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COVID-19, Mobility Restriction Policies and Stock Market Volatility: A Cross-Country Empirical Study

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CAMA Working Paper 40/2023
August 2023

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Abstract

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Keywords

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JEL Classification

G10, G11, G12

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ISSN 2206-0332

Covid-19, Mobility Restriction Policies and Stock Market Volatility: A Cross-Country Empirical Study

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Abstract

This study investigates the impact of Covid-19 infections and mobility restriction policies on stock market volatility. We estimate panel data models for seven countries using daily data from February 12, 2020 to April 14, 2021. Our results show that the number of new cases of Covid-19 infections and the introduction of mobility restriction policies plays a crucial role in shaping stock market volatility during the pandemic. We found that new cases of Covid-19 infections and mobility restrictions policies increase stock market jumps, rather than increase continuous volatility. We also find that mobility restriction policies lessen the impact of new Covid-19 cases on stock market volatility.

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1. Introduction

The Covid-19 pandemic began in early 2020 and has profoundly impacted the global economy and financial markets. Governments worldwide enforce lockdowns, travel restrictions, and social distancing measures to halt the spread of the virus. These measures caused disruptions to businesses, supply chains, and consumer spending patterns. Consequently, investors and financial markets faced significant uncertainties and challenges. The Covid-19 pandemic and the worldwide lockdown restrictions imposed by governments led to the largest annual decline in World GDP since this measure was created in 1961 by the World Bank.

This paper investigates the impact of new cases of Covid-19 infections and government-imposed mobility restrictions on stock market volatilities of the U.S., Canada, Australia, Germany, France, Japan, and China using daily panel data from February 12, 2020 to April 14, 2021. We use a well-recognized measure of mobility restriction policies from the Oxford Covid-19 Government Response Tracker, also known as the "stringency index," to gauge the level of restrictions on mobility imposed by government policies.[1] From here, we use the terms "mobility policy restrictions" and "stringency index" interchangeably to simplify matters.

Figure 1 highlights a slightly negative correlation between continuous volatility and new cases of Covid-19 infections, compared to a more positive correlation between jump volatility and new Covid-19 cases. Figure 2 presents a contrasting view to the previous figure, displaying a positive correlation between the stringency index and continuous volatility. When analyzing volatility, there is a closer relationship between stringency index and continuous volatility than jump volatility. It is also important to note that individual countries display unique characteristics when analyzing volatility separately.

This article contributes to the literature by providing a deeper understanding of what components of stock market realized volatility (continuous or jump volatility) is affected by new

[1] The stringency index is a composite measure based on nine response indicators, including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100(100 = strictest). For more information, please see https://ourworldindata.org/covid-stringency-index.

cases of Covid-19 infections and mobility restriction policies.[2] We identify four streams of literature that examine the effect of Covid-19 on the stock market. The first stream of research was pioneered by Baker et al. (2020a) and investigates the impact of the Covid-19 pandemic on the initial crash of the stock market in March 2020. Among others, Cox et al. (2020), Doko Tchatoka et al. (2022), Liu et al. (2021), and Mazur et al. (2021) also conducted studies on this topic. The second stream of literature examines the impact of Covid-19 uncertainty on stock market volatility (see, for example, Baker et al. (2020b), Zhang et al., 2020, He et al., (2020a), Endri et al., (2021), Harjoto et al., 2020).

Almeida et al. (2020), Brueckner et al. (2023), Brueckner and Vespignani (2021), He et al. (2020b), Zhang and Hamori (2021), and Mazur et al. (2020), study the third stream of literature focusing on the impact of the pandemic on the different stock market sectors and indexes. The fourth stream of literature concerns how government intervention, such as mobility restrictions and vaccinations, affects the stock market. Studies by Aharon and Siev (2021), Ashraf (2020), Remba et al. (2020), Zaremba et al. (2020), and Bakry et al. (2022) also explore this topic. This research paper falls under two streams: the stream that explores the correlation between the uncertainty caused by Covid-19 and the volatility of the stock market, as well as the stream that studies the effects of government mobility restrictions discussed in the existing literature.

Our results indicate that new Covid-19 cases and mobility restriction policies increase the stock market's volatility during the Covid-19 pandemic. We further break down the realized volatility of the stock market into jumps and continuous volatility. We found that new cases of Covid-19 infections and mobility restrictions policies increase stock market jumps rather than continuous volatility, providing important insights for market participants. These results support the notion that market participants closely react to public health announcements and government actions, resulting in heightened volatility in the stock market. We also introduce in our model the interaction term between new cases of Covid-19 infections and mobility restriction policies. The

[2] Note that jumps in volatility provide a rapidly moving but persistent factor driving volatility, unlike continuous volatility.

results indicate mobility restriction policies lessen the impact of new Covid-19 cases on stock market volatility.

The rest of the paper is structured as follows: Section 2 presents the literature review; Section 3 provides the methodology and data; results are presented and discussed in Section 4, and Section 5 concludes.

2. Literature Review

There has been a significant increase in studies examining the transmission mechanism of Covid-19 uncertainty on stock market volatility. Albulescu (2021) explores how official announcements of new cases of Covid-19 infections affect market volatility in the U.S. The findings show that financial market volatility in the U.S. increases when there is a surge in worldwide infections and fatality rates. Baek et al. (2020) also found that the news on Covid-19 significantly impacted the volatility of the U.S. stock market. However, Cheng (2020) found that Chicago Board Options Exchange's Volatility Index (VIX) futures prices underreacted to the early stages of the Covid-19 pandemic. Li et al. (2020) extended the investigation to pandemic uncertainty indices and European markets. They found that the Disease Equity Market Volatility tracker (IDEMV) had significant predictive power for the volatility of France and U.K. stock markets. Mazur et al. (2021) also extended the published research by exploring specific components of market volatility. They investigated the U.S. stock market performance during the Covid-19 pandemic and found that loser stocks exhibiting extreme volatility were negatively correlated with stock returns. Our paper further extends the literature by examining pandemic uncertainty indices in relation to the volatility components of jump and continuous volatility across international markets.

