# Exploring and Evaluating the Impact of COVID-19 on Mobility Changes in Singapore

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## Abstract

This paper analyzes the changes in mobility trends due to the impact of the COVID-19 pandemic in Singapore in the six different sectors: Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces and Residential. The period of observation is from 15 February 2020 to 18 August 2021. The observed patterns obtained from the descriptive data analysis sheds light on the effectiveness of social distancing measures in Singapore as well as the level of compliance among the country's residents. Correlation analysis is used to explore the relationship between different sectors during the pandemic period. The results reveal a strong sense of compliance with government policies and personal responsibility to social distance. We establish that the Transit Stations Sector, and Retail and Recreation Sector are two of the most sensitive sectors to mobility changes, while Grocery and Pharmacy Sector is the most unaffected one as it is considered as a necessity during the pandemic.

## Keywords
COVID-19, Singapore, mobility, social distancing measures, descriptive statistics, correlation analysis

## 1. Introduction
The coronavirus disease 2019 (COVID-19) has impacted us globally. It is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) (Pung et al. 2020). With initial cases reported in December 2019, COVID-19 can spread through droplets when an infected individual breathes, talks, or sneezes. The infected ones can suffer from severe respiratory conditions and even death. As of 23 December 2021, there have been 276,436,619 confirmed cases in the world, out of which 5,374,744 resulted in death, according to the World Health Organization (2021). This number is still growing. Ever since COVID-19 was officially declared a global pandemic on 11 March 2020, efforts have been put into alleviating the disease's impacts and strengthening responses to the new variants.

In Singapore, on 23 January 2020, the first imported COVID-19 case was confirmed by Ministry of Health of Singapore (MOH) (Abdullah and Kim 2020). Advisories were released to the public to counter the spread of the virus such as frequent sanitizing and mask usage in the public. Over a period of less than a month, seeing that there had been many unlinked local cases, the Singapore government increased the Disease Outbreak Response System Condition (DORSCON) from Yellow to Orange (which indicates the disease is severe and spread easily from person to person) on 7 February 2020. This resulted in large-scale events being cancelled or deferred. Workplaces had to adopt regular health checks and monitoring. On 23rd March 2020, Singapore barred entry from all short-term visitors to Singapore except for employees of essential services and their dependents.

To further contain the transmission, Singapore Government implemented a "Circuit Breaker" (CB), from 7 April to ensure stricter social distancing measures. During this period, businesses were required to adopt work-from-home measures and schools needed to shift to home-based learning. Attractions, recreational facilities, and religious buildings were closed, and people were encouraged to stay home except when going for essential services such as medical appointments. Seeing a significant decline in the number of community cases, Singapore started to embark on a three-phase reopening process as shown in Figure 1. Phase One ("Safe Re-opening") was in effect from 2 June 2020 where people were allowed to slowly return to work, school and healthcare services were open. Families could visit their extended families such as grandparents but restricted to each household allowing up to 2 visitors per day. Then, on 18 June 2020, Singapore government implemented Phase Two ("Safe Transition"). In this phase, small group gatherings and dine-in were resumed and sports facilities were opened with reduced capacity and safe-distancing measures. As the situation improved, Phase Three ("Safe Nation") was put in place on 28 December 2020. Singapore was slowly resuming to the new normal capacity, and it was expected to stay in this state until effective vaccination.

