distributes four regional equity-related indices and two sector-specific volatility indices, both focused on CBOE market option rates of ETFs. A Sydney-based consultative and trading firm Tryple has developed in conjunction with the MIAX opt Market. The VIX share index, which calculates all share indices using the conventional method VIX, but the S&P 500 ETF (SPY) is not calculated by CBOE. The other one is the VIX share index. SPIKE monitors the forecasted value of SPDR S&P 500 ETF (SPY), the world's largest trading mutual fund, over a 30-day span. The index is determined using the popular technique CBOE of the variance swap, which also uses a patented "risk dragging" approach (which does not raise the referred risk of options except because of the adjustments in mid-rate) to catch prices of live options, which is expected to trigger volatile fluctuations in the index. It has been the first tacit volatility measure centered on the market commodity listed. In January 2001, the QQV Index was adopted and the implied volatility resulting from the options Black and Scholes QQQ formula was measured; with the initial CBOE VIX approach, American Exchange implemented similar methods. In June 2014, the QQV Index was discontinued. Figures 1, 2 and 3 shows that the Covid-19 has increased volatility expectations, which is captured by the CBOE volatility index (VIX), often referred to as the "fear index" and caused a major drop in the S&P500 and the Dow Jones. The peak for VIX was on 27 March 2020, when it reached a value of 65.54, only to descend quickly to 41.67 on 9 April 2020, the lowest value since 6 March 2020. These results suggest that the stimulus package announced on 24 March 2020 might have decreased volatility expectations.

The main findings indicate changes in cases and deaths associated with Covid-19 have had an impact on the volatility of the Dow Jones and S&P500, even when they have occurred in countries other than the US. However, there is little evidence that they have had an impact on the stock returns themselves, once changes in conditional volatility are considered. Moreover, the research provides evidence of a regime switch (from a low to a high volatility regime) in the final week of February 2020, between the expectations of volatility and financial aid returns.

METHODOLOGY AND DATA

Data on the number of Covid-19 reported cases and deaths at the daily level is collected from the website https://ourworldindata.org/. Data on the VIX, the S&P500 and the Dow Jones index (prices and volume) is collected from Yahoo! Finance. The data covers the period from 8 April 2019 to 9 April 2020. In the analysis, countries considered are as of 31 March 2020 having had at least 1,000 Covid-19 reported deaths. These countries are: Italy (11591), Spain (7340), China (3309), the US (3170), France (3024), Iran (2757), and the UK (1408).

A GARCH(1,1) model is employed with robust standard errors (Generalized Autoregressive Conditional Heteroskedasticity (GARCH) is a statistical model used to estimate the volatility of stock returns), using the following specification conditional, mean equation (eq. 1) and variance equation (eq. 2):

Eq (1) $y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 VIX_t + \alpha_3 Volume_t + \sum \beta_i D_i + s_t$

Eq(2) $\sigma^2_t = \exp(\lambda_0 + \lambda_1 X_t) + \gamma_0 s_{t-1} + \gamma_1 \sigma^2_{t-1}$

where yt and Volume t are the first-difference of the price and trading volume (in logs) of the Dow Jones or S&P500 at time t, respectively, st are the innovations, σ^2 is the conditional variance, and Di are day-of-the week dummies. The variables related to Covid-19 reported cases and deaths are represented by Xt, which is equal to the first-difference in ln(1 + xt), where ln represents the natural logarithm function and xt is either the cumulative (i.e., since records began) reported number of cases (Total cases) or the ^{t}cumulative reported number of deaths (Total deaths) at time t. Importantly, the impact of Covid-19 cases and deaths is estimated by extending the common GARCH(1,1) model with a multiplicative heteroscedasticity component (Harvey (1976), Judge et al. (1985)).

RESULTS

The results for the GARCH(1,1) model for cases and deaths in the US are reported in Table 1. Panel A reports the results for the Dow Jones index, and Panel B for the S&P500 index. In both panels, the results for Total cases (Ln) and Total deaths (Ln) in the conditional mean equation suggest that neither variable affects stock market returns. However, the latter has a positive impact on multiplicative heteroscedasticity (as reported in the column named "HET") in equation of conditional variance. On the other hand, for both the conditional mean and the conditional variance equation, the coefficients on Total cases (Ln), Total cases, and Total deaths are insignificant. Results on the control variables indicate that there is a negative association between stock market returns and perceptions of uncertainty, consistent with previous literature on the VIX-US stock-market return relationship (Mollick & Assefa, 2013, Fernandes et al., 2014).

Trading volume is positively correlated with stock returns for the Dow Jones index (but not for the S&P500), which is consistent with previous literature on a contemporary correlation between stock returns and trade volumes using GARCH models (Lee & Rui (2002)).

Table 2 summarizes the Dow Jones findings, taking into account cases and deaths registered in China (Panel A) and Italy (Panel B). The results show that the total number of cases reported in China (in logs) has a negative impact on the returns on the US stock market, but is not correlated with this Heteroscedasticity conditional. Total deaths (Ln) coefficients are negligible in any of the conditional mean, or conditional equation of variance. In Italy, on the other hand, in the conditional mean equation, the coefficients on overall deaths and cases are negligible, but in the conditional variance equation they are considerably positive. Total cases (Ln), total deaths (Ln), and cumulative cases have a positive effect on the equation of conditional variance, but not on the equation of conditional mean. For either the conditional mean or the conditional variance equation the coefficients on Total deaths are negligible.

Table 3 shows the results of Covid-19 cases and deaths in Spain (Panel A) and the Britain (Panel B). As with Table 2, the study reports only the Dow Jones results. The coefficients in the conditional variance equation on Total Cases (Ln) and Total Deaths (Ln) imply that both variables increase volatility in the US stock market. The number of cases reported in Spain has a more pronounced impact on the volatility of Dow Jones than in the UK. On the other hand, the total death toll in the UK has a stronger impact on the volatility of Dow Jones than the number of deaths in Spain. Total cases (Ln) also have a statistically important effect on Dow Jones, for Spain.

The results reported in Table 4 deal with the impact of COVID -19 cases and deaths in Iran (Panel A) and France (Panel B) on the Dow Jones. They suggest that Iran's total number of cases and deaths have a positive impact on the volatility of the Dow Jones, but do not affect its returns. In France total deaths (Ln) have a statistically significant impact on the Dow Jones volatility. The Total Deaths (Ln) coefficient in the conditional variance equation is currently the largest of the seven countries considered.

Extensions

VAR models

In this section, a VAR-X model is employed (VAR models with exogenous covariates) to examine the impact of reported cases and deaths (exogenous variables) on stock market returns, trading volume, and the VIX returns (endogenous variables). Vector autoregression (VAR) is a stochastic process model used to capture the linear interdependencies among multiple time series. A VAR model describes the evolution of a set of k variables (called endogenous variables) over the same sample period ($t = 1, ..., T$) as a linear function of only their past values. The variables are collected in a k -vector (($k \times 1$)-matrix) y^t , which has the i^{th} element, yi^t , the observation at time t of the i^{th} variable. For example, if the i^{th} variable is GDP, then yi^t is the value of GDP at time t. For the sake of brevity, this study only reports the coefficients on the variables related to reported cases and deaths, and do not report the results for the endogenous variables.

