This study investigates the impacts of pandemic-induced economic policy uncertainties (PIEPU) on the S&P500, Nasdaq-100, and Dow Jones indexes (stock returns). To this aim, for the first time, newly created IDEMV (the Infectious Disease Equity Market Volatility index henceforth, PIEPU index) is used. The Autoregressive Distributed Lag (ARDL) model and the Toda and Yamamoto (Journal of Econometrics, 1995, 66, pp. 225–250) causality test are applied for the 2009–2020 period. Empirical findings indicate that rises in the PIEPU index lead to falls of only the S&P500 and Dow Jones indexes. Corporations in the tech-heavy Nasdaq100 index do not negatively respond to rises in the PIEPU index. Additionally, the negative impacts of the rises in the specifically COVID-19 based-constructed PIEPU (DCOVPIEPU) index on the S&P500 and Dow Jones indexes are higher than the negative impacts of the general PIEPU index. This can be interpreted to mean that the larger the magnitude and spread rate of a pandemic, the larger the negative impacts on stock returns. In the sample period of this study, COVID-19 is the largest and most destructive pandemic compared to H1N1 and Ebola.

**KEYWORDS**
COVID-19, Infectious Disease IDEMV Index, stock exchanges

1 | INTRODUCTION

COVID-19 pandemic as a multidimensional phenomenon attracted many scholars to examine its impacts in different areas such as public health (Heymann & Shindo, 2020; Polychronis & Roupa, 2020), education (Dennis, 2020; Torda, 2020), economy (Alhassan et al., 2020; Siddiquei & Khan, 2020; Singh & Neog, 2020), environment (Alola & Bekun, 2020; Balsalobre-Lorente et al., 2020), trade (Escaith & Khorana, 2021; Vidya & Prabheesh, 2020). On the other hand, the COVID-19 pandemic (known as the “great lockdown” in the IMF report (2020)\(^1\) to echo the Great Depression) has heightened unprecedented uncertainties in the economy and led to massive losses for businesses. According to Baker, Bloom, Davis, and Terry (2020), the magnitude of uncertainty caused by this pandemic is larger than the 2008 financial crisis and close to that of the Great Depression. Hence, rising economic uncertainties may have negative impacts on stock exchanges. Therefore, this study aims to investigate the potential impacts of the pandemic-induced economic policy uncertainties (PIEPU) on US stock exchanges through the S&P500, Nasdaq-100, and Dow Jones indexes. To this aim, the newly created Infectious Disease Equity Market Volatility (IDEMV\(^2\)) Index by Baker, Bloom, Davis, Kost, et al. (2020) is used. To the best of our knowledge, this is the first attempt using this index in an empirical study related to stock exchanges.

2 | CONSTRUCTION OF IDEMV INDEX

The IDEMV was constructed as a news-based index. In the construction of this index, first, articles across approximately 3000 US newspapers are scanned and terms that mention at least one term in each of ID, E, M, and V are counted in the following four sets:

\(^1\)For full report, refer to: https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/

\(^2\)For technical details of this index, refer to: https://www.policyuncertainty.com/infectious_EMV.html.
ID: (epidemic, pandemic, virus, flu, disease, Coronavirus, Mers, Sars, Ebola, H5N1, H1N1)
E: (economic, economy, financial)
M: ("stock market", equity, equities, “Standard and Poors”)
V: (volatility, volatile, uncertain, uncertainty, risk, risky)

Second, the raw IDEMV counts are scaled by the count of all articles on the same day. Lastly, the resulting series are multiplicatively rescaled to scale equity market volatility (EMV) series in the EMV tracker, which is formulated as follows:

\[ \text{EMV}_t = \frac{\#(E \cap M \cap V \cap \text{Monetary Policy})_t}{\#(E \cap M \cap V)_t} \]  

(1)

where \( \# \) is the count of newspaper articles in the EMV sets. The \( \text{EMV}_t \) is the value of the overall EMV tracker, which was constructed based on different weighted article categories that mention one or more terms in each category. The sample formula presented above was constructed to show the importance of “monetary policy,” which is one of the items in these categories affecting EMV. To show the importance of fiscal policy in the EMV Tracker (2020), we would substitute “monetary policy” with “fiscal policy” in this formula.

