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Associations Between Mobility Indices and the COVID-19 Pandemic in Thailand

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ABSTRACT

This study aims to examine the associations between the Coronavirus disease 2019 (COVID-19) pandemic and alternative indicators. Specifically, Apple mobility index, Google community mobility index, and Nighttime-light (NTL) data are used for empirical analyses using ordinary least squares (OLS) and panel regressions as research methods. Results produced by OLS models show that Apple's subcategory of driving activity and Google's subcategory of visiting transit places are negatively associated with the number of COVID-19 cases. To extend the spatiotemporal details of this analysis, we formulate the panel data by integrating the monthly provincial indicators of Apple mobility index, NTL index, and the COVID-19 infected cases. Both fixed- and random-effects panel regression models indicate that Apple's driving and walking mobility subcategories are negatively associated with the COVID-19 infected cases. By contrast, the relationship between the NTL index and the intensity of the COVID-19 outbreak is inconclusive. These findings suggest that Apple's mobility index can be applied as an alternative and timely indicator of economic activity, particularly for observing the near real-time intensity of mobility and transportation volume. In addition, these findings can serve as a resource for developing spatial models for urban planning and geographical impacts.

Keywords: Apple mobility trend reports, Google community mobility reports, night-time light, COVID-19, Thailand**,** panel data regression

INTRODUCTION

Since the first reported case in Mainland China in December 2019, the Coronavirus disease 2019 (COVID-19) has spread globally. In March 2020, the World Health Organization (WHO) identified the disease as a pandemic (World Health Organization [WHO], 2020). By June 2022, the global total number of confirmed cases had reached 533 million (World Health Organization [WHO], 2022), and over 6.3 million deaths had been reported (WHO, 2022). The pandemic has led to a deterioration in economies and financial markets, incurring systematic risks for foreign exchange rates, interest rates, gross domestic product (GDP), unemployment, and global trade (Kartal, 2021). Specifically, the COVID-19 pandemic is generally recognized as one of the most influential global phenomena that the world economy has experienced in modern history. In addition, during 2020–2021, the number of infections increased despite the international distribution of vaccines, mainly caused by variants resulting from multiple mutations of COVID-19 and the low vaccination rate in several countries.

To cope with the COVID-19 outbreak, most countries implemented various public health prevention measures, including state quarantine, home isolation, and travel restrictions. These policies aimed to mitigate the outbreak of the pandemic. Globally, conventional measures included social distancing along with mobility restrictions or lockdown policies. In particular, the mobility restrictions included encouraging people to work from home.

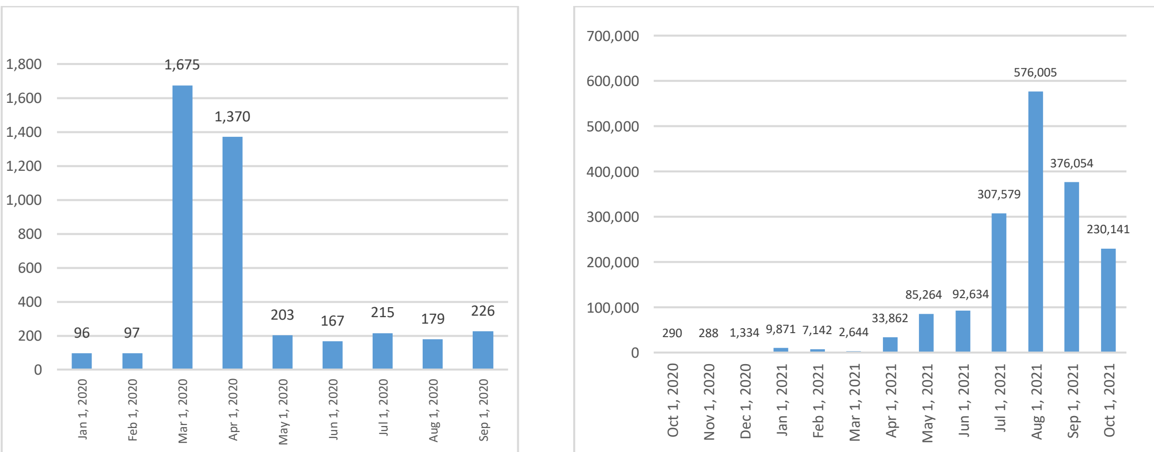
In response to the first major wave of the outbreak, Thailand imposed the first mobility restriction measure in April 2020, prohibiting many activities and business operations in various locations such as shopping centers, clubs, bars, and gyms. A night-time curfew was also imposed, and work-from-home practices were officially required by the government.

The second major wave occurred during the period of July–September 2021. With the outbreak of the Delta variant, the imposed lockdown was more intense during this second major wave (World Health Organization [WHO], 2021). Specifically, as shown in Figure 1, the total number of confirmed cases in Thailand during this period (July–September 2021) was 1,259,407, whereas the first wave had resulted in only 3,017.

Figure 1

Monthly COVID-19 infections in Thailand

First major wave (March–May 2020)   Second major wave (July–September 2021



Note. Data are from "Centre of Epidemiological Information," by Bureau of Epidemiology, Ministry of Public Health, 2021. Copyright 2021 by Ministry of Public Health.

Despite their aim of reducing the number of infections, mobility restrictions incur a substantial economic cost because they significantly dampen most economic activity. Therefore, a government must carefully weigh the costs and benefits of any mobility restriction or lockdown policy. Oh et al. (2021) estimated that during January – August 2020, the global GDP fell by over 10% caused by mobility restrictions. During periods of strict mobility restrictions due to the pandemic, a concern was that the economic damage of the mobility restriction policies might outrun the benefit of lower infection rates. However, the number of studies investigating the relationship between the pandemic and mobility restrictions is highly limited, especially with respect to Thailand. Thus, studying such a relationship is crucial for gaining further insights into the effect of individual mobility on infection rates. With the public accessibility of various near real-time mobility data, the analyses can be carried out with higher accuracy in spatiotemporal dimensions (Holmdahl & Buckee, 2020). Based on these facts and the urgent need for supportive information, this study mainly focuses on examining the association between COVID-19 infections and mobility indicators. In particular, the near real-time data produced by Apple and Google provide the main mobility indicators. Furthermore, the satellite-based socioeconomic indicator Nighttime Light (NTL) index was incorporated to explore the feasibility of integrating multidimensional data. Ultimately, the main findings obtained from this investigation can deepen the insights on behavioral response and mobility, which is useful for future city and regional planning.