The results reported in Table 5 depict a slightly different picture from those for the GARCH(1,1) models. For the US, Total cases (Ln) enters the equation for stock market returns with a negative and statistically significant coefficient and it also has a positive and statistically significant coefficient in the equation for the VIX returns, consistent with the view that Covid-19 has increased volatility expectations. However, the results for Total cases (Ln) are counter-intuitive: they tend to increase the return on the Dow Jones index, and they decrease the VIX. Even Total cases (Ln) in Iran increases the returns on the Dow Jones (but deaths decrease it). The results Total deaths (Ln) for Italy, Iran, and France suggest a negative impact on the returns of the Dow Jones returns, and for Iran there is also a positive impact on the VIX. The results for Total cases (Ln) suggest a negative impact on the Dow Jones returns for the UK, and a positive impact on the VIX for cases in Italy and the UK. Total deaths (Ln) in the US and the UK reduce the trading volume for the S&P500. To understand whether the counter-intuitive results reported in Table 5 are due to the consideration of reported cases and deaths in the same equation, the study examine separately for reported cases and deaths. The results, reported in the Appendix (Table A2), suggest that the coefficients for the reported deaths in the US have the same sign as in Table 5, and the magnitude of the coefficients found in these results increases. The results for the other countries remain similar, in most cases. In particular, Total deaths (Ln) in Italy and France have a negative impact on the Dow Jones returns, and a positive impact on the VIX returns.

The significant relationship between Covid-19 cases and deaths and the US stock market returns using VAR models, along with some counter-intuitive results, suggest that neglecting changes in conditional heteroscedasticity might lead to wrong inferences on the channel through which Covid-19 cases affect the stock market.

Structural breaks and Markov-Switching models

Has Covid-19 caused a structural break in the relationship between the stock market returns and volatility expectations?

The study tries to address this question. First of all, a Supremum Wald test for an OLS regression is run, where the dependent variable is the log returns on the Dow Jones and the S&P500, and the independent variable is the returns on the VIX. The results suggest a structural break in the relationship between stock market returns and the VIX returns occurred on 28 February 2020. Then, a Markov-Switching model with two states is run. The study considers the following simple specification:

Eq (3) $y_t = \mu_s + \varphi_s VIX_t + v_s$

Where $s \in (1,2)$. The results reported in Table Appendix - A3 suggest that in the high-volatility state (state 1), the coefficient on VIX is -0.28 for the Dow Jones equation and -0.27 for the S&P500. In the low volatility state (state 2), the coefficient decreases, in magnitude, to around -0.09 for both indices. The values for p11 and p21 suggest that both states are highly persistent. Figures 4 and 5 graphs the probability of state 1 and state 2 over time for the Dow Jones (the one for S&P500 is virtually the same). Somewhat consistent with the results of the

Supremum Wald test, the switch in states occurs around the 26 of February 2020. The result for a specification considering even the first lag of VIX log returns is reported in the Online Appendix, Table A3. The results are virtually the same as those reported in Table Appendix - A3, although the first lag of the VIX returns is insignificant in the high-volatility state.

What could be the cause of these results? Several news during that week could have generated such a phenomenon, but two of them stand out. First of all, on Sunday 23 February, the World Health Organization (WHO) announced the highest level of alert related to Covid-19(Economic Times). Moreover, on 24 February 2020, the Trump administration asked for $1.25 billion from Congress to respond to the Covid-19 crisis(Economic Times).

CONCLUSIONS

This paper is an attempt to investigate the impact and volatility of Covid-19 on the Global returns (including the indices Dow Jones and S&P500). Based on data of 9 April 2020 and GARCH(1,1) models, the results show that, apart from the number of cases reported in logs, there is no impact on the US stock market returns due to the COVID 19 changes in the number of cases and deaths in the US and other countries mostly affected by the Covid 19 crisis over the first three months of 2020 (China, Italy, Spain, UK, Iran and France). Nonetheless, Dow Jones and S&P 's conditional heteroscedasticity is seen to have a significant effect. VAR forecasts show a detrimental effect on the returns for Dow Jones and a favorable influence on VIX in Italy and France. VIX INDIA has not impacted too much and the value is 24.7275 approximately. A comparitive analysis states that VXAZN, is approximately, 45.27 being high among other companies during this Pandemic situation. Finally, the Markov-Switching analysis shows that the scale of the detrimental impact of VIX on stock returns rose by three times by the end of February. Future research opportunities: - The current research tried to analyze impact of COVID 19 deaths on stock market volatility. Future studies can be done with the same research problem in different settings, context, or location.

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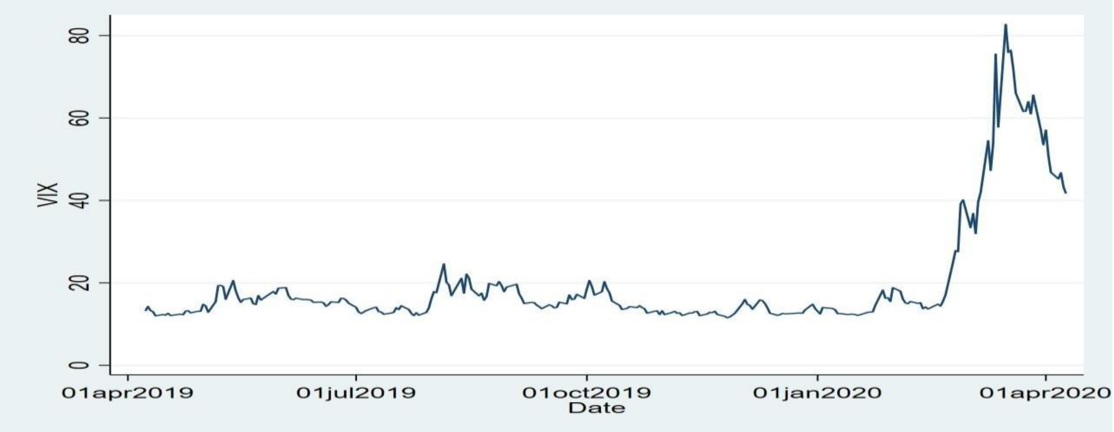


