Multi-regime Forecasting Model for the Impact of COVID-19 Pandemic on Volatility in Global Equity Markets

Nazli Sila Alan
Assistant Professor of Finance
Dolan School of Business, Fairfield University
nalan@fairfield.edu

Robert F. Engle
Michael Armellino Professor of Management and Financial Services
Stern School of Business, New York University
rengle@stern.nyu.edu

Ahmet K. Karagozoglu
Visiting Scholar
Volatility and Risk Institute, Stern School of Business, New York University
&
C.V. Starr Distinguished Professor of Finance and Investment Banking
Zarb School of Business, Hofstra University
akk473@nyu.edu, finakk@hofstra.edu

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Abstract

Using a multi-regime forecasting model, we investigate the impact of COVID-19 pandemic on market volatility. We show that daily number of active cases and the *Curvature* are significant predictors of daily cross-section of both realized volatility and the GJR-GARCH volatility in global equity markets. We estimate realized volatilities using intraday 5-minute returns for 46 country specific ETFs and daily GARCH volatilities are estimated using the stock market indices of 88 countries around the world. We find that stricter policy responses by individual countries, measured by higher OxCGRT *Stringency Index* levels, result in lower stock market volatilities while increased negative managerial sentiment, extracted from earnings call transcripts, causes an increase in realized volatilities.

Keywords: Multi-regime forecasting, COVID-19, coronavirus pandemic, volatility, Stringency Index, earnings call transcripts, sentiment, curvature

JEL Classifications: G01, G12, G15

1. Introduction

Coronavirus pandemic of 2020 presents significant challenges to market participants compared to historical episodes of economic downturns, financial crises and natural disasters. With the exception of world wars and early 19^{th} century flu pandemic, the global scale and unprecedented early devastation caused by relatively unknown nature of the viral infections increased the uncertainty in financial markets to a level that made forming expectations about the future much higher than ever before. In this paper, we investigate the impact of COVID-19 pandemic on volatility in global equity markets using a multi-regime forecasting model we propose.

Fueling the uncertainty in financial markets is the multifaceted impact of the pandemic. Although past economic and financial crises resulted in policy responses, regulations and improvements in resilience of the market in terms of identifying the drivers of risk, measuring exposures and forecasting recovery, COVID-19 pandemic poses new challenges that impact various asset classes differently. We utilize a broad database of global equity market indices, country specific exchange traded funds (ETF), earnings call transcripts and coronavirus infection data to develop a multi-regime forecasting model and provide empirical evidence for the relationship between COVID-19 infections and financial market volatility with a global perspective.

We use two different measures of equity market volatility, a GARCH time-series model based on global stock indices and realized volatility based on intraday prices of country specific ETFs, to differentiate how the pandemic induced uncertainty is observed in the market. Furthermore, we use textual analysis of earnings call transcripts of publicly traded firms in various countries to link managerial negative sentiment due to the pandemic to the broader equity market volatility.

Using text-based methods, i.e. the newspaper-based Equity Market Volatility (EMV) tracker, Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) show that the impact of recent COVID-19 pandemic on the U.S. stock market volatility has been larger than any previous infectious disease outbreak. Also focusing on U.S. firms with different characteristics, Albuquerque, Koskinen, Yang, and Zhang (2020) show that, during the first quarter of 2020, firms with higher environmental and social ratings have significantly higher returns and lower return volatilities than other firms, while Alfaro, Chari, Greenland, and Schott (2020) find that firms with high capital intensity as well as leverage, and firms that are in industries more conducive to disease transmission have higher COVID-19-related losses in market value. Guerrieri, Lorenzoni, Straub, and Werning (2020) present a theoretical model for the "economic shocks associated to the COVID-19 epidemic such as shutdowns, layoffs, and firm exits" that exhibit the features of Keynesian supply shocks which trigger changes in aggregate demand larger than the shocks themselves.

As we observed in stock markets around the world during the first few months of 2020, COVID-19 has had a major impact on the stability of global financial markets and caused large swings in stock prices. Volatility for most stock markets reached an all-time high in the second and third week of March between the 12th and 20th as the number of new COVID-19 cases increased exponentially in most countries. In Figure 1, we present the daily median realized volatilities (RV), calculated using 5-minute intraday returns for 46 country specific ETFs and GARCH volatilities, estimated using GJR-GARCH specification for daily stock index returns of 88 countries as well as the CBOE VIX for the U.S. The dates with the largest increase in volatility levels are marked (February 24th, March 9th, and March 16th) along with the day when RV returned to its pre-pandemic levels (April 3rd). GARCH and RV volatility levels for seven of our sample countries are shown in Panels A and B of Figure 2 where U.S. stock market has reached peak volatility level on March 16th, 4 days after the Italian market, and the volatility levels for all countries have been declining since then.[1]

In our empirical analysis, we document a complex relation between the pandemic metrics and stock market volatility. We show that daily number of active cases and the *Curvature* are significant predictors of daily cross-section of both realized volatility and the GJR-GARCH volatility in global equity markets. We also find that the stringency of the governments' policy response to the pandemic is a significant factor in bringing down volatility levels globally. Baker, Bloom, Davis, Kost, Sammon, and Viratyosin (2020) also indicate that "the policy response to the COVID-19 pandemic provides the most compelling explanation for its unprecedented impact on the stock market" volatility in the U.S. Finally, our analysis of the earnings calls in 38 countries during the pandemic shows that the negative sentiment of the language used in the calls further contributed to stock market volatility in those countries.

[1] The seven countries in Figure 2 are CHN (China), DEU (Germany), ESP (Spain), GBR (United Kingdom), ITA (Italy), KOR (Korea), and USA.

2. Theoretical Framework

Financial markets respond to expectations of future cash flows. As the coronavirus has spread, it became clear that the economic costs will be enormous. This has happened at different rates in different countries. To some extent this is to be expected as the contamination rate is not known and policies that are applied are different. This paper examines the volatility of broad country stock indices as a function of expected contamination on a daily basis using daily data from 2020. Furthermore, we use high-frequency data on country ETFs to obtain an alternative measure of volatility. We present a simple theoretical framework with a multi-regime forecasting model for volatility using a measure we refer to as *Curvature*.

Atkeson (2020) presents a simple SIR model of the progression of COVID-19 which is represented as Markov model of the spread of an epidemic in a population. The expected number of cases in simple epidemiological models is given by

$$\log\left(n_{i,t}\right) = \beta_0 + \beta_1 \log\left(n_{i,t-1}\right) + \beta_2 z_{t-1} + u_{i,t} \tag{0}$$

Under strong assumptions, β_1 is an estimate of R_0 which is the "basic reproductive ratio." This is typically thought to be around two for the coronavirus and forecasts epidemics when it is greater than one. The variables *z* are other factors such as the contamination in other countries and the number of non-contaminated individuals and non-linearities in the relationship. The residuals may be heteroskedastic reflecting changes in the uncertainty around predictions.

Financial markets might use forecasts from this model to predict damages and hence market valuations of country's publicly traded capital stock. If the fitted value of this equation predicts the level of the market, the residuals should correlate with the return.

Figure 3 shows the *log*(*Active Cases*) calculated as the 3-day moving average for the same set of seven countries as Figure 2. From this plot, we infer the following model and damage forecasting equation.

According to the plot, there appear to be three regimes: (i) Slow growth in log cases. (ii) Rapid growth in log cases (this is the well-known exponential growth period). (iii) Gradual tapering off with cases asymptoting at a high level (it will presumably decline to some normal level at some point).

Suppose the growth rates are relatively well understood but the times at which the switches between the regimes occur are uncertain. Then, markets must use the data on COVID-19 cases to predict the ultimate damages and hence, the stock market values.

Let the switch points be t_1 and t_2, from slow-to-rapid growth and from rapid growth-to-tapering off period, respectively. Let's define the time at which the peak occurs as t_{max}. This growth path for each of the regimes can be described with the following parameters: (i) Growth rate for the slow period is a. (ii) Growth rate for the rapid period is $a + b$. (iii) Growth rate for the tapering off period is $a + b$ but curvature is $-g$.

Hence, letting $y = \log(Cases)$

$$y = at + b(t - t_1)(t > t_1) + g(t - t_2)^2(t > t_2) \tag{2}$$

then by calculation,

$$t_{max} = t_2 - \frac{a+b}{2g} \tag{3}$$

and

$$y_{max} = at_{max} + b(t_{max} - t_1) + g(t_{max} - t_2) \tag{4}$$

We simulate t_1 and t_2 for 1000 countries and present the details in Appendix 1. Regressing simulated y_{max} on cases, infection rate, and curvature, we see that the coefficients change over time, reflecting the complex process of the pandemic. Largest coefficients are for the curvature and the constant. Although the coefficient for the case variable is small, it is generally significant. The infection rate is not as important once curvature is included in the regression. In short, there is a lot of information in the case-history but it is complex to interpret. We suggest the curvature is like acceleration and our empirical implementation of it is a very good indicator of switching from acceleration to deceleration. We hypothesize that the curvature of active cases is a powerful predictor of daily cross section of volatility in global equity markets. We proceed to test our hypothesis using two different measures of volatility together with additional control variables in a panel setting.

3. Data and Variables

We obtain the daily GARCH volatility measure for 88 countries from the NYU's Volatility and Risk Institute (see Table 1, Panel A for a list of these countries).[2] Daily volatility is estimated using the equity market index level returns based on the GJR- GARCH(1,1) model:

$$r_t = \mu + \varepsilon_t,\ \varepsilon_t = \sigma_t z_t \tag{5}$$

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{6}$$

[2] https://vlab.stern.nyu.edu/

$$\text{where } I_{t-1} = \begin{cases} 0 \; if \; r_{t-1} \geq \mu \\ 1 \; if \; r_{t-1} < \mu \end{cases} \tag{7}$$

and coefficients μ, ω, α, γ, β are estimated simultaneously by maximizing the log likelihood.

We also calculate realized volatility using 5-minute returns for ETFs on 46 countries (see Table 1, Panel B). Intraday ETF prices are obtained from the NYSE Trades and Quotes (TAQ) database. COVID-19 pandemic related variables (cases, deaths, recoveries, and active cases) are downloaded from the Johns Hopkins University (JHU) website.[3] Stringency index is downloaded from the University of Oxford (OxCGRT) website.[4] We use the Textual Data Analytics of Transcripts database from the S&P Global Market Intelligence (GMI) to extract metrics based on natural language processing (NLP) for 6,500 publicly traded firms from 38 countries, and calculate a *Negative Sentiment* variable for all earnings calls during our sample period. Our sample period spans from January 22nd through May 1st of 2020.

Realized volatility is calculated for each day as the sum of squared 5-minute returns plus the squared overnight return.

$$RV_t = r_{O/N,t}^2 + \sum_{i=1}^{78} r_{i,t}^2 \tag{8}$$

where $r_{O/N,t}$ is the overnight log return of the ETF on day *t*, $r_{i,t}$ is the log return in the i^{th} 5-minute interval of the trading day *t*. In Figure 1, we present the daily median realized volatilities for 46 country specific ETFs and GARCH volatilities for stock indices of 88 countries, as well as the CBOE VIX for the U.S. The dates with the largest increase in volatility levels are marked (Feb 24, Mar 9, and Mar 16) along with the day volatility returned to its pre-pandemic levels (Apr 3). Interestingly, all three of the large spike days are Mondays and they are reflecting the preceding weekend's events altogether. By Feb 24th, Italy became the worst-hit country in Europe and investors started worrying about the effect of closures on supply chains. The day before Mar 9th, Italy's northern region was issued a lockdown (which was extended to the whole country on Mar 10th). During the weekend before Mar 16th, situation in the U.S. became dire, many states announced school closures, and travel bans were issued or expanded.