This paper is organized as follows. The second section summarizes the related publications, while the third and the fourth parts introduce the data and the research methodologies, respectively. The fifth section elaborates on the results of empirical analyses. The last section summarizes the main findings and suggests future implications.

LITERATURE REVIEW

Several studies have examined the effect of mobility restrictions on the number of COVID-19 infections (Fauver et al., 2020; Li et al., 2020; Tian et al., 2020; Xu & Li, 2020; Yang et al., 2020). The literature review was divided into two sections with country-specific characteristics: (1) Asia; and (2) Europe and the United States (US). During the initial phase of the pandemic, many Asian countries decided to respond aggressively to control the COVID-19 outbreak; official actions included international travel restrictions, state-quarantine programs, and mobility tracking measures (Osewe, 2021). In addition, wearing of facemasks was more widely adopted among Asians, as compared to Americans and Europeans. Furthermore, people of most Asian residents were more willing to cooperate with all imposed policies.

Asian countries

Fang et al. (2020)studied the effects of Wuhan city's lockdown policy by using panel fixed-effect regression. Data obtained from Baidu Migration and the daily statistics of COVID-19 confirmed cases during the first quarter of 2020 showed that the lockdown policy effectively flattened the daily infections, which was significant given that Wuhan city was the epicenter of the pandemic.

Kraemer et al. (2020) studied the effects of mobility restriction policy on the COVID-19 epidemic in China by using multiple methodologies, including a stochastic susceptible infectious-recovered model. They modeled the spatiotemporal evolution of COVID-19 in 33 provinces in China and suggested that mobility restriction effectively reduced the disease transmission.

In the Philippines,Camba and Camba (2020) used robust least squares regression on Apple mobility trend and Google mobility index. Their findings revealed that the COVID-19 pandemic had the greatest impact by increasing the number of work-from-home employees, followed by less use of public transportation, less time of walking, and declining workplace visits.

Europe and the United States

Sulyok and Walker (2021) studied the relationship between mobility and COVID-19 mortality across Scandinavian countries by using

Google community mobility and Stringency index. The COVID-19 mortality rate in Sweden was higher than that of its neighboring countries due to fewer restriction measures, suggesting that higher stringency of measures is associated with a lower death rate.

In the case of the US, Sen et al. (2020)studied the effect of lockdown policies on COVID-19 hospitalizations in four states: Colorado, Minnesota, Ohio, and Virginia. The results suggest that cumulative hospitalization is associated with the intensity of stay-at-home measures. Using daily mobility data derived from aggregated and anonymized mobile phone data, Badr et al. (2020)identified the association between mobility patterns and the transmission of COVID-19 in 25 states. Social distancing and mobility restrictions were found to be effective policies for reducing the rate of COVID-19 transmission. Pei et al. (2020) examined the impact of intervention timing on COVID-19 cases. The results indicate that social distancing and other COVID-19 control measures are associated with significant reduction in infections in metropolitan areas. In addition, by implementing such measures a week earlier, an approximate 54% reduction in the death rate may have been achieved.

Using the Google community mobility index,Oh et al. (2021)studied the association between mobility restrictions and reduction in the number of COVID-19 cases in 34 OECD economies, together with Singapore and Taiwan. Their study indicates that restrictions on social mobility reduced the COVID-19 transmission in many countries, especially during the early stages of the pandemic.

DATA

This study uses time-series data collected from publicly accessible sources. Table 1 summarizes the main features and links used to access the original data.

Table 1

Characteristics and Sources of Data

	Data	**Source**	**Frequency**	**Spatial resolution**	**URL**
1	Number of confirmed COVID-19 cases	Center of Epidemiological Information, Bureau of Epidemiology, Ministry of Public Health	Daily	Province	https://covid19.ddc.moph.go.th
2	Google community mobility index	Google community mobility report	Daily	Nationwide	https://www.google.com/covid19/mobility/
3	Apple mobility index	Apple mobility trend report	Daily	Province	https://covid19.apple.com/mobility
4	Nighttime-Light index (NTL)	Google Earth Engine	Monthly	Province	https://nattapong.users.earthengine.app/view/thailand-monthly-indicators-satellite-data

To formulate the data set covering the periods of major waves of the pandemic, we obtained the time series of daily confirmed cases from the official database of Thailand's Ministry of Public Health (MoPH) for the period February 1, 2020 to October 31, 2021. In all regression analyses, the data are transformed into a logarithmic scale to represent the non-linear relationship with other variables.

