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# Mobility's Impact on COVID-19 Cases in ASEAN: A Panel Data Regression Study

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## Abstract:

**Objective:** This study aimed to analyze the impact of community mobility on the Corona virus disease 2019 (COVID-19) cases in ASEAN countries using panel data regression.

**Material and Methods:** The Google Mobility Report and World Health Organization (WHO) COVID-19 Global Data were analyzed from February 15, 2020, to October 13, 2022. Three distinct periods were examined: pre-vaccination, vaccination rollout, and post-herd immunity. Panel data regression models were employed to assess the impact of various mobility factors on daily COVID-19 cases.

**Results:** The analysis revealed that mobility patterns significantly influenced COVID-19 case numbers during the pre-vaccination period. As vaccination programs progressed and herd immunity was achieved, the impact of mobility on new cases diminished. The models explained with $R^2$ were between 20.15% and 33.33% of the variations in case numbers across the periods.

**Conclusion:** This study emphasizes the importance of community mobility in COVID-19 transmissions. Effective vaccination strategies and public health measures are crucial in mitigating the impact of mobility on disease spread.

**Keywords**: ASEAN, COVID-19, herd immunity, mobility, panel regression

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## Introduction

The Coronavirus disease 2019 (COVID-19) pandemic caused a global health crisis, with human mobility accelerating its spread. Studies show a strong link between increased mobility and higher COVID-19 cases, particularly through close contact in public spaces, transportation, and social activities[1,2,3]. In the highly urbanized ASEAN regions, the pandemic's impact was severe, affecting over 650 million people across 10 countries. As of May 25, 2024, the World Health Organization (WHO) reports 37,003,383 confirmed cases and 369,525 deaths in the Association of Southeast Asian Nations (ASEAN)[4].

Regional cooperation focused on joint efforts such as mobility restrictions and vaccination programs. With widespread vaccinations, herd immunity is expected, protecting vulnerable individuals[5] and reducing disease spread. A study using Structural Equation Modeling (SEM) linked mobility behavior to vaccination outcomes[6]. This study hypothesizes that higher vaccination rates will reduce mobility's impact on COVID-19 cases, and once herd immunity is achieved, mobility will have little effect.

Unlike previous studies using cross-sectional[2,7] or time-series[8,9] analyses, this study employs panel data regression to examine the impact of mobility on COVID-19 cases in 8 ASEAN countries from February 15, 2020, to October 13, 2022. Using mobility indicators and models like Common Effects (CEM), Fixed Effects (FEM), and Random Effects (FEM), we aim to capture dynamic mobility changes and their effects on infections, considering national variations in regional pandemic responses.

Panel data regression allows for analyzing temporal and spatial variations, providing a nuanced view of the spread of COVID-19. This approach is key to understanding the pandemic's dynamic nature across regions and time. While previous studies mainly focused on developed countries[10-12] or limited time periods[13-15], this study examines mobility's impact on COVID-19 across 3 phases: before vaccination, during vaccination, and post-herd immunity. The findings aim to improve the understanding of mobility's role in infections in ASEAN and offer insights for policymakers regarding the efforts made by the government and society to limit people's mobility before and after a vaccine is found, in order to minimize the spread of COVID-19.

## Material and Methods

This study uses a quantitative, observational design to analyze the relationship between human mobility and COVID-19 transmission in ASEAN countries. Data for new COVID-19 cases were obtained from the WHO COVID-19 Reports[16], which provides daily updates on confirmed cases globally. Mobility data were sourced from Google Mobility Reports[17], which tracks changes in human mobility across 6 categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. The Google Mobility Reports use aggregated, anonymized data from users who have enabled location history on their smartphones, establishing a baseline using median values from a 5-week pre-pandemic period. Index values are calculated as percentage changes relative to this baseline, with values ranging from -100 (complete decrease) to +100 (maximum increase), and 0 indicating no change[18]. Mobility changes are reported relative to this baseline. Google ensures transparency through publicly available documentation, detailing its methodology, privacy safeguards, and potential limitations, such as smartphone access disparities. For both data sources, data were collected for 8 ASEAN countries (excluding Brunei and Vietnam due to missing or incomplete data) from February 15, 2020, to October 13, 2022. Research variables are listed in Table 1.