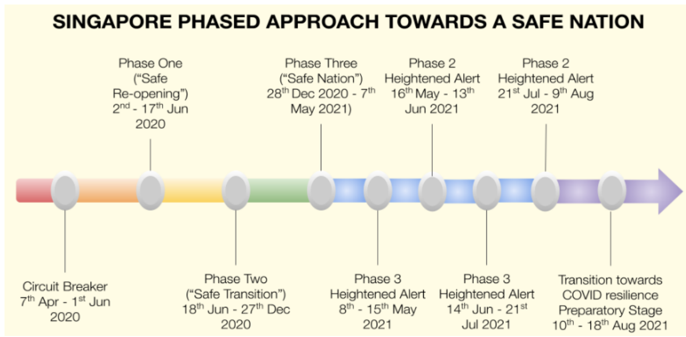

Figure 1. A Safe Singapore in multiple phases

In the first week of May 2021, new COVID-19 virus variant, the "Delta variant" had been reported in Singapore. The number of locally transmitted and unlinked cases once again crept up, resulting in Singapore entering the first Phase Three Heightened Alert (HA) on 8 May 2021. In this phase, the number of persons in social gatherings and large-scale events were reduced to curb the infection rates and minimise the likelihood of forming infection clusters. However, the number of new cases continued with an upward trend. MOH announced tighter social distancing measures, i.e., Phase Two HA which lasted from 16 May to 13 June 2021. On 14 June 2021, observed that the transmission rate had slowed down, but unlinked cases continued to develop, Singapore gradually eased into the second Phase Three HA in two stages with further easing of measures on 21 June 2021. In July 2021, Singapore experienced emergence of new clusters in specific entertainment venues and fishery port. With that, the social distancing measures were once again tightened, as Singapore entered Phase Two HA on 22 July 2021 for the second time to further reduce the impact of the growing clusters. By 9 August 2021, it was reported that approximately 70% of the Singapore population would have completed the vaccination regime. Therefore, the measures were reviewed and gradually relaxed into a Preparatory Stage in the period of 10 August to 18 August 2021, where plans were made for Singapore to enter her transition phases to re-open the economy and resume further activities.

The Singapore's strategy to defend against COVID-19, if complied, would have undoubtedly impacted the mobility in Singapore across different sectors. These chosen sectors include Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces and Residential. Movements in the Retail and Recreation sector can be analysed using mobility data from places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. Grocery and Pharmacy consists of grocery/farmer markets, food warehouses, specialty food shops, drug stores and pharmacies. Meanwhile, Parks' mobility comprises of traffic in local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens. Transit Stations refer to public transport hubs such as subway, bus, and train stations. Finally, mobility in Residential and Workplaces refer to movements in places of residence and places of work respectively (Google LLC 2020).

With this background, this paper aims to investigate the impact of COVID-19 transmission and safety measures put in place, on the changes in mobility observed in the six different sectors. The research questions include: How do Singapore's social distancing policies impact changes in mobility pattern across sectors? How do these changes correlate to each other? The observed patterns obtained from the descriptive data analysis can give evidence to the level of compliance to social distancing measures in Singapore and the impact on the businesses in these sectors. Correlation analysis will be used to evaluate the relationship between different sectors during the pandemic period across different phases. The main contribution of the paper is in its practical perspective where the investigations in mobility change by analyzing the real data to gain more insights. The insights drawn from our investigations provide useful guidance to businesses and urban planners to take appropriate actions and make plans for a more pandemic resilient city in the future. The scientific contribution includes a systematic approach to analyze the mobility changes in six sectors by using statistical approaches during the COVID-19 pandemic situation.

## 2. Literature Review

The survey conducted by Shah et al. (2021) assessed the differences of the mental well-being and "knowledge, attitude, and practices (KAP)" between "healthcare professionals (HCP) and non-healthcare professionals (non-HCP)" using a combination of assessment items in the Health Belief Model and the Mental Health Continuum—Short Form (MHC-SF). The assessment focused on "personal hygiene" (Shah et al. 2021) as well as social distancing measure compliance differences between these two groups. HCP was also being surveyed about the "compliance risk factors" (Shah et al. 2021) with preventive measures amongst themselves. The study pointed out that HCP held higher regards for personal hygiene and were "1.5 times more willing to comply with personal hygiene" (Shah et al. 2021) while both groups demonstrated similar sentiments towards social distancing measures.

On the topic of governmental responses to the pandemic, Dickens et al. (2020) explored and investigated the effectiveness of a "sustainable and public-health driven exit strategy" for COVID-19 by comparing several exit strategies. It was found that the strategy that promoted gradual easing of social distancing measures would lower the number of cases while reducing the volume of current COVID-19 patients at the same time faster and more effectively compared to its no exit counterpart. Such result has contributed towards policy making in Singapore and other countries by providing evidence supporting that "gradual release exit strategies" (Dickens et al. 2020) would be more beneficial and could be implemented with remarkable success with proper and timely deployment plans.