As a result of all these steps and instructions so far, we can conclude that the IDEMV, constructed on the volatilities through the EMV tracker, including ID terms, will give us a kind of pandemic-induced economic policy uncertainty index. Therefore, the IDEMV index will henceforth be replaced with the pandemic-induced economic uncertainty (PIEPU) index in this study. Especially in regards to the COVID-19 pandemic, using this index may provide a wide range of application fields to researchers who want to test the impacts of PIEPU in their empirical models. This daily index is available as of 1985. It is believed that the findings of this study will also support some empirical studies (Arouiri et al., 2016; Christou et al., 2017; Ongan & Gocer, 2017; Paule-Vianez et al., 2020; Peng et al., 2018) that test the impacts of changes in the economic policy uncertainty (EPU) index on US stock returns. The EPU index, created by Baker et al. (2016), was also constructed based on newspaper articles (with similar technical instructions to those for the PIEPU index). However, the EPU index (2020) does not specifically consider the uncertainties caused by pandemics, like the PIEPU index, which was used in this study.

3 | DATA AND EMPIRICAL MODELS

3.1 | Data

We obtained the data of the S&P500, Nasdaq-100, and Dow Jones indexes from the Federal Reserve Bank of St. Louis (FED, 2020). The data of the IDEMV (henceforth, PIEPU) index, created by Baker, Bloom, Davis, Kost, et al. (2020), were obtained from https://www.policyuncertainty.com/infectious_EMV.html. We used daily series and the sample period of the study is January 05, 2018 to May 18, 2020, with 2862 observations.

3.2 | Empirical models

To investigate the potential impacts of pandemic-induced economic uncertainties on US stock returns, we apply both the Autoregressive Distributed Lag (ARDL) model and Toda and Yamamoto (1995) causality test. Appropriate analysis methods and casualty test were selected according to the results of the unit root tests.

3.2.1 | ARDL model

In this model, we use the following linear ARDL model by Pesaran et al. (2001) in error correction form:

\[ \Delta \text{SR}_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \Delta \text{SR}_{t-j} + \sum_{j=0}^{q} \alpha_{2j} \Delta \text{PIEPU}_{t-j} + \alpha_3 \text{SR}_{t-1} \\
+ \alpha_4 \Delta \text{PIEPU}_{t-1} + \varepsilon_t \]  

(2)

where SR and PIEPU are stock returns (indexes) and PIEPU index, respectively. \( p \) and \( q \) are optimum lags determined by using Akaike information criteria (AIC). \( \varepsilon_t \) is the innovation at time \( t \). We expect the sign of \( \alpha_4 \) to be negative, since rises in the PIEPU index will lead to falls in SR in the long run. This model is separately applied to the S&P500, Nasdaq, and Dow Jones indexes. Additionally, to consider-include the specific impacts of the COVID-19 pandemic on stock indexes, Model 1 is transformed to the following Model 2 with an additional new variable (index):

\[ \Delta \text{SR}_t = \alpha_0 + \sum_{j=1}^{p} \alpha_j \Delta \text{SR}_{t-j} + \sum_{j=0}^{q} \alpha_{2j} \Delta \text{PIEPU}_{t-j} \\
+ \sum_{j=0}^{r} \alpha_{3j} \Delta (\text{DCOVPIEPU})_{t-j} + \alpha_6 \Delta \text{SR}_{t-1} + \alpha_5 \text{PIEPU}_{t-1} \\
+ \alpha_8 (\text{DCOVPIEPU})_{t-1} + \varepsilon_t \]  

(3)

where DCOVPIEPU is specifically COVID-19 based-constructed PIEPU variable (index). We created this index based on the equation: DCOVPIEPU = DCOV + PIEPU, where DCOV is dummy variable, which is given the value of 0 and 1 before and after January 21, 2020, respectively. This is the date of the first confirmed case of this pandemic in the United States. We expect the sign of \( \alpha_6 \) to be negative and its size to be higher than \( \alpha_5 \) in Equation (2), because, in our sample period, the COVID-19 is the largest pandemic when compared to the H1N1 and Ebola.