[3] https://coronavirus.jhu.edu/map.html and https://github.com/CSSEGISandData/COVID-19

[4] See https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker We use the Stringency Index based on Oxford University's revised calculation as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values as explained at https://www.bsg.ox.ac.uk/sites/default/files/OxCGRT.%20What%27s%20changed%2024%20April%202020.pdf

Figure 4 shows the relation between *Log*(*Active Cases*) vs. Realized Volatility and GARCH Volatility in each of its two columns. The relation is plotted for five dates, the four dates mentioned above (Feb 24, Mar 9, Mar 16, Apr 3) and the last day of our sample period with available data from most countries, Apr 30th. We can see from these charts, as case numbers increase, volatility also increases.

For COVID-19 pandemic related variables, we calculate *Active Cases* as confirmed cases minus the number of deaths and recoveries. Due to the case reporting and time zone differences across the countries, we calculate the three-day moving average of the *Active Cases* and use that in all of our variable constructions and analyses. Using the three-day moving average of *Active Cases*, we calculate *Curvature*, which is an empirical implementation of equation (4), as follows:

$$Curvature[k]_t = log(Active\ Cases_t) + log(Active\ Cases_{t-k}) - 2 * log\left(Active\ Cases_{t-\frac{k}{2}}\right) \quad (9)$$

where *k* is the lag parameter. Based on the 14-day incubation period of the coronavirus (or the 14-day quarantine period recommended following a positive COVID-19 test or exposure to COVID-19 positive patients), we use *k*=14.[5] Figure 5 shows the relation between daily median GARCH volatility for global equity markets and the mean *Curvature*, with *k*=14, for a cross-section of 88 countries. We observe that in general global mean *Curvature* level is positive and increasing while global median GARCH volatility is increasing. On average, negative *Curvature* values suggest that the virus is decelerating; however, if there are reinfections associated with reopening businesses/economies, we would expect to see curvature (acceleration) turn positive and lead to higher volatility again. We also perform our empirical test using 7-day and 4-day lag parameters. While we use *Active Cases* and *Curvature* in our main estimations of multi-regime forecasting model, we also investigate the *Infection Rate* as an alternative measure of disease propagation:

$$Infection\ Rate[k]_t = log(Active\ Cases_t) - log(Active\ Cases_{t-k}) \quad (10)$$

Our policy variable, *Stringency Index*, is an aggregated government policy score based on data collected by The Oxford COVID-19 Government Response Tracker (OxCGRT). It measures the strictness of the government's response to the pandemic in terms of school closures, restrictions in movement, testing, and contact tracing, etc.

[5] Alvarez, Argente, and Lippi (2020) build a model of the optimal lockdown policy and suggest a severe lockdown beginning two weeks after the outbreak.

We extract *Negative Sentiment* for all earnings calls released during our sample period from the S&P GMI Textual Data Analytics.[6] They calculate Negative Sentiment as the ratio of total number of negative words to total number of Master words in the same transcript, where negative words is a count of the tokens derived from all the sentences of transcript that are present in the negative dictionary of Loughran-McDonald[7]. We further classify the earnings calls into two groups, based on whether they mention at least one COVID-19 related word ('coronavirus', 'COVID', 'pandemic', and 'epidemic') or not. Then, for each day, we separately calculate the average negative sentiment for the earnings calls that mention COVID-19 and those that do not, and calculate the difference between the two averages. *Negative Sentiment Differential* (NSD) is then, the moving average of the difference in negative sentiment of these two groups.

Pope and Zhao (2017) and Zhao (2017) use the Textual Data Analytics derived from Earnings Call Transcripts by the S&P Global Market Intelligence. S&P GMI's unique dataset, produced by using natural language processing (NLP), machine learning (ML) and linguistic text processing (LTP) techniques, contain, among other variables, negative sentiment derived from the transcripts of earnings calls. The choice of an extraction method for the tone is an important consideration and S&P Global uses the reference lexicon in the dictionary developed by Loughran and McDonald (2011) which has been utilized by numerous studies to capture the tone of firm–related textual documents. Price, Doran, Peterson, and Bliss (2012), using textual data analysis, examine the incremental informativeness of quarterly earnings calls and find that the linguistic conference call tone is a significant predictor of abnormal returns and trading volumes, indicating that managers' superior information about firms' prospects gets revealed in the linguistic tone they use during the conference calls. Pope and Zhao (2017) apply NLP to S&P 500 corporate earnings call transcripts to dissect the tone, complexity, and overall level of engagement with analysts as indicators of earnings sentiment. Mayew and Venkatachalam (2012) analyze the sentiment of earnings calls, while impact of managerial sentiment on investors' perception is analyzed by Davis, Matsumoto, and Zhang (2015). Demers and Vega (2014) find that textual analysis of managerial

[6] Ramelli and Wagner (2020) suggest that the sophisticated investors appear to have started pricing in the effects of the coronavirus already in the first part of January 2020 before managers or analysts started paying attention to them according to the earnings conference calls.

[7] We use the negative sentiment variable derived from the portion of earnings call transcripts which is attributed to the executives of the firm, i.e. variables calculated from the transcript sentences containing executive's speech, presentation and answers to questions posed to them.

sentiment is incrementally informative about the future firm-specific volatility. Alternatively, Baker, Bloom, Davis, and Terry (2020a) indicate that newspaper-based economic uncertainty, and subjective uncertainty in business expectation surveys provide real-time forward-looking measures of COVID-induced uncertainty.

4. Empirical Results

To investigate the effect of COVID-19 pandemic on global market volatility, we estimate the following cross-sectional time series regressions for two different measures of volatility, i.e. RV and GARCH:

Model 1:

$$log(Volatility)_t = \alpha + b_1 log(Active\ Cases)_{t-1} + b_2 Curvature[k]_{t-1} + \varepsilon \quad (11)$$

Model 2:[8]

$$log(Volatility)_t = \alpha + b_1\ log(Active\ Cases)_{t-1} + b_2 Curvature[k]_{t-1} + b_3 \Delta Stringency\ Index_{t-1} + \varepsilon \quad (12)$$

Model 3:

$$log(Volatility)_t = \alpha + b_1\ log(Active\ Cases)_{t-1} + b_2 Curvature[k]_{t-1} + b_3 NSD_{t-1} + \varepsilon \quad (13)$$

where *Volatility* is either the realized volatility (RV) or the GARCH volatility and *NSD* is the negative sentiment differential extracted from earnings call transcripts. While Model 1 is our basic implementation of the multi-regime forecasting estimation, Model 2 includes the changes in the stringency index to control for effects of policy responses to the pandemic on volatility. Model 3 includes managerial negative sentiment as an alternative control variable.

Table 2 presents the descriptive statistics for our variables. We present detailed descriptive statistics of equity market volatilities and our COVID-19 pandemic variables for a cross section of selected 23 countries in Panel A of Appendix 2 (Table A.2).[9]

[8] In Appendix 3, we also estimate model 2 including the alternative measure of disease propagation as follows:

$$log(Volatility)_t = \alpha + b_1 log(Active\ Cases)_{t-1} + b_2 log(Infection\ Rate[k])_{t-1} + b_3 Curvature[k]_{t-1} + \varepsilon$$

[9] We present the panel unit root tests for both volatility measures, RV and GARCH volatility, in Appendix 2, Table A.2 Panel B. Based on the results (four tests total, one for unit root in the entire panel, three for unit root in individual time series), we reject the null hypothesis that there is unit root in log(RV). Although, the null hypothesis that there is unit root in individual time series of log(GARCH Volatility) cannot be rejected, Levin, Lin & Chu test statistic suggests that in the panel, log(GARCH Volatility) does not contain unit root.

We present our panel estimations for the relation between COVID-19 variables and daily global market volatility in Tables 3 and 4, using country-specific ETF transaction price-based RV and country stock index-based GJR-GARCH volatility, respectively. Our panel specifications include both time fixed-effects and country fixed-effects (in models for RV, cross-section of 46 and in models for GARCH, cross-section of 88 countries). We observe that estimated coefficients on lagged *log*(*Active Cases*) as well as on lagged *Curvature*, with lag parameter k=14, are positive and significant for both RV and GARCH volatility in all three models. Results indicate that the *Curvature* is a significant (at 1% and 5% for RV and GARCH, respectively) predictor of daily cross-section of volatility in global equity markets.

Comparing Tables 3 and 4, we observe that the estimated coefficient on lagged changes in stringency index is negative but only significant for GARCH volatility. This result indicates that policy response of increased stringency leads to a decrease in the volatility estimated from daily time-series of stock index returns. Estimated coefficient on negative sentiment differential, extracted from earnings call transcripts is positive and significant only for RV (in Table 4). This finding suggests that, within the multi-regime forecasting framework, cross-section of daily realized volatility estimated from intraday ETF returns increases with higher negative managerial sentiment. In summary, we see that policy response has an impact on daily closing price volatility, while the managerial negative sentiment of firms has an effect on intraday stock price-based volatility.

In Appendix 3, we present the results with alternative lag parameters, i.e. k=7 and k=4. Figure A.3 shows the daily mean *Curvature* values for cross-section of 88 countries with different lag parameters k.[10] Although estimated coefficients on lagged *Curvature* are positive for both measures of volatility, as lag parameter k decreases, significance of *Curvature* decreases in all three models, supporting the choice of 14-day lag parameter for the calculation of *Curvature* in our multi-regime forecasting framework. Furthermore, results presented in Appendix 4 suggest that *Infection Rate* as an alternative measure of disease propagation does not appear to be significant in panel estimations for GARCH volatility for any lag parameter. In panel estimations for RV with 14-day lag parameter, coefficient on *Infection Rate* is found to be insignificant as well.

[10] When k is small, the signal is received quickly but because the case measure is noisy, the curvature is noisy. When k is large, the signal is clearer but it takes longer to see it.

As indicated in Tables 3 and 4, we estimate the multi-regime forecasting models for volatility with panel specification using calendar date as time fixed-effects. Since spread of the coronavirus is reported to start on different calendar days across various countries and its reporting rate may not be uniform throughout the globe, we use an alternative panel specification with COVID Onset fixed-effects which includes the number of days since the first positive case of COVID-19 is reported for each country in panel regressions. In Table 5, we present the results for Models 1 and 2 with a counter which is the *number of days since the first case* of the coronavirus is reported in the JHU database as an alternative to account for the effects of time in our multi-regime forecasting models. In both models and for both types of volatility estimations, when COVID Onset fixed-effects is used, estimated coefficients on *Curvature* (with 14-day lag parameter) are all positive and increase in significance as well as magnitude compared to those from the original time fixed-effects panel specifications. Perhaps this is not surprising because two countries that have the same number of days since first reported COVID-19 infection will have the same time fixed-effect even though the calendar days are different. In the multi-regime model, if the regime changes were known then they would be perfectly collinear with the fixed effects and the curvature would not be important. Since estimated coefficients on *Curvature* are found to be highly significant with the COVID Onset fixed-effects specification, the random timing or regime change is supported. We view this result as confirmation of multi-regime forecasting model to be capturing the regime change in the pandemic volatility relation.