The data include community mobility and new cases with a 5-day lag (t+5) to account for COVID-19 incubation[19], typically 5-6 days. The study examines 392 observations ($N \times T$) for 3 periods: Period 1 (February 15, 2020 – October

**Table 1** Research variable

| Indicator | Notation | Variable | Unit |
|---|---|---|---|
| COVID-19 | Y | New cases | Cases |
| Community mobility | $X_1$ | Mobility in retail and recreation | % |
| | $X_2$ | Mobility in grocery and pharmacy | % |
| | $X_3$ | Mobility in parks | % |
| | $X_4$ | Mobility in transit stations | % |
| | $X_5$ | Mobility in workplace | % |
| | $X_6$ | Mobility in residential | % |

12, 2020), marking COVID-19's emergence in ASEAN, before vaccines were available; Period 2 (June 1, 2021 – January 27, 2022), aligning with the start of vaccination efforts; and Period 3 (February 15, 2022–October 13, 2022), assuming widespread vaccinations and herd immunity. This assumption is based on findings by Tetteh et al. (2020)[20] that vaccination coverage of approximately 60% is generally sufficient to achieve herd immunity, assuming a vaccine efficacy of 80% (see Table 2). It is important to acknowledge that the actual threshold for herd immunity can vary depending on various factors.

Figure 1 shows the study diagram of this study. It starts with data and data cleaning, the methods involved, theassumptions test, and the resulting model and conclusions.

### Statistical analysis

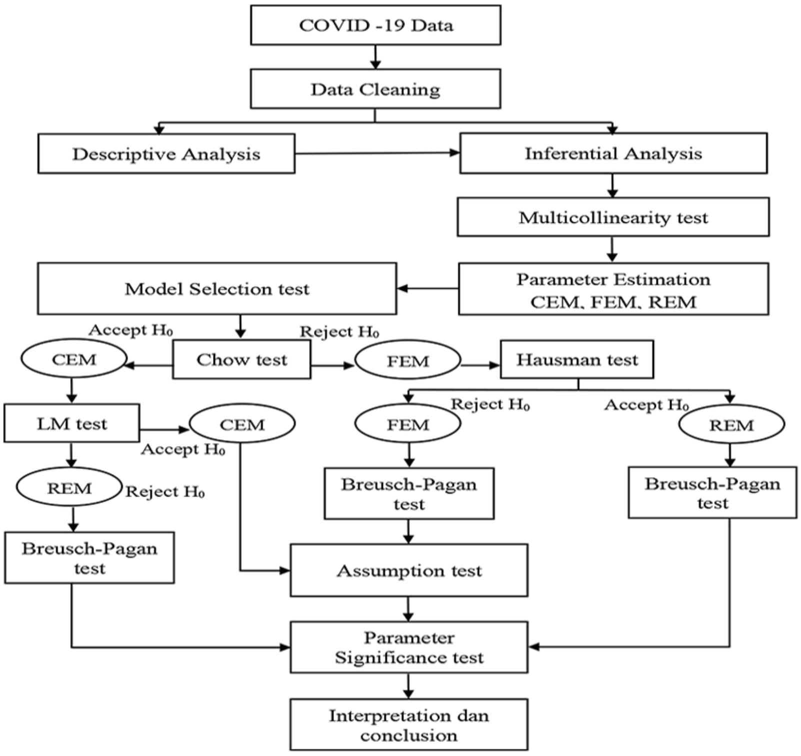
Panel data regression analysis was conducted using FEM, CEM, and REM. Panel data combine cross-sectional and time-series observations. Multicollinearity was tested using the Variance Inflation Factor (VIF), with values over 10 indicating its presence. The Chow test compared FEM and CEM, selecting FEM if the F-statistic exceeded the critical value. The Hausman test then determined whether FEM or REM was more appropriate. The Hausman test assumes no correlation between regressors and the error term, favoring REM if true. If the test statistic exceeds the critical value, FEM is preferred. For REM, the Lagrange Multiplier (LM) test evaluates whether REM outperforms CEM, with a significant result confirming REM as the better model.

The Breusch-Pagan test assessed temporal or individual effects in the model. Heteroscedasticity and autocorrelation were tested, with Robust Covariance Matrix Estimation applied if assumptions were violated. Adjusted $R^2$, F-tests, and t-tests evaluated model relevance. The final model was interpreted using R for analysis and Python for visualizations.

## Results

The quantity of newly diagnosed instances of COVID-19 in ASEAN by period to characterize the COVID-19 trend in each nation (Figure 2).