Fig.1: VIX values from 8 April 2019 to 9 April 2020

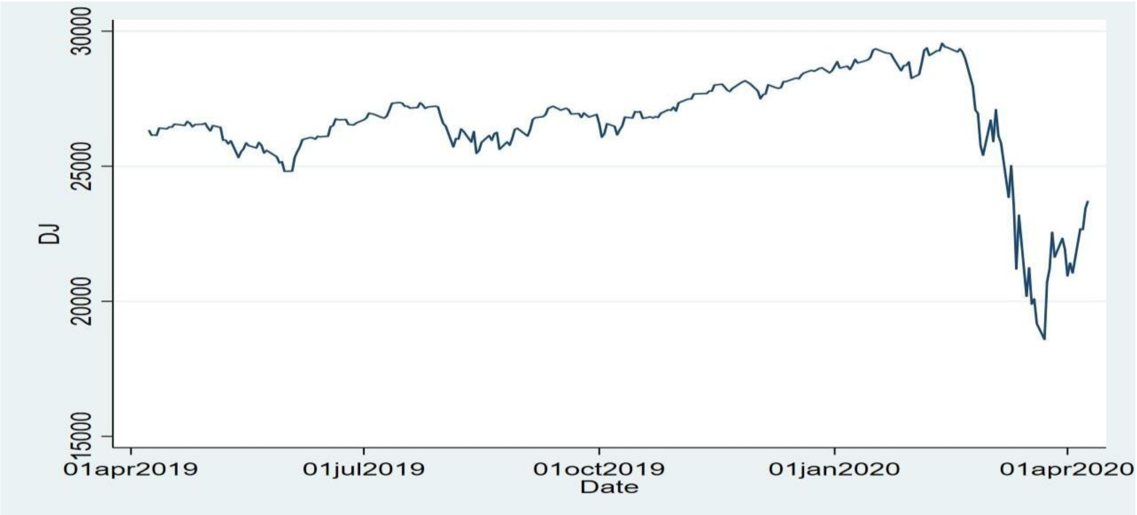


Fig.2: S&P500 values from 8 April 2019 to 9 April 2020

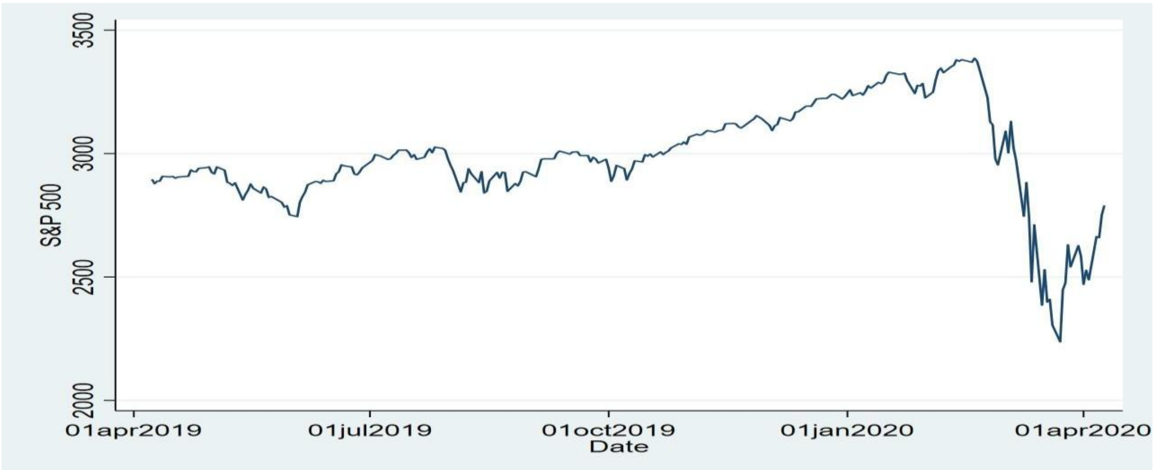


Fig.3: Dow Jones index values from 8 April 2019 to 9 April 2020

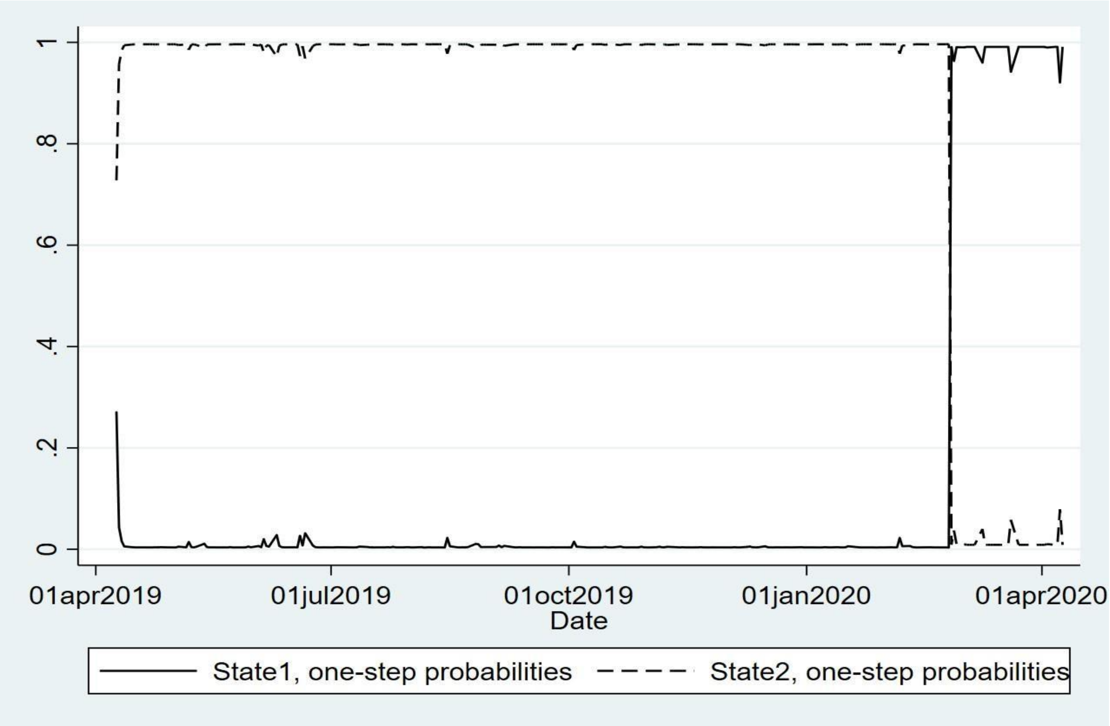


Fig.4: Markov-Switching model for the Dow Jones: state probabilities from 8 April 2019 to 9 April 2020

