MK406: Individual final report

The impact of mobility restriction to the spread out of Covid-19 cases in Thailand

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Introduction

The Covid‑19 has spread quickly from China since December 2019 and was identified as a pandemic in March 2020 (WHO, 2020). It has caused over 271 million infected cases and 5.31 million deaths as of December, 2021 (Government health ministries, 2021). The spread out of Covid-19 has deteriorated many economic and financial indicators including foreign exchange rate and interest rate deteriorated (Kartal, 2021; Kartal et al., 2020). There are numerous negative impacts following those indicators, therefore, Covid-19 pandemic is considered as the most influential global phenomenon that the world has ever experienced (Bloomberg, 2020). In addition, the increasing number of infected cases is still rising despite the distribution of vaccines. Mainly because of the mutation of new Covid-19 variants, as well as, low vaccination rate in some countries. Hence, the policy makers come up with many different ways to limit the spread out of Covid-19 as much as possible.

There are a variety of public health prevention measures, such as state quarantine, home isolation and travel restrictions. These policies are aimed to decrease the probability that infected people will spread out the virus to non-infected one. The mobility restrictions or lockdown policies have been a basis policy responses to the outbreak of Covid-19. The mobility restrictions aim to encourage people to work from home and straighten the social distance in order to reduce the infected case. The reason behind the travel and mobility restriction as a public health measure is that it will limit activities outside people's accommodation, including working, shopping and eating out at the restaurants in which these activities will increase the chance of transmission from the infected one to numerous people in public.

A mobility restriction has multiple levels, for example the lowest level is curfew policy that restricts people from being outside the residential area at the specific time (normally at the late night and very early morning). In case of the serious lockdown, people are not allowed to be outside their residence except for important activities such as grocery shopping and medical appointments, therefore most of the companies implement working from home policy. The level of lockdown policy mostly depends on the severity of the Covid-19 cases. The first mobility restriction measure in Thailand associated with Covid-19 occurs in April, 2020 that shopping centers, clubs, bars and gyms are forced to be closed, and people are prohibited to leave their accommodation at a certain time. Another more serious lockdown is in July until October, similar to previous lockdown, and everyone is encouraged to stay at home except for an important activity. The lockdown in July is much more serious than the previous due to the Delta variants that have increased transmissibility (WHO, 2021).

Although, mobility restrictions could help reduce the number of infected cases, it comes with a huge cost due to lower economic activities. Therefore, the government must carefully weigh the cost and benefit of any mobility restriction or lockdown policy before implementing. Large scale mobility restrictions make a significant change to the behavioral and social prescription. Global GDP growth has fallen by over 10% from the mobility resrictions (Juhwan Oh et al., 2021). In addition, in the case of Thailand that uses the lock down policy for 3 months, KKP research (2021) estimated that this measure will highly impact the Thai economy and the expected GDP is forecasted to decrease by over 1% due to lower spending. At the beginning there is still a concern that the economic damage of the mobility restriction policy will be greater than the impact from more people who become sick or die due to Covid-19 virus. However, the recent studies on the link between mobility restrictions and decrease in viral transmission, and a recent analysis of GDP and death rates suggested that less control over the spread out of Covid-19 tend to be associated with more economic loss. Therefore, at the beginning of the spread out, a country will decide to close down the broader area in order to reduce the number of cases from international travelers. However, In the circumstance that there is a large number of infected people and the government is unable to handle the situation, lockdown policies could be picked to deal with this issue. Normally, mobility restriction is implemented when a country faces a significant increase in infected cases with low vaccination. The following problems are high hospitality rates and the hospitals can't no longer accept more patients.