The first period exhibits a narrower range of cases, indicating less variability. The second period shows a wider range, suggesting higher fluctuations. The third period appears to have a slightly narrower range, potentially indicating stabilization. Significant differences exist in case distributions. The presence of outliers and positive skewness in many countries suggest that specific events or changes in testing strategies led to periods of exceptionally high caseloads (Figure 2).




FEM=fixed effects model, CEM=common effects model, REM=random effects model, LM=lagrange multiplier test

**Figure 1** Study diagram

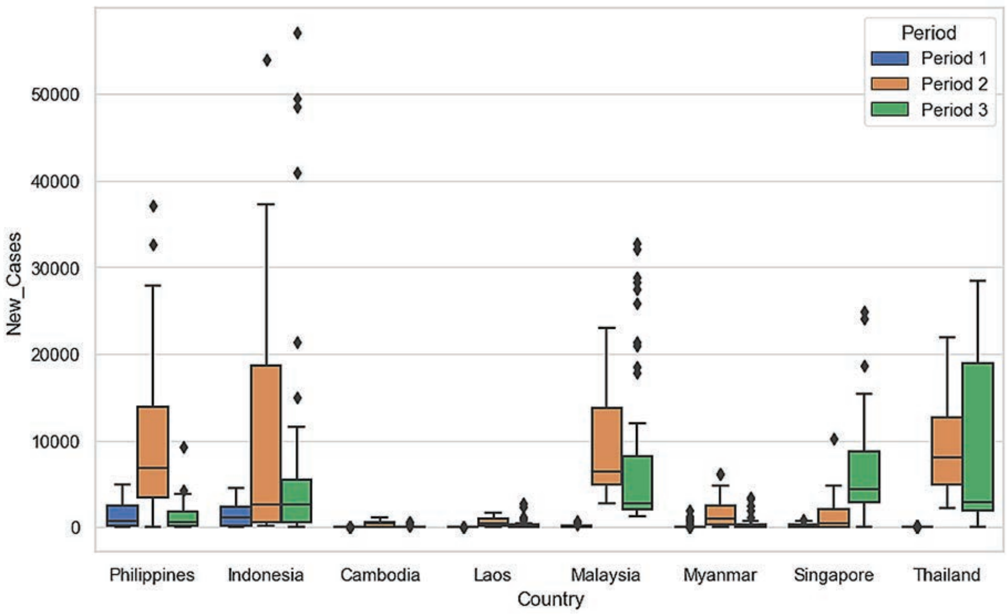



**Figure 2** New cases of COVID-19 per country in ASEAN by period

Mobility increased across most categories from Period 1 to Period 3, reflecting eased restrictions and a return to normalcy. Transit stations showed significant declines in periods 1 and 2 due to restrictions and remote work. Workplace mobility rose in Period 3, signaling a return to offices. Residential mobility consistently increased, reflecting remote work and reduced social activities. Grocery and pharmacy mobility grew due to essential needs, while Parks and Retail & Recreation showed mixed trends, with smaller increases in later periods (Figure 3).

Outliers observed in figures 2 and 3 were acknowledged but not treated, as they reflect real variations in mobility and COVID-19 transmissions. The Fixed Effects and Random Effects models used are robust to such heterogeneity, ensuring unbiased results.

### Panel regression analysis

Multicollinearity was detected, particularly in the 'retail and recreation' variable (VIF >10), which was removed before re-estimation. FEM, CEM, and REM were compared using the Chow and Hausman tests. REM with two-way effects was selected for Period 1, REM with individual effects for Period 2, and FEM with individual effects for Period 3 (Table 3). Diagnostic tests for heteroskedasticity and autocorrelation were performed, and robust standard errors, such as White or Newey-West estimators, were applied to address these issues.

### Estimated model parameters

Estimated outcomes using the chosen model are summarized in Table 4.