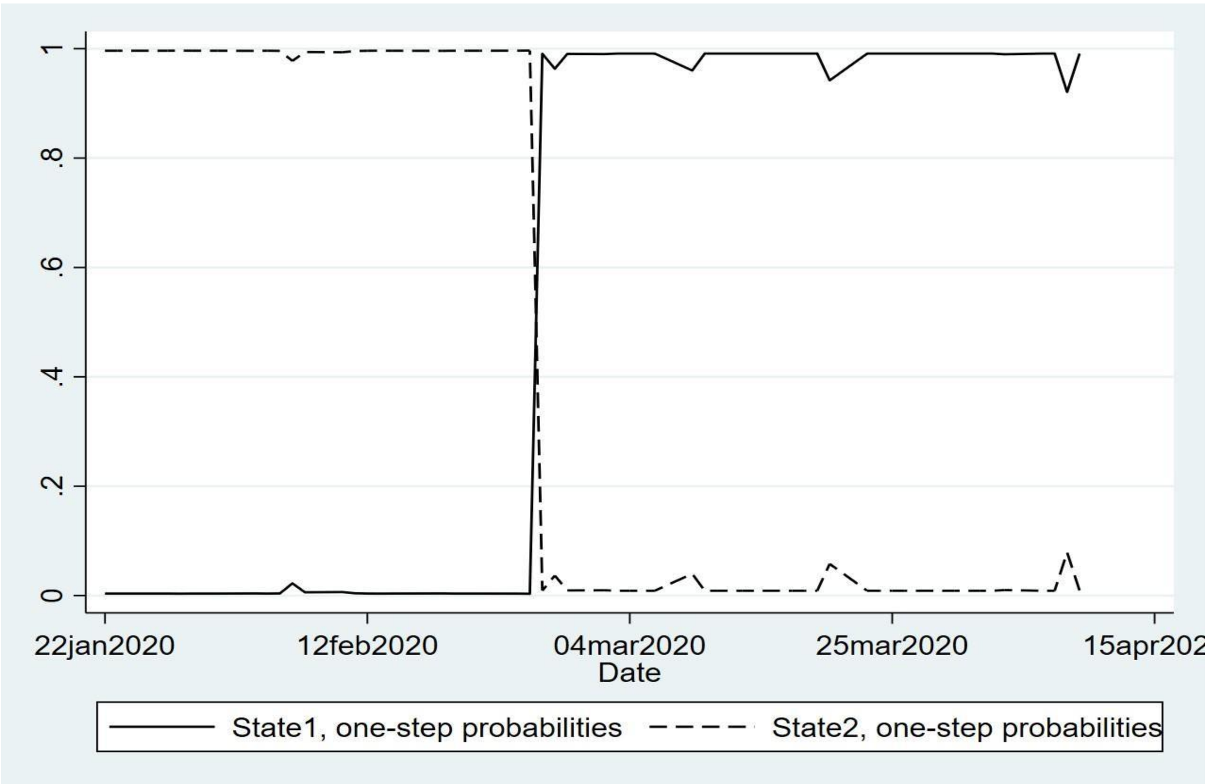


Fig.5: Markov-Switching model for the Dow Jones: state probabilities from 22 January 2020 to April 2020

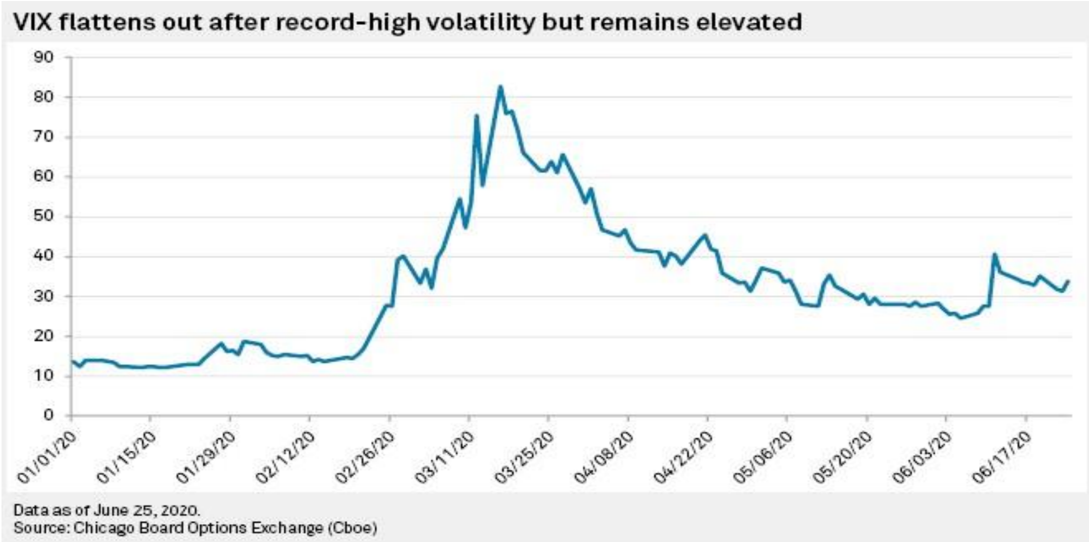
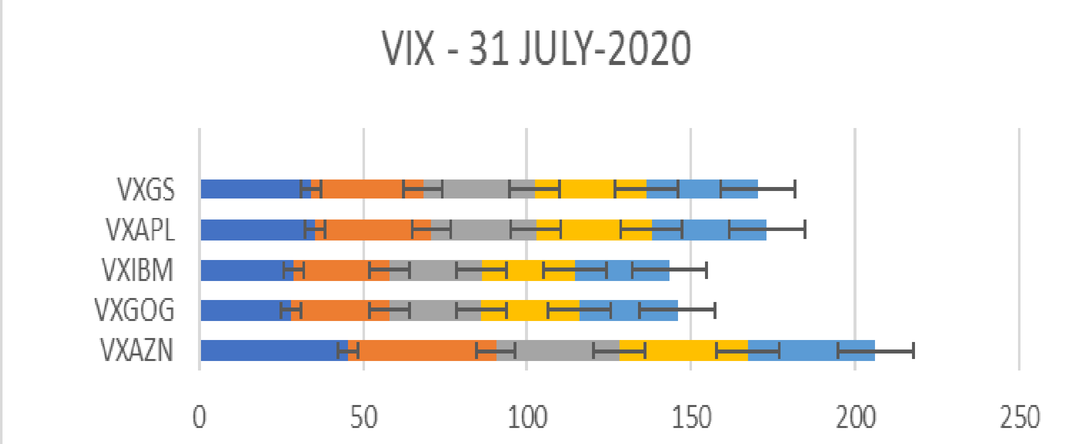


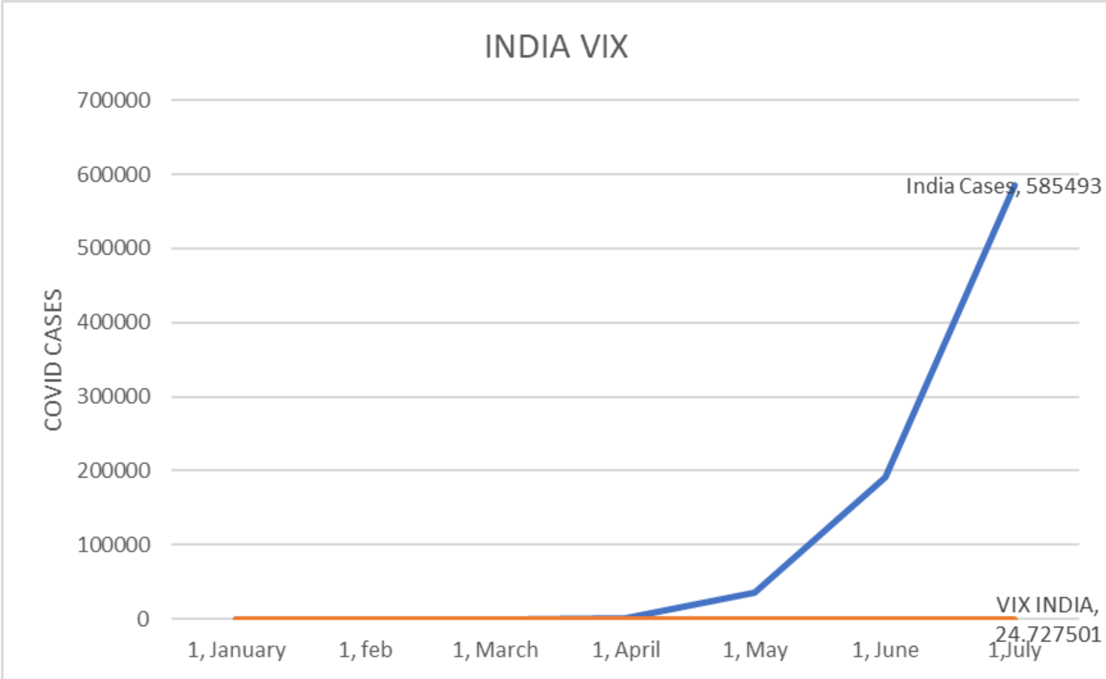
Fig.6: VIX Flattens : Dated 25 June



	VXAZN	VXGOG	VXIBM	VXAPL	VXGS	
Open	45.27	28.08	29.02	35.38	33.97	
High	45.27	29.93	29.02	35.38	34.4	
Low	37.66	28.08	28.13	31.98	33.93	
Close*	39.02	29.87	28.57	35.21	34.08	
Adj Close**	39.02	29.87	28.57	35.21	34.08	