The expanding literature on Covid-19 has also examined the market settings that drive or mitigate volatility. Engelhardt et al. (2021) investigated whether trust affected global stock market volatility during the Covid-19 pandemic and found that the volatility of stock markets was significantly lower in high-trust countries. Hsu and Tang (2022) studied the relationship between investor sentiment and the unexpected component of stock market volatility during the Covid-19 pandemic. The authors found that greater Covid-19-related investor sentiment is associated with higher stock market uncertainty. Anastasiou et al. (2022) explored the predictive power of a positive search volume index for Covid-19 (i.e., a proxy for investors' sentiment during the Covid-19 pandemic). They found that investor sentiment positively (negatively) predicts the stock return (Volatility) during Covid-19. Our research contributes further to the literature by investigating the role mobility restriction policies impacts volatility.

With specific regard to how mobility restriction policies affect stock markets, Remba et al. (2020) conducted a study to determine if government actions to control the spread of Covid-19 impacted stock market stability. The authors found that non-pharmaceutical interventions significantly increased volatility in the stock market. According to Aharon and Siev (2021) and Ashraf (2020), government restrictions have a negative impact on stock market returns by hindering economic activity. This implies that restrictions raise public awareness about the pandemic, which may increase fear leading to a negative response in stock markets. Zaremba et al. (2020) similarly show that non-pharmaceutical government interventions significantly increase volatility in the stock market. Bakry et al. (2022) find not all markets react in the same way. Their research reveals government actions increase volatility in emerging markets but decrease volatility in developed markets. We therefore attempt to resolve these conflicting findings by analyzing the impact of mobility restrictions in international markets through separating jump from continuous volatility.

3. Methodology and Data

For this study, we use daily data from seven countries' stock market indices: the U.S. (S&P 500), Canada (GSPTSE), Australia (S&P/ASX 200), Germany (GDAXI), France (FCHI), Japan (N225), and China (SSEC). Our analysis covers the period from February 12, 2020 to April 14, 2021. To estimate volatility, we use a 5-minute return series approach following Andersen and Bollerslev (1997), Andersen et al. (2007), and Huang and Tauchen (2005). We obtained the data from the Refinitiv (Datascope) database to generate our volatility measures. Before estimating the returns, we removed overnight prices from the data. Data description and sources, descriptive statistics and unit root tests are detailed in Appendix A, tables A1, A2 and A3 respectively. The data was adjusted to account for weekends and public holidays in each country. The discrete-time high-frequency return is defined as follows:

$$r_{t,\Delta} = p_t - p_{t-\Delta} \tag{1}$$

where $p_{t,}$ is the t-th high-frequency log price, and $N = 1/\Delta$ is the number of infill observations for the 5-minute sampling interval. The realized variance is defined as the sum of squared high-frequency returns as given by:

$$RV_t(\Delta) = \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2 \to \int_{t-1}^{t} \sigma_s^2 \, ds + \sum_{k=1}^{N(t)} J_{t,j}^2 , \quad as \quad N \to \infty \tag{2}$$

where $\int_{t-1}^{t} \sigma_s^2 ds$ is the integrated volatility, $\sum_{k=1}^{N_t} J_{t,j}^2$ is the quadratic variation of the jump component. In the high-frequency finance literature, the realized variance is mostly referred to as realized volatility. We decompose the daily RV into its continuous and jump components; this study employs the approach documented in Giot et al. (2010), where the jump volatility (JV) and continuous volatility (CV) are estimated as follows.

$$JV_{t,\alpha}(\Delta) = I_{t,\alpha}(\Delta)[RV_t(\Delta) - BV_t(\Delta)], \qquad I_{t,\alpha}(\Delta) \equiv I[Z_t(\Delta) > \phi_\alpha] \tag{3}$$

$$CV_{t,\alpha}(\Delta) = \left[1 - I_{t,\alpha}(\Delta)\right]\left[RV_t(\Delta) + I_{t,\alpha}(\Delta)BV_t(\Delta)\right] \tag{4}$$

Where BV_t is the realized bi-power variation of Barndorff-Nielsen and Shephard (2004), which can be formally defined as:

$$BV_t(\Delta) = \frac{\pi}{2} \frac{N}{N-1} \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}| \to \int_{t-1}^{t} \sigma_s^2 ds, \quad as\, N \to \infty \tag{5}$$

Following Giot et al. (2010), we use a conservative significance level of α=0.01% for identifying the significant jumps. The Z statistic for jumps is defined as:

$$Z_t(\Delta) = \Delta^{-1/2} \frac{[RV_t(\Delta) - BV_t(\Delta)]RV_t(\Delta)^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5)max\{1, TQ_t(\Delta)BV_t(\Delta)^{-2}\}]^{1/2}} \quad (6)$$

where $\mu_1 = \sqrt{2/\pi}$, $TQ(\Delta)$ is the Tri-Power Quarticity, which is a robust jump estimator and can be defined as:

$$TQ_t(\Delta) = \frac{N}{N-2} \frac{N}{[2^{2/3}\Gamma(7/6)\Gamma(1/2)]^3} \sum_{j=3}^{1/\Delta} \left|r_{t+j\Delta,\Delta}\right|^{4/3} \left|r_{t+(j-1)\Delta,\Delta}\right|^{4/3} \left|r_{t+(j-2)\Delta,\Delta}\right|^{4/3} \quad (7)$$

To examine the relationships between volatility and new cases of Covid-19 infections, we estimate Equation 8 using the following panel data regression models as commonly applied in the extant literature: (i) pooled ordinary least square (pooled OLS); (ii) fixed effect (F.E.); and (iii) random effect (RE) models. We employ the most restrictive model as our benchmark model in Table 1, Column (4). Our benchmark model, which captures country and time-fixed effects is:

$$Volatility_{it} = \alpha_i + \beta X_{it} + \delta_t + \mu_i + \varepsilon_{it} \quad (8)$$

where the subscripts i *and* t denote countries $(i = 1, 2, .., n)$ and time $(t = 1,2, \ldots, T)$, ε_{it} is the overall error term, volatility is the outcome variable (*i.e.*, realized volatility (RV), continuous volatility (CV), and jump volatility (JV)) for country *i* at time *t*, X is a vector of predictors (*i.e.*, new Covid-19 case index (RCI), stringency index, the volatility index (VIX), Absres (absolute residuals)) for country *i* at time *t*, α_i is is the unknown intercept for each country, δ_t is the unknown coefficient for the time regressors (*t*), μ_i within-entity error term and β is represents a common effect across countries controlling for individual and time heterogeneity.