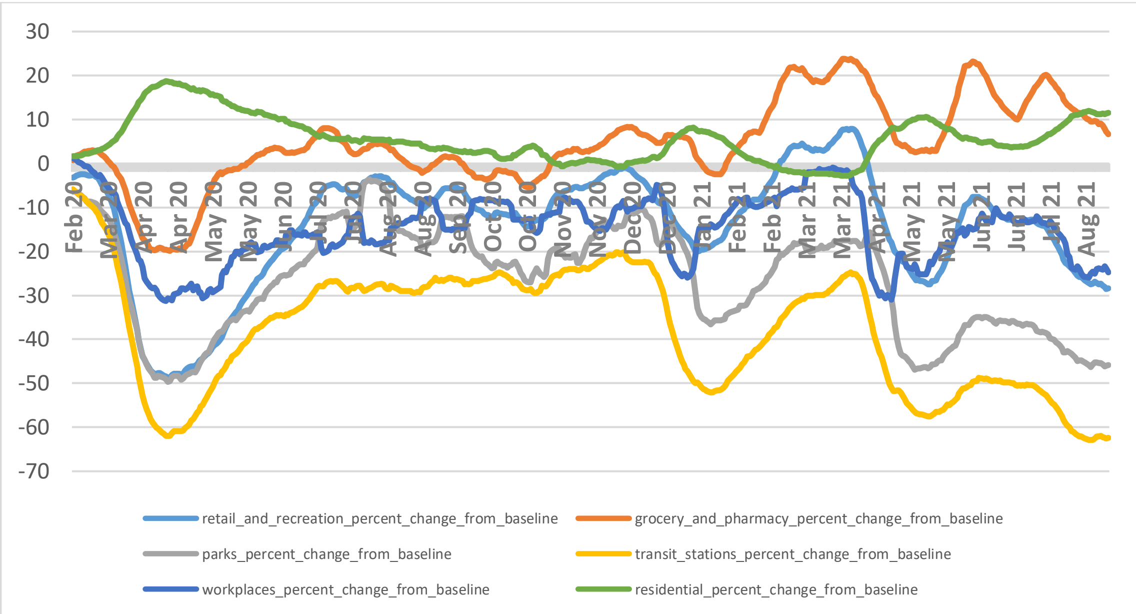
Publicly accessible as alternative data for monitoring the global COVID-19 pandemic, the Google community and Apple mobility indices were developed by analyzing and aggregating users' search behaviors on Google and Apple maps, respectively. The Google community mobility index is categorized into six visited locations: retail and recreational places, workplaces, transit stations, residential areas, groceries and pharmacies, and parks. Specifically, the time series for these locations indicate the nationwide aggregated index of each category. Figure 2 illustrates the example of the Google community mobility index in Thailand, with all values represented in the original units computed by Google.

By comparison, the Apple mobility index is computed at the provincial level and is represented in two classifications based on transportation modes: walking and driving. To characterize its non-linear relationships with other variables, we converted the Apple mobility index to a logarithmic scale. Figure 3 depicts an example of the Apple mobility index in the case of six provinces in Thailand, with all values shown in the original units calculated by Apple.

The NTL index was also included in this study to present the provincial density of economic activities, given that NTL has been conventionally acknowledged as the alternative indicator representing the socioeconomic condition, including the case of Thailand **(**Luenam & Puttanapong, 2020; Puttanapong et al**.**, 2022; Sangkasem & Puttanapong, 2022**).** As exemplified in Figure 4, this index is the provincial average of NTL density captured by SNPP/VIIRS satellite[1]**.** This satellite was launched by NASA in 2011**.** All data produced by this satellite are publicly accessible via the service of Google Earth Engine.

Figure 2

Google Community Mobility Index – Thailand (With 15-day Moving Average)

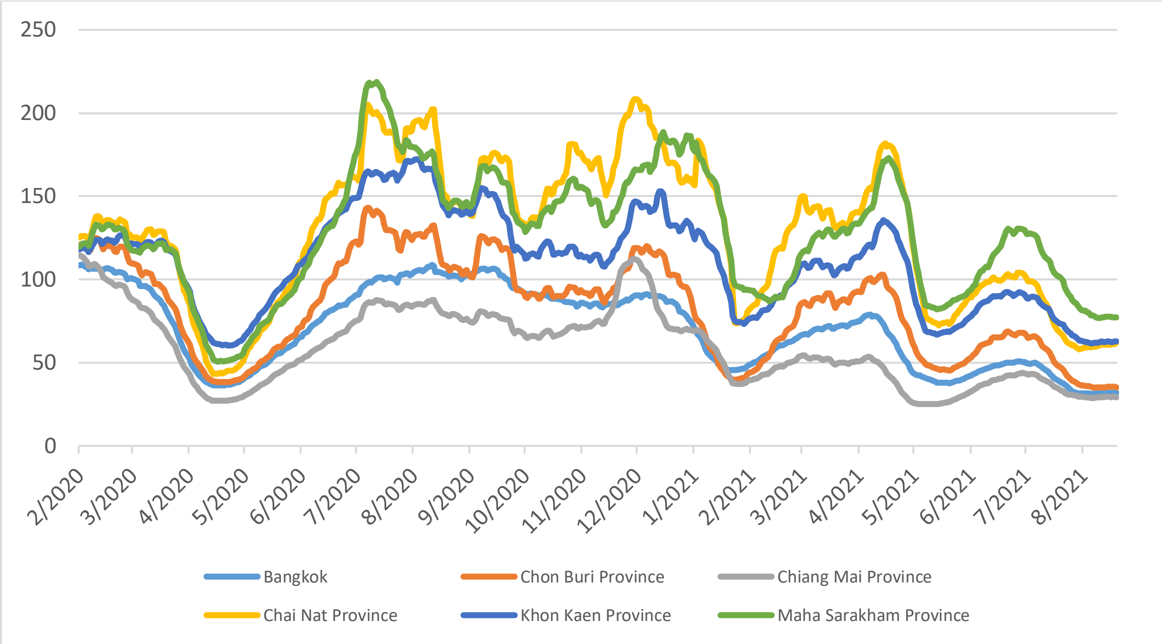


Note. The reference value is the pre-COVID period (January 2020), in which Google community mobility index = 0.0. Data are from "Google Community Mobility Index," by Google LLC, 2020 (https://www.google.com/covid19/mobility/). In the public domain.

[1] The full technical title of this satellite is Suomi National Polar-orbiting Partnership (SNPP) using Visible Infrared Imaging Radiometer Suite (VIIRS).