FIG.7: Comparative Study of VIX ON DIFFERENT COMPANIES

*Close price adjusted for splits.**Adjusted close price adjusted for both dividends and splits. Source: WHO Reports



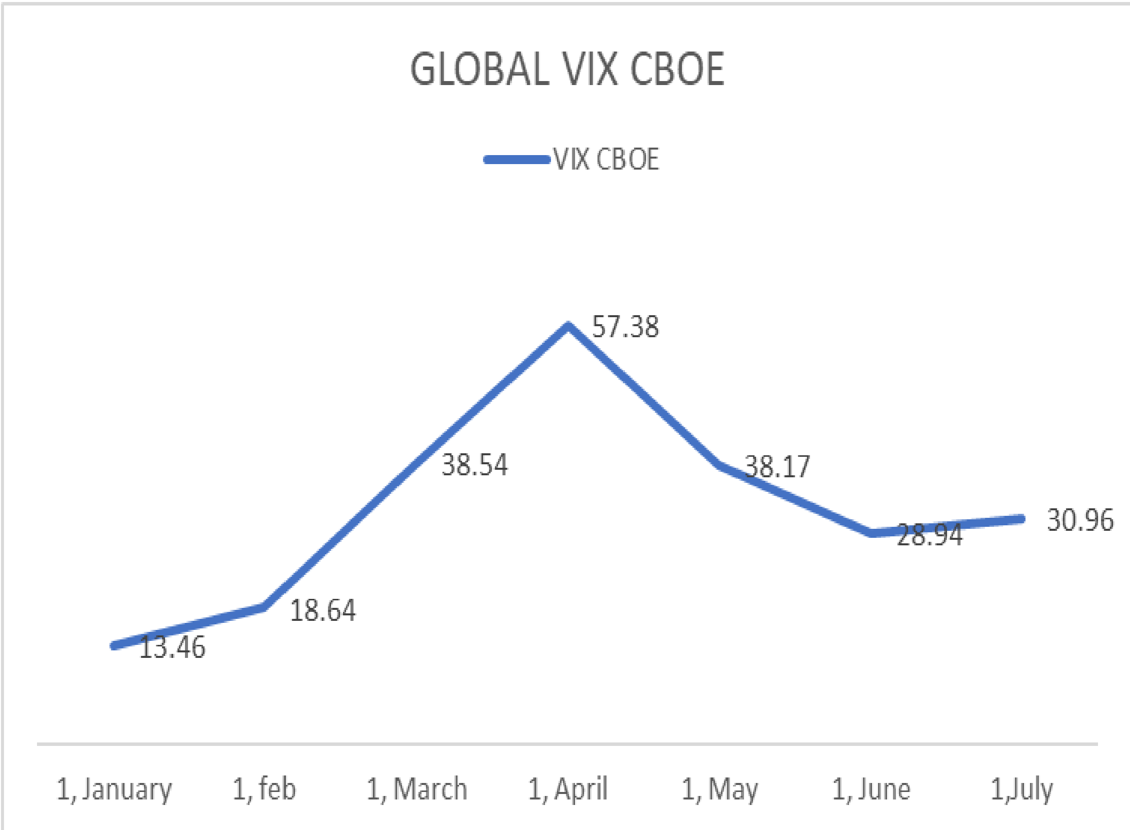
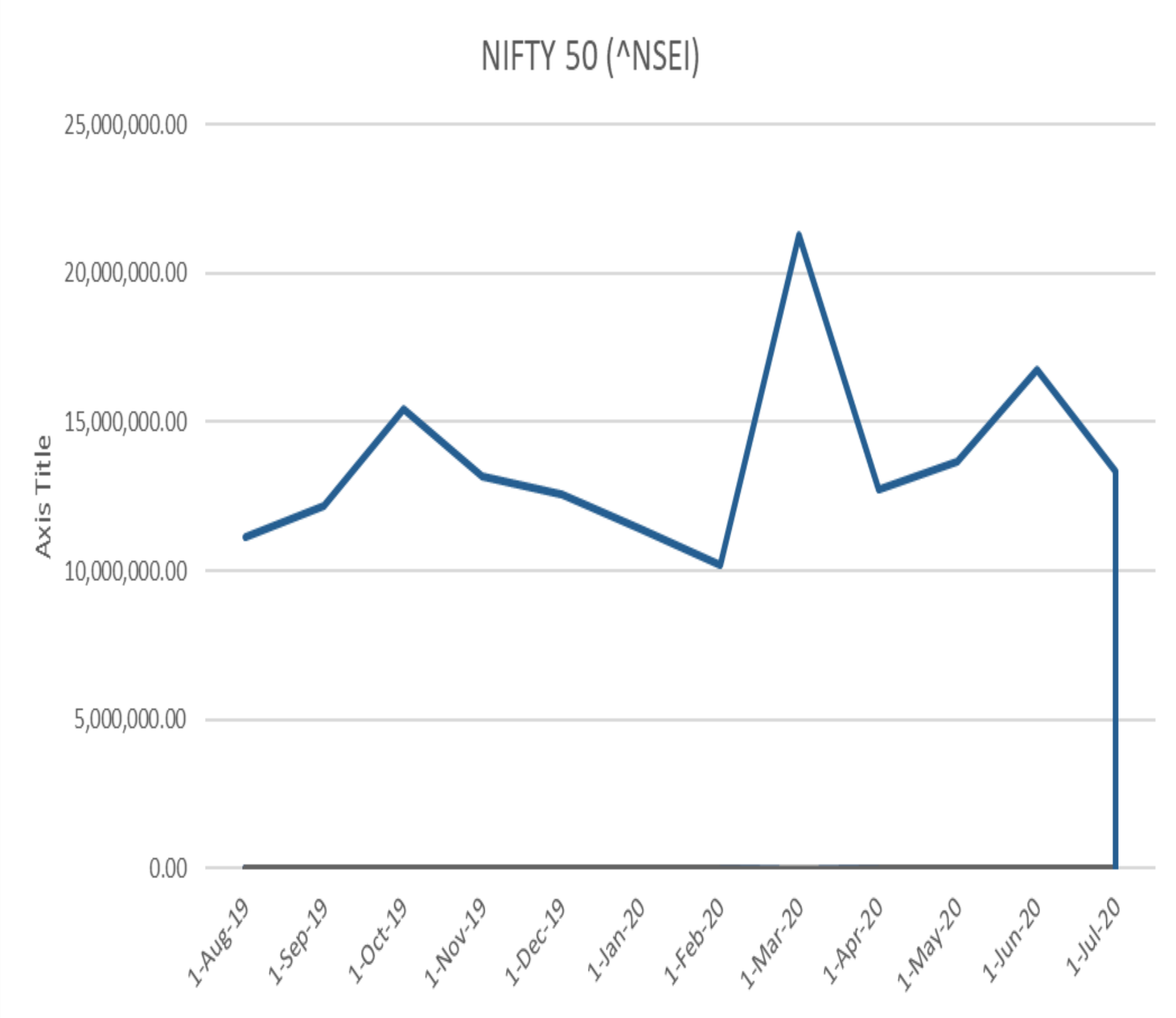