In Appendix 5, we provide robustness tests for our model 1 (equation 11) based on alternative approaches to account for effects of time in our panel estimations. First alternative we employ is using the level of global cases and *Curvature* based on global total active cases for all 88 countries. We identify this panel specification with GLB in our presentation of panel estimations in Table A.5. As a second alternative to time fixed-effects, we use the level of cases in the U.S. and corresponding *Curvature* variable based on active cases reported in the U.S., which we refer to as spillover from the U.S. and identify it with SUS. Results presented in Table A.5 show that, for both volatility measures RV and GARCH, estimated coefficients on *Curvature* remain positive and highly significant in GLB and SUS panel specifications. While results in Appendix 5 support our multi-regime forecasting model specification for the relation between equity market volatility and coronavirus pandemic, they also present the rather interesting spillover hypotheses that magnitude of the pandemic at the global and the U.S. level impacts the equity market volatility of individual countries.

5. Conclusions

This paper presents a multi-regime forecasting framework for analyzing the impact of COVID-19 pandemic on volatility in global equity markets. We hypothesize that the *Curvature* of active cases is a powerful predictor of daily cross section of volatilities. We test our hypothesis using two different measures of volatility together with additional control variables in a panel setting. We show that the daily number of active cases and the *Curvature* are significant predictors of daily cross-section of both realized volatility and the GJR-GARCH volatility in global equity markets over the period of January 22nd to May 1st of 2020.

We estimate realized volatilities using intraday 5-minute returns for 46 country specific ETFs and daily GARCH volatilities are estimated using the stock market indices of 88 countries around the world. We use the Textual Data Analytics of Transcripts database of the S&P Global Market Intelligence for 6,500 publicly traded firms from 38 countries to calculate negative sentiment differentials during our sample period. We find that stricter policy responses by individual countries, measured by higher OxCGRT *Stringency Index*, result in lower stock market volatilities while increased negative managerial sentiment, extracted from earnings call transcripts, causes an increase in realized volatilities.

Results based on alternative panel specifications support our multi-regime forecasting model for the relation between equity market volatility and the coronavirus pandemic; while offering rather interesting spillover hypotheses that magnitude of the pandemic at the global and the U.S. level impacts the equity market volatility of individual countries.

References

Albuquerque, Rui A., Yrjo J. Koskinen, Shuai Yang, and Chendi Zhang (2020). “Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash.” *European Corporate Governance Institute – Finance Working Paper* No. 676/2020.

Alfaro, Laura, Anusha Chari, Andrew Greenland, and Peter K. Schott (2020). “Aggregate and Firm-Level Stock Returns During Pandemics, in Real Time.” *NBER Working Paper* No. 26950.

Alvarez, Fernando, David Argente, and Francesco Lippi (2020). “A Simple Planning Problem for COVID-19 Lockdown.” *NBER Working Paper* No. 26981.

Atkeson, Andrew (2020). “What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios.” *NBER Working Paper* No. 26867.

Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle J. Kost, Marco C. Sammon, and Tasaneeya Viratyosin (2020). “The Unprecedented Stock Market Impact of COVID-19.” *NBER Working Paper* No. 26945.

Baker, Scott R., Nicholas Bloom, Steven J. Davis, and Stephen J. Terry (2020a). “COVID-Induced Economic Uncertainty.” *NBER Working Paper* No.26983.

Baker, Scott R., Nicholas Bloom, and Stephen J. Terry (2020b). “Using Disasters to Estimate the Impact of Uncertainty.” *NBER Working Paper* No. 27167.

Davis, A.K., Ge, W., Matsumoto, D., and Zhang, J. L.(2015). “The effect of manager-specific optimism on the tone of earnings conference calls.” *Review of Accounting Studies* 20, pp. 639–673.

Demers, E., and Vega, C. (2014). “Understanding the role of managerial optimism and uncertainty in the price formation process: evidence from the textual content of earnings announcements.” Working paper. University of Virginia.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, (1993). “On the relation between the expected value and the volatility of nominal excess return on stocks.” *Journal of Finance* 48, pp.1779–1801.

Guerrieri, Veronica ,Guido Lorenzoni, Ludwig Straub, and Iván Werning (2020). “Macroeconomic Implications of COVID-19 Can Negative Supply Shocks Cause Demand Shortages.” *NBER Working Paper* No. 26918.

Loughran, Tim and Bill McDonald (2011). "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks". *Journal of Finance* 66.1, pp. 35–65.

Mayew, William J., and Mohan Venkatachalam. (2012). "The Power of Voice: Managerial Affective States." The *Journal of Finance* 67 (1), pp. 1–43.

Pope, David, and Frank Zhao (2017). "Capital Markets Hanging on Every Word: Natural Language Processing Unlocks New Frontier in Corporate Earnings Sentiment Analysis". *S&P Global Market Intelligence Quantamental Research Paper*.

Price, McKay S., James S. Doran, David R. Peterson, and Barbara A. Bliss (2012). "Earnings Conference Calls and Stock Returns: The Incremental Informativeness of Textual Tone". *Journal of Banking and Finance* 36.4, pp. 992–1011.

Ramelli, Stefano, and Alexander F. Wagner (2020). "Feverish Stock Price Reactions to COVID-19." *Swiss Finance Institute Research Paper Series* 20-12.

Zhao, Frank (2017). "Natural Language Processing, Part I: Primer, Unveiling the Hidden Information in Earnings Calls". *S&P Global Market Intelligence Quantamental Research Paper*.

Table 1, Panel A

List of 88 Countries and Equity Market Indices used for GARCH Volatility Estimations

No	ISO code	Country Name	Equity Market Index Name
1	ARE	United Arab Emirates	Abu Dhabi Securities Market General Index
2	ARG	Argentina	S&P MERVAL Argentina Index
3	AUS	Australia	S&P/ASX 200
4	AUT	Austria	Vienna Stock Exchange Austrian Traded Index
5	BEL	Belgium	BEL 20 Index
6	BGD	Bangladesh	Bangladesh DSE Broad Index
7	BGR	Bulgaria	SOFIX Index
8	BHR	Bahrain	Bahrain Bourse All Share Index
9	BIH	Bosnia and Herzegovina	Sarajevo Stock Exchange Index 30
10	BRA	Brazil	Ibovespa Brasil Sao Paulo Stock Exchange Index
11	BWA	Botswana	S&P Botswana BMI USD
12	CAN	Canada	S&P/TSX Composite Index
13	CHE	Switzerland	Swiss Market Index
14	CHL	Chile	Santiago Stock Exchange IPSA Index
15	CHN	China	Shanghai Shenzhen CSI 300 Index
16	CIV	Cote d'Ivoire	S&P Cote D'Iviore Broad Market Index
17	COL	Colombia	Colombia COLCAP Index
18	CYP	Cyprus	Cyprus Stock Exchange General Index
19	CZE	Czech Republic	Prague Stock Exchange Index
20	DEU	Germany	Deutsche Boerse AG German Stock Index DAX
21	DNK	Denmark	OMX Copenhagen 20 Index
22	ECU	Ecuador	Ecuador Guayaquil Stock Exchange BVG
23	EGY	Egypt, Arab Rep.	Egyptian EGX 30 Price Return Index
24	ESP	Spain	IBEX 35 Index
25	EST	Estonia	OMX Tallinn Index
26	FIN	Finland	OMX Helsinki 25 Index
27	FRA	France	CAC 40 Index
28	GBR	United Kingdom	FTSE 100 Index
29	GHA	Ghana	Ghana Stock Exchange Composite Index
30	GRC	Greece	Athens Stock Exchange General Index
31	HKG	Hong Kong SAR, China	Hong Kong Hang Seng Index
32	HRV	Croatia	Croatia Zagreb Stock Exchange Crobex Index
33	HUN	Hungary	Budapest Stock Exchange Budapest Stock Index
34	IDN	Indonesia	Jakarta Stock Exchange Composite Index
35	IND	India	S&P BSE SENSEX Index
36	IRL	Ireland	ISEQ All-Share Index
37	IRQ	Iraq	Iraq Stock Exchange Index
38	ISL	Iceland	OMX Iceland All-Share Index
39	ISR	Israel	Tel Aviv 35 Index
40	ITA	Italy	FTSE MIB Index
41	JAM	Jamaica	Jamaica Stock Exchange Market Index
42	JOR	Jordan	Amman Stock Exchange General Index
43	JPN	Japan	Nikkei 225
44	KAZ	Kazakhstan	Kazakhstan Stock Exchange Index KASE

Table 1, Panel A (continued)

List of 88 Countries and Equity Market Indices used for GARCH Volatility Estimations

No	ISO code	Country Name	Equity Market Index Name
45	KEN	Kenya	Nairobi Securities Exchange Ltd All Share Index
46	KOR	Korea, Rep.	Korea Stock Exchange KOSPI Index
47	KWT	Kuwait	Boursa Kuwait Premier Market Index
48	LBN	Lebanon	Blom Stock Index
49	LKA	Sri Lanka	Sri Lanka Colombo Stock Exchange All Share Index
50	LTU	Lithuania	OMX Vilnius Index
51	LUX	Luxembourg	Luxembourg Stock Exchange LuxX Index
52	LVA	Latvia	OMX Riga Index
53	MAR	Morocco	Morocco Casablanca Stock Exchange CFG 25
54	MEX	Mexico	Mexican Stock Exchange Mexican Bolsa IPC Index
55	MMR	Myanmar	Solactive Myanmar-Focused Asia Index
56	MNG	Mongolia	Mongolia Stock Exchange Top 20 Index
57	MYS	Malaysia	FTSE Bursa Malaysia KLCI Index - Kuala Lumpur Comp. Index
58	NGA	Nigeria	Nairobi Securities Exchange Ltd All Share Index
59	NLD	Netherlands	AEX-Index
60	NOR	Norway	Oslo Stock Exchange OBX Index
61	NZL	New Zealand	S&P/NZX All Index
62	OMN	Oman	Muscat Securities MSM 30 Index
63	PAK	Pakistan	Karachi Stock Exchange KSE100 Index
64	PAN	Panama	Bolsa de Valores de Panama General Index
65	PER	Peru	Bolsa de Valores de Lima General Sector Index
66	PHL	Philippines	Philippines Stock Exchange PSEi Index
67	POL	Poland	Warsaw Stock Exchange WIG Total Return Index
68	PRT	Portugal	PSI All-Share Index Gross Return
69	ROU	Romania	Bucharest Stock Exchange Trading Index
70	RUS	Russian Federation	MOEX Russia Index
71	SAU	Saudi Arabia	Tadawul All Share TASI Index
72	SGP	Singapore	Straits Times Index STI
73	SVK	Slovak Republic	Slovakia SAX 16
74	SWE	Sweden	OMX Stockholm 30 Index
75	TCD	Chad	Solactive Dubai Price Index
76	THA	Thailand	Stock Exchange of Thailand SET 50 Index
77	TUN	Tunisia	Tunisia Stock Exchange TUNINDEX
78	TUR	Turkey	Borsa Istanbul 100 Index
79	TWN	Taiwan, China	Taiwan Stock Exchange Weighted Index
80	TZA	Tanzania	Tanzania Share Index Real Time
81	UGA	Uganda	Uganda SE All Share Index
82	UKR	Ukraine	Ukraine PFTS Index
83	USA	United States	S&P 500 Index
84	VEN	Venezuela, RB	Caracas Stock Exchange Stock Market Index
85	VNM	Vietnam	Vietnam Hanoi Stock Exchange Equity Index
86	ZAF	South Africa	FTSE/JSE Africa Top40 Tradeable Index
87	ZMB	Zambia	Lusaka Stock Exchange All Share Index
88	ZWE	Zimbabwe	Zimbabwe Stock Exchange Industriali Index