Figure 3

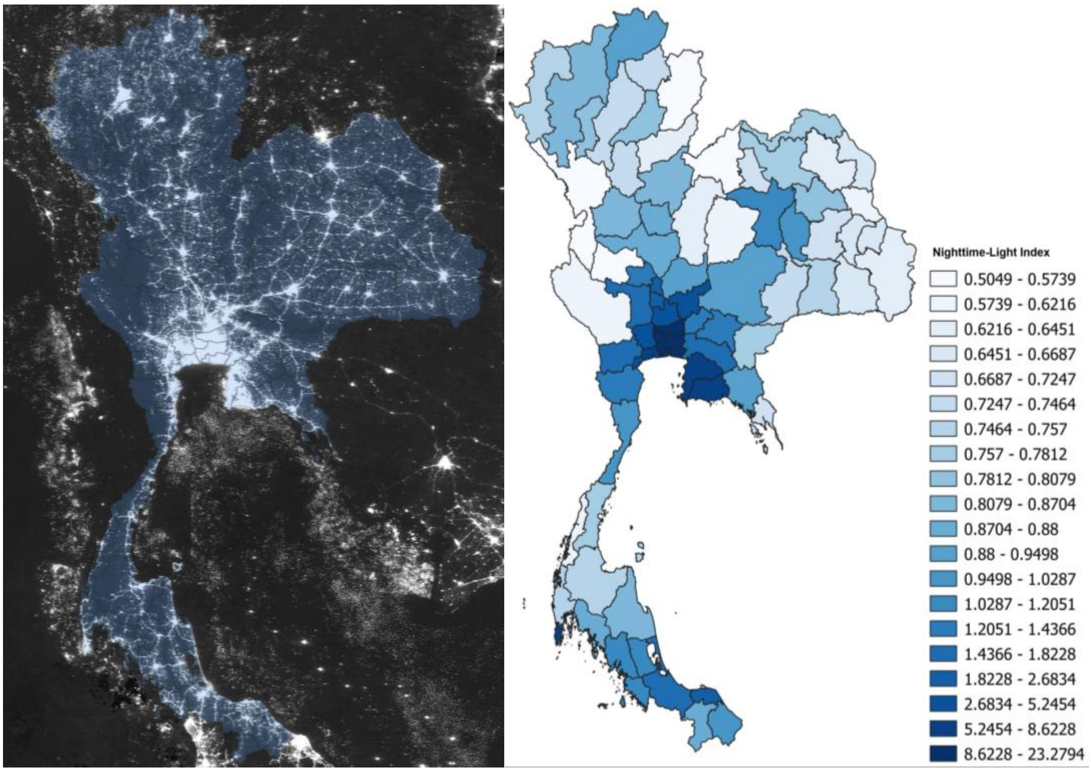
Apple Mobility Index – Thailand (Examples of Six Provinces With 15-day Moving Average)



Note. The reference value is the pre-COVID period (January 2020), in which Apple mobility index = 100. Data are from "Apple Mobility Index," by Apple Inc., 2020 (https://covid19.apple.com/mobility). In the public domain.

Figure 4

Example of Nighttime-Light (NTL) Data and Provincial Average NTL Index



Note. Adapted from *VIIRS Nighttime-Light Map*, by Google Earth Engine, 2022 (https://earthengine.google.com/). Copyright 2022 by Google LLC.

RESEARCH METHODS

To examine the associations between mobility restriction, economic activity, and COVID-19 cases, we divided the quantitative analyses into two parts: (1) OLS and (2) panel regressions.

OLS regression

OLS is a regression method for estimating an unknown parameter in a regression model. In this study, OLS regression is applied for quantifying the relationships between each mobility indicator and the number of COVID-19 infections. This investigation is mathematically shown in Equation (1).

$$logCOVID_i = \alpha + \beta \, logMobiliy_i + u_i \quad \text{Eq. (1)}$$

where:

logCOVID$_i$ = logarithm of the number of new confirmed COVID-19 cases of province *i*

logMobility$_i$ = logarithm of Apple mobility index or logarithm of Google community mobility index of province *i*

β = slope coefficient

α = intercept coefficient

u_i = error term with independent and identically distributed (i.i.d.) property

Specifically, given that the Apple mobility index has two categories of transportation modes, Equation (1) can be modified by incorporating these subcategories, yielding Equation (2). All monthly data applied are national-level aggregate indices.

$$logCOVID_i = \alpha + \beta_1 \, logWaking_i + \beta_2 \, logDriving_i + u_i \quad \text{Eq. (2)}$$

where:

logCOVID$_i$ = logarithm of the number of new confirmed COVID-19 cases of province *i*

logWaking$_i$ = logarithm of Apple mobility index based on volume of walking in province *i*

logDriving$_i$ = logarithm of Apple mobility index based on volume of driving in province *i*

$\beta_1, \ \beta_2$ = slope coefficients

α = intercept coefficient

u_i = error term with independent and identically distributed (i.i.d.) property

Likewise, Equation (1) is extended to incorporate all six subcategories of mobility indicators, as shown in Equation (3). As in the previous model, all monthly datasets applied to this Equation are national-level aggregate indicators.

$$logCOVID_i = \alpha + \beta_1 \, logRetail_i + \beta_2 \, logGrocery_i + \beta_3 \, logPark_i + \beta_4 \, logTransit_i + \beta_5 \, logWork_i + \beta_6 \, logResidential_i + u_i \quad \text{Eq. (3)}$$

where:

logCOVID$_i$ = logarithm of the number of new confirmed COVID-19 cases

logRetail$_i$ = logarithm of volume of visiting retail shops and recreation places

logGrocery$_i$ = logarithm of volume of visiting grocery and pharmacy shops

logPark$_i$ = logarithm of volume of visiting parks

logTransit$_i$ = logarithm of volume of visiting transportation transit places

logWork$_i$ = logarithm of volume of visiting workplaces and offices

logResidential$_i$ = logarithm of volume of staying in residential areas

$\beta_1, \ \beta_2, \ \beta_3, \ \beta_4, \ \beta_5, \ \beta_6$ = slope coefficients

α = intercept coefficient

u_i = error term with independent and identically distributed (i.i.d.) properties