FIG.8: VIX INDIA, VIX GLOBAL

Source:CBOE



	1-Aug-19	1-Sep-19	1-Oct-19	1-Nov-19	1-Dec-19	1-Jan-20	1-Feb-20	1-Mar-20	1-Apr-20	1-May-20	1-Jun-20	1-Jul-20	31-Jul-20
Open	11,060.2	10,960.9	11,515.4	11,886.6	12,137.0	12,202.1	11,627.4	11,387.3	8,584.10	9,533.50	9,726.85	10,323.8	11,139.5
High	11,181.4	11,694.8	11,945.0	12,158.8	12,293.9	12,430.5	12,246.7	11,433.0	9,889.05	9,598.85	10,553.1	11,341.4	11,150.4
Low	10,637.1	10,670.2	11,090.1	11,802.6	11,832.3	11,929.6	11,175.0	7,511.10	8,055.80	8,806.75	9,544.35	10,299.6	11,026.6
Close*	11,023.2	11,474.4	11,877.4	12,056.0	12,168.4	12,169.8	11,201.7	8,597.75	9,859.90	9,580.30	10,302.1	11,202.8	11,073.4
Adj Close**	11,023.2	11,474.4	11,877.4	12,056.0	12,168.4	12,169.8	11,201.7	8,597.75	9,859.90	9,580.30	10,302.1	11,202.8	11,073.4
Volume	11,153,1	12,210,0	15,461,0	13,178,0	12,549,8	11,415,8	10,198,2	21,303,0	12,736,3	13,675,9	16,778,8	13,319,8	0

FIG. 9: NIFTY 50

NSE - NSE Real Time Price. Currency in INR

Source:CBOE

Table1: DowJonesandS&P500returns,confirmedcasesanddeathsinUS:GARCH(1,1)estimations.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: DJ	DJ	HET	ARCH	DJ	HET	ARCH
VIX (Ln)	-0.09248***			-0.09115***		
	(-15.91113)			(-19.19042)		
DJ Volume (Ln)	0.00349***			0.00366***		
	(4.16533)			(4.35646)		
Total cases US (Ln)	-0.00078	3.79771				
	(-0.08052)	(1.48067)				
Total deaths US (Ln)				0.00403	6.26513***	
				(0.13229)	(3.91956)	
L.arch			0.37344***			0.56223*
			(2.78406)			(1.69465)
L.garch			0.62656***			0.43777
			(4.67102)			(1.31949)
Constant	0.00271***	-12.95160***		0.00285***	-12.19853***	
	(3.99266)	(-21.24999)		(3.74083)	(-14.21064)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: S&P	S&P	HET	ARCH	S&P	HET	ARCH
VIX (Ln)	-0.08896***			-0.08419***		
	(-11.28792)			(-13.59934)		
S&P Volume (Ln)	0.00271*			0.00244		
	(1.66688)			(1.52637)		
Total cases US (Ln)	0.00238	2.88302				
	(0.83423)	(1.45893)				
Total deaths US (Ln)				0.00373	5.86446***	
				(0.17927)	(4.03894)	
L.arch			0.35512***			0.39232*
			(3.18469)			(1.73373)
L.garch			0.64488***			0.60768***
			(5.78332)			(2.68541)
Constant	0.00274***	-13.17376***		0.00286***	-12.98332***	
	(4.19120)	(-23.35180)		(4.22528)	(-14.41055)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254

Notes: The columns DJ (for Panel A) and S&P (for Panel B) report the results for the conditional mean equation. The column ARCH reports the results for the conditional variance equation, where L.arch is Gt−1 in eq. (2) and L.GARCH is σ^2_{t-1} in eq. (2). The column HET reports the results for λ_0 and λ_1. z-statistics are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Dow Jones returns, confirmed cases and deaths in China and Italy: GARCH(1,1) estimations.

Panel A: China	(1) DJ	(2) HET	(3) ARCH	(4) DJ	(5) HET	(6) ARCH
VIX (Ln)	-0.08996***			-0.09061***		
	(-17.95870)			(-17.92019)		
DJ Volume (Ln)	0.00351***			0.00355***		
	(4.23446)			(4.10268)		
Total cases China (Ln)	-0.00076**	-1.91435				
	(-2.16283)	(-1.01120)				
Total deaths China (Ln)				0.00065	-0.85711	
				(0.68104)	(-0.73732)	
L.arch			0.48324***			0.46318**
			(2.84300)			(2.53870)
L.garch			0.51676***			0.53682**
			(3.04015)			(2.94231)
Constant	0.00284***	-12.35573***		0.00280***	-12.43143***	
	(3.88205)	(-22.49513)		(3.70929)	(-20.38921)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254

Panel B: Italy	(1) DJ	(2) HET	(3) ARCH	(4) DJ	(5) HET	(6) ARCH
VIX (Ln)	-0.09171***			-0.09248***		
	(-16.30672)			(-18.04409)		
DJ Volume (Ln)	0.00323***			0.00334***		
	(4.10911)			(4.33213)		
Total cases Italy (Ln)	-0.00358	1.89134***				
	(-0.78029)	(3.22251)				
Total deaths Italy (Ln)				-0.00924	5.53276***	
				(-0.73895)	(3.71579)	
L.arch			0.24381**			0.27715*
			(2.04155)			(1.86831)
L.garch			0.75619***			0.72285***
			(6.33190)			(4.87277)
Constant	0.00268***	-13.77162***		0.00272***	-13.47748***	
	(4.21642)	(-13.91825)		(4.23892)	(-13.70457)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254

Notes: The column DJ reports the results for the conditional mean equation. The column ARCH reports the results for the conditional variance equation, where L.arch is ϵ_{t-1} in eq. (2) and L.GARCH is σ^2_{t-1} in eq. (2). The column HET reports the results for λ_0 and λ_1. Z Statistics are reported in the parentheses.***p<0.001,**p<0.05,*p<0.

Table 3: Dow Jones returns, confirmed cases and deaths in Spain and the UK: GARCH(1,1) estimations.