4. Empirical Findings

Table 1 shows the relationship between the independent variables (i.e., new Covid-19 case index (RCI), stringency index, volatility index (VIX), Absres (absolute residuals)) and the dependent variable stock market volatility. Our measures of stock market volatility are RV., CV, and JV. The table is divided into three panels. Panel A: the dependent variable is RV., Panel B: the dependent variable is CV, and Panel C: the dependent variable is JV. These tables include the regression outcomes for each panel using different model specifications. The results are presented in four columns: (1) Pooled OLS, (2) Period Fixed Effect (FE.), (3) Country FE., and (4) Country & Period F.E. Note that our benchmark model is the strictest criterion (Column 4).

Panel A consistently shows a positive and statistically significant association between the RCI and RV across all model specifications. The coefficient values range from 0.0139 to 0.0199 and are statistically significant at conventional levels in all cases. These findings suggest that an increase in the RCI is associated with higher levels of realized volatility in the stock market. The positive coefficient indicates that a rise in new cases of Covid-19 infections is linked to an increase in market volatility.

Furthermore, the stringency index shows a positive relationship with RV, with coefficient values ranging from 0.0092 to 0.0120. These coefficients are statistically significant across all specifications, although pooled OLS and period F.E. are only statistically significant at the 10% level. This implies that higher mobility restrictions implemented by governments contribute to a sizable increase in stock market volatility. This is consistent with Zaremba et al. (2020), who found that government interventions to curb the spread of Covid-19 increase stock market volatility. However, the authors do not distinguish between continuous and jump volatilities. In addition, the VIX index also shows a positive relationship with RV, with coefficient values ranging from 0.0974 to 0.2440. This coefficient is statistically significant at conventional levels in all model specifications. The absolute residuals (Absres) coefficient also indicates a positive and statistically significant association with RV, with coefficient values ranging from 0.2170 to 0.2910. In all model specifications, the coefficients show that the interaction between the stringency index and realized volatility is negative and statistically significant. The values range from -0.0031 to -0.0037, suggesting that mobility policy restriction lessens the impact of new cases of Covid-19 infections on the stock market volatility.

In Panel B, where the measure of stock market volatility is CV, the coefficient values and significance levels vary across different model specifications. The coefficient values for RCI range from 0.0036 to 0.0009, indicating that an increase in RCI is associated with higher levels of CV.

However, the coefficient is only statistical significance in the pooled OLS specifications in Column (1). The stringency index coefficients are statistically insignificant for all cases. The VIX index shows a consistently positive relationship with CV. The coefficient values range from 0.0974 to 0.2440, and they are statistically significant across all model specifications.

Additionally, the Absres coefficient shows a positive and statistically significant association with CV, with coefficient values ranging from 0.0810 to 0.1230. This positive relationship remains consistent across all model specifications, indicating that higher absolute residuals contribute to increased continuous volatility in the stock market. The coefficients of the interaction term, RCI*stringency is negative, ranging from -0.0031; however, none of the coefficients is statistically significant.

In Panel C, the measure of stock market volatility is jump volatility. The coefficient values and significance levels offer valuable insights into the impact of these variables on jump volatility. Consistently, the findings indicate a positive and statistically significant association between the RCI and JV across all model specifications. The coefficient values range from 0.0094 to 0.0103, and their statistical significance remains robust at the 5% level. Therefore, these results suggest that an increase in the RCI leads to higher levels of jump volatility in the stock market. This implies that the contributions from the jump component primarily drive the relationship observed between RCI and RV in Panel A. Similarly, the stringency index exhibits a positive relationship with JV with coefficient values ranging from 0.0097 to 0.0102. In all model specifications, except for period F.E., these coefficient values are statistically significant at the 10% and 5% levels.

Additionally, the VIX index shows a positive relationship with JV, where only the pooled OLS and period F.E. specifications exhibit statistical significance at the 1% level. Furthermore, the Absres variable demonstrates a positive and significant relationship with JV, with coefficient values ranging from 0.1370 to 0.1670. These coefficient values remain statistically significant, indicating that higher absolute residuals contribute to higher jump volatility in the stock market. The interaction term RCI*stringency displays a negative and statistically significant coefficient across all model specifications, ranging from -0.0031 to -0.0030.

Overall, the findings suggest that the number of new Covid-19 infections and mobility restriction policies play a crucial role in shaping market volatility. The analysis indicates that jump volatility largely drives the observed realized volatility in the stock market, while the link to continuous volatility is much weaker. These results support the notion that market participants closely react to public health announcements and government actions, resulting in heightened volatility in the stock market. The interaction term RCI*stringency indicates that the combination of effective new cases of Covid-19 infections and mobility restriction policies may help mitigate market volatility.

4.1 Marginal Effect

In this section, we compute the marginal effect of different measures of volatility on new cases of Covid-19 infections in terms of mobility restriction policies (stringency index). Equations 11, 12 and 13 show results of the partial derivative of RV, CV and J. to mobility restriction policies (RCI), respectively. To conserve space, we discuss our benchmark model specification (country and time fixed effect) displayed in Column (4) of Table 1. These partial derivatives are taken from Table 1 A, B and C, respectively.

$$\frac{\partial(RV_{i,t})}{\partial(RCI_{i,t})} = 0.020 - 0.0036\ (Stringeny\ index) \tag{11}$$

$$\frac{\partial(CV_{i,t})}{\partial(RCI_{i,t})} = 0.001 - 0.0005\ (Stringeny\ index) \tag{12}$$

$$\frac{\partial(JV_{i,t})}{\partial(RCI_{i,t})} = 0.010 - 0.0031\ (Stringeny\ index) \tag{13}$$

Equations (11) to (13) show that the relationship between realized volatility (Equation 11) and both new Covid-19 cases and the stringency index is driven by jump volatility (Equation 13) rather than continuous volatility (Equation 12). Specifically, the constant coefficient which measures the change in RCI is 0.020 for RV (Equation 11), compared to 0.010 for JV, however, this constant coefficient is 10 times smaller for CV. Similarly, the interaction coefficient provides strong evidence that the main driver of the impact of new cases of Covid-19 on stock market RV is the JV rather than CV. This interaction coefficient is -0.0036 and -0.0035 in Equation (11) and Equation (13), respectively. However, is more than seven times smaller for Equation (12).

In Figures 3 A, B and C, we show these respective partial derivatives over the sample range of the stringency index (0-100). For all three cases, the marginal effect of different volatility measures on new Covid-19 infections in terms of mobility restriction policies (stringency index) is negative and statistically significant at conventional levels.