Panel regression

The Apple mobility index is further utilized to investigate relationships at the provincial level. In addition, given that the NTL index can represent the intensity of economic activities in each province, this section carried out the relevant analysis by using the monthly provincial datasets of the (1) number of new COVID-19 infections; (2) Apple mobility index; and (3) the NTL index. Each indicator is transformed into the year-on-year change of logarithm value because many provinces in Thailand have a constant seasonal pattern of economic outputs, primarily driven by the harvest cycle in agriculture and/or seasonal tourism activity. Equations (4) and (5) indicate the mathematical forms of fixed-effect regression.

$$logCOVID_{i,t} - logCOVID_{i,t-12} = \beta_1\left(logDriving_{i,t} - logDriving_{i,t-12}\right) + \beta_2\left(logNTL_{i,t} - logNTL_{i,t-12}\right) + \alpha_0 + \alpha_i + \lambda_t + u_{i,t}$$

Eq. (4)

$$logCOVID_{i,t} - logCOVID_{i,t-12} = \beta_1\left(logWalking_{i,t} - logWalking_{i,t-12}\right) + \beta_2\left(logNTL_{i,t} - logNTL_{i,t-12}\right) + \alpha_0 + \alpha_i + \lambda_t + u_{i,t}$$

Eq. (5)

where:

logCOVID$_{i,t}$ = logarithm of the number of new confirmed COVID-19 cases of province *i* in month *t*

logWalking$_{i,t}$ = logarithm of Apple mobility index of walking in province *i* in month *t*

logDriving$_{i,t}$ = logarithm of Apple mobility index of driving in province *i* in month *t*

logNTL$_{i,t}$ = logarithm of Nighttime Light (NTL) index of province *i* in month *t*

β_1, β_2 = slope coefficients

α_0 = common intercept coefficient

α_i, λ_t = fixed-effect coefficients

$u_{i,t}$ = error term with independent and identically distributed (i.i.d.) properties

Alternatively, analysis of panel data can be undertaken by using the random-effect technique, with the mathematical specifications shown in Equations (6) and (7).

$$logCOVID_{i,t} - logCOVID_{i,t-12} = \beta_1\left(logDriving_{i,t} - logDriving_{i,t-12}\right) + \beta_2\left(logNTL_{i,t} - logNTL_{i,t-12}\right) + \alpha_i + u_{i,t}\ ;\ \alpha_i \sim N(0, \sigma_\alpha^2)\ ,\ u_{i,t} \sim N(0, \sigma_u^2)$$

Eq. (6)

$$logCOVID_{i,t} - logCOVID_{i,t-12} = \beta_1\left(logWalking_{i,t} - logWalking_{i,t-12}\right) + \beta_2\left(logNTL_{i,t} - logNTL_{i,t-12}\right) + \alpha_i + u_{i,t}\ ;\ \alpha_i \sim N(0, \sigma_\alpha^2)\ ,\ u_{i,t} \sim N(0, \sigma_u^2)$$

Eq. (7)

where:

logCOVID$_{i,t}$ = logarithm of the number of new confirmed COVID-19 cases of province *i* in month *t*

logWalking$_{i,t}$ = logarithm of Apple mobility index of walking in province *i* in month *t*

logDriving$_{i,t}$ = logarithm of Apple mobility index of driving in province *i* in month *t*

logNTL$_{i,t}$ = logarithm of Nighttime Light (NTL) index of province *i* in month *t*

β_1, β_2 = slope coefficients

α_i = random-effect coefficient

$u_{i,t}$ = error term with independent and identically distributed (i.i.d.) property

All computations in this study are carried out by using STATA**.** The results are shown and discussed in the next section**.**

RESULTS

Following the specifications of datasets and regression techniques discussed in previous sections, the results of OLS regression are discussed in Section 5.1, and the outcomes generated by panel regressions are then presented in Section 5.2

Results obtained from OLS regression

Table 2 displays the OLS estimations of Equations (2) and (3). The results reveal two key findings. First, a statistically significant non-linear association is observed between COVID-19 infections ($logCOVID_i$) and the driving subcategory of Apple's mobility index ($logDriving_i$), with the coefficient of –9.501. However, the relationship between the COVID-19 infections ($logCOVID_i$) and the walking subcategory of Apple's mobility index ($logWalking_i$) is not statistically significant. Second, the OLS estimation of Equation (3) shows that the only statistically significant association is observed between the COVID-19 infections ($logCOVID_i$) and the subcategory of transportation transit (*logTransit*$_i$) of Google mobility index, while all other subcategories are not statistically significant.

These results imply that an increase in COVID-19 infections can be associated with a reduction in driving activity and the number of people going to transit stations. The decreases in mobility are mainly caused by the imposed lockdown policy and social distancing. In addition, rising concerns related to health and hygiene might influence people to work from home and use less public transportation. In summary, the outcomes of OLS regressions confirm that the number of COVID-19 cases is negatively associated with particular subcategories of mobility indices produced by Apple and Google.

Table 2

Results Obtained From OLS Regression

Dependent variable: *LogCOVID*

	Equation (2)	Equation (3)
logWalking	2.482	
	(3.490)	
logDriving	-9.501**	
	(3.412)	
logRetail		6.321
		(4.330)
logGrocery		1.654
		(3.376)
logPark		-3.562
		(3.988)
logTransit		-4.618*
		(2.487)
logWorkplace		0.0621
		(3.574)
logResidential		0.505
		(9.762)
constant	17.06***	-0.782
	(2.789)	(59.61)
Observations	22	21
R^2	0.569	0.885
adj. R^2	0.524	0.835

Note. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Results obtained from the panel regressions

The Apple mobility index provides spatial resolution of the provincial level, enabling the formulation of panel data and associated regression analysis. In addition, the monthly NTL index is included to incorporate the intensity of economic activity of each province. Table 3 shows the obtained outcomes of using both fixed- and random-effect specifications.

The first and the third columns of Table 3 represent the estimations of Equations (4) and (6), using the mobility index's driving subcategory (*Δyoy_logDriving*) and NTL index (*Δyoy_logNTL*) as independent variables. Results obtained from the fixed- and random-effects methods are similar, affirming the statistically significant association between the number of COVID-19 cases and both independent variables. In particular, both variables are negatively associated with the number of COVID-19 confirmed cases, implying that the outbreak can reduce the volume of road transportation and dampen economic activity.