Understanding the effectiveness of the travel restriction such as lockdown policy is important for controlling the spread out of Covid-19. By utilizing the near real-time mobility data from private companies, we can obtain information about the change in people's movement in the specific time (Buckee et al.,2020). Other with the infected cases, we can find the relationship and the impact of mobility restriction to the reduction in infected cases. The effectiveness of mobility restriction and lockdown policy could be different due to countries' specific characteristics. Furthermore, policy makers are challenged with the appropriate policy responses in order to balance the cost and benefit of the mobility restriction policies. To summarize, this paper will mainly focus to the following questions:

1. What is association between change in infected cases and each of mobility indicators

2. What are the impact of change in Apple mobility index and Google community mobility index to the change in infected cases

Literature review

There are several research papers examining the effect of mobility restrictions on the Covid-19 infected cases. With the country's specific characteristics, we divide the literature review into 2 sections: (i) Asia (ii) Europe and the United States area. The reason why the literature reviews are divided into these 2 sections are the government respondent toward the spread out of Covid-19 and culture differences between these 2 areas. At the beginning of the epidemic outbreak, many asian countires decided to react aggressively to stop the spread of the Covid-19 in the early stage, including international travel restrictions, state-quarantine program and contract-tracking (Wall Street Journal, 2020). In addition, the culture of difference such as wearing facemasks is widely more accepted among Asians compared with Americans and Europeans. In addition, Asians are better at taking advice and follow the Covid-19 restrictions (Teo Yik-Ying, 2020).

Section 1: Asia

Fang, Wang, and Yan (2020),who focus particularly on the the lockdown of the city of Wuhan by using panel fixed effect with inter-city population migration data from Baidu Migration and the daily new confirmed COVID-19 cases from 23 January to 29 February 2020, found out that lockdown policy play a significant role in flattening the daily infected cases given the city of Wuhan is an epicenter.

The study from Kramer et al. (2020) studied the effect of human mobility and control measures on the Covid-19 epidemic in China by using multiple methodologies including a stochastic susceptible infectious-recovered model to describe the temporal-spatial evolution of the Covid-19 across 33 provincial regions in China, Bayesian and Chain Monte-Carlo methods to distinguish a transmission dynamic network that help evaluate the national policies effectiveness. While the mobility data obtained from Baidu Migra represented human mobility in China. They found that the only epicenter of the early stage was Hubei and by the late January Beijing and Guangdong became secondary epicenters. The result also suggested that the spread of Covid-19 in China mainly came from community transmission within regions and mobility restriction is an effective tool to reduce the transmission for the government.

For the study of the effect of the restriction in economic activity on the control over Covid-19 case in the Philippines, Cambra et al. (2020) used the robust least square regression via the method of MM-estimation. The data used for representing economic activity are Apple mobility index and Google community mobility index. The major findings reveal that the highest impact on the spread out of Covid-19 is staying at home, followed by less visiting transit stations , less use of public transport, less amount of walking, and less workplace visits respectively.

Section 2: Europe and The United States area

Sulyok and Walker (2021) studied the mobility and Covid-19 mortality across Scandinavian countries by using Google community mobility and Stringency index in generalized additive and modeling. The researchers found out that mortality rates in Sweden were greater than its neighboring countries due to lower Covid-19 restriction measures. The key results suggested that higher stringency shows more association with lower death rate compared to mobility. They recommended the policy makers to focus on control of government regulations rather than restraining the mobility such as the use of public information campaigns or mask wearing restrictions.

Move to the case study from The United States. Sen, Karaca-Mandic, and Georgiou (2020) conducted research on the effect of lockdown policy to Covid-19 hospitalizations in 4 states: Colorado, Minnesota, Ohio, and Virginia. The result suggested that cumulative hospitalizations for COVID-19 deviated from projected best-fit exponential growth rates after stay-at-home order was implemented. Badr et al. (2020) also used a mathematical modeling study to identify the association between mobility patterns and the transmission of Covid-19 in 25 states across the United States by using Daily mobility data derived from aggregated and anonymised mobile phone data, provided by Teralytics. They found that social distancing and decrease in mobility is an effective way to reduce Covid-19 transmission. Another study in the United States, Pei et al. (2020) conducted a research on the impact of intervention timing on Covid-19 cases. The result indicated that social distancing and other Covid-19 control measures were associated with the significant reduction of infected cases in metropolitan areas. In addition, They found that if the same controls were implemented just 1 week earlier the death rate could have been reduced by approximately 54%.