4.2 Robustness Analysis

In this section, we will assess the robustness of our results by examining three alternative specifications. These are: using alternative economic volatility measures as control variables (Table 2), employing random effect estimations (Table 3), and analyzing new Covid-19 deaths instead of new Covid-19 cases (Table 4).

In Table 2, we present estimations of our benchmark model displayed in Table 1, Column (4), but using the following additional control variables: (1) Twitter-based Economic Uncertainty (TEU), (2) Infectious Disease Equity Market Volatility Tracker (DIEMV)), and (3) include both (1) and (2) simultaneously. Following the same criterion as in Table 1 in Panel A, Panel B, and Panel C the dependent variables are RV, CV and JV (respectively). The main results on the coefficient of interest (e.g., RCI, stringency index, and RCI*stringency) are consistent with our benchmark specification in Table 1, Column (4) in terms of sign and magnitude. Although, the statistical significance decreases slightly for the RCI coefficients. Consistent with our benchmark estimation, the interaction term between RCI and the stringency index has a negative sign and a statistically significant coefficient of -0.0037 across all model specifications compared to -0.0036 in our benchmark model.

In Table 3, we show results for our benchmark model using random effect estimations, in columns (1), (2) and (3), we present estimates for RV, CV and JV, respectively. Results are similar to those observed in our benchmark estimation, showing positive statistically significant coefficients on RCI and stringency index and a negative coefficient for the interaction term between RCI and stringency index, however, this coefficient is not statistically significant at conventional levels for the estimation where the dependent variable is RV.

Finally, in Table 4, we replace the variable new Covid-19 cases for new Covid-19 deaths in our benchmark models in Table 1. Results show that new Covid-19 death coefficients are positive and statistically significant, ranging from 0.012 to 0.016. Results are also positive from Column (1) to (4) for the stringency index, although they are only statistically significant for country F.E.

(3) and country and period F.E. (4). The interaction coefficient between new Covid-19 deaths and stringency index is negative and statistically significant at conventional levels also country F.E. (3) and country and period F.E. (4).[3]

5. Conclusion

This study explores the impact of new cases of Covid-19 infections and mobility policy restrictions on realized, continuous and jump volatility measures of the stock market during the Covid-19 pandemic. We use daily panel data from February 12, 2020 to April 14, 2021 for the benchmark stock market indexes for seven countries: U.S., Canada, Australia, Germany, France, Japan, and China.

We find that both new cases of Covid-19 infections and mobility restriction policies play a crucial role in shaping market volatility. The analysis suggests that jump volatility largely drives realized volatility in the stock market, while the links to continuous volatility is much weaker. These results support the notion that market participants closely react to public health announcements and government actions, resulting in heightened volatility in the stock market. We also find that mobility restriction policies lessen the impact of new Covid-19 cases on stock market volatility. Our results are robust to the following different specifications: using alternative measures of economic volatility measures as control variables, employing random effect estimation, and replacing Covid-19 deaths as a proxy for new Covid-19 cases.

[3] Note that for the interaction coefficient of reference, estimations (1) Polled OLS and (2) period FE, the coefficients are very close in magnitude and statistically significant at 20%.

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Tables

Table 1: Panel Regression Results for Covid-19 Cases

Panel A: Dependent Variable is RV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RCI	0.0139**	0.0103*	0.0136***	0.0199***
	(0.001)	(0.001)	(0.000)	(0.000)
Stringency	0.0092*	0.0120*	0.0103***	0.0109***
	(0.001)	(0.001)	(0.000)	(0.000)
VIX	0.1480***	0.0974***	0.2440***	0.1870**
	(0.002)	(0.002)	(0.003)	(0.008)
Absres	0.2910***	0.2170***	0.2550***	0.2080***
	(0.003)	(0.005)	(0.003)	(0.004)
RCI*Stringency	-0.0031*	-0.0037*	-0.0035***	-0.0036***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0465**	-0.0321	-0.0467***	-0.0313***
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	2,059	2,058	2,059	2,058
R^2	0.5480	0.6820	0.5690	0.6900
Adj. R^2	0.5470	0.6260	0.5670	0.6340
Countries	7	7	7	7

Panel B: Dependent Variable is CV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RCI	0.0036***	0.0009	0.0031	0.0007
	(0.000)	(0.000)	(0.000)	(0.000)
Stringency	-0.0006	0.0017	0.0003	0.0013
	(0.000)	(0.000)	(0.000)	(0.000)
VIX	0.0892***	0.0308**	0.1800***	0.0821
	(0.001)	(0.001)	(0.003)	(0.007)
Absres	0.1230***	0.0810***	0.0895**	0.0722**
	(0.002)	(0.002)	(0.003)	(0.002)
RCI*Stringency	-0.0002	-0.0005	-0.0004	-0.0005
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0106**	-0.0012	-0.0107	-0.0012
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	2,059	2,058	2,059	2,058
R^2	0.5270	0.7640	0.5900	0.7760
Adj. R^2	0.5260	0.7220	0.5870	0.7350
Countries	7	7	7	7

Panel C: Dependent Variable is JV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RCI	0.0103**	0.0094*	0.0104**	0.0092**
	(0.001)	(0.001)	(0.000)	(0.000)
Stringency	0.0099*	0.0102	0.0099**	0.0097*
	(0.001)	(0.001)	(0.000)	(0.001)
VIX	0.0586***	0.0666***	0.0639	0.1050
	(0.002)	(0.002)	(0.003)	(0.012)
Absres	0.1670***	0.1370**	0.1660**	0.1350*
	(0.003)	(0.006)	(0.006)	(0.006)
RCI*Stringency	-0.0030*	-0.0031*	-0.0030**	-0.0031*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0359**	-0.0309*	-0.0360**	-0.0301**
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	2,059	2,058	2,059	2,058
R^2	0.3060	0.4130	0.3120	0.4210
Adj. R^2	0.3040	0.3090	0.3090	0.3160
Countries	7	7	7	7

Note: Standard errors are presented below the corresponding coefficients in brackets. The asterisks ***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively.