The second and the fourth columns of Table 3 show the estimated coefficients of Equations (5) and (7), employing the fixed- and random-effects methods, respectively. Apple's walking subcategory index (*Δyoy_logWalking*) and NTL index (*Δyoy_logNTL*) are independent variables; the former has a statistically negative relationship with the number of COVID-19 cases, whereas the latter does not have statistically significant association for either equation. All results obtained from Equations (4)–(7) statistically identify the relationship of the Apple mobility index, especially in the driving subcategory, with the intensity of the COVID-19 pandemic. In addition, these results align with those in Table 2, suggesting the potential of using Apple's driving mobility index as an alternative indicator for timely monitoring.

Table 3

Results Obtained From Panel Regression Models

Dependent variable: *LogCOVID*

	Equation (4)	Equation (5)	Equation (6)	Equation (7)
$\Delta yoy\_logDriving$	-1.487***		-1.429***	
	(0.351)		(0.344)	
$\Delta yoy\_logWalking$		-6.562**		-6.780***
		(2.080)		(1.993)
Δyoy_logNTL	-8.631***	-2.720	-6.919***	0.430
	(1.563)	(5.536)	(1.219)	(4.935)
constant	4.870***	19.08***	4.611***	19.54***
	(0.982)	(5.312)	(0.970)	(5.088)
Observations	1,330	151	1,330	151
R^2- overall	0.041	0.145	0.041	0.134
R^2- within	0.044	0.145	0.043	0.143
R^2- between	0.119	0.116	0.111	0.131
Fixed Effects	Yes	Yes	No	No

Note. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Main contributions and limitations

The main contribution of this study is the introduction of the use of near real-time data; Google community mobility and Apple mobility indices. Compared with conventional economic data that becomes available after approximately 30–45 days for official publications, the Google community and Apple mobility indices can be obtained approximately 3–4 days after the activities occur. Analogous to numerous studies emphasizing the significance of alternative indicators representing human activities (Huang et al., 2020; Kraemer et al., 2020; Oliver et al., 2020; Sills et al., 2020), the mobility indices can potentially be used as the near real-time data sources for monitoring the COVID-19 pandemic, providing timely information to policymakers regarding the collective responses with respect to daily activities. In addition, this study used datasets incorporating spatial resolution at the provincial level and temporal coverage that includes the periods of the two major outbreaks caused by the Alpha and the Delta variants in 2020 and 2021, respectively. This spatiotemporal coverage ensures sufficient detail for empirical analyses.

The main limitations of this study are threefold.

First, the OLS regression model might contain multicollinearity influenced by the Google community mobility index, including subcategories of locations and activities that are correlated. Correction techniques (e.g., ridge and lasso regressions) must be applied (Chan et al., 2022; Chen, 2012).

Second, both Google and Apple mobility indicators are formulated from the data of users who have agreed to share their information with Google and Apple. However, these datasets might not fully represent the mobility of the total population in Thailand, yielding biased results. These concerns and suggested corrections have been documented in many publications. In addition, any future studies should include the use of multi-frequency data in the analyses. (Huang et al., 2018; Jiang et al., 2019; Li et al., 2020; Martín et al., 2019).

Lastly, none of the models in this study include other variables that could influence the COVID-19 pandemic, such as the vaccination rate, effectiveness of social distancing regulation, Internet and transportation infrastructure, awareness and collaboration of individuals, or the accuracy of identifying infected individuals (Almagro & Orane-Hutchinson, 2022; Chiou & Tucker, 2020; Lou et al., 2020).

The obtained results suggest the need for further research. Specifically, social media data are informative sources for studying key features of human mobility (Hasan & Ukkusuri, 2014; Isaacman et al., 2011; Sirkeci & Yucesahin, 2020; Wang et al., 2015; Wu et al., 2014). Therefore, spatial simulations can be developed to forecast the geographical impacts of transportation investment, urban planning, government policy and climate change (Haase et al., 2010; Hermes & Poulsen, 2012; Ma et al., 2014; Subbiah et al., 2013; Zhang et al., 2014).

CONCLUSION

This study investigates the relationship between the COVID-19 pandemic and mobility indicators, namely Google community and Apple mobility indices. The official statistics of daily COVID-19 infections were obtained from Thailand's Ministry of Public Health. The results obtained from OLS show that Apple's driving mobility and Google's transportation transit indices are negatively associated with the number of COVID-19 infections. Results from both fixed- and random-effect models of panel regressions indicate that Apple's driving and walking mobility indices provide negative relationships with the outbreak of the COVID-19 pandemic. The outcomes of this empirical investigation suggest future applications of examining the spatial distributions of spontaneous mobility and long-term relocation. Specifically, these empirical findings can serve as the foundation for spatial simulations applicable for urban planning and geographical studies.

REFERENCES

Almagro, M., & Orane-Hutchinson, A. (2022). JUE Insight: The determinants of the differential exposure to COVID-19 in New York city and their evolution over time. *Journal of Urban Economics*, *127*, 103293. https://doi.org/https://doi.org/10.1016/j.jue.2020.103293

Badr, H. S., Du, H., Marshall, M., Dong, E., Squire, M. M., & Gardner, L. M. (2020). Association between mobility patterns and COVID-19 transmission in the USA: A mathematical modelling study. *The Lancet Infectious Diseases*, *20*(11), 1247-1254. https://doi.org/10.1016/S1473-3099(20)30553-3

Camba, A. C. J., & Camba, A. L. (2020). The effects of restrictions in economic activity on the spread of COVID-19 in the Philippines: Insights from Apple and Google mobility indicators. *The Journal of Asian Finance, Economics and Business*, *7*(12), 115-121. https://doi.org/10.13106/JAFEB.2020.VOL7.NO12.115

Chan, J. Y., Leow, S. M., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.W., & Chen, Y.L. (2022). Mitigating the multicollinearity problem and its machine learning approach: A review. *Mathematics*, *10*(8). https://doi.org/10.3390/math10081283