Table 1, Panel B

List of 46 Country ETFs used for Intraday Realized Volatility Calculations

No	Symbol	ISO code	Country Specific ETF
1	ECH	CHL	iShares MSCI Chile ETF
2	EDEN	DNK	iShares MSCI Denmark ETF
3	EFNL	FIN	iShares MSCI Finland ETF
4	EGPT	EGY	VanEck Vectors Egypt Index ETF
5	EIDO	IDN	iShares MSCI Indonesia ETF
6	EIRL	IRL	iShares MSCI Ireland ETF
7	EIS	ISR	iShares MSCI Israel ETF
8	ENOR	NOR	iShares MSCI Norway ETF
9	ENZL	NZL	iShares Trust iShares MSCI New Zealand ETF
10	EPHE	PHL	iShares MSCI Philippines ETF
11	EPOL	POL	iShares MSCI Poland ETF
12	EPU	PER	iShares MSCI Peru ETF
13	ERUS	RUS	iShares MSCI Russia ETF
14	EWA	AUS	iShares MSCI Australia ETF
15	EWC	CAN	iShares MSCI Canada ETF
16	EWD	SWE	iShares MSCI Sweden ETF
17	EWG	DEU	iShares MSCI Germany ETF
18	EWH	HKG	iShares MSCI Hong Kong ETF
19	EWI	ITA	iShares MSCI Italy ETF
20	EWJ	JPN	iShares MSCI Japan ETF
21	EWK	BEL	iShares MSCI Belgium ETF
22	EWL	CHE	iShares MSCI Switzerland ETF
23	EWM	MYS	iShares MSCI Malaysia ETF
24	EWN	NLD	iShares MSCI Netherlands ETF
25	EWO	AUT	iShares MSCI Austria ETF
26	EWP	ESP	iShares MSCI Spain ETF
27	EWQ	FRA	iShares MSCI France ETF
28	EWS	SGP	iShares MSCI Singapore ETF
29	EWT	TWN	iShares MSCI Taiwan ETF
30	EWU	GBR	iShares MSCI United Kingdom ETF
31	EWW	MEX	iShares MSCI Mexico ETF
32	EWY	KOR	iShares MSCI South Korea ETF
33	EWZ	BRA	iShares MSCI Brazil ETF
34	EZA	ZAF	iShares MSCI South Africa ETF
35	GREK	GRC	Global X MSCI Greece ETF
36	ICOL	COL	iShares MSCI Colombia ETF
37	INDA	IND	iShares MSCI India ETF
38	MCHI	CHN	iShares MSCI China ETF
39	NGE	NGA	Global X MSCI Nigeria ETF
40	PAK	PAK	Global X MSCI Pakistan ETF
41	PGAL	PRT	Global X MSCI Portugal ETF
42	QAT	QAT	iShares Trust iShares MSCI Qatar ETF
43	SPY	USA	SPDR S&P 500 ETF Trust
44	THD	THA	iShares MSCI Thailand ETF
45	TUR	TUR	iShares MSCI Turkey ETF
46	VNM	VNM	VanEck Vectors Vietnam ETF

Table 2

Descriptive Statistics for Global Equity Market Volatility and COVID-19 Pandemic
January 22 to May 1, 2020

	N	mean	median	stdev	5th percentile	95th percentile
Log(RV-5min)	3,240	4.417	4.429	1.652	1.741	7.274
Log(GARCH Volatility)	5,894	3.202	3.199	0.754	1.907	4.378
Log(Active Cases)	6,336	7.796	7.767	4.662	1.792	13.638
Curvature(A,k=14)	5,456	-0.016	-0.016	0.823	-1.142	1.590
Curvature(A,k=7)	5,896	-0.013	0.000	0.380	-0.522	0.568
Curvature(A,k=4)	6,160	-0.006	0.000	0.198	-0.272	0.271
InfectionRate(A,k=14)	5,456	1.169	0.764	1.452	-0.490	4.081
InfectionRate(A,k=7)	5,896	0.553	0.270	0.820	-0.280	2.223
InfectionRate(A,k=4)	6,160	0.304	0.121	0.502	-0.173	1.302
Stringency Index	5,752	45.86	46.82	35.71	0.00	94.71
Negative Sentiment Differential	1,344	0.002	0.002	0.003	-0.003	0.006

RV is the realized volatility calculated using intraday 5-minute returns of country specific ETFs. GARCH is the GJR-GARCH volatility using country stock index levels (GARCH volatilities are obtained from https://vlab.stern.nyu.edu/). Curvature(A, *k*=14) indicates that lag parameter *k*=14 is used for the log(Active Cases). ‡ Stringency Index is from the Oxford University's revised calculation of the stringency index as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values. † NSD is the *Negative Sentiment Differential* extracted from earnings call transcripts. All variables are based on 3-day average *log(Active Cases)*.

$Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

$Infection\ Rate[k]_t = log(Active\ Cases)_{(t)} - log(Active\ Cases)_{(t-k)}$

Table 3

Relation between COVID-19 Pandemic and Daily Global Market Volatility based on intraday Realized Volatility using Country-specific ETF Transaction Prices

Model 1: $log(RV)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + c

Model 2: $log(RV)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + b(3) $\Delta log(Stringency\ Index^{‡})_{t-1}$ + c

Model 3: $log(RV)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + b(3) $NSD^{\dagger}_t$ + c

where $Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

January 22 to May 1, 2020

	Log(Daily Realized Volatility)$_t$		
Log(Active Cases)$_{t-1}$	0.068	0.067	0.080
	[4.39]***	[3.85]***	[5.03]***
Curvature(A,k=14)$_{t-1}$	0.061	0.050	0.092
	[3.59]***	[2.80]***	[3.57]***
ΔLog(Stringency Index)$_{t-1}$		-0.133	
		[-1.39]	
Negative Sentiment Differential$_t$			52.230
			[2.26]**
Intercept	2.002	1.880	1.455
	[13.84]***	[9.89]***	[8.67]***
Time Fixed-Effects	**YES**	**YES**	**YES**
Country Fixed-Effects	**YES**	**YES**	**YES**
R-Sq-within	0.795	0.783	0.851
R-Sq-between	0.221	0.035	0.352
N	2,655	2,278	1,000

RV is the realized volatility calculated using intraday 5-minute returns of country specific ETFs. Curvature(A, k=14) indicates that lag parameter k=14 is used for the l*og(Active Cases)*. ‡ Stringency Index is from the Oxford University's revised calculation of the stringency index as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values. † NSD is the *Negative Sentiment Differential* extracted from earnings call transcripts. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

Table 4

Relation between COVID-19 Pandemic and Daily Global Market Volatility based on GJR-GARCH Volatility using Country Stock Index Levels

Model 1: $log(GARCH)_t$ = b(1) $log(Active\ Cases)_{t\text{-}1}$ + b(2) $Curvature[k]_{t\text{-}1}$ + c

Model 2: $log(GARCH)_t$ = b(1) $log(Active\ Cases)_{t\text{-}1}$ + b(2) $Curvature[k]_{t\text{-}1}$ + b(3) $\Delta log(Stringency\ Index^{\ddagger})_{t\text{-}1}$ + c

Model 3: $log(GARCH)_t$ = b(1) $log(Active\ Cases)_{t\text{-}1}$ + b(2) $Curvature[k]_{t\text{-}1}$ + b(3) $NSD^{\dagger}_t$ + c

where $Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t\text{-}k)} - 2{*}log(Active\ Cases)_{(t\text{-}k/2)}$

January 22 to May 1, 2020

	Log(Daily GARCH Volatility)$_t$		
Log(Active Cases)$_{t\text{-}1}$	0.067	0.066	0.049
	[4.00]***	[3.77]***	[3.31]***
Curvature(A,k=14)$_{t\text{-}1}$	0.017	0.018	0.022
	[2.10]**	[2.09]**	[2.32]**
ΔLog(Stringency Index)$_{t\text{-}1}$		-0.085	
		[-1.99]**	
Negative Sentiment Differential$_t$			-10.417
			[-0.82]
Intercept	2.632	2.619	2.641
	[66.99]***	[48.93]***	[56.50]***
Time Fixed-Effects	**YES**	**YES**	**YES**
Country Fixed-Effects	**YES**	**YES**	**YES**
R-Sq-within	0.671	0.649	0.878
R-Sq-between	0.239	0.259	0.289
N	4,783	3,861	1,079

GARCH is the GJR-GARCH volatility using country stock index levels (GARCH volatilities are obtained from https://vlab.stern.nyu.edu/). Curvature(A, *k*=14) indicates that lag parameter *k*=14 is used for the log(Active Cases). ‡ Stringency Index is from the Oxford University's revised calculation of the stringency index as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values. † NSD is the Negative Sentiment Differential extracted from earnings call transcripts. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

Table 5

Panel Specifications with *COVID Onset* Fixed-Effects for the Relation between COVID-19 Pandemic and Daily Global Market Volatility

Model 1: $log(Volatility)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + c

Model 2: $log(Volatility)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + b(3) $\Delta log(Stringency\ Index^{\ddagger})_{t-1}$ + c

where $Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

In Panel A *Volatility* = RV, which is based on intraday Realized Volatility using Country-specific ETFs Prices

In Panel B *Volatility* = GARCH, which is based on GJR-GARCH Volatility using Country Stock Index Levels

January 22 to May 1, 2020

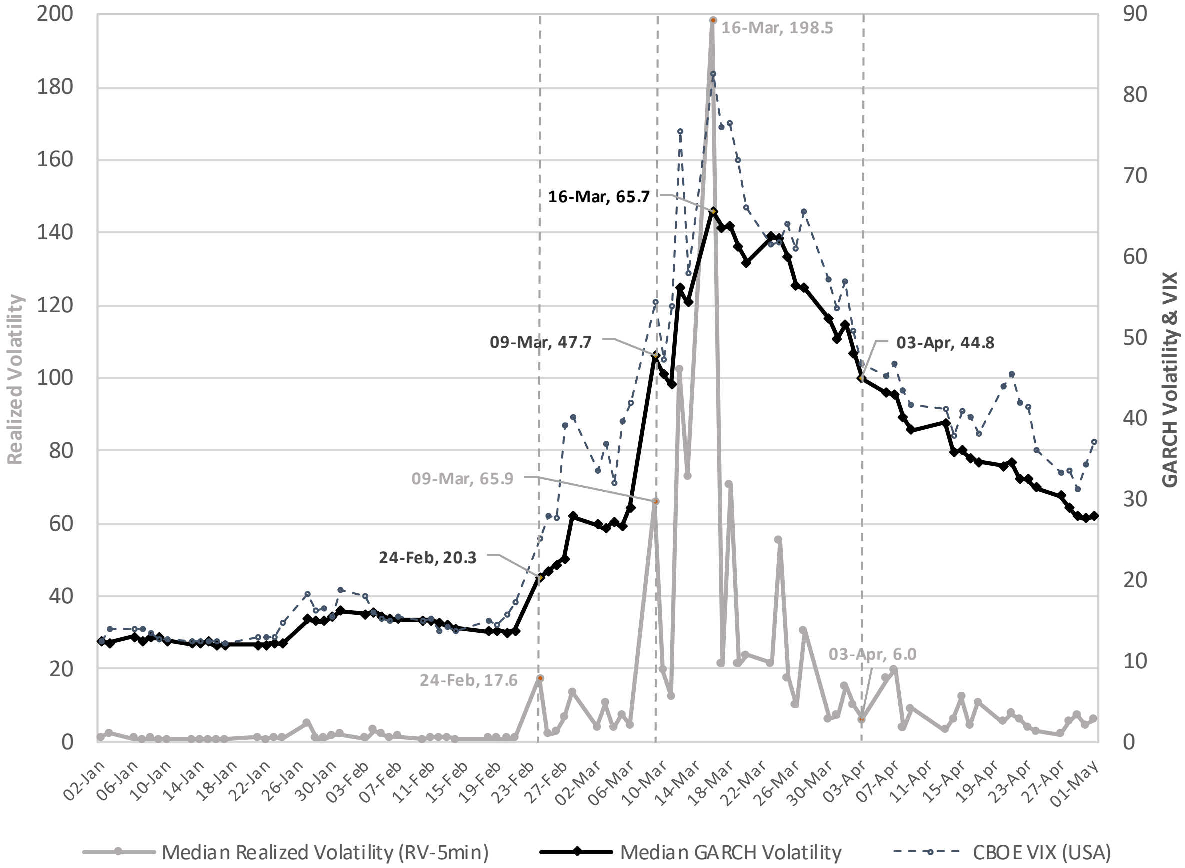
	Panel A		Panel B	
	Log(Daily Realized Volatility)$_t$		**Log(Daily GARCH Volatility)$_t$**	
	Model 1	**Model 2**	**Model 1**	**Model 2**
Log(Active Cases)$_{t-1}$	0.167	0.167	0.116	0.115
	[3.17]***	[2.96]***	[6.48]***	[6.08]***
Curvature(A,k=14)$_{t-1}$	0.284	0.244	0.075	0.056
	[6.30]***	[5.63]***	[6.01]***	[5.07]***
ΔLog(Stringency Index)$_{t-1}$		-2.423		-0.556
		[-8.66]***		[-7.63]***
Intercept	4.728	4.317	3.218	3.162
	[14.52]***	[8.64]***	[51.63]***	[34.66]***
Covid Onset Fixed-Effects	**YES**	**YES**	**YES**	**YES**
Country Fixed-Effects	**YES**	**YES**	**YES**	**YES**
R-Sq-within	0.146	0.197	0.178	0.208
R-Sq-between	0.144	0.052	0.112	0.068
N	2,348	2,129	3,716	3,275