A similar topic to Dickens et al.'s (2020), a paper by Ansah et al. (2021) modified the SIDARTHE model, commonly used to represent 8 health stages of a pandemic, to improve the accuracy of the prediction model for COVID-19 infection trajectory by evaluating the number of confirmed cases in Singapore in two governmental response scenarios: mitigation versus containment. This model would also be used for estimation of the projected actual COVID-19 infection cases in Singapore. The number of projected confirmed cases would then be compared with the number of projected actual cases, revealing the latter as 1.65 times the prior, or around 40% of actual cases unreported. As for the two responses, a mitigation type would lead to an earlier peak infection compared to a "containment intervention" (Ansah et al. 2021), which would lead to a higher number of infected and confirmed COVID-19 cases and deaths. Therefore, a containment response involving stringent contact tracing and quarantine currently adopted in Singapore would be necessary to lower the infection volume in the country. Additionally, Pung et al. (2020) investigated recent COVID-19 clusters in Singapore by conducting interviews and field investigations as well as analyzing medical records with the aim to understand the nature of COVID-19 and responses to curb the spread. It was found that pre-pandemic community settings were considered favourable for COVID-19 transmission. Such findings, therefore, supported stringent surveillance and contact tracing measures to be adopted to avert infections within the population.

Government response to the pandemics would undoubtedly generate mixed sentiments among citizens. A study by Raamkumar et al. (2020) developed a recurrent neural network (RNN) model to classify the textual topics from social media comments during COVID-19 into one of the four key areas found in the Health Belief Model (HBM): perceived severity, perceived susceptibility, perceived barriers, and perceived benefits. The comments about social distancing measures implemented by the government were selected and then manually labeled before training the model to an acceptable degree of accuracy. Within the study period, it could be inferred from the results that netizens discussed about the susceptibility and benefits of the measures more often than the severity and barriers.

From the healthcare perspective, the paper by Lim et al. (2020) expressed genuine concerns about risks of nosocomial infection during the outbreak and hypothesized that stricter screenings for suspected COVID-19 cases in the hospital were necessary for earlier isolation. This was done by comparing the extra cost incurred by expanded screening criteria (ESC), since additional testing to confirm a COVID-19 patient would result in a higher cost, to the extra cost avoided by preventing secondary transmission. Researchers could then show that ESC would be more cost-saving in all scenarios considered. Therefore, it was concluded that ESC would not only identify and isolate cases more promptly, but it would also be within acceptable cost margin, so ESC should be considered as one of the responses to lower the risk of nosocomial transmission.

## 3. Data and Methods

The data was collected was from Google COVID-19 Community Mobility Report for Singapore (Google LLC, 2020). Although the data are constantly updated, we only limit the use of the data up to 18 August 2021. As explained in the website, the data points were collected as the percentage of changes in movements observed in six different sectors, namely Retail and Recreation, Grocery and Pharmacy, Parks, Transit Stations, Workplaces and Residential. Google's reports were collected from anonymized users who had voluntarily turned on their Location History settings. The daily baseline was taken from the median value of the corresponding day of the week from the 5-week period before widespread disruption (3rd Jan - 6 Feb 2020).

In this paper, we focus on two main statistical analysis approaches, namely descriptive statistics, and correlation analysis. Descriptive statistics are used to describe and summarize the collected data in ways that are meaningful and useful for understanding the mobility trends in six sectors. We will also focus on changes across different phases, as illustrated in Figure 1. Line graphs are used to illustrate the changes in percentage over time and within each phase. Box plots are then used to visually display the distribution of movement percentage changes. Mobility change correlation analysis between sectors will be programmed using Pandas, a Python library for data manipulation and analysis, as well as Seaborn, a library to create statistical graphics in Python. The correlation analysis is used to investigate which sector pairs are the most correlated and which sector is the most highly correlated to the others across the study period for each phase.