Panel A: Spain	(1) DJ	(2) HET	(3) ARCH	(4) DJ	(5) HET	(6) ARCH
VIX (Ln)	-0.09417***			-0.09163***		
	(-16.97360)			(-20.34891)		
DJ Volume (Ln)	0.00271***			0.00365***		
	(4.03132)			(4.85695)		
Total cases Spain (Ln)	-0.01666**	7.35771***				
	(-2.01990)	(4.15300)				
Total deaths Spain (Ln)				0.02469	4.89638***	
				(1.25305)	(3.99500)	
L.arch			0.12831			0.66294***
			(1.63121)			(3.81133)
L.garch			0.87169***			0.33706*
			(11.08219)			(1.93784)
Constant	0.00278***	-15.00339***		0.00295***	-11.98395***	
	(4.36416)	(-9.29465)		(3.88628)	(-29.95159)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254
Panel B: UK	**(1) DJ**	**(2) HET**	**(3) ARCH**	**(4) DJ**	**(5) HET**	**(6) ARCH**
VIX (Ln)	-0.09095***			-0.09185***		
	(-18.18275)			(-21.05162)		
DJ Volume (Ln)	0.00346***			0.00363***		
	(4.35971)			(5.23316)		
Total cases UK (Ln)	0.00419	5.01511**				
	(0.56654)	(2.32102)				
Total deaths UK (Ln)				0.02191	7.11939***	
				(0.63998)	(9.42693)	
L.arch			0.64007**			0.70851***
			(2.03517)			(6.37144)
L.garch			0.35993			0.29149***
			(1.14445)			(2.62131)
Constant	0.00276***	-12.11182***		0.00299***	-11.89459***	
	(3.64565)	(-16.72109)		(4.04006)	(-43.80292)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254

Notes: The column DJ reports the results for the conditional mean equation. The column ARCH reports the results for the conditional variance equation, where L.arch is— Gt—1 in eq. (2) and L.GARCH is σ^2 t-1 in eq. (2). The column HET reports the results for $\lambda 0$ and $\lambda 1$. Z Statistic are reported in the parentheses.***p<0.001,**p<0.05,*p<0.1

Table4: DowJonesreturns,confirmedcasesanddeathsinIranandFrance: GARCH(1,1) estimations .

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Iran	DJ	HET	ARCH	DJ	HET	ARCH
VIX (Ln)	-0.09262***			-0.09261***		
	(-17.51399)			(-17.77609)		
DJ Volume (Ln)	0.00328***			0.00329***		
	(4.37196)			(4.42524)		
Total cases Iran (Ln)	-0.00026	2.78603***				
	(-0.08266)	(3.96987)				
Total deaths Iran (Ln)				-0.00343	4.25569***	
				(-0.33918)	(3.24414)	
L.arch			0.26662**			0.27811**
			(2.27801)			(2.49052)
L.garch			0.73338***			0.72189***
			(6.26619)			(6.46465)
Constant	0.00266***	-13.53876***		0.00267***	-13.42253***	
	(4.12987)	(-15.72893)		(4.17541)	(-17.70398)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: France	DJ	HET	ARCH	DJ	HET	ARCH
VIX (Ln)	-0.09069***			-0.09370***		
	(-17.32048)			(-14.94865)		
DJ Volume (Ln)	0.00361***			0.00306***		
	(4.05064)			(4.23616)		
Total cases France (Ln)	0.00099	-2.54427				
	(0.56201)	(-0.48169)				
Total deaths France (Ln)				-0.00651	8.78966***	
				(-0.37679)	(3.89525)	
L.arch			0.46210***			0.18685
			(2.74098)			(1.03843)
L.garch			0.53790***			0.81315***
			(3.19061)			(4.51905)
Constant	0.00282***	-12.46053***		0.00275***	-14.11226***	
	(3.67322)	(-22.38098)		(4.40271)	(-7.53445)	
Weekday dummies	YES	NO	NO	YES	NO	NO
Observations	254	254	254	254	254	254

Notes: The column DJ reports the results for the conditional mean equation. The column ARCH reports the results for the conditional variance equation, where L.arch is ϵ_{t-1} in eq. (2) and L.GARCH is σ^2_{t-1} in eq. (2). The column HET reports the results for λ_0 and λ_1. Z Statistic are reported in the parentheses.***p<0.001,**p<0.05,*p<0.1

Table 5: VAR-X models: Total cases and total deaths.

VARIABLES	(1) DJ	(2) DJ Volume	(3) VIX	(4) S&P	(5) S&P Volume	(6) VIX
Total cases US (Ln)	-0.05650***	0.16683	0.26605***	-0.05381***	0.09129	0.26690***
	(-6.41649)	(1.25566)	(6.46494)	(-6.58459)	(0.56827)	(6.52261)
Total deaths US (Ln)	0.04193***	-0.24111	-0.22211***	0.03827***	-0.44880**	-0.22212***
	(4.30611)	(-1.64097)	(-4.88060)	(4.23203)	(-2.52434)	(-4.90514)
Total cases China (Ln)	0.00142	0.03340	-0.01365	0.00130	0.05734	-0.00280
	(0.27970)	(0.46737)	(-0.57686)	(0.26462)	(0.63595)	(-0.11498)
Total deaths China (Ln)	-0.00759	-0.00468	0.09530**	-0.00586	0.01275	0.08316*
	(-0.76773)	(-0.03364)	(2.07094)	(-0.62962)	(0.07448)	(1.79552)
Total cases Italy (Ln)	0.00209	0.17839*	0.09324***	0.00273	0.13839	0.09449***
	(0.32381)	(1.90327)	(3.13550)	(0.45695)	(1.19916)	(3.19280)
Total deaths Italy (Ln)	-0.04442***	-0.08061	0.06237	-0.04612***	-0.29652	0.06283
	(-3.49628)	(-0.43744)	(1.06689)	(-3.91651)	(-1.30392)	(1.07731)
Total cases Spain (Ln)	-0.01291	0.04709	0.05462	-0.01493	-0.14805	0.06224
	(-1.25123)	(0.32161)	(1.12118)	(-1.54482)	(-0.82672)	(1.27474)
Total deaths Spain (Ln)	-0.00891	-0.11714	0.01135	-0.00762	-0.15881	0.01141
	(-0.95633)	(-0.88594)	(0.25792)	(-0.87162)	(-0.98073)	(0.25833)
Total cases UK (Ln)	-0.02209**	0.12966	0.15293***	-0.02094**	0.10920	0.15734***
	(-2.03388)	(0.83518)	(2.99938)	(-2.07598)	(0.58321)	(3.10572)
Total deaths UK (Ln)	-0.00656	-0.18903	-0.07369	-0.00710	-0.47398**	-0.07794
	(-0.56407)	(-1.13761)	(-1.35032)	(-0.65500)	(-2.35512)	(-1.43122)
Total cases Iran (Ln)	0.04861***	0.15045	0.00132	0.04092***	0.23666	0.00695
	(3.39996)	(0.71933)	(0.01958)	(3.06607)	(0.92107)	(0.10344)
Total deaths Iran (Ln)	-0.09940***	0.00211	0.20077**	-0.08925***	-0.37521	0.19757*
	(-4.59167)	(0.00667)	(1.96692)	(-4.42676)	(-0.96676)	(1.94799)
Total cases France (Ln)	-0.00391	-0.00025	0.06702*	-0.00512	-0.09132	0.06726*
	(-0.45958)	(-0.00207)	(1.66041)	(-0.65093)	(-0.60712)	(1.67162)
Total deaths France (Ln)	-0.03524***	-0.01545	0.07994	-0.03612***	-0.12494	0.08323*
	(-3.31204)	(-0.10014)	(1.58291)	(-3.66244)	(-0.66296)	(1.65103)
Observations	250	250	250	250	250	250

Notes: The columns DJ and S&P report the results for the log returns of the Dow Jones and S&P500, respectively. The columns DJ Volume and S&P Volume report the results for the daily first-difference in trading volume (in logs). The column VIX reports the results for the daily first-difference in VIX prices (in logs). Endogenous variables and constant included but not reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Markov-Switching models: Dow Jones and S&P500 return versus VIX returns.