COVID Onset fixed-effects is measuring the number of days since the first positive case of COVID-19 is reported for each country. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

Figure 1

Daily Median Realized Volatility and GARCH Volatility for Global Equity Markets and VIX(USA)†

January 22 to May 1, 2020



† VIX(USA) is the CBOE's Volatility Index (VIX). Realized volatility is calculated for 46 countries using intraday 5-minute returns of country specific ETFs. GARCH volatility is the GJR-GARCH volatility using country stock index levels for 88 countries.

Figure 2, Panel A

Daily GARCH Volatility for selected 7 countries January 22 to May 1, 2020

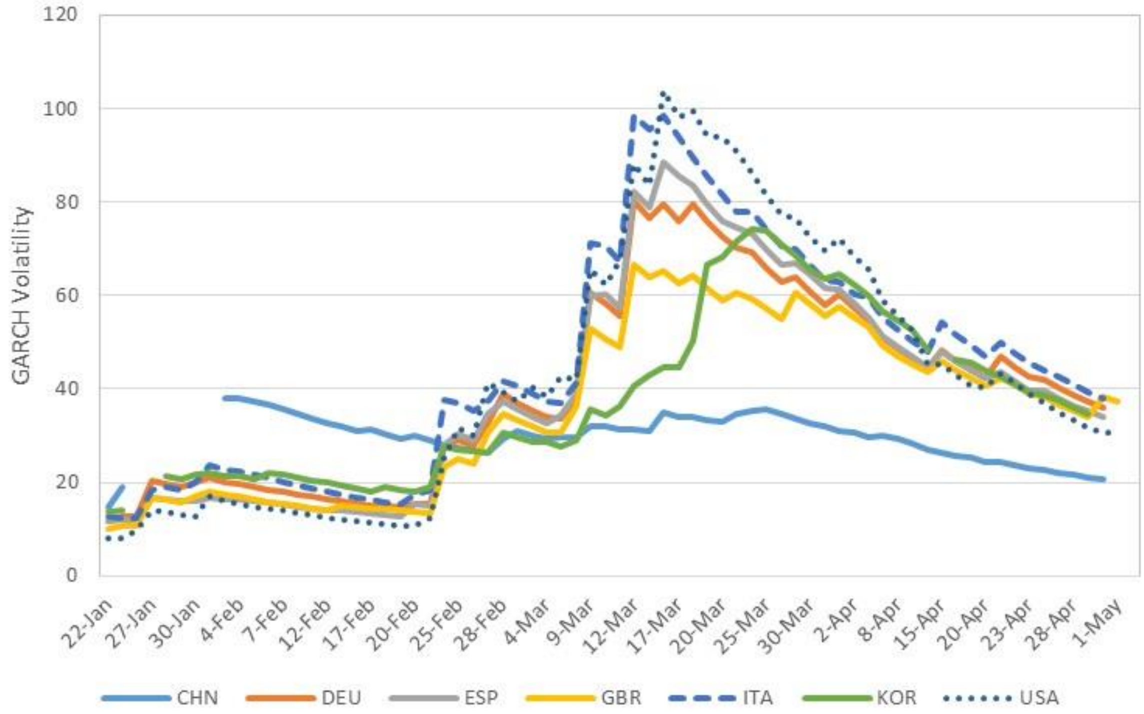


Figure 2, Panel B

Daily Realized Volatility (5-min) for selected 7 countries January 22 to May 1, 2020

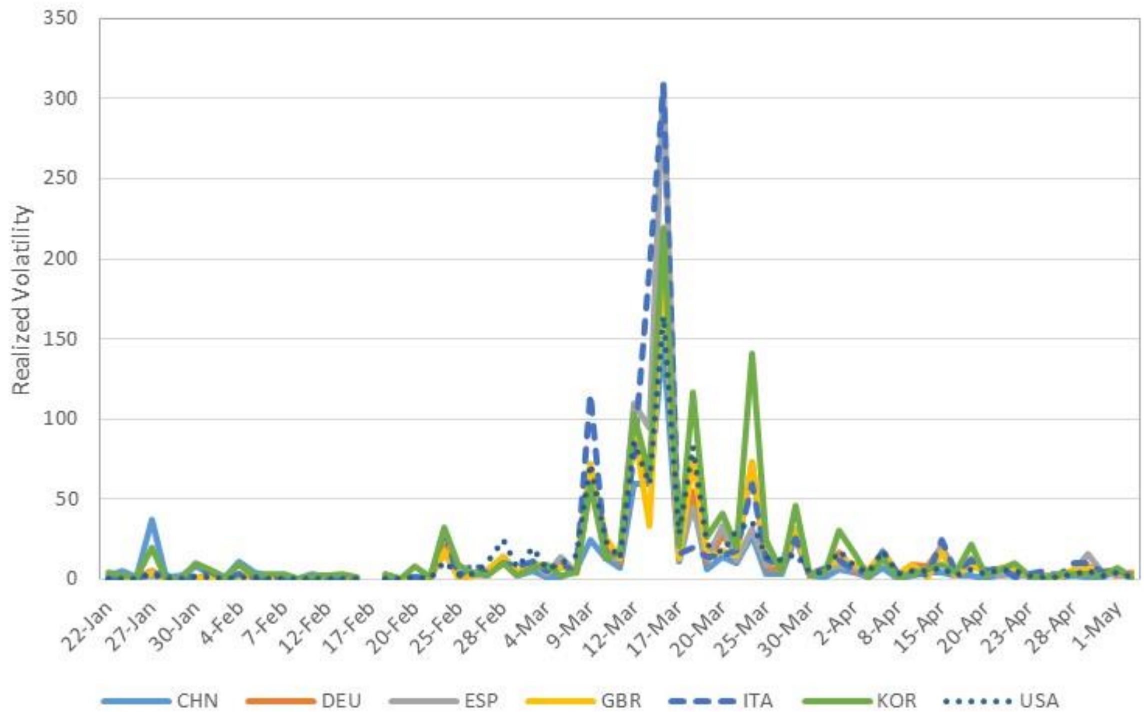
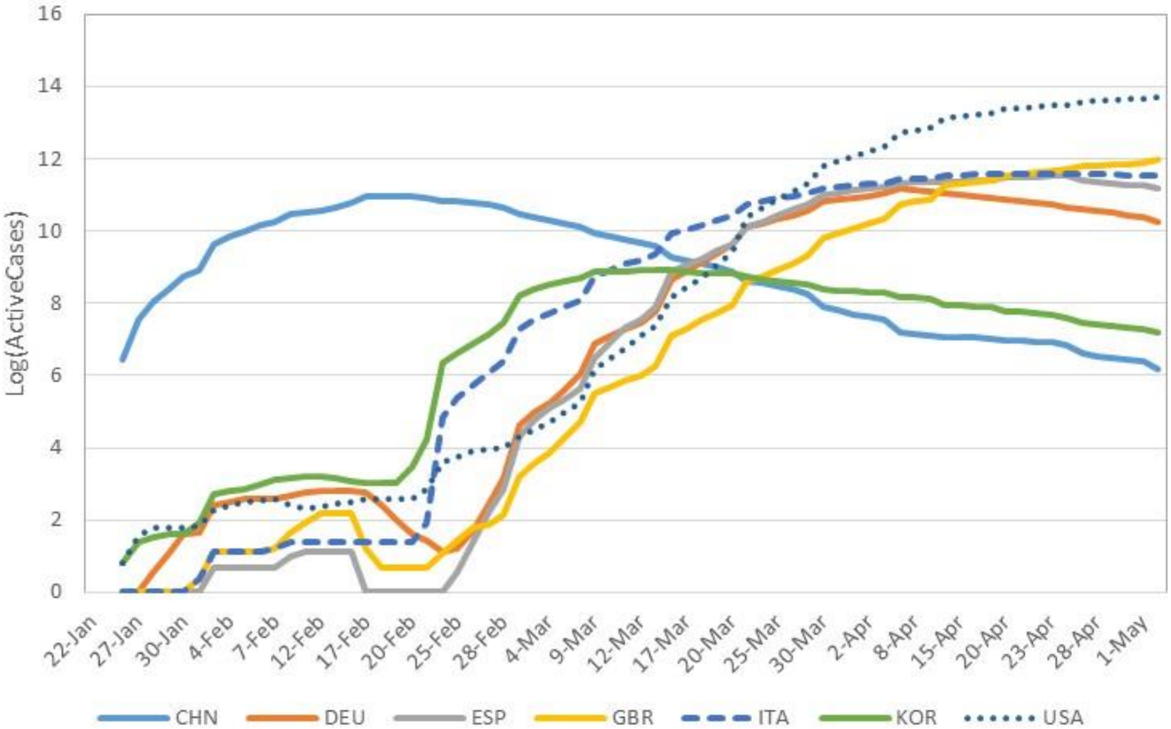


Figure 3

Daily COVID-19 Cases† for selected 7 countries
January 22 to May 1, 2020



† COVID-19 case variable is based on the 3-day average of *log(Active Cases)*.