Oh et al. (2021) studied the association between mobility restrictions and the reduction of Covid-19 cases in 34 OECD countries together with Singapore and Taiwan by using Google community mobility index. The key findings was social mobility restriction can reduce the Covid-19 transmission in many countries especially in the early stages. However, the magnitude of the impact was lower in the late phase of the pandemic wave.

Research gap

Most of existing literature is conducted in the year 2020, therefore the number of observations used in the model was not up to date. Since there are continuous changes on the Covid-19 restriction measures and the new various, hence these effects didn't show in the result. In addition, other variables that could directly affect the spread out of Covid-19 cases were not included in the studies such as people's caution behavior regarding Covid-19 and vaccination rate. Lastly some papers used mobility that is not publicly accessible, therefore it could be difficult for further studies.

Data and research methods

Data

This study is a time series data collected from secondary research between 1 February 2021 to 30 November 2021 collected daily in order to demonstrate the effectiveness of the mobility restriction during an outbreak of 2 Covid-19 variants: Alpha and Delta in Thailand.

Data	Source of Data	Unit
The number of confirmed Covid-19 new cases	Our world in data	people
Google community mobility index	Google community mobility report	percentage change from the baseline
Apple mobility index	Apple mobility trend report	-

Independent variable

The data that this paper uses to represent the mobility of people in Thailand is the Apple mobility index and Google community mobility index in Thailand. This data is collected from mobile device-based global positioning systems (GPS) information obtained from people who agree to share their position and movement to Apple and Google. The mobility index from Google community mobility index is categorized in 6 visited locations: retail and recreational places, workplaces, transit stations, residential areas, groceries and pharmacies, and parks. On the other hand, For Thailand, the Apple mobility index is divided into 2 activities: walking and driving. In order to obtain the change in mobility movement, Google community mobility and Apple mobility index are transformed to the logarithm from. In addition, to reduce the effect of multicollinearity, Google community mobility and Apple mobility index will be in the separate model.

Outcome variable

The outcome variable in this paper is the daliy change in infected cases in Thailand. In order to obtain the daliy change in infected cases, we first gathered the number of confirmed new cases on a given day in Thailand starting from 1 February 2021 to 30 November 2021, then transformed these data into the logarithmic form.

Methodology

In order to accomplish the research objective on finding the impact of mobility restriction to infected Covid-19 cases, the mythology will divide into 2 parts which are linear regression and multiple regression. Linear regression or ordinary least squares regression is a method that is used to estimate the unknown parameter in the regression model. In this paper, simple linear regression is used to identify the relationship of each mobility indicator to the infected Covid-19 cases by plotting each indicator against the infected cases. As a result, we can obtain the relationship of each independent variable to infected cases, as well as, the impact of each variable to infected cases.

The simple linear regression equation:

$$COVID = \beta_0 + \beta_i x_i + u_i$$

Where:

COVID = log of the number of daily new Covid-19 cases

x = the mobility index

β = parameter estimate

u = error term

For the next part, we also use linear regression but extended to multiple regression in order to insert more than 1 variable of mobility indexes to explain the change in infected cases.

The multiple linear regression equation for Google community mobility index:

$$COVID = \beta_0 + \beta_1 RETAILlag + \beta_2 PHARlag + \beta_3 PARKlag + \beta_4 TRANlag + \beta_5 WORKlag + \beta_6 RESTlag + u$$

Where:

COVID = log of the number of daily new Covid-19 cases

RETAILlag = visit of retail and recreation percent change from baseline

PHARlag = visit of grocery and pharmacy percent change from baseline

PARKlag = visit of parks percent change from baseline

TRANlag = visit of transit stations percent change from baseline

WORKlag = visit of workplaces percent change from baseline

RESTlag = visit of residentials percent change from baseline

The multiple linear regression equation for Apple mobility index:

$$COVID = \beta_0 + \beta_1 logWalkinglag + \beta_2 logDrivinglag + u$$

Where:

COVID = log of the number of daily new Covid-19 cases

logWalkinglag = log of the walking Apple mobility index

logDrivinglag = log of the driving Apple mobility index

β = parameter estimate

u = error term

This regression will use a time lag of 14 days in order to include the effect of Covid-19 incubation period and the delay of Covid-19 test. The simple linear regression run by Microsoft Excel and the multiple regression analysis will be conducted through STATA.