Chen, G. J. (2012). A simple way to deal with multicollinearity. *Journal of Applied Statistics*, *39*(9), 1893-1909. https://doi.org/10.1080/02664763.2012.690857

Chiou, L., & Tucker, C. (2020). Social distancing, internet access and inequality. *National Bureau of Economic Research Working Paper Series*, *No. 26982*. https://doi.org/10.3386/w26982

Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the Novel Coronavirus (2019-nCoV) in China. *Journal of Public Economics*, *191*, 104272. https://doi.org/https://doi.org/10.1016/j.jpubeco.2020.104272

Fauver, J. R., Petrone, M. E., Hodcroft, E. B., Shioda, K., Ehrlich, H. Y., Watts, A. G., Vogels, C. B. F., Brito, A. F., Alpert, T., Muyombwe, A., Razeq, J., Downing, R., Cheemarla, N. R., Wyllie, A. L., Kalinich, C. C., Ott, I. M., Quick, J., Loman, N. J., Neugebauer, K. M., . . . Grubaugh, N. D. (2020). Coast-to-coast spread of SARS-CoV-2 during the early epidemic in the United States. *Cell*, *181*(5), 990-996.e995. https://doi.org/https://doi.org/10.1016/j.cell.2020.04.021

Haase, D., Lautenbach, S., & Seppelt, R. (2010). Modeling and simulating residential mobility in a shrinking city using an agent-based approach. *Environmental Modelling & Software*, *25*(10), 1225-1240. https://doi.org/https://doi.org/10.1016/j.envsoft.2010.04.009

Hasan, S., & Ukkusuri, S. V. (2014). Urban activity pattern classification using topic models from online geo-location data. *Transportation Research Part C: Emerging Technologies*, *44*, 363-381. https://doi.org/https://doi.org/10.1016/j.trc.2014.04.003

Hermes, K., & Poulsen, M. (2012). A review of current methods to generate synthetic spatial microdata using reweighting and future directions. *Computers, Environment and Urban Systems*, *36*(4), 281-290. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2012.03.005

Holmdahl, I., & Buckee, C. (2020). Wrong but useful — What Covid-19 epidemiologic models can and cannot tell us. *New England Journal of Medicine*, *383*(4), 303-305. https://doi.org/10.1056/NEJMp2016822

Huang, X., Li, Z., Jiang, Y., Li, X., & Porter, D. (2020). Twitter reveals human mobility dynamics during the COVID-19 pandemic. *PLoS One*, *15*(11), e0241957. https://doi.org/10.1371/journal.pone.0241957

Huang, X., Wang, C., & Li, Z. (2018). Reconstructing flood inundation probability by enhancing near real-time imagery with real-time gauges and tweets. *IEEE Transactions on Geoscience and Remote Sensing*, *56*, 4691-4701. https://doi.org/10.1109/TGRS.2018.2835306

Isaacman, S., Becker, R., Cáceres, R., Kobourov, S., Martonosi, M., Rowland, J., & Varshavsky, A. (2011). Identifying important places in people's lives from cellular network data. In K. Lyons, J. Hightower, & E.M. Huang (Eds.), *Pervasive 2011: Pervasive Computing*. Springer. https://doi.org/10.1007/978-3-642-21726-5_9

Jiang, Y., Li, Z., & Ye, X. (2019). Understanding demographic and socioeconomic biases of geotagged Twitter users at the county level. *Cartography and Geographic Information Science*, *46*(3), 228-242. https://doi.org/10.1080/15230406.2018.1434834

Kartal, M. T. (2021). The effect of COVID-19 pandemic on oil prices: Daily evidence from Turkey. *Energy Research Letters,1*(4), 1-4. https://doi.org/10.46557/001c.18723

Kraemer, M. U. G., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D. M., null, n., du Plessis, L., Faria, N. R., Li, R., Hanage, W. P., Brownstein, J. S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O. G., & Scarpino, S. V. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*, *368*(6490), 493-497. https://doi.org/10.1126/science.abb4218

Li, Z., Huang, X., ye, X., & Li, X. (2020). ODT flow explorer: Extract, query, and visualize human mobility. *ArXiv:2011.12958*. ARXVI. https://arxiv.org/abs/2011.12958

Lou, J., Shen, X., & Niemeier, D. (2020). Are stay-at-home orders more difficult to follow for low-income groups? *Journal of Transport Geography*, *89*, 102894. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2020.102894

Luenam, A., & Puttanapong, N. (2020). Modelling and analyzing spatial clusters of leptospirosis based on satellite-generated measurements of environmental factors in Thailand during 2013-2015. *Geospat Health*, *15*(2), 217-224. https://doi.org/10.4081/gh.2020.856

Ma, J., Heppenstall, A., Harland, K., & Mitchell, G. (2014). Synthesising carbon emission for mega-cities: A static spatial microsimulation of transport CO2 from urban travel in Beijing. *Computers, Environment and Urban Systems*, *45*, 78-88. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2014.02.006

Martín, Y., Cutter, S., & Li, Z. (2019). Bridging Twitter and survey data for the evacuation assessment of Hurricane Matthew and Hurricane Irma. *Natural Hazards Review*. https://doi.org/10.1061/(ASCE)NH.1527-6996.000035

Oh, J., Lee, H.-Y., Khuong, Q. L., Markuns, J. F., Bullen, C., Barrios, O. E. A., Hwang, S.-s., Suh, Y. S., McCool, J., Kachur, S. P., Chan, C.-C., Kwon, S., Kondo, N., Hoang, V. M., Moon, J. R., Rostila, M., Norheim, O. F., You, M., Withers, M., . . . Gostin, L. O. (2021). Mobility restrictions were associated with reductions in COVID-19 incidence early in the pandemic: Evidence from a real-time evaluation in 34 countries. *Scientific Reports*, *11*(1), 13717. https://doi.org/10.1038/s41598-021-92766-z