## 4. Results and Discussions

### 4.1 Descriptive Analysis

Since the government's safe management measurements were based on the spread of COVID-19 virus, the pandemic's unpredictability resulted in fluctuations in the mobility of the six sectors. These changes in mobility trend are plotted on a line graph as shown in Figure 2. We observed that all sectors had extended large fluctuations from 5 April to 14 July 2020. For example, the mobility in the Residential sector had increased up to 55% compared to the pre-COVID baseline, while the other three sectors, Retail and Recreation, Parks, Transit Stations and Workplaces, had decreased up to 83%. Only the Grocery and Pharmacy sector showed a slight decline to slightly below 0%. After 14 July 2020, all sectors were seen to have stabilized at certain values, for example the Residential sector's mobility decreased and stabilized at around 20% above the baseline. After this stabilization, all sectors' mobility changes converged towards 0%. This mobility trend continued, with a few exceptions during public holidays, until 15 May 2021, where larger fluctuations observed and then slightly converged towards 0%. On 19 July 2021, a similar trend of a large fluctuation and then convergence to 0% re-emerged until 18 August 2021, the end of the study period.

In terms of the individual trends of the percentage mobility change, there were different changes observed across different sectors. For example, the Grocery and Pharmacy sector did not seem to have a large movement change as compared to the other sectors. Residential had a positive percentage change for all the days observed in the period of this study. Parks had mostly seen negative mobility changes, except for several days with positive changes. Meanwhile, Retail and Recreation, Transit Stations and Workplaces experienced a negative mobility change during the February 2020 - August 2021 period. The observed trends could be caused by CB which was rolled out from 7 April to 1 June 2020. During this period, most activities were suspended, and people minimized travelling. Home Based Learning (HBL) was implemented for all schools and non-essential businesses were ordered to cease (Ansah et al. 2021), so there was little need to commute to schools or places of work. Naturally, the mobility in Transit Stations and Workplaces would also drop. Meanwhile, the mobility in the Residential sector would increase drastically, exceptions might be seen on weekends or public holidays when people might not leave their households as often. Moreover, closure of shops would also inevitably result in a decrease in footfall in the Retail and Recreational sector.

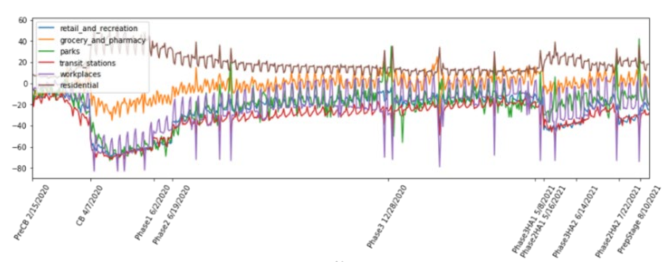


Figure 2. Line graph of Mobility change for six sectors over the study period

Table 1 summarizes some descriptive statistics, such as mean, standard deviation (Std), minimum (Min) and maximum (Max) values, Quartiles 1, 2 and 3 (Q1, Q2 and Q3) across six different sectors. The Transit Stations sector has the highest mean mobility change over this period (15 February 2020 – 18 August 2021), as shown by a mean of -32.26%.

This is followed by Retail and Recreation, Workplaces and Parks. On the other hand, Residential has increased by 18.47%. The sector with the lowest mean change is Grocery and Pharmacy with a decrease of 1.48%. Meanwhile, the standard deviation observed for each sector is quite large: the largest is 20.02% in Workplaces and the smallest is 9.74% in Grocery and Pharmacy.

Table 1. Descriptive analysis for mobility change from 15 Feb 2020 to 18 Aug 2021

| | **Retail and Recreation** | **Grocery and Pharmacy** | **Parks** | **Transit Stations** | **Workplaces** | **Residential** |
|---|---|---|---|---|---|---|
| **Mean** | -25.52 | -1.48 | -21.74 | -32.26 | -22.41 | 18.47 |
| **Std** | 16.67 | 9.74 | 18.45 | 14.39 | 20.02 | 9.79 |
| **Min** | -70.00 | -35.00 | -73.00 | -75.00 | -83.00 | 5.00 |
| **Q1** | -31.00 | -6.00 | -27.00 | -37.00 | -32.00 | 12.00 |
| **Q2** | -20.00 | 0.00 | -18.00 | -29.00 | -21.00 | 16.00 |
| **Q3** | -14.00 | 5.00 | -11.00 | -23.00 | -9.00 | 22.00 |
| **Max** | -3.00 | 25.00 | 42.00 | -9.00 | 7.00 | 55.00 |