Figure 4

Log(Active Cases) vs. Realized Volatility and GARCH Volatility on
Feb 24, Mar 9, Mar 16, Apr 3, Apr 30, 2020

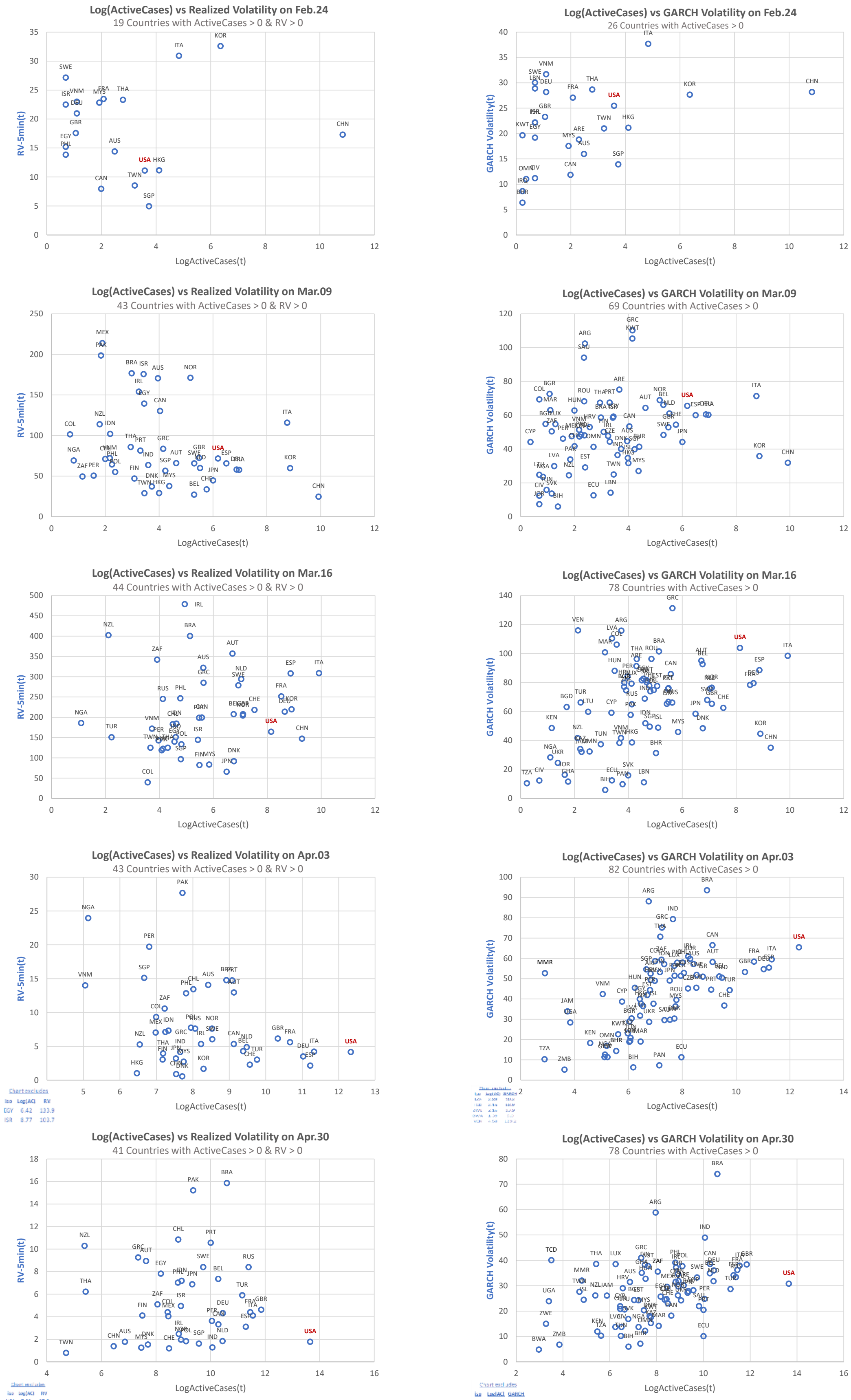
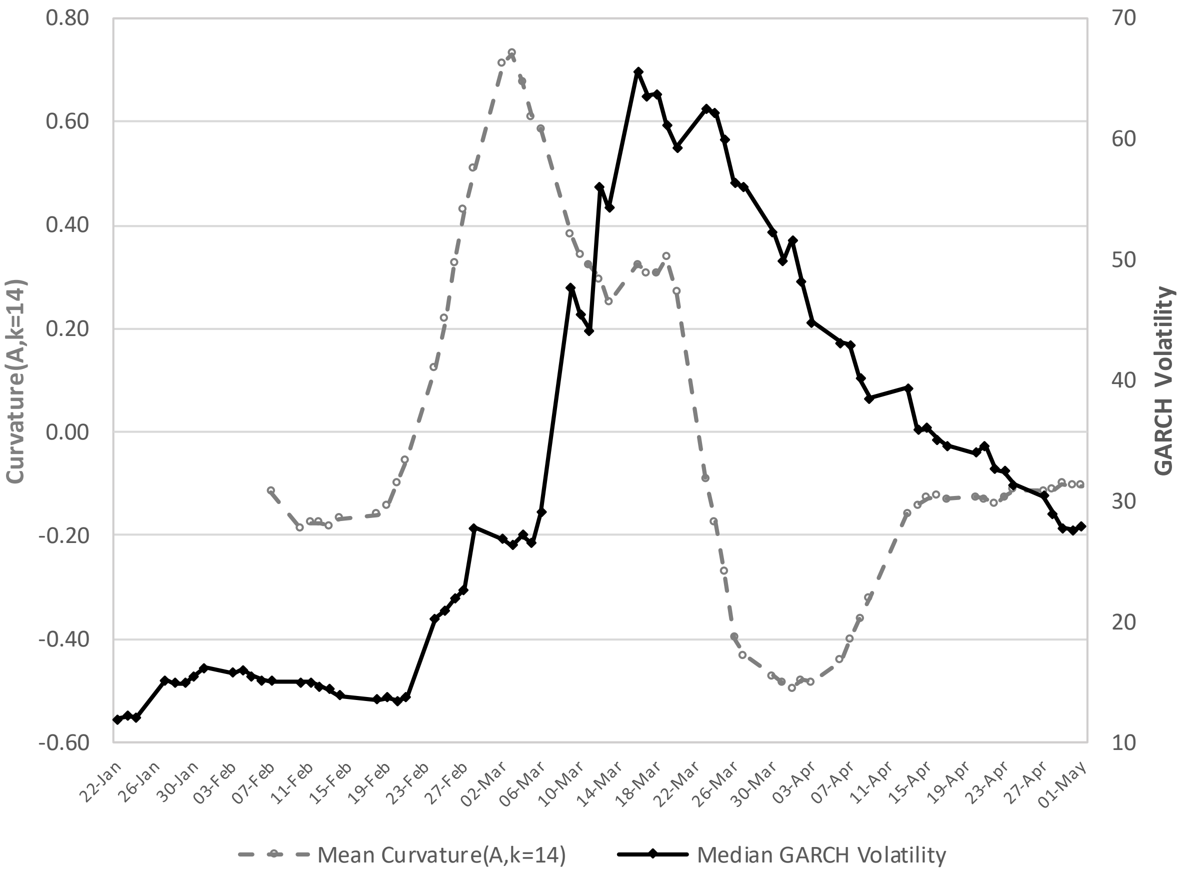


Figure 5

Daily Median GARCH Volatility for Global Equity Markets vs Mean Global COVID-19 Curvature†

January 22 to May 1, 2020



† COVID-19 Curvature is calculated using:

$Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

where case variable is based on the 3-day average of log(Active Cases) and lag parameter k is 14.

APPENDIX 1

Simulation Modeling

We simulate a series of switching points (each simulation could be thought of as a separate country). For the simulations, let t_1 and t_2 have the following distributions:

$$t_1 \sim rnd * 30$$

$$t_2 \sim t_1 + rnd * 80$$

where rnd is a uniform random variable on (0,1). Hence, the mean of t_1 is 15 days and the mean of t_2 is 55 days. According to Figure 2, most countries seem to have reached t_2 by the beginning of May. While China and Korea seem to have entered the concave region first, U.S. is the last one to get there among the seven countries in Figure 2. It should also be noted that the minimum value that t_2 can take is 1, therefore, theoretically, a country can be in the concave region from the beginning.

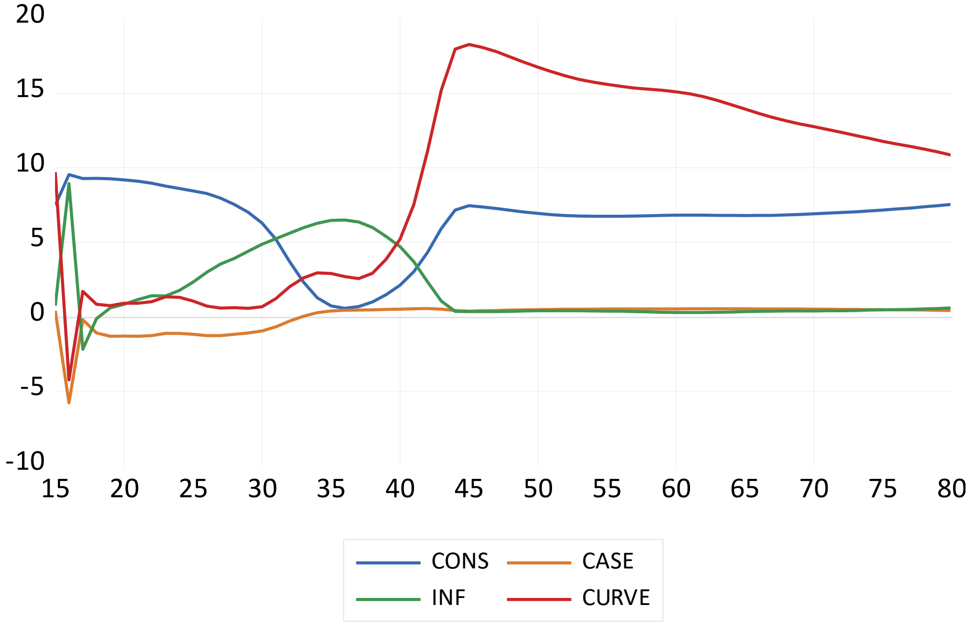
For 1000 countries, we draw values of t_1 and t_2. Then, assuming $a = .05$ (which doubles in 20 days), $b = .09$ (which means the growth rate is $.14$ per day and will double in 5 days), and $g = -.003$, the mean of t_{max} is 78 days, which means we expect the countries to reach peak number of cases in about 2.5 months from their first case.

Financial markets may reflect the estimate of y_{max} based on partial information. Suppose markets observe the current and lagged levels of cases. They might use rates of change and accelerations as other measures. More sophisticated statistical procedures could be adopted but may not be appropriate given the simple nature of the model.

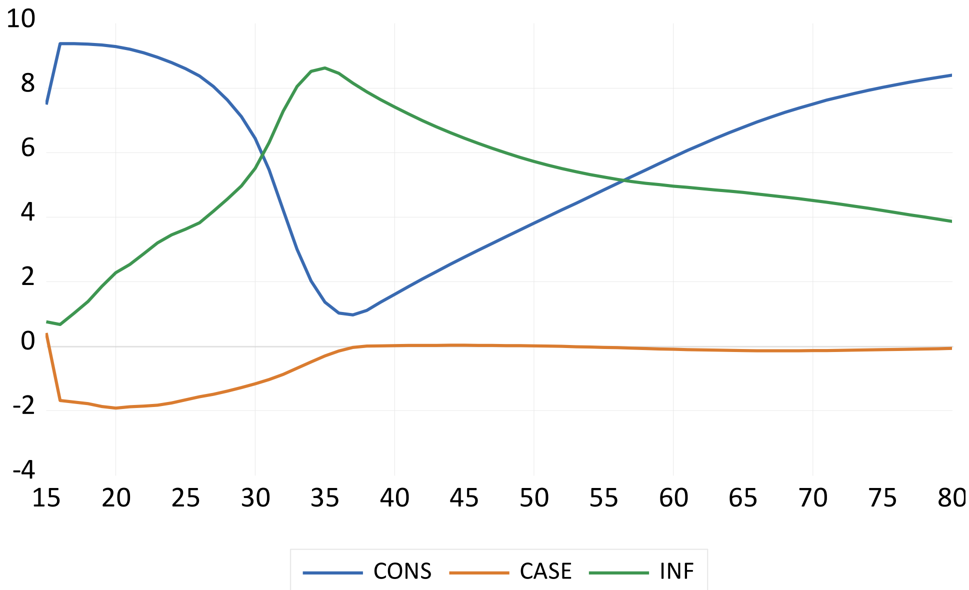
We regress y_{max} on $c,\ y_t,\ (y_t - y_{t-k}),\ \left(y_t + y_{t-k} - 2y_{t-\frac{k}{2}}\right)$, letting k=14 days which is the typical quarantine period. We run this model for all days from day 15 to day 80. If day 1 is Jan 22 when many measurements began, then day 80 would be mid-April. Coefficient estimates for each variable and day are shown in Figure A1, Panel A. We also run the model without the curvature variable, and the corresponding coefficients are presented in Panel B of Figure A1.