The $R^2$ values ranged from 20.2% to 33.3%, indicating a moderate fit with 20.2% for Period 1, explaining mobility's effect on case variation. Due to the complexity of model, in social science, $R^2$ values between 0.10 and 0.50 are acceptable[21]. Mobility impacts varied: before vaccinations, increases in grocery, parks, workplaces, and residential mobility raised cases, while public transport

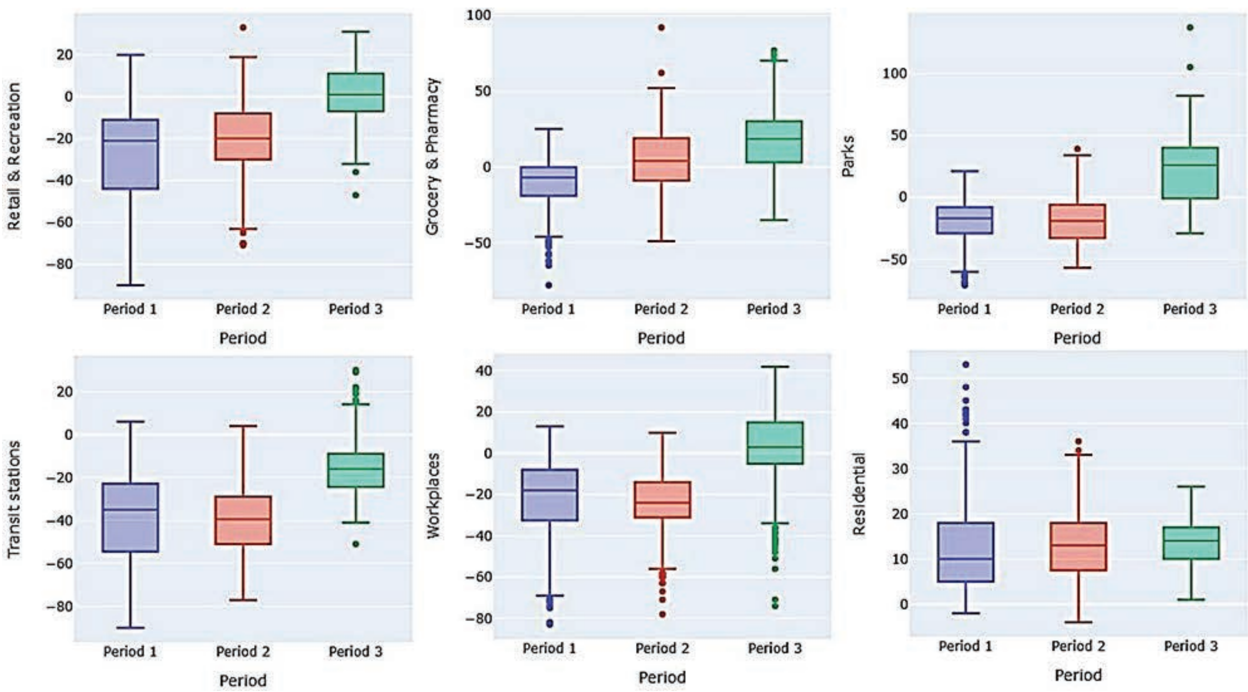



**Figure 3** Mobility categories in ASEAN by period

**Table 2** Vaccination data as of February 15, 2022

| Country | First confirmed cases | Vaccine effective date | Fully vaccinated per 100 |
|---|---|---|---|
| Thailand | January 13, 2020 | June 07, 2021 | 70.4 |
| Vietnam | January 23, 2020 | March 08, 2021 | 73.3 |
| Singapore | January 23, 2020 | December 30, 2020 | 88.5 |
| Malaysia | January 25, 2020 | February 24, 2021 | 78.5 |
| Cambodia | January 27, 2020 | February 10, 2021 | 81.4 |
| Philippines | January 30, 2020 | March 01, 2021 | 55,5 |
| Indonesia | March 02, 2020 | January 13, 2021 | 49.1 |
| Brunei Darussalam | March 10, 2020 | April 03, 2021 | 91.4 |
| Myanmar | March 23, 2020 | January 27, 2021 | 35.1 |
| Laos | March 24, 2020 | November 25, 2021 | 57.4 |

Source: https://asean.org

**Table 3** Summary of model selection test results

| Period | Test | Statistic test | p-value | Decision | Model selected | Breusch-pagan test (p-value) |
|---|---|---|---|---|---|---|
| Before vaccine | Chow test | 35.35 | <0.0001* | Reject $H_0$ | FEM | Two-way effect (0.000) |
| | Hausman test | 0.46 | 0.9936 | Fail to Reject $H_0$ | REM | |
| | Lm test | 1,198.20 | <0.0001* | Reject $H_0$ | REM | |
| During vaccine | Chow test | 21.45 | <0.0001* | Reject $H_0$ | FEM | Individual effect (0.000) |
| | Hausman test | 3.99 | 0.6783 | Fail to Reject $H_0$ | REM | |
| | LM test | 377.16 | <0.0001* | Reject $H_0$ | REM | |
| After herd immunity | Chow test | 9.29 | <0.0001* | Reject $H_0$ | FEM | Individual effect (0.000) |
| | Hausman test | 34.20 | <0.0001* | Reject $H_0$ | FEM | |