3.2.2 | Causality test

To support the results of the ARDL model, we apply the Toda and Yamamoto (1995) causality test. We expect causalities from the

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2For technical instruction details of this index, refer to Baker et al. (2019) and https://www.policyuncertainty.com/EMV_.monthly.html
3For terms in the categories, refer to: https://www.policyuncertainty.com/EMV_.monthly.html
4For the technical detail of the EPU index, refer to: https://www.policyuncertainty.com/methodology.html
PIEPU and DCOVPIEPT indexes to the S&P500, Nasdaq-100 and, Dow Jones indexes in the following models:

\[
SR_t = \beta_0 + \sum_{i=1}^{p} \beta_i SR_{t-i} + \sum_{i=1}^{d_{max}} \beta_2^i \text{PIEPU}_{t-i} + \epsilon_t \tag{4}
\]

\[
SR_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i SR_{t-i} + \sum_{i=1}^{d_{max}} \alpha_2^i \text{DCOVPIEPU}_{t-i} + \epsilon_t \tag{5}
\]

where \( p \) is the optimal lag and \( d_{max} \) is the degree of maximum integration of variables. The null hypothesis of this test is "there is no causality." If \( \beta_2 = 0 \), then we will decide that there is no causality from the PIEPU index to SR; if \( \alpha_2 = 0 \), then we will decide that there is no causality from DCOVPIEPU to SR.

**4 | EMPIRICAL RESULTS**

Before running the models, we must first make sure the series are stationary. To this aim, we apply the ADF (Dickey & Fuller, 1981), PP (Phillips & Perron, 1988), and KPSS (Kwiatkowski et al., 1992) unit root tests. The results of these three tests are reported in Table 1.

Test results in Table 1 indicate that the series is stationary at different levels. Hence, to test long-run relations, we apply the bounds testing cointegration approach by Pesaran et al. (2001). The results of bound testing are reported in Table 2. The null hypothesis of this test is that there is "No cointegration."

Test results in Table 2 indicate that the series have significant long-run (cointegration) relations, since the F-statistics of the models are higher than the upper bounds at 1% and 5% levels. Hence, to estimate the coefficients, we apply the ARDL model. Test results of this approach for Model 1 (without specific COVID-19 effect) and Model 2 (with specific COVID-19 effect) are reported in Tables 3 and 4, respectively.

Test results of normalized long-run estimates of Model 1 (without specific COVID-19 effect) in Table 3 indicate that rises in the PIEPU index lead to falls of only the S&P500 and Dow Jones indexes. Furthermore, the negative impacts of rises in the PIEPU index on the Dow Jones index (−0.026) are higher than the negative impacts on the S&P500 index (−0.018). There is no significant impact of the PIEPU index on the tech-heavy Nasdaq-100 index. This can be interpreted to mean that tech-heavy corporations do not negatively respond to rises in the PIEPU index in the long run. Furthermore, the negative impacts of rises in the PIEPU index on these three indexes are similar in the short run. The error correction mechanisms work since their coefficients are significantly negative. Test results of Model 2 (with specific COVID-19 effect) are reported in Table 4.

Test results of normalized long-run estimates in Model 2 (with specific COVID-19 effect) in Table 4 indicate that the rises in the

**TABLE 1 Unit root test results**

|                | ADF          | PP           | KPSS   |
|----------------|--------------|--------------|--------|
| SR(S&P500)     | −11.66***    | −61.90***    | 0.03***|
| SR(Nasdaq – 100)| −12.55***    | −61.02***    | 0.03***|
| SR(Dow Jones)  | −11.62***    | −61.89***    | 0.03***|
| PIEPU          | −2.52(0.10)  | −1.50(0.12)  | 678.87 |
| ΔPIEPU         | −12.73***    | −206.01***   | 0.17***|
| DCOVPIEPU      | −2.34(0.15)  | −1.67(0.12)  | 725.24 |
| Δ(DCOVPIEPU)   | −12.62***    | −72.91***    | 0.01***|

Note: Critical values in the KPSS test are 0.73, 0.46, and 0.34 for 1%, 5%, and 10%, respectively. p-values are in the parenthesis. Δ: First differences. *** denotes significance at 1% level. ADF: Augmented Dickey Fuller Test. PP: Phillips-Perron Test. KPSS: Kwiatkowski-Phillips-Schmidt-Shin Test.