Figure A.1

Panel A: Simulated Coefficients including Curvature



Panel B: Simulated Coefficients excluding Curvature



APPENDIX 2

Table A.2, Panel A

Detailed Descriptive Statistics for Cross Section of Selected 23 Countries: Equity Market Volatility & COVID-19 Pandemic

	Log(RV-5min)					Log(GARCH Volatility)					Stringency Index				
			Percentile					Percentile					Percentile		
iso	N	median	5th	95th	stdev	N	median	5th	95th	stdev	N	median	5th	95th	stdev
AUS	72	4.29	1.47	7.90	1.90	70	3.52	2.31	4.22	0.71	71	19.44	7.94	70.78	25.51
AUT	72	4.91	2.00	7.21	1.64	70	3.69	2.61	4.51	0.69	74	49.73	0.00	84.79	37.47
BEL	72	4.16	1.24	6.49	1.65	70	3.71	2.57	4.42	0.63	74	23.94	0.00	83.60	35.96
CAN	72	4.24	0.97	7.08	1.85	71	3.65	1.94	4.44	0.95	71	13.89	2.78	79.90	36.25
CHN	72	3.78	2.13	6.65	1.33	65	3.41	3.05	3.60	0.18	74	57.95	44.59	66.42	8.22
DEU	72	4.22	1.23	6.86	1.65	70	3.66	2.69	4.34	0.57	74	37.57	7.14	78.97	30.80
ESP	72	3.97	1.29	6.95	1.72	70	3.63	2.55	4.41	0.64	73	47.10	0.00	89.41	37.92
FIN	72	4.21	2.13	6.61	1.41	70	3.68	2.67	4.15	0.57	74	45.50	7.14	75.13	30.56
FRA	72	4.26	1.29	6.96	1.74	70	3.67	2.65	4.33	0.60	74	36.31	10.72	93.38	37.02
GBR	72	4.31	1.02	7.05	1.74	71	3.60	2.60	4.16	0.58	74	11.11	0.00	82.27	35.68
HKG	72	3.72	1.97	6.68	1.44	67	3.29	2.98	3.81	0.28	74	55.95	41.67	69.84	12.60
IND	72	4.22	1.15	7.18	1.80	66	3.58	2.57	4.49	0.74	74	30.36	5.42	100.00	43.14
ITA	72	4.32	1.52	7.12	1.65	70	3.73	2.73	4.54	0.60	74	87.43	2.78	94.58	35.10
JPN	72	3.65	1.20	6.56	1.53	69	3.48	2.81	4.01	0.42	74	48.40	2.78	51.18	18.29
KOR	72	4.20	2.20	7.40	1.48	68	3.58	2.89	4.26	0.47	74	58.46	0.00	83.46	25.36
NLD	72	4.15	1.11	6.86	1.64	70	3.62	2.58	4.31	0.59	74	48.80	0.00	82.00	38.85
NZL	72	4.53	2.58	7.50	1.48	69	3.22	2.14	3.87	0.59	74	19.44	0.00	97.35	40.08
RUS	72	4.67	2.38	7.94	1.52	70	3.61	2.72	4.20	0.55	74	26.20	0.00	92.86	38.86
SGP	72	3.69	1.37	6.65	1.54	73	3.40	2.24	4.12	0.62	37	74.07	37.70	91.80	21.91
SWE	72	4.35	1.34	6.95	1.68	70	3.61	2.57	4.17	0.57	74	18.25	0.00	47.35	20.42
TUR	72	4.04	2.17	6.58	1.30	71	3.53	2.96	4.07	0.39	74	25.26	2.78	80.42	31.74
TWN	72	3.84	1.87	6.90	1.40	63	3.40	3.01	3.92	0.29	74	29.36	19.44	32.01	4.64
USA	72	4.19	1.49	7.04	1.70	73	3.69	2.37	4.54	0.76	74	28.18	0.00	71.58	30.73

Table A.2, Panel A (continued)
Detailed Descriptive Statistics for Cross Section of Selected 23 Countries: Equity Market Volatility & COVID-19 Pandemic

	Log(Active Cases)					Curvature(A,k)			InfectionRate(A,k)		
			Percentile			k=14	k=7	k=4	k=14	k=7	k=4
iso	N	median	5th	95th	stdev	mean	mean	mean	mean	mean	mean
AUS	72	5.23	1.79	8.46	2.67	-0.14	-0.04	-0.03	0.87	0.41	0.26
AUT	72	6.26	0.00	9.09	3.83	-0.03	0.01	0.00	1.26	0.57	0.31
BEL	72	6.35	0.00	10.27	4.31	-0.01	0.00	0.00	1.63	0.77	0.42
CAN	72	5.21	0.96	10.27	3.60	-0.06	-0.01	-0.01	1.46	0.72	0.43
CHN	72	8.81	6.45	10.94	1.58	-0.19	-0.05	-0.01	-0.35	-0.11	-0.02
DEU	72	8.22	1.07	11.09	4.04	-0.16	-0.08	0.01	1.46	0.73	0.41
ESP	72	8.39	0.00	11.51	4.83	-0.06	0.00	0.02	1.79	0.84	0.46
FIN	72	4.94	0.00	7.76	3.26	-0.05	-0.01	-0.01	1.15	0.55	0.31
FRA	72	8.19	1.60	11.47	4.13	-0.05	-0.09	-0.06	1.59	0.76	0.41
GBR	72	6.68	0.00	11.84	4.47	-0.06	-0.03	-0.02	1.82	0.89	0.47
HKG	72	4.18	2.26	6.53	1.37	-0.11	-0.04	-0.02	0.52	0.25	0.16
IND	72	4.41	0.00	10.02	3.78	-0.06	-0.02	0.05	1.50	0.75	0.39
ITA	72	9.65	0.00	11.58	4.50	-0.08	-0.04	-0.07	1.79	0.86	0.46
JPN	72	6.38	1.76	9.33	2.42	-0.11	-0.05	-0.02	1.13	0.58	0.33
KOR	72	7.76	1.61	8.90	2.59	-0.13	-0.08	-0.05	0.88	0.44	0.23
NLD	72	6.70	0.00	10.43	4.45	0.01	-0.02	-0.02	1.68	0.78	0.42
NZL	72	1.95	0.00	6.81	2.80	-0.04	-0.04	-0.01	0.91	0.40	0.20
RUS	72	3.72	0.00	11.34	4.32	-0.03	-0.05	-0.05	1.72	0.85	0.45
SGP	72	4.65	1.98	9.54	2.35	-0.07	-0.05	-0.03	1.14	0.59	0.34
SWE	72	6.68	0.00	9.70	3.82	-0.03	-0.07	0.00	1.50	0.73	0.36
TUR	72	1.64	0.00	11.26	4.99	-0.01	-0.03	0.00	1.81	0.83	0.44
TWN	72	3.56	2.06	5.73	1.29	-0.09	-0.03	-0.01	0.46	0.22	0.14
USA	72	7.77	1.79	13.64	4.69	-0.05	-0.04	-0.03	1.88	0.90	0.51

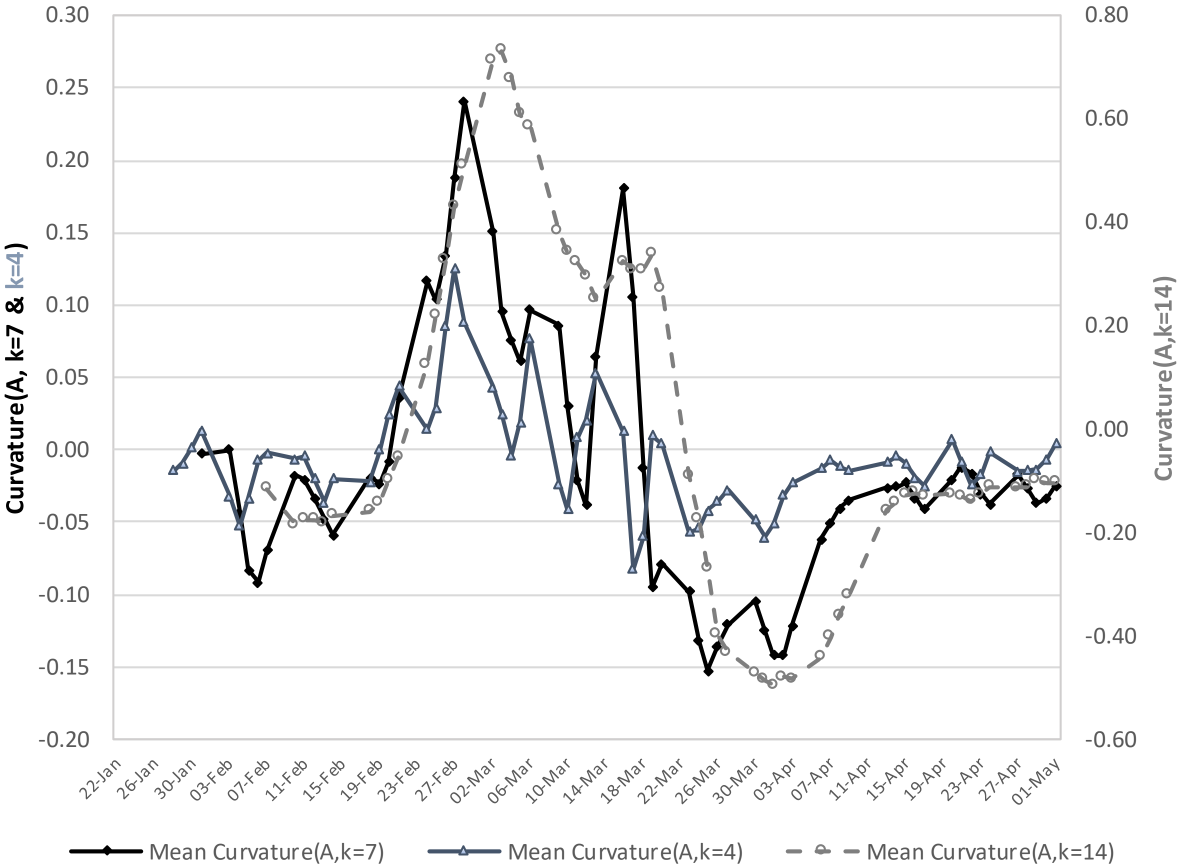
Table A.2, Panel B
Panel Unit Root Tests for Realized Volatility (RV-5min) and GARCH Volatility

	Log(RV-5min)		Log(GARCH Volatility)	
Unit Root Testing Methods†	**Statistic (Prob.‡)**	**Obs. (#of Cross Sections)**	**Statistic (Prob.‡)**	**Obs. (#of Cross Sections)**
Ho: Unit root (assuming common unit root process)				
(a) Levin, Lin & Chu t*	-5.954	3,296	-3.338	4,949
	(0.0000)	(44)	(0.0004)	(63)
Ho: Unit root (assuming individual unit root processes)				
(b) Im, Pesaran and Shin W-stat	-4.308	3,296	1.525	4,949
	(0.0000)	(44)	(0.9364)	(63)
(c) ADF - Fisher Chi-square	157.61	3,296	90.08	4,949
	(0.0000)	(44)	(0.9934)	(63)
(d) PP - Fisher Chi-square	464.92	3,520	91.89	4,988
	(0.0000)	(44)	(0.9903)	(63)

†Automatic selection of maximum lags based on SIC and Newey-West automatic bandwidth selection and Bartlett kernel. Exogenous variables are the individual effects. ‡ Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

APPENDIX 3

Figure A.3
Daily Mean Global COVID-19 Curvature† with various values of the *k* parameter
January 22 to May 1, 2020



† COVID-19 Curvature is calculated using:
$Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$
where case variable is based on the 3-day average of *log(Active Cases)* and lag parameter k=14, k=7 and k=4.