Result analysis and discussion

Correlation Analysis

Each change in mobility index is tested whether they show some degree of correlation with the change in new confirmed Covid-19 cases. The scatter plot with R-square and simple linear regression is chosen for this analysis. Figure 1 Shows that there are negative corresponding correlation patterns between log of the number of new COVID-19 daily infections

(COVID) with RETAILlag, PHARlag, TRANlag, WORKlag, and PARKlag. On the other hand, the correlation between COVID Restlag turned out to be positive. According to Figure 2 that shows the relationship of log of the number of new COVID-19 daily infections (COVID) with logWALKlag and logDRIVElag. It shows that both logDRIVElag and logWALKlag have a negative correlation with COVID.

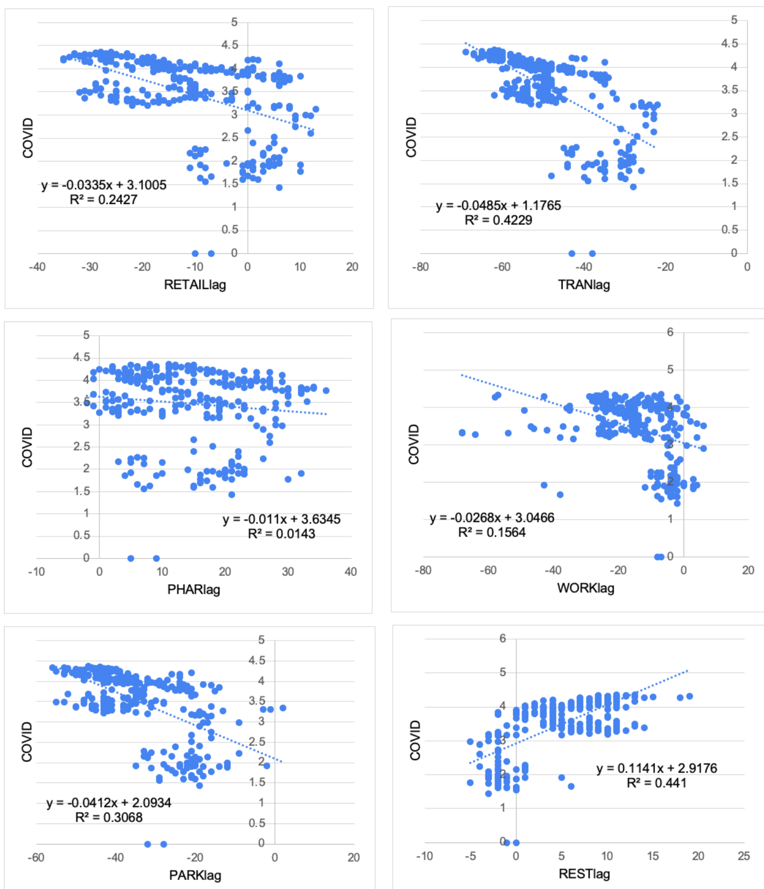

Figure 1: scatter plot showing the correlation between COVID and Google community mobility index

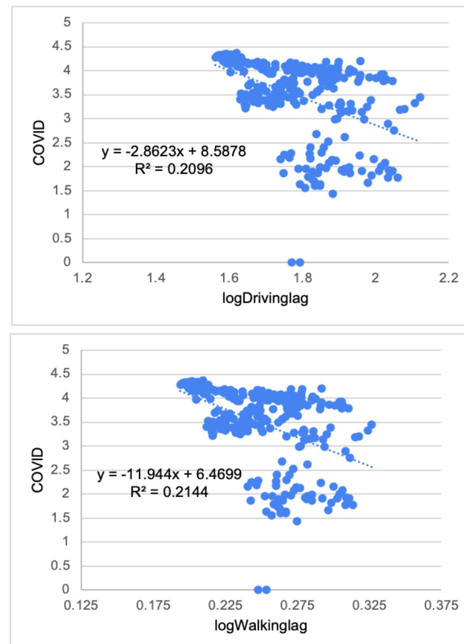

Figure 2: scatter plot showing the correlation between COVID and Apple mobility index