Table 2: Robustness Check – Panel Regression Results for Covid-19 Cases with Alternative Volatilities Measures

Panel A: Dependent Variable is RV			
	(1)	(2)	(3)
VARIABLES	Period FE	Period FE	Period FE
RCI	0.0101	0.0102	0.0103*
	(0.001)	(0.001)	(0.001)
Stringency	0.0120*	0.0119*	0.0120*
	(0.001)	(0.001)	(0.001)
TEU	-0.3150		-0.3510
	(0.087)		(0.091)
DIMEU		0.0942	0.1420
		(0.015)	(0.016)
VIX			0.0975***
			(0.002)
Absres	0.2350***	0.2350***	0.2180***
	(0.006)	(0.006)	(0.005)
RCI*Stringency	-0.0037*	-0.0037*	-0.0037*
	(0.000)	(0.000)	(0.000)
Constant	-0.0276	-0.0297	-0.0305
	(0.002)	(0.002)	(0.002)
Observations	2,058	2,058	2,058
R^2	0.6690	0.6690	0.6820
Adj. R^2	0.6110	0.6110	0.6250
Countries	7	7	7

Panel B: Dependent Variable is CV			
	(1)	(2)	(3)
VARIABLES	Period FE	Period FE	Period FE
RCI	0.0006	0.0008	0.0009
	(0.000)	(0.000)	(0.000)
Stringency	0.0017	0.0017	0.0017
	(0.000)	(0.000)	(0.000)
TEU	0.0688		0.0676
	(0.037)		(0.037)
DIMEU		0.0082	0.0167
		(0.001)	(0.001)
VIX			0.0308**
			(0.001)
Absres	0.0864***	0.0864***	0.0810***
	(0.002)	(0.002)	(0.002)
RCI*Stringency	-0.0005	-0.0005	-0.0005
	(0.000)	(0.000)	(0.000)
Constant	-0.0007	-0.0003	-0.0016
	(0.001)	(0.001)	(0.001)
Observations	2,058	2,058	2,058
R^2	0.7590	0.7590	0.7640
Adj. R^2	0.7160	0.7160	0.7220
Countries	7	7	7

Panel C: Dependent Variable is JV			
	(1)	(2)	(3)
VARIABLES	Period FE	Period FE	Period FE
RCI	0.0093*	0.0093*	0.0094*
	(0.001)	(0.001)	(0.001)
Stringency	0.0103	0.0102	0.0102
	(0.001)	(0.001)	(0.001)
TEU	-0.3840		-0.4180
	(0.082)		(0.084)
DIMEU		0.0860	0.1250
		(0.011)	(0.012)
VIX			0.0667***
			(0.002)
Absres	0.1480**	0.1480**	0.1370**
	(0.006)	(0.006)	(0.006)
RCI*Stringency	-0.0031*	-0.0031*	-0.0031*
	(0.000)	(0.000)	(0.000)
Constant	-0.0269	-0.0293*	-0.0289*
	(0.002)	(0.002)	(0.002)
Observations	2,058	2,058	2,058
R^2	0.4010	0.4010	0.4130
Adj. R^2	0.2950	0.2950	0.3090
Countries	7	7	7

Note: Standard errors are presented below the corresponding coefficients in brackets. The asterisks ***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively.

Table 3: Robustness Check - Panel Regression Results for Covid-19 Cases across Different Volatilities using Random Effect.

	(1)	(2)	(3)
VARIABLES	RV	CV	JV
RCI	0.0139***	0.0034*	0.0104***
	(0.000)	(0.000)	(0.000)
Stringency	0.0092***	-0.0004	0.0099***
	(0.000)	(0.000)	(0.000)
VIX	0.1480***	0.1450***	0.0620**
	(0.004)	(0.004)	(0.003)
Absres	0.2910***	0.1020***	0.1660***
	(0.004)	(0.004)	(0.006)
RCI*Stringency	-0.0032***	-0.0003	-0.0030***
	(0.000)	(0.000)	(0.000)
Constant	-0.0465***	-0.0107*	-0.0359***
	(0.001)	(0.0001)	(0.001)
Observations	2,059	2,059	2,059
Countries	7	7	7

Note: Standard errors are presented below the corresponding coefficients in brackets. The asterisks ***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively.

Table 4: Robustness Check - Panel Regression Results for Covid-19 Death

Panel A: Dependent Variable is RV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RDI	0.0160**	0.0122	0.0147***	0.0107***
	(0.001)	(0.001)	(0.000)	(0.000)
Stringency	0.0113	0.0141	0.0115***	0.0117***
	(0.001)	(0.001)	(0.000)	(0.000)
VIX	0.1490***	0.0942***	0.2520***	0.1970**
	(0.002)	(0.002)	(0.003)	(0.007)
Absres	0.2910***	0.2200***	0.2530***	0.2100***
	(0.003)	(0.005)	(0.003)	(0.004)
RDI*Stringency	-0.0035	-0.0041	-0.0036***	-0.0036***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0581*	-0.0414	-0.0546***	-0.0364**
	(0.003)	(0.003)	(0.001)	(0.001)
Observations	2,059	2,058	2,059	2,058
R^2	0.5390	0.6780	0.5610	0.6850
Adj. R^2	0.5380	0.6210	0.5580	0.6280
Countries	7	7	7	7

Panel B: Dependent Variable is CV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RDI	0.0073**	0.0036	0.0064***	0.0030
	(0.000)	(0.000)	(0.000)	(0.000)
Stringency	0.0028	0.0042	0.0033	0.0033
	(0.000)	(0.000)	(0.000)	(0.001)
VIX	0.0880***	0.0300**	0.1770***	0.0827**
	(0.001)	(0.001)	(0.003)	(0.007)
Absres	0.1220***	0.0814***	0.0886**	0.0725**
	(0.002)	(0.002)	(0.003)	(0.002)
RDI*Stringency	-0.0009*	-0.0012*	-0.0011	-0.0009
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0265***	-0.0121	-0.0246**	-0.0107
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	2,059	2,058	2,059	2,058
R^2	0.5360	0.7650	0.5960	0.7760
Adj. R^2	0.5350	0.7230	0.5940	0.7350
Countries	7	7	7	7

Panel C: Dependent Variable is JV				
	(1)	(2)	(3)	(4)
VARIABLES	Pooled OLS	Period FE	Country FE	Country & Period FE
RDI	0.0088	0.0086	0.0084**	0.0077**
	(0.001)	(0.001)	(0.000)	(0.000)
Stringency	0.0084	0.0099	0.0082**	0.0084*
	(0.001)	(0.001)	(0.000)	(0.001)
VIX	0.0605***	0.0643***	0.0750**	0.1140
	(0.002)	(0.002)	(0.003)	(0.011)
Absres	0.1690***	0.1390**	0.1650**	0.1370*
	(0.003)	(0.006)	(0.006)	(0.006)
RDI*Stringency	-0.0025	-0.0030	-0.0025**	-0.0026*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.0315	-0.0293	-0.0300**	-0.0257**
	(0.003)	(0.003)	(0.001)	(0.001)
Observations	2,059	2,058	2,059	2,058
R^2	0.2910	0.4050	0.2980	0.4120
Adj. R^2	0.2900	0.3000	0.2940	0.3060
Countries	7	7	7	7

Note: Standard errors are presented below the corresponding coefficients in brackets. The asterisks ***, **, and * indicate the significance at the 1%, 5%, and 10% level, respectively.