Table A.3 Models for RV
Using Alternative Lag Parameters for the Relation between COVID-19 Pandemic and Daily Global Market Volatility

Model 1: $log(Volatility)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + c

Model 2: $log(Volatility)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + b(3) $\Delta log(Stringency\ Index^{‡})_{t-1}$ + c

Model 3: $log(Volatility)_t$ = b(1) $log(Active\ Cases)_{t-1}$ + b(2) $Curvature[k]_{t-1}$ + b(3) $NSD^{†}_t$ + c

where $Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

In Panel A *Volatility* = RV, which is based on intraday Realized Volatility using Country-specific ETFs Prices

In Panel B *Volatility* = GARCH, which is based on GJR-GARCH Volatility using Country Stock Index Levels

Panel A

January 22 to May 1, 2020

	Log(Daily Realized Volatility)$_t$					
	k=7			k=4		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Log(Active Cases)$_{t-1}$	0.075	0.075	0.085	0.075	0.078	0.085
	[4.30]***	[3.88]***	[4.99]***	[4.07]***	[3.86]***	[5.03]***
Curvature(A,k)$_{t-1}$	0.081	0.077	0.095	0.001	0.042	0.051
	[2.02]**	[1.76]*	[1.68]*	[0.02]	[0.50]	[0.68]
ΔLog(Stringency Index)$_{t-1}$		-0.146			-0.162	
		[-1.50]			[-1.52]	
Negative Sentiment Differential$_t$			38.075			33.600
			[2.62]**			[3.35]***
Intercept	2.470	2.343	2.231	2.288	2.148	2.009
	[24.10]***	[15.96]***	[13.53]***	[19.81]***	[10.01]***	[13.64]***
Time Fixed-Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Country Fixed-Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
R-Sq-within	0.798	0.785	0.843	0.797	0.783	0.840
R-Sq-between	0.256	0.087	0.312	0.263	0.116	0.340
N	2,880	2,421	1,111	3,015	2,485	1,175

RV is the realized volatility calculated using intraday 5-minute returns of country specific ETFs. *Curvature(A, k)* indicates that lag parameter *k* is used for the l*og(Active Cases)*. ‡ Stringency Index is from the Oxford University's revised calculation of the stringency index as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values. † NSD is the Negative Sentiment Differential extracted from earnings call transcripts. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

Table A.3 Models for GARCH
Using Alternative Lag Parameters for the Relation between COVID-19 Pandemic and Daily Global Market Volatility

Model 1: *log(Volatility)*$_t$ = b(1) *log(Active Cases)*$_{t-1}$ + b(2) *Curvature[k]*$_{t-1}$ + c
Model 2: *log(Volatility)*$_t$ = b(1) *log(Active Cases)*$_{t-1}$ + b(2) *Curvature[k]*$_{t-1}$ + b(3) Δ*log(Stringency Index*‡*)*$_{t-1}$ + c
Model 3: *log(Volatility)*$_t$ = b(1) *log(Active Cases)*$_{t-1}$ + b(2) *Curvature[k]*$_{t-1}$ + b(3) *NSD*$^{†}_{t}$ + c
where *Curvature[k]*$_t$ = *log(Active Cases)*$_{(t)}$ + *log(Active Cases)*$_{(t-k)}$ – 2**log(Active Cases)*$_{(t-k/2)}$
In Panel B *Volatility* = GARCH, which is based on GJR-GARCH Volatility using Country Stock Index Levels

Panel B

January 22 to May 1, 2020

	Log(Daily GARCH Volatility)$_t$					
	k=7			k=4		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Log(Active Cases)$_{t-1}$	0.073	0.073	0.052	0.076	0.076	0.052
	[4.13]***	[3.89]***	[3.63]***	[4.12]***	[3.81]***	[3.65]***
Curvature(A,k)$_{t-1}$	0.029	0.027	0.020	0.042	0.047	0.054
	[1.83]*	[1.59]	[1.16]	[1.67]*	[1.75]*	[2.03]**
ΔLog(Stringency Index)$_{t-1}$		-0.085			-0.078	
		[-2.07]**			[-1.94]*	
Negative Sentiment Differential$_t$			-5.181			-1.492
			[-0.59]			[-0.22]
Intercept	2.674	2.688	2.748	2.663	2.682	2.685
	[72.33]***	[50.48]***	[61.60]***	[74.44]***	[41.15]***	[52.26]***
Time Fixed-Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Country Fixed-Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
R-Sq-within	0.677	0.663	0.879	0.680	0.663	0.880
R-Sq-between	0.242	0.271	0.231	0.234	0.276	0.220
N	5,217	4,111	1,197	5,475	4,228	1,262

GARCH is the GJR-GARCH volatility using country stock index levels (GARCH volatilities are obtained from https://vlab.stern.nyu.edu/). *Curvature(A, k)* indicates that lag parameter *k* is used for the l*og(Active Cases)*. ‡ Stringency Index is from the Oxford University's revised calculation of the stringency index as of April 28, 2020, i.e. Stringency Index prior to April 28 are not the original (legacy) values. † NSD is the Negative Sentiment Differential extracted from earnings call transcripts. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

APPENDIX 4

Table A.4
Using Alternative Measure of Disease Propagation for the Relation between COVID-19 Pandemic and Daily Global Market Volatility

$log(Volatility)_t = b(1)\ log(Active\ Cases)_{t-1} + b(2)\ Infection\ Rate[k]_{t-1} + b(3)\ Curvature[k]_{t-1} + c$
where $Infection\ Rate[k]_t = log(Active\ Cases)_{(t)} - log(Active\ Cases)_{(t-k)}$
$Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$
In Panel A *Volatility* = RV, which is based on intraday Realized Volatility using Country-specific ETFs Prices
In Panel B *Volatility* = GARCH, which is based on GJR-GARCH Volatility using Country Stock Index Levels

January 22 to May 1, 2020

	Panel A			Panel B		
	Log(Daily Realized Volatility)$_t$			Log(Daily GARCH Volatility)$_t$		
	k=14	k=7	k=4	k=14	k=7	k=4
Log(Active Cases)$_{t-1}$	0.058	0.062	0.064	0.064	0.071	0.074
	[3.35]***	[3.47]***	[3.54]***	[3.38]***	[3.77]***	[3.90]***
Infection Rate(A,k)$_{t-1}$	0.029	0.089	0.163	0.009	0.019	0.032
	[1.36]	[3.24]***	[3.76]***	[0.67]	[1.02]	[1.25]
Curvature(A,k)$_{t-1}$	0.060	0.079	0.009	0.017	0.028	0.041
	[3.54]***	[1.96]*	[0.12]	[2.04]**	[1.82]*	[1.61]
Intercept	1.992	2.437	2.244	2.630	2.670	2.659
	[13.42]***	[23.19]***	[19.18]***	[65.94]***	[70.00]***	[72.58]***
Time Fixed Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
Country Fixed Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
R-Sq-within	0.796	0.799	0.799	0.671	0.677	0.681
R-Sq-between	0.174	0.200	0.222	0.239	0.243	0.236
N	2,655	2,880	3,015	4,783	5,217	5,475

RV is the realized volatility calculated using intraday 5-minute returns of country specific ETFs. GARCH is the GJR-GARCH volatility using country stock index levels (GARCH volatilities are obtained from https://vlab.stern.nyu.edu/). *Curvature(A, k)* and *Infection Rate(A, k)* indicate that lag parameter *k* is used for the l*og(Active Cases)*. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.

APPENDIX 5

Table A.5

Panel Specifications with Time Fixed Effects (TFE) vs Global Cases & Curvature (GLB) vs USA Cases & Curvature (SUS) for the Relation between COVID-19 Pandemic and Daily Global Market Volatility

Model 1: $log(Volatility)_t = b(1)\ log(Active\ Cases)_{t-1} + b(2)\ Curvature[k]_{t-1} + c$

where $Curvature[k]_t = log(Active\ Cases)_{(t)} + log(Active\ Cases)_{(t-k)} - 2*log(Active\ Cases)_{(t-k/2)}$

In Panel A *Volatility* = RV, which is based on intraday Realized Volatility using Country-specific ETFs Prices

In Panel B *Volatility* = GARCH, which is based on GJR-GARCH Volatility using Country Stock Index Levels

January 22 to May 1, 2020

	Panel A			**Panel B**		
	Log(Daily Realized Volatility)$_t$			**Log(Daily GARCH Volatility)$_t$**		
	(TFE)	**(GLB)**	**(SUS)**	**(TFE)**	**(GLB)**	**(SUS)**
Log(Active Cases)$_{t-1}$	0.068	0.209	0.161	0.067	0.120	0.068
	[4.39]***	[6.75]***	[3.68]***	[4.00]***	[7.73]***	[3.64]***
Curvature(A,k=14)$_{t-1}$	0.061	0.107	0.186	0.017	0.016	0.065
	[3.59]***	[3.81]***	[5.05]***	[2.10]**	[2.02]**	[5.94]***
Log(Active Cases[GLB])$_{t-1}$		-0.397			-0.147	
		[-6.27]***			[-4.43]***	
Curvature[GLB](A,k=14)$_{t-1}$		1.918			0.557	
		[21.99]***			[12.27]***	
Log(Active Cases[USA])$_{t-1}$			0.036			0.025
			[1.11]			[1.72]*
Curvature[USA](A,k=14)$_{t-1}$			1.056			0.220
			[35.61]***			[13.17]***
Intercept	2.002	8.714	3.554	2.632	4.680	2.833
	[13.84]***	[14.21]***	[50.92]***	[66.99]***	[13.82]***	[56.21]***
Time Fixed-Effects	**YES**	No	No	**YES**	No	No
Country Fixed-Effects	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
R-Sq-within	0.795	0.485	0.282	0.671	0.545	0.330
R-Sq-between	0.221	0.226	0.217	0.239	0.249	0.248
N	2,655	2,655	2,655	4,783	4,783	4,783

TFE is time fixed-effects, GLB is global cases & curvature, SUS is spillover from the US. RV is the realized volatility calculated using intraday 5-minute returns of country specific ETFs. GARCH is the GJR-GARCH volatility using country stock index levels (GARCH volatilities are obtained from https://vlab.stern.nyu.edu/). *Curvature(A, k=14)* indicate that lag parameter *k=14* is used for the l*og(Active Cases)*. All variables are based on 3-day average *log(Active Cases)* in Panel Regressions. Panel regressions include both time fixed-effects and country-level fixed-effects. ***, **, * indicate significance at 1%, 5%, and 10%, respectively. t-statistics based on robust standard errors are displayed in brackets.