**TABLE 2 Cointegration test results**

| Model        | (1) S&P 500 | (2) Dow Jones | (3) Nasdaq-100 |
|--------------|-------------|--------------|---------------|
| Model 1      | 9.14**      | 11.05***     | 10.26***      |
| Model 2      | 8.48***     | 10.14***     | 7.17**        |

Critical values

|          | 10% | 5%  | 1%  |
|----------|-----|-----|-----|
| Lower bounds (for k = 1) | 5.59 | 6.56 | 8.74 |
| Upper bounds (for k = 1)  | 6.26 | 7.30 | 9.63 |
| Lower bounds (for k = 2)  | 4.19 | 4.87 | 6.34 |
| Upper bounds (for k = 2)  | 5.06 | 5.85 | 7.52 |

Note: The values are F-statistics. k is the number of independent variables. *** and ** denote significances at 1% and 5% levels.
|                  | Unnormalized long-run | Normalized long-run | Short-run |
|------------------|-----------------------|---------------------|-----------|
|                  | (1) S&P500 (2) Dow Jones (3) Nasdaq-100 | (1) S&P500 (2) Dow Jones (3) Nasdaq-100 | (1) S&P 500 (2) Dow Jones (3) Nasdaq-100 |
| $SR_{t-1}$      | 0.85*** (0.00)        | 0.85*** (0.00)      | 0.87*** (0.00) |
| $SR_{t-2}$      | 0.19*** (0.00)        | 0.22*** (0.00)      | 0.16*** (0.00) |
| $SR_{t-3}$      | -0.07*** (0.00)       | -0.07*** (0.00)     | -0.05*** (0.00) |
| $SR_{t-4}$      | -0.01 (0.30)          | -0.026*** (0.00)    | -0.013 (0.19) |
| PIEPUₜ         | 0.007 (0.44)          | 0.0001 (0.31)       | -0.018* (0.07) |
| PIEPUₜ₋₁       | -0.008 (0.43)         | -0.009 (0.41)       | -0.009 (0.41) |
| PIEPUₜ₋₂       | -0.004 (0.68)         | -0.006 (0.57)       | -0.006 (0.57) |
| PIEPUₜ₋₃       | -0.0002** (0.04)      | -0.0002** (0.03)    | -0.0001 (0.15) |
| PIEPUₜ₋₄       | -0.0001 (0.22)        | -0.026*** (0.00)    | -0.013 (0.19) |
| Constant        | 0.09*** (0.00)        | 0.14*** (0.00)      | 0.11*** (0.00) |
| $R^2$           | 0.99                  | 0.99                | 0.99      |
| $R^2$           | 0.99                  | 0.99                | 0.99      |
| $F$             | 395909.2 (0.00)       | 270077.8 (0.00)     | 508615.1 (0.00) |
| $DW$            | 2.00                  | 1.99                | 1.99      |
| $X^2_{BG}$      | 0.57 (0.75)           | 0.75 (0.69)         | 0.07 (0.96) |

**Note:** p-values are in the parenthesis. *, **, and *** denote significances at 10%, 5%, and 1% levels.
### TABLE 4  Long-run and short-run ARDL model results (Model 2: With specific COVID-19 effect)