*significance at α=0.05, FEM=fixed effects model, REM=random effects model, LM=lagrange multiplier test

**Table 4** Estimated model parameters for each period

| Parameters | Period 1 (p-value) | Standard errors | Period 2 (p-value) | Standard errors | Period 3 (p-value) | Standard errors |
|---|---|---|---|---|---|---|
| Intercept | -347.35 (0.269) | 313.95 | -13211.02 (<0.001)* | 2720.87 | | |
| Retail and recreation ($X_1$) | | | -86.05 (0.266) | 77.43 | -46.45 (0.809) | 192.41 |
| Grocery and pharmacy ($X_2$) | 28.24 (<0.001)* | 5.14 | 234.23 (<0.001)* | 57.63 | 147.76 (0.053) | 75.95 |
| Parks ($X_3$) | 32.75 (<0.001)* | 4.86 | 14.67 (0.735) | 43.34 | -101.82 (0.153) | 71.02 |
| Transit stations ($X_4$) | -38.34 (<0.001)* | 5.93 | -480.98 (<0.001)* | 70.78 | -266.09 (0.087) | 155.17 |
| Workplace ($X_5$) | 23.69 (<0.001)* | 4.70 | 13.59 (0.694) | 34.54 | -35.30 (0.589) | 65.28 |
| Residential ($X_6$) | 64.67 (<0.001)* | 13.73 | -203.55 (0.119) | 130.66 | -159.33 (0.582) | 289.13 |
| $R^2$ | 20.2% | | 33.3% | | 21.6% | |
| Adjusted $R^2$ | 19.1% | | 32.3% | | 19.0% | |

*significance at α=0.05

reduced them. During vaccinations, grocery mobility still raised cases, and public transport had a negative impact. Post-herd immunity and mobility had no significant effect on cases. Model 3 (Fixed Effects) excludes an intercept, as fixed effects account for time-invariant characteristics, making a global intercept unnecessary.

### Model estimates for period 1

The model estimates for individual effects (country) and time effects for period one can be found in Supplementary Tables 1 and 2.

### Model estimates for period 2

The country with the highest individual influence on COVID-19 cases in ASEAN during the second period was Indonesia, while Laos had the smallest individual influence. The model estimates for individual effects (country) for period two can be found in Supplementary Table 3.

### Model estimation for period 3

During this period, it has been established that Indonesia was the only country exhibiting a significant positive influence on the number of COVID-19 cases in ASEAN, as shown in Table 5.

**Table 5** Constant coefficient of individual effects for period 3

| Country | Intercept | p-value |
|---|---|---|
| Philippines | 2,751.10 | 0.4689 |
| Indonesia | 7,372.04 | 0.0090* |
| Cambodia | -988.86 | 0.7419 |
| Laos | -1,982.19 | 0.4370 |
| Malaysia | 4,346.30 | 0.0730 |
| Myanmar | 1,371.06 | 0.6858 |
| Singapore | 2,522.32 | 0.0924 |
| Thailand | -1,077.29 | 0.6493 |

*significance at α=0.05

## Discussion

The COVID-19 pandemic significantly altered mobility patterns in ASEAN. This study examined mobility's relationship with COVID-19 transmissions across 3 periods. In the initial phase, mobility restrictions reduced public transport use, with a 95% drop in transit activity in the Philippines[22]. Awareness of transmission risks increased private transport use[23,24], while residential mobility rose as people stayed home. This rise correlated with higher case numbers, potentially due to work-from-home policies or increased household gatherings, as noted by Suraya et al. (2021)[25].

As vaccination efforts progressed, the impact of mobility on COVID-19 transmissions diminished, though public health measures like mask-wearing and social distancing remained crucial. During the second period, ASEAN countries faced a COVID-19 resurgence due to the Delta variant. Despite cases peaking in mid-2021, many shifted towards 'living with COVID-19,' and mobility returned to normal by mid-2021. Studies show a growing disconnect between increased mobility and virus spread[13], as reflected in the model results. Epidemiologist Dicky Budiman points to low testing and slow vaccinations as key factors behind high infection rates in ASEAN countries[26].