Figures

Figure 1: Continuous and Jump Volatilities vs. the Average Values of Covid-19 Cases

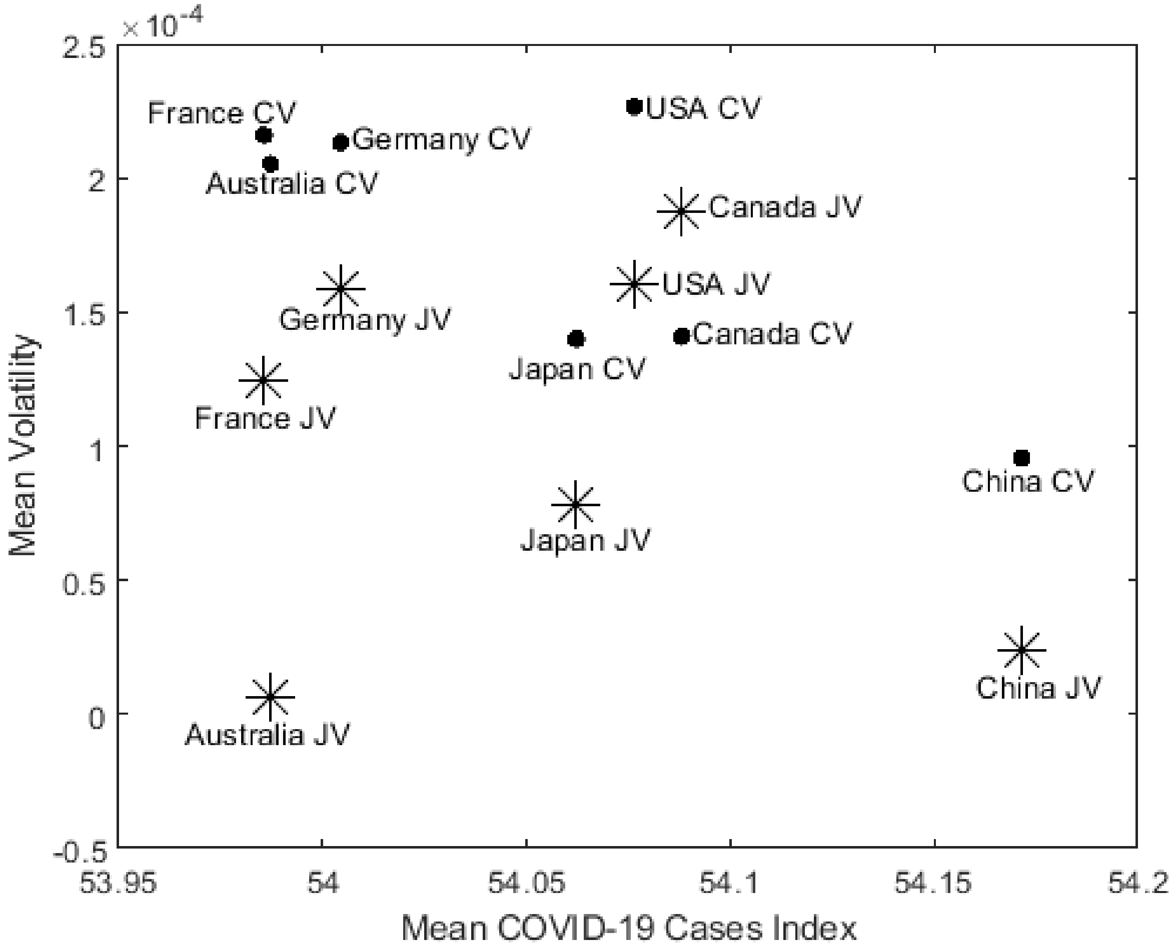

Figure 1 plots the average values of continuous and jump volatilities against the average values of COVID-19 cases. The x-axis shows the mean values of Covid-19 cases index, the y-axis shows the mean values of continuous Volatility (CV) and jump volatility (JV).