|                | Unnormalized long-run | Normalized long-run | Short-run |                |                |                |                |                |                |                |
|----------------|----------------------|---------------------|-----------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
|                | (1) S&P500          | (2) Dow Jones       | (3) Nasdaq-100 | (1) S&P500     | (2) Dow Jones   | (3) Nasdaq-100 |                  | (1) S&P500     | (2) Dow Jones   | (3) Nasdaq-100 |
| \( SR_{t-1} \) | 0.85*** (0.00)      | 0.85*** (0.00)      | 0.87*** (0.00) |                |                |                | \( \Delta SR_{t-1} \) | -0.13*** (0.00) | -0.13*** (0.00) | -0.11*** (0.00) |
| \( SR_{t-2} \) | 0.20*** (0.00)      | 0.22*** (0.00)      | 0.16*** (0.00) |                |                |                | \( \Delta SR_{t-2} \) | 0.06** (0.00)   | 0.08*** (0.00)   | 0.04*** (0.00)   |
| \( SR_{t-3} \) | -0.06*** (0.00)     | -0.08*** (0.00)     | -0.04*** (0.00) |                |                |                | \( \Delta PIEPU_t \) |                |                |                |
| PIEPU\(_t\)   | 0.0001 (0.24)       | 0.0001 (0.30)       | 0.0001 (0.35) | 0.0008 (0.27)  | 0.006 (0.32)   | 0.007 (0.37)   | \( \Delta DCOVPIEPU_t \) |                |                |                |
| DCOVPIEPU\(_t\)| -0.006*** (0.00)   | -0.0008*** (0.00)  | -0.0003 (0.12) | -0.04*** (0.00) | -0.05*** (0.00) | -0.02 (0.12)   | ECT\(_t-1\)   | -0.01*** (0.00) | -0.01*** (0.00) | -0.01*** (0.00) |
| Constant       | 0.10*** (0.00)      | 0.14*** (0.00)      | 0.10*** (0.00) | 6.88*** (0.00) | 9.11*** (0.00) | 7.55*** (0.00) | Constant       | 0.10*** (0.00) | 0.14*** (0.00) | 0.10*** (0.00) |
| \( R^2 \)     | 0.99                | 0.99                | 0.99        | 0.99           | 0.99           | 0.99           | \( R^2 \)     | 0.34           | 0.40           | 0.25           |
| \( \overline{R}^2 \) | 0.99              | 0.99                | 0.99        | 0.99           | 0.99           | 0.99           | \( R^2 \)     | 0.33           | 0.38           | 0.24           |
| \( F \)       | 48096.9 (0.00)      | 451971.9 (0.00)     | 678180.8   | 480296.9       | 451971.9       | 678180.8       | \( F \)       | 25.49 (0.00)   | 29.78 (0.00)   | 18.79 (0.00)   |
| \( DW \)      | 1.99                | 1.99                | 1.99       | 1.99           | 1.99           | 1.99           | \( DW \)      | 1.99           | 1.99           | 1.99           |
| \( \chi^2_{BG} \) | 0.08 (0.95)        | 1.59 (0.45)         | 0.09 (0.95) | 0.08 (0.95)   | 1.59 (0.45)   | 0.09 (0.95)   | \( \chi^2_{BG} \) | 0.08 (0.95)   | 1.59 (0.45)   | 0.09 (0.95)   |

*Note: p-values are in the parenthesis. *, **, and *** denote significances at 10%, 5%, and 1% levels.*
PIEPU index have no significant impacts on any of the three stock indexes. However, rises in the specifically COVID-19 based-constructed PIEPU (DCOVPIEPU) index lead to falls of only the S&P500 and Dow Jones indexes. Comparison of the EIEPU and DCOVPIEPU indexes (variables) in Model 1 and Model 2 indicate that negative impacts of rises in the DCOVPIEPU index on the S&P500 and Dow Jones indexes are higher (0.04; 0.05 in Table 4) than the negative impacts of the general EIEPU index (0.018; 0.026 in Table 3). This can be interpreted to mean that the larger the magnitude and spread rate of a pandemic, the larger the negative impacts on stock returns. In the sample period of this study, the COVID-19 is the largest and most destructive pandemic compared to the H1N1 and Ebola.

Additionally, test results of the Toda and Yamamoto (1995) causality test are reported in Table 5. It should be noted that this causality test approach was selected because the series of the study are stationary at different levels.

Test results in Table 5 indicate that there are causalities from the DCOVPIEPU index only to the S&P500 and Dow Jones indexes. These findings completely affirm-support the results of the ARDL model since we could not find a causal relationship from the DCOVPIEPU index to the tech-heavy Nasdaq-100 index. Furthermore, the Dow Jones index is most negatively affected by the rises in the DCOVPIEPU index, similar to what happens with the ARDL model and the PIEPU index. Descriptive statistics and CUSUM charts of both models are reported in Table A1 and Figures A1 and A2. It should also be noted that the empirical findings of this study affirm the findings of past studies that focus on the impacts of COVID-19 on stock markets. For instance, Alber and Saleh (2020) applied the generalized method of moments (GMM) procedure for the stock markets of the Gulf Cooperation Council (GCC) countries. They found that the COVID-19 pandemic has negative impacts on the returns of the stock in these countries. Le et al. (2020) applied the panel-regression model for the Vietnam stock market and found that this pandemic has significant negative impacts on stock returns. Basistha and Bora (2021) used the generalized autoregressive conditional heteroscedasticity model for India and found that COVID-19 has increased the volatility during the pandemic period. Burdekin and Harrison (2021) applied the pooled ordinary least squares (OLS) analysis for 80 countries. They found that this pandemic worsened relative stock market performances. Shehzad et al. (2020) used the asymmetric power GARCH model for the United States, Italy, Japan, and China. They found that COVID-19 negatively affects the stock returns of the S&P 500. They also found no negative impacts on the Nasdaq composite index. Khan et al. (2020) applied the panel data analysis for major stock markets and found that this pandemic negatively affected these markets. Although this study mainly affirms the findings of the studies mentioned above, it differs from them in two ways. First, we created and used our COVID-19 based-constructed index (DCOVPIEPU), as explained in the empirical model section. Second, it also compares the magnitude and spread rate of COVID-19 with previous pandemics such as H1N1 and Ebola.