Robust Least Squares Regression Results

There were 650 observations of the data on daily new COVID-19 infections cases change and mobility changes in Thailand, starting from February 15, 2020 to December 9, 2021. Table 1 shows the result from multiple regression of COVID and other 6 variables of change in Google community mobility index (RETAILlag, PHARlag, PARKlag, TRANlag, WORKlag, and RESTlag). The result of the coefficient estimate shows that RETAILlag, PHARKlag, WORKlag, and RESTlag have a positive effect on the change of number of new infected cases (COVID).

With the coefficient of 0.025, 0.040, 0.015 and 0.141 respectively. While RETAILlag, PHARKlag, and RESTlag showed a statistically significant result with 95% confidence level, WORKlag showed a statistically significant result at 90% confidence level. Meanwhile, the correlation of PARKlag and TRANlag shows negative signs with statistically significant results with 95% confidence level. with COVID with coefficients of -0.0191 and -0.0308 respectively. The R-squared value of this model is 0.6359 and adjusted R-squared value is 0.6281.

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. reg COVID RETAILlag PHARlag PARKlag TRANlag WORKlag RESTlag
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Source	SS	df	MS			
				Number of obs	=	289
				F(6, 282)	=	82.07
Model	127.697795	6	21.2829658	Prob > F	=	0.0000
Residual	73.1259963	282	.259312044	R-squared	=	0.6359
				Adj R-squared	=	0.6281
Total	200.823791	288	.697304831	Root MSE	=	.50923

COVID	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
RETAILlag	.0251102	.0122299	2.05	0.041	.0010368	.0491836
PHARlag	.0403244	.0076879	5.25	0.000	.0251914	.0554574
PARKlag	-.0191314	.0090316	-2.12	0.035	-.0369093	-.0013536
TRANlag	-.0308628	.0106798	-2.89	0.004	-.051885	-.0098406
WORKlag	.0149776	.0081513	1.84	0.067	-.0010676	.0310228
RESTlag	.1411496	.0356964	3.95	0.000	.0708843	.2114148
_cons	.6136542	.4461907	1.38	0.170	-.264633	1.491941

Table 1: Multiple regression model for COVID and Google community mobility index

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. reg COVID logDrivinglag logWalkinglag
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Source	SS	df	MS			
				Number of obs	=	288
				F(2, 285)	=	42.53
Model	45.7476577	2	22.8738289	Prob > F	=	0.0000
Residual	153.264928	285	.537771676	R-squared	=	0.2299
				Adj R-squared	=	0.2245
Total	199.012585	287	.693423643	Root MSE	=	.73333

COVID	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logDrivinglag	19.84961	8.29792	2.39	0.017	3.516629	36.1826
logWalkinglag	-93.77505	34.235	-2.74	0.007	-161.1606	-26.38952
_cons	-8.467851	6.253726	-1.35	0.177	-20.7772	3.8415

Table 2: Multiple regression model for COVID and Apple mobility index

Table 2 demonstrates the robust least squares regression result of COVID and Apple mobility index. The result presents the positive sign of logDRIVElag but negative sign of logWALKINGlag. With the coefficient of 19.84961 and -93.77505 respectively. Therefore, the lower percentage change in driving could reduce the percentage of infected cases. The R-squared value of this model is 0.2299 and adjusted R-squared value is 0.2245.

Key advantage and Limitations

One of key advantages of this paper is that it uses near real-time data; Google community mobility and Apple mobility index. Compared with other economic data that takes approximately 1-1.5 month to publish, Google community mobility and Apple mobility index can be obtained only 3-4 days after the activities occur. Normally, the policy makers could not make any change to the policy or measure as the impact of the measure is often available after the policies end. This data can be used as a real-time monitor of the current situation, and can immediately make changes before it's too late. In addition, this paper provides data that is up-to-date that takes into account the current situation. To elaborate, another advantage of this paper is it shows how change in mobility restriction impacts the change in Covid-19 cases which takes into account 2 spread out of Covid variants: Alpha and Delta variants in Thailand which is the variant of concern in the current situation. In addition, the data give useful detail in each mobility index, for example Google community mobility index can tell specifically on the place of destination; retail and recreational places, workplaces, transit stations, residential areas, groceries and pharmacies, and parks. An Apple mobility index can tell whether the index comes from walking or driving.