Figure 2: Continuous and Jump Volatilities vs. the Stringency Index

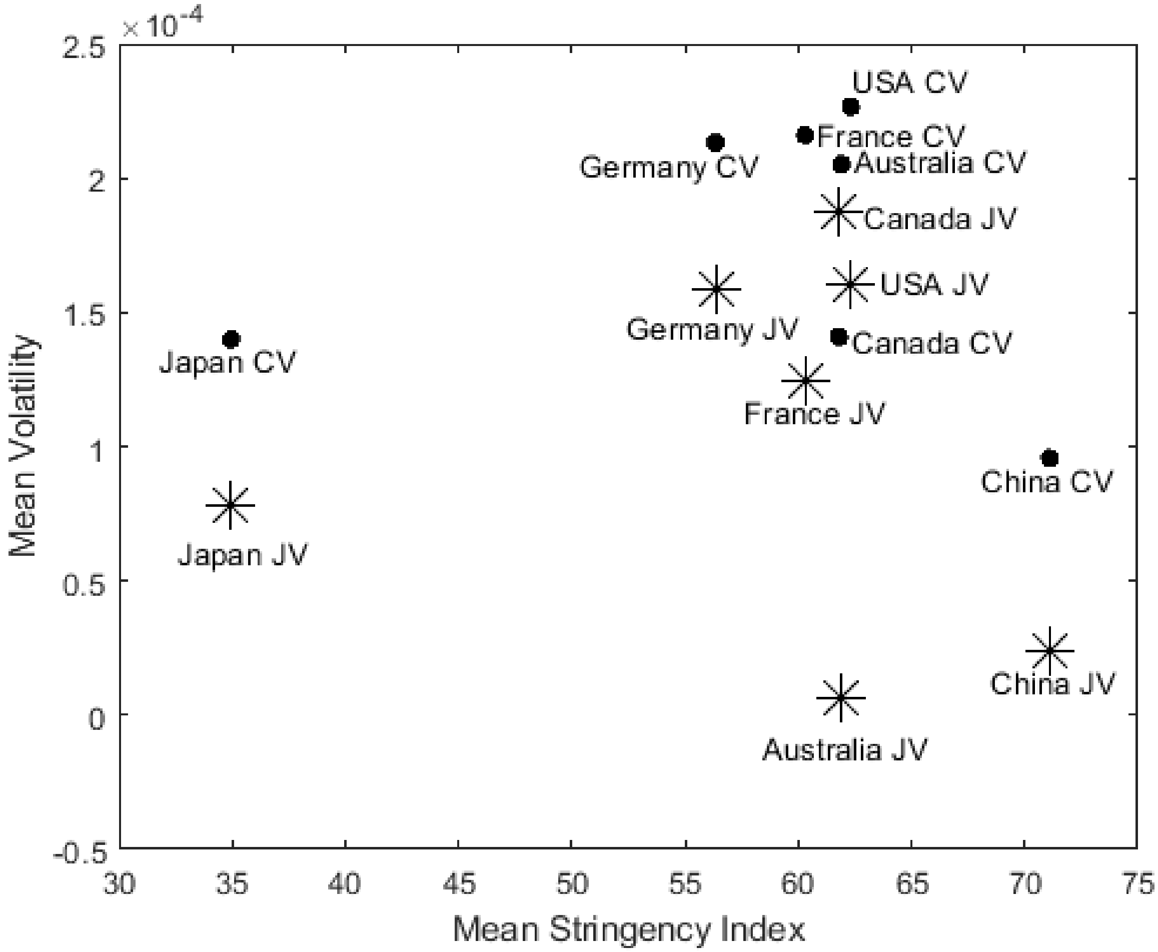

Figure 2 plots the mean values of continuous and jump volatilities against the average values of stringency index. The x-axis shows the mean values of stringency index which ranges from 0 to 100 (100 = strictest), the y-axis shows the mean values of continuous Volatility (CV) and jump volatility (JV).

Figure 3: Marginal Effects of Different Measures of Volatility on New Cases of Covid-19 Infections in Terms of Mobility Restriction Policies (Stringency Index)

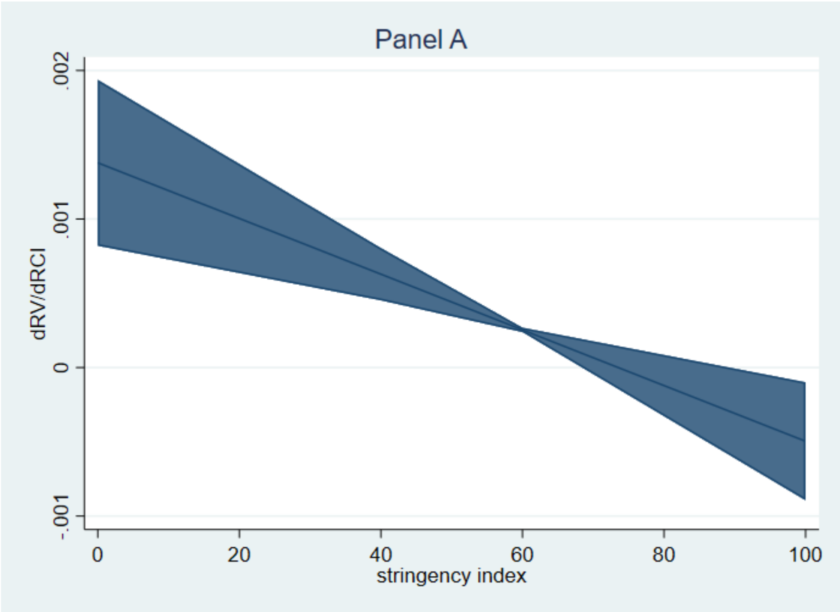

Figure 3, Panel A shows the marginal effects of new Covid-19 cases on realized volatility, conditional on government measures (stringency index). The x-axis depicts the stringency index which ranges from 0 to 100 (100 = strictest), the y-axis depicts the effect COVID-19 cases on realized volatility across sample values of stringency index.

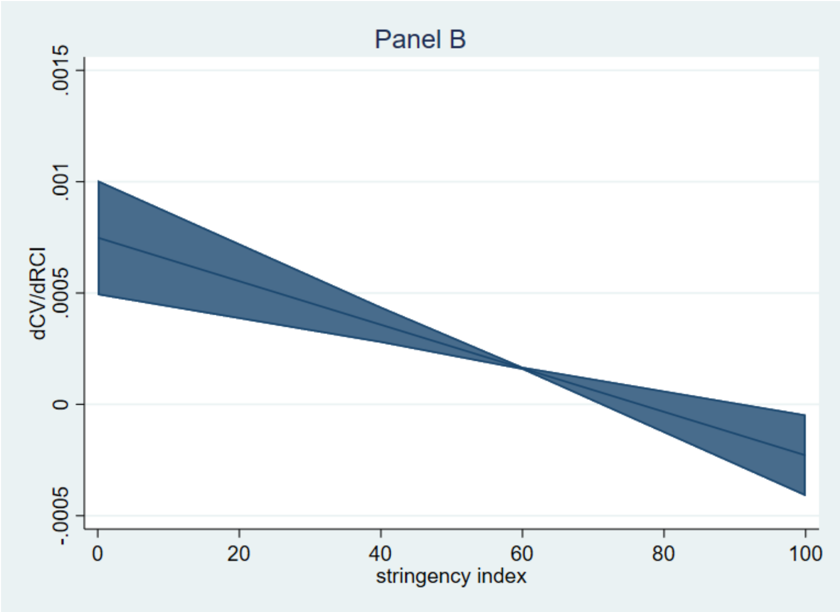

Figure 3, Panel B shows the marginal effects of new Covid-19 cases on continuous volatility, conditional on stringency index. The x-axis depicts the stringency index which ranges from 0 to 100 (100 = strictest), the y-axis depicts the effect COVID-19 cases on continuous volatility across sample values of stringency index.