Oliver, N., Letouzé, E., Sterly, H., Delataille, S., De Nadai, M., Lepri, B., Lambiotte, R., Benjamins, R., Cattuto, C., Colizza, V., Cordes, N. d., Fraiberger, S. P., Koebe, T., Lehmann, S., Murillo, J., Pentland, A. S., Pham, P. N., Pivetta, F., Salah, A. A., . . . Vinck, P. (2020). Mobile phone data and COVID-19: Missing an opportunity? *ArXiv: 2003.12347*. ARXIV. https://arxiv.org/abs/2003.12347

Osewe, P. (2021*). Pandemic preparedness and response strategies: COVID-19 lessons from the Republic of Korea, Thailand, and Viet Nam*. Asian Development Bank. https://www.adb.org/sites/default/files/publication/743746/pandemic-preparedness-covid-19-lessons.pdf

Pei, S., Kandula, S., & Shaman, J. (2020). *Differential effects of intervention timing on COVID-19 spread in the United States*. MedRxiv. https://doi.org/10.1101/2020.05.15.20103655

Puttanapong, N., Martinez, A., Bulan, J. A., Addawe, M., Durante, R. L., & Martillan, M. (2022). Predicting poverty using geospatial data in Thailand. *ISPRS International Journal of Geo-Information*, *11*(5). https://doi.org/10.3390/ijgi11050293

Sangkasem, K., & Puttanapong, N. (2022). Analysis of spatial inequality using DMSP-OLS nighttime-light satellite imageries: A case study of Thailand. *Regional Science Policy & Practice*, *14*(4), 828-849. https://doi.org/https://doi.org/10.1111/rsp3.12386

Sen, S., Karaca-Mandic, P., & Georgiou, A. (2020). Association of stay-at-home orders with COVID-19 hospitalizations in 4 states. *JAMA*, *323*(24), 2522-2524. https://doi.org/10.1001/jama.2020.9176

Sills, J., Buckee, C. O., Balsari, S., Chan, J., Crosas, M., Dominici, F., Gasser, U., Grad, Y. H., Grenfell, B., Halloran, M. E., Kraemer, M. U. G., Lipsitch, M., Metcalf, C. J. E., Meyers, L. A., Perkins, T. A., Santillana, M., Scarpino, S. V., Viboud, C., Wesolowski, A., & Schroeder, A. (2020). Aggregated mobility data could help fight COVID-19. *Science*, *368*(6487), 145-146. https://doi.org/10.1126/science.abb8021

Sirkeci, I., & Yucesahin, M. M. (2020). Coronavirus and migration: Analysis of human mobility and the spread of Covid-19. *Migration Letters*, *17*(2), 379-398. https://doi.org/10.33182/ml.v17i2.935

Subbiah, R., Lum, K., Marathe, A., & Marathe, M. (2013). Activity based energy demand modeling for residential buildings. *IEEE PES Innovative Smart Grid Technologies Conference (ISGT),* (pp. 1-6). http://dx.doi.org/10.1109/ISGT.2013.6497822

Sulyok, M., & Walker, M. D. (2021). Mobility and COVID-19 mortality across Scandinavia: A modeling study. *Travel Medicineand Infectious Disease*, *41*, 102039. https://doi.org/10.1016/j.tmaid.2021.102039

Tian, H., Liu, Y., Li, Y., Wu, C.-H., Chen, B., Kraemer, M. U. G., Li, B., Cai, J., Xu, B., Yang, Q., Wang, B., Yang, P., Cui, Y., Song, Y., Zheng, P., Wang, Q., Bjornstad, O. N., Yang, R., Grenfell, B. T., . . . Dye, C. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*, *368*(6491), 638-642. https://doi.org/10.1126/science.abb6105

Wang, Y., Yuan, N., Lian, D., Xu, L., Xie, X., Chen, E., & Rui, Y. (2015). Regularity and conformity*. Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining Sydney, NSW, Australia. Association for Computing Machinery* (pp. 1275-1284). https://doi.org/10.1145/2783258.2783350

World Health Organization. (2020). *WHO Thailand situation report - 1*. WHO. https://cdn.who.int/media/docs/default-source/searo/thailand/20200206-tha-sitrep-01-ncov-final.pdf?sfvrsn=7c8cb671_0

World Health Organization. (2021). *WHO Thailand situation report - 201*.WHO. https://cdn.who.int/media/docs/default-source/searo/thailand/2021_09_16_eng-sitrep-201-covid19.pdf?sfvrsn=3a249ade_5

World Health Organization. (2022). *Coronavirus disease (COVID-19) weekly epidemiological update and weekly operational update*. WHO. https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19---15-june-2022

Wu, L., Zhi, Y., Sui, Z., & Liu, Y. (2014). Intra-urban human mobility and activity transition: Evidence from social media check-in data. *PLoS One*, *9*(5), e97010. https://doi.org/10.1371/journal.pone.0097010

Xu, S., & Li, Y. (2020). Beware of the second wave of COVID-19. *The Lancet*, *395*(10233), 1321-1322. https://doi.org/10.1016/S0140-6736(20)30845-X

Yang, C., Sha, D., Liu, Q., Li, Y., Lan, H., Guan, W. W., Hu, T., Li, Z., Zhang, Z., Thompson, J. H., Wang, Z., Wong, D., Ruan, S., Yu, M., Richardson, D., Zhang, L., Hou, R., Zhou, Y., Zhong, C., . . . Ding, A. (2020). Taking the pulse of COVID-19: A spatiotemporal perspective. *International Journal of Digital Earth*, *13*(10), 1186-1211. https://doi.org/10.1080/17538947.2020.1809723

Zhang, D., Huang, J., Li, Y., Zhang, F., Xu, C.-Z., & He, T. (2014). Exploring human mobility with multi-source data at extremely large metropolitan scales. *MobiCom'14: The 20th Annual International Conference on Mobile Computing and Networking* (pp. 201-212). Association for Computing Machinery. https://doi.org/10.1145/2639108.2639116