However, the flaws of this paper is that it only applies the linear regression model method. In case that the pattern of relationship of variables is not linear, the result could be bias. Secondly, the model might contain multicollinearity from Google community mobility index because some visited places are closely related such as retails and grocery places. Thirdly, the mobility indicators in this paper are only from the users that agree to give the information to Google and Apple. Hence, it might not be able to fully represent the mobility of the population of Thailand and the result might be biased to Apple and Google users. Lastly, our model does not take into account other variables that could affect the Covid-19 cases such as vaccination rate, the degree of inter-house mixing, the effectiveness of social distancing regulation and the ability to detect and control the virus. Additionally, by implementing the restriction itself could encourage protective behavior such as wearing face masks and normalize the distancing. Therefore, our result could not show the impact of mobility separately from other variables.

Conclusion

This paper's objective is to find the effectiveness of mobility restriction in Thailand during the spread out of Alpha and Delta variants. Therefore we impose 2 research questions: (i) What is the association between change in infected cases and each mobility indicator and (ii) What are the impact of change in Apple mobility index and Google community mobility index to the change in infected cases. The data that we use is daily confirmed new Covid-19 cases as a response variable and mobility are represented from Google community mobility and Apple mobility index.

For the methodology we use simple linear regression to answer the first question. The result shows that change in Covid-19 cases is negatively correlated with most of the variables except for the visit to the resident place that shows a positive relationship. From this, we interpreted that the negative correlation between Covid-19 cases and mobility index might come from the reason that increasing in Covid-19 cases cause people to go out less frequently, however, the R-square in every association test is less than 0.5.

To answer the second question, we use a multiple regression to see the impact of mobility to Covid-19 cases with 14 time lag. The result shows that RETAILlag, PHARKlag, WORKlag, and RESTlag have a positive effect on the change of number of new infected cases (COVID). RETAILlag, PHARKlag, and RESTlag are significant at 95% confidence level and WORKlag is significant at 90% confidence level. This can imply lower economic activities in visiting retail and recreation places, pharmacy and grocery stores, workplaces and residential areas after 14 days could reduce the separation of Covid-19. However, there is a negative coefficient in visiting parks and transit stations with the number of new infected cases. For the Apple mobility index and new Covid-19 cases, we found a positive coefficient in the Driving index with 95% confidence level. This could be concluded that the lower driving activity could lower daily new Covid-19 cases. However the result also shows the negative coefficient of the Walking index.

Policy recommendations

It is important for policymakers to take into account the effectiveness of mobility restriction in COVID 19 response and other economic impacts imposed on society and the way of living. Since, Covid-19 is still continuing to spread out over the world, the country needs to adjust to a new normal way of living. According to the evidence from this study and also other related studies, mobility restriction can be an effective tool for lowering the infected case.

However, limiting mobility could lead to decrease in economic activities and that will lower the net income generated in the country. Therefore, at the current situation that people have to live with the Covid-19, policy makers should strategies that enhance social distancing as well as generate economic value such as working from home systems and digital payment.

Suggestions for future research

Firstly, we suggested further research using a different methodology to find the relationship between Covid-19 cases in mobility in other patterns other than linear one as this paper only used robust least square regression. Secondly, the impact to Covid-19 cases could be more precise if there are more explanatory variables that related to the change in case such as social distancing restrictions, mask wearing behaviors and the ability to detect the Covid-19. Therefore, the further research is suggested to include other variables other than economic perspective such as countries specific characteristics and the different types of Covid-19 variants. Thirdy, this paper used daily new covid cases which is high frequency data. One of the examples that the researchers could use to lower the volatility of the data is using a moving average method. Lastly, the researcher should closely monitor and continue to update the change of the current situation, since the spread out of Covid-19 still growing and the mutation still occurs.

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