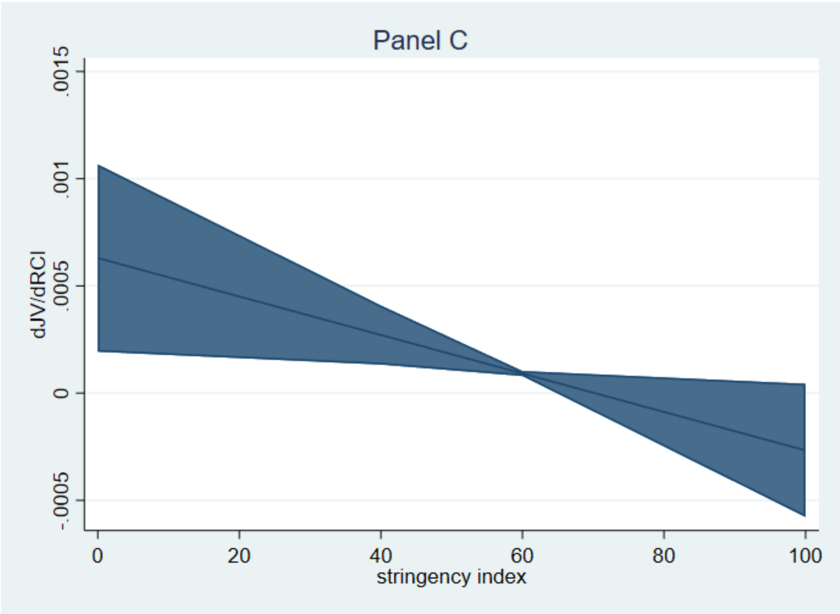

Figure 3, Panel C shows the marginal effects of new Covid-19 cases on jump volatility, conditional on stringency index. The x-axis depicts the stringency index which ranges from 0 to 100 (100 = strictest), the y-axis depicts the effect COVID-19 cases on jump volatility across sample values of stringency index.

Appendix A: Descriptive Statistics

Table A1: Data Description

Variable	Description	Source
Realized Volatility (RV)	Realized Volatility measures the actual variation of an asset's price over a specific period. We estimate the daily realized volatility by using 5-minutes high-frequency return series for each index.	Refinitiv (DataSCope) database
Continuous Volatility (CV)	Continuous Volatility refers to the degree of price fluctuations in a financial asset without accounting for sudden jumps or gaps in prices. This is estimated by removing the jump component of volatility from realized volatility.	Refinitiv (Datascope) database
Jump Volatility (JV)	Jump Volatility captures the abrupt and significant price movements in financial markets, often caused by unexpected events or news. It quantifies the impact of these sudden jumps on asset prices. This is estimated by removing the continuous component of volatility from realized volatility.	Refinitiv (DataScope) database
COVID-19 Case Index (RCI)	The COVID-19 Case Index is a metric that tracks the number of confirmed COVID-19 cases over a specific period. It helps gauge the severity and spread of the pandemic.	https://data.mendeley.com/datasets/yhs329pd7d/1
COVID-19 Death Index (RDI)	The COVID-19 Death Index measures the number of confirmed COVID-19-related deaths over a particular timeframe. It provides insights into the impact of the pandemic on mortality.	https://data.mendeley.com/datasets/yhs329pd7d/1
Volatility index (VIX)	The Volatility Index, often referred to as the VIX, is a popular measure of market volatility and investor sentiment. It reflects the market's expectation of future price volatility and is often used as a gauge of market risk. We downloaded the daily VIX data for each country.	Refinitiv (DataScope) database
Absolute Residuals (Absres)	Absolute Residuals represent the absolute differences between observed data points and predicted values from our regression model. We employ the absolute residual as an alternative measure of volatility.	Refinitiv (DataScope) database
Stringency Index	The Stringency Index quantifies the strictness of government measures, regulations, and restrictions. It is often used to evaluate the level of response to events like the COVID-19 pandemic. The index which ranges from 0 to 100 (100 = strictest)	https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker
Twitter-based Economic Uncertainty (TEU) Index	Twitter-based Economic Uncertainty refers to a metric derived from analyzing tweets related to economic topics. It provides insights into public sentiment and uncertainty regarding economic conditions. We employ the TEU which accounts for the total number of daily English-language tweets containing both Uncertainty terms as well as Economy terms.	https://www.policyuncertainty.com/twitter_uncert.html)
Infectious Disease Equity Market Volatility Tracker (DIEMV)	The Infectious Disease Equity Market Volatility Tracker measures market volatility in response to infectious disease outbreaks. It helps assess the economic impact of such health crises on financial markets.	Economic Policy Uncertainty database: (https://www.policyuncertainty.com/infectious_EMV.html)

Table A2: Descriptive Statistics

VARIABLES	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis	N
RV	0.0003	0.0000	0.0170	0.0008	9.4480	132.9000	2,059
CV	0.0002	0.0000	0.0052	0.0004	6.3710	53.8400	2,059
JV	0.0001	0.0000	0.0145	0.0006	14.4800	279.6000	2,059
VIX (ln)	0.0271	0.0077	0.1207	0.1347	2.1260	10.2900	2,059
RCI (ln)	3.9650	1.9240	4.5120	0.2440	-2.9700	25.6600	2,059
RDI (ln)	3.9590	2.5630	4.5250	0.2080	-0.4200	11.3100	2,059
Absres	0.0111	0.0000	0.1310	0.0134	3.3960	20.0000	2,059
Stringency (ln)	3.9750	1.0220	4.4770	0.5620	-3.0200	14.0300	2,059
TEU (ln)	5.6510	4.6530	6.5560	0.3520	0.0774	3.1410	2,059
DIEMU (ln)	3.0490	0.0000	4.7270	0.7070	-1.0050	5.7830	2,059

Table A3: Unit Root Test

	ADF		PP	
	Statistics	P-value	Statistics	P-value
RV	71.33	0.00	224.11	0.00
CV	111.07	0.00	205.68	0.00
JV	80.98	0.00	316.81	0.00
VIX	14.72	0.40	37.74	0.00
RCI	48.46	0.00	148.24	0.00
RDI	82.13	0.00	344.08	0.00
Absres	183.80	0.00	436.68	0.00
Stringency	81.72	0.00	83.94	0.00
TEU	29.90	0.01	54.54	0.00
DIEMU	72.84	0.00	294.64	0.00

The tests used are the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test for panel date.