### 5 | CONCLUSION

The world is experiencing unprecedented uncertainty due to the COVID-19 pandemic. This study investigates the impacts of PIEPU on the S&P500, Nasdaq-100, and Dow Jones indexes (stock returns). Our findings indicate that economic policy uncertainties caused by pandemics have significantly negative impacts on stock returns (except for the Nasdaq-100 index). These negative impacts increase more in direct proportion to the magnitude of the pandemic, as we detected in this study concerning the case of COVID-19. Thus, these findings may show policymakers, investors, and businesses that public health and universal healthcare investments are essential for financial markets and economies following the COVID-19 pandemic.

### CONFLICT OF INTEREST

We confirm that this work is original and has not been published elsewhere nor is it currently under consideration for publication elsewhere.

**Table 5** Toda and Yamamoto (1995) causality test results

|        | $d_{max}$ | Chi-Square | Prob. |
|--------|-----------|------------|-------|
| PIEPU → S&P500 | 14 [LR, FPE, AIC] | 1 | 13.77 | 0.54 |
| DCOVPIEPU → S&P500 | 10 [LR, FPE, AIC] | 1 | 26.92*** | 0.00 |
| PIEPU → DowJones | 16 [FPE, AIC] | 1 | 13.49 | 0.70 |
| DCOVPIEPU → DowJones | 10 [LR, FPE, AIC, HQ] | 1 | 37.07*** | 0.00 |
| PIEPU → Nasdaq | 9 [LR, FPE, AIC, HQ] | 1 | 8.16 | 0.61 |
| DCOVPIEPU → Nasdaq | 5 [LR, FPE, AIC, HQ] | 1 | 4.95 | 0.54 |

Abbreviations: AIC, Akaike information criterion; FPE, final prediction error; HQ: Hannan-Quinn information criterion; LR, sequential modified LR test statistic (each test at 5% level).
DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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**APPENDIX A**

|                | Log(PIEPU) | Log(S&P500) | Log(DOW Jones) | Log(Nasdaq-100) |
|----------------|------------|-------------|----------------|-----------------|
| **Mean**       | 1.98       | 7.49        | 9.69           | 8.33            |
| **Median**     | 0.00       | 7.57        | 9.72           | 8.40            |
| **Maximum**    | 8.83       | 8.13        | 10.29          | 9.19            |
| **Minimum**    | 0.00       | 6.52        | 8.79           | 7.15            |
| **Std. Dev.**  | 2.31       | 0.36        | 0.34           | 0.48            |
| **Skewness**   | 0.58       | –0.30       | –0.18          | –0.17           |
| **Kurtosis**   | 2.04       | 2.06        | 2.16           | 2.01            |
| **Jarque-Bera**| 270.3      | 147.3       | 99.1           | 130.8           |
| **Probability**| 0.00       | 0.00        | 0.00           | 0.00            |
| **Sum**        | 5657.63    | 21435.65    | 27733.01       | 23840.46        |
| **Sum Sq. Dev.**| 15317.74 | 380.8993    | 335.535        | 648.8037        |
| **Observations**| 2862      | 2862        | 2862           | 2862            |

*Note: The differences of max. and min. values and standard deviations of the variables are low. The number of observations is enough.*
FIGURE A1  CUSUM charts of Model 1 (without specific COVID-19 effect)
FIGURE A2  CUSUM charts of Model 2 (with specific COVID-19 effect)