In the post-vaccination phase, mobility returned to pre-pandemic levels, and the link to COVID-19 transmissions weakened, suggesting that vaccinations and natural immunity reduced transmission risk. Indonesia was the only country with a significant rise in cases during herd immunity, likely due to its large, under-vaccinated population. Demographic and socioeconomic factors across countries require further study. While vaccines help break transmission chains, they are not enough alone; strict health protocols and mobility restrictions are still essential. The pandemic underscores the need for coordinated efforts and community adherence to health measures.

Excluding Brunei and Vietnam may impact the generalizability of the results. Brunei lacked mobility data, limiting analysis, while Vietnam's unusual pandemic trajectory, marked by Delta variant surges and low vaccination rates, could introduce variability[27,28]. This exclusion may affect findings, especially in countries with more stable pandemic trends.

## Conclusion

The COVID-19 pandemic significantly altered mobility patterns and disease transmission in ASEAN countries. Our study highlights that mobility was crucial in shaping the pandemic's trajectory, especially before widespread vaccinations. As vaccination rates increased and restrictions eased, the influence of mobility on case numbers decreased, with effects varying by period and country. To effectively manage future pandemics, it is vital to understand the relationship between human behavior, public health policies, and viral transmissions. Future research should examine the long-term impacts of the pandemic on mobility and public health in order to enhance preparedness and response strategies. The data transformation and distribution test could be implemented in further research to get a robust result.

## Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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**Supplementary Table 1** Constant coefficient of individual effect for period 1

| Country | Residual |
|---|---|
| Philippines | 918.60 |
| Indonesia | 878.15 |
| Cambodia | -480.83 |
| Laos | -393.33 |
| Malaysia | -265.10 |
| Myanmar | -65.53 |
| Singapore | -430.55 |
| Thailand | -161.42 |

**Supplementary Table 2** Constant coefficient of time effect for period 1

| Time | Residual | Time | Residual |
|---|---|---|---|
| February 15, 2020 | 11.20 | June 19, 2020 | -76.03 |
| February 20, 2020 | 18.41 | June 24, 2020 | -21.60 |
| February 25, 2020 | -27.73 | June 29, 2020 | -52.51 |
| March 1, 2020 | -15.00 | July 4, 2020 | -14.87 |
| March 6, 2020 | -13.98 | July 9, 2020 | 61.49 |
| March 11, 2020 | -48.14 | July 14, 2020 | -37.02 |
| March 16, 2020 | -79.32 | July 19, 2020 | -54.96 |
| March 21, 2020 | -29.32 | July 24, 2020 | -16.97 |
| March 26, 2020 | -62.54 | July 29, 2020 | 47.05 |
| March 31, 2020 | -53.30 | August 3, 2020 | 80.70 |
| April 5, 2020 | -40.44 | August 8, 2020 | 41.00 |
| April 20, 2020 | -133.10 | August 13, 2020 | 86.44 |
| April 15, 2020 | -79.31 | August 18, 2020 | 24.96 |
| April 20, 2020 | -78.08 | August 23, 2020 | 80.22 |
| April 25, 2020 | 5.77 | August 28, 2020 | 52.27 |
| April 30, 2020 | -67.89 | September 2, 2020 | 89.89 |
| May 5, 2020 | -65.78 | September 7, 2020 | 14.29 |
| May 10, 2020 | -29.10 | September 12, 2020 | 132.32 |
| May 15, 2020 | -105.25 | September 17, 2020 | 101.97 |
| May 20, 2020 | -97.41 | September 22, 2020 | 144.40 |
| May 25, 2020 | -106.10 | September 27, 2020 | 37.25 |
| May 30, 2020 | -26.84 | October 2, 2020 | 189.37 |
| June 4, 2020 | -50.87 | October 7, 2020 | 235.79 |
| June 9, 2020 | -53.66 | October 12, 2020 | 136.99 |
| June 14, 2020 | -54.70 | | |

**Supplementary Table 3** Constant coefficient of individual effects for period 2

| Country | Residual |
|---|---|
| Philippines | 1,382.69 |
| Indonesia | 8,059.62 |
| Cambodia | −2,863.05 |
| Laos | −8,384.96 |
| Malaysia | 1,006.07 |
| Myanmar | 1,090.08 |
| Singapore | 2,204.62 |
| Thailand | −2,495.08 |