	(1)	(2)
Panel A: DJ	State1	State2
VIX	-0.2801***	-0.0874***
	(-7.6860)	(-19.8652)
Constant	-0.0007	0.0005*
	(-0.1112)	(1.8433)
Observations	254	254
Sigma1	0.0358	
Sigma2	0.0042	
p11	0.9911	
p21	0.0033	
Panel B: S&P	State1	State2
VIX	-0.2695***	-0.0894***
	(-7.0515)	(-27.1880)
Constant	-0.0003	0.0007***
	(-0.0568)	(2.8671))
Observations	254	254
Sigma1	0.0321	
Sigma2	0.0038	
p11	0.9913	
p21	0.0033	

Notes: This table reports the results of a Markov-Switching model for the Dow Jones (Panel A) and S&P500 (Panel B). The model allows for two state-dependent intercepts and variance parameters, switching the coefficient on the VIX returns. p11 is the estimated probability of staying in state 1 in the next period given that the process is in state 1 in the current period. Similarly, p21 is the probability of transitioning to state 1 from state 2. Sigma1 and sigma2 are the estimated standard deviations for state 1 and state 2, respectively. z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 1: S&P500 returns, confirmed cases and deaths in China, Italy, Spain, the UK, Iran and France: GARCH(1,1) estimations.

	(1)	(2)	(3)	(4)
VARIABLES	S&P	HET	S&P	HET
Total cases China (Ln)	-0.00057	-5.56031		
	(-1.46184)	(-1.23210)		
Total deaths China (Ln)			0.00064	-2.73862
			(0.52778)	(-0.92280)
Total cases Italy (Ln)	-0.00133	1.80990***		
	(-0.89585)	(4.05862)		
Total deaths Italy (Ln)			-0.01105	5.91951***
			(-0.90439)	(4.24020)
Total cases Spain (Ln)	-0.01445	7.02309***		
	(-1.59997)	(3.01442)		
Total deaths Spain (Ln)			0.00456	4.73733***
			(0.11787)	(5.29250)
Total cases UK (Ln)	0.00290	2.13696		
	(0.51272)	(1.18041)		
Total deaths UK (Ln)			0.01455	7.01218***
			(0.45114)	(8.96176)
Total cases Iran (Ln)	-0.00100	2.99992***		
	(-0.37534)	(4.78570)		
Total deaths Iran (Ln)			-0.00432	4.62626***
			(-0.44290)	(3.82008)
Total cases France (Ln)	-0.00048	-2.61013		
	(-0.40460)	(-0.98234)		
Total deaths France (Ln)			-0.00864	9.14983***
			(-0.66893)	(5.77460)
Observations	254	254	254	254

Notes: The column S&P reports the results for the conditional mean equation. The column HET reports the results for λ_0 and λ_1. VIX (Ln), S&P Volume, and constants are included but not reported. z-statistics are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table 2: VAR-X models: Results considering total cases and total deaths separately

VARIABLES	(1) DJ	(2) Volume	(3) VIX	(4) DJ	(5) Volume	(6) VIX
Total cases US (Ln)	-0.03775*** (-3.18995)	-0.08767 (-0.50799)	0.08344			
Total cases China (Ln)	0.00499	0.04572	-0.00837			
	(1.07445)	(0.67534)	(-0.39310)			
Total cases Italy (Ln)	-0.01258	0.21527*	0.12104***			
	(-1.46557)	(1.71943)	(3.07443)			
Total cases Spain (Ln)	-0.00190	-0.00941	-0.04822			
	(-0.14296)	(-0.04846)	(-0.78953)			
Total cases UK (Ln)	0.00029	-0.15148	-0.06649			
	(0.02140)	(-0.77837)	(-1.08640)			
Total cases Iran (Ln)	0.01553	-0.00561	-0.02373			
	(1.41182)	(-0.03496)	(-0.47064)			
Total cases France (Ln)	0.00597	0.05335	0.07440			
	(0.49953)	(0.30589)	(1.35647)			
Total deaths US (Ln)				0.06311***	-0.32152*	-0.28699***
				(5.85545)	(-1.91634)	(-5.77352)
Total deaths China (Ln)				-0.00433	0.00327	0.06957*
				(-0.54927)	(0.02661)	(1.91248)
Total deaths Italy (Ln)				-0.05717***	0.28840	0.23571***
				(-4.02110)	(1.30298)	(3.59441)
Total deaths Spain (Ln)				0.00225	-0.09739	0.01359
				(0.21567)	(-0.60059)	(0.28289)
Total deaths UK (Ln)				0.00604	-0.15469	-0.13373*
				(0.37657)	(-0.61947)	(-1.80749)
Total deaths Iran (Ln)				-0.00116	0.16245	0.11178*
				(-0.08721)	(0.78709)	(1.82791)
Total deaths France (Ln)				-0.05670***	0.20460	0.25219***
				(-3.63843)	(0.84340)	(3.50878)
Observations	250	250	250	250	250	250

Notes: The column DJ reports the results for the log returns of the Dow Jones index. The column Volume reports the results for the daily first-difference in trading volume (in logs). The column V IX reports the results for the daily first-difference in VIX prices (in logs). Constant included but not reported. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Markov-Switching models: Dow Jones and S&P500 returns versus VIX returns

	(1)	(2)
Panel A: DJ	State1	State2
VIX	-0.2644***	-0.0883***
	(-7.1430)	(-20.4060)
VIX (first lag)	0.0503	-0.0101**
	(1.5672)	(-2.4417)
Constant	-0.0023	0.0005*
	(-0.3382)	(1.9260)
Observations	253	253
Sigma1	0.0350	
Sigma2	0.0041	
p11	0.9910	
p21	0.0033	
Panel B: S&P	State1	State2
VIX	-0.2534***	-0.0900***
	(-6.5284)	(-27.4398)
VIX (first lag)	0.0510	-0.0075**
	(1.4227)	(-2.1901)
Constant	-0.0019	0.0007***
	(-0.3483)	(2.9264)
Observations	253	253
Sigma1	0.0311	
Sigma2	0.0038	
p11	0.9912	
p21	0.0033	

Notes: This table reports the results of a Markov-Switching model for the Dow Jones (PanelA) and

S&P500 (Panel B). The model allows for two state-dependent intercepts and variance parameters, switching the coefficient on the VIX returns. p11 is the estimated probability of staying in state 1 in the next period given that the process is in state 1 in the current period. Similarly, p21 is the probability of transitioning to state 1 from state 2. Sigma1 and sigma2 are the estimated standard deviations for state 1 and state 2, respectively. z-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.