Such observation can be seen in Figure 3: multiple anomalies are marked on the left tail of Retail and Recreation, Parks, Transit Stations and Workplaces, while multiple anomalies are seen on the right tail of Residential. These anomalies are of great interest to us since they highlight a drastic change in mobility across the sectors. This means that the prior three sectors witnessed a critical decrease in movement while Residential had a significant increase. The one exception is Grocery and Pharmacy which only has 2 anomalies on the right tail and 4 on the left. We suspect that the anomalies may be due to the extreme mobility change that took place due to CB, HA and other phases. Thus, it would make sense to look at the changes within each phase. We then apply the same descriptive analysis on the respective phases to gain more insights. Due to the page limit, we only cover the most interesting observations.

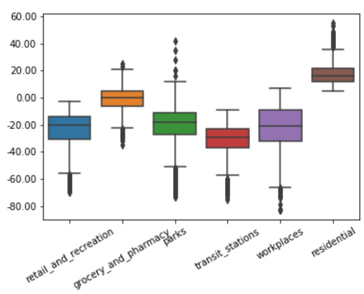


Figure 3. Box plot for Mobility change of six sectors over the study period

**Pre CB (before 7 April 2020) and CB (7 April - 1 June 2020)**

From Figure 4, before CB, the mobility changes for all sectors were rather stable from 15 February until 16 March 2020, after which, larger mobility changes were observed across sectors. For example, Transit Stations sector had a rather small variation during this period, with the lowest and highest changes at 9% and 22%, respectively. After 16 March, the mobility significantly was dropped from a 16% decrease to a 40% decrease. The same trend could be observed for other sectors. Despite not having to enter CB yet, efforts to stay at home and limit footfall could be seen. Until 16 March 2020, seven Covid-19 clusters had been identified (Wei et al 2020) and in Singapore Prime Minister (PM)'s address on 12 March, PM Lee urged residents to minimize social gathering and scale down communal activities. This shows that there had been some awareness even before lockdown measurements were put in place.

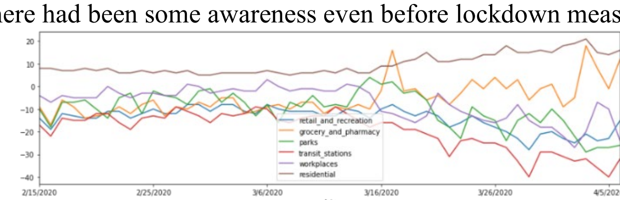


Figure 4. Line graph of Mobility change for six sectors before CB

As observed in Figure 5, the highest median mobility change is indicated by the 16% decrease from Transit Station, and this sector also has the highest daily decrease at 40%. It means that commuting by public transport was the most affected during this period. Since people were taking their own measures to minimize gathering, it was natural that transit stations saw fewer people. Moreover, the anomalies on the right tail of Grocery and Pharmacy suggest a significant increase in mobility in this sector. Knowing that CB was going to be implemented on 7 April 2020, residents tended to go to markets/supermarkets to stock up.

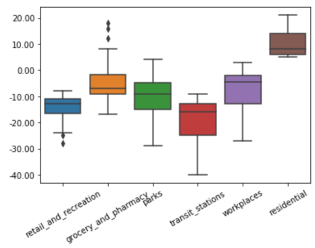


Figure 5. Box plots of Mobility change for six sectors before CB

The CB period itself shows little fluctuation across sectors, according to Figure 6. Sector Retail and Recreation, Parks and Transit Stations decrease in mobility rapidly from 7 to 27 April 2020 and remain almost plateau from 27 April to 1 June 2020. Chen et al. (2020) explained that all business or social activities were to be moved online and those that could not do so were to be suspended during CB. Attractions were closed as well, and eateries could only allow takeaways. Interestingly, we do notice seasonality in Residential and Workplace as the rise and fall patterns are repeated weekly. The local minima of Residential and the local maxima of Workplaces are coincided on weekends (11-12 April, 18-19 April, 25-26 April, ...), as expected since people would have not worked during the baseline period's weekends, resulting in a lesser mobility change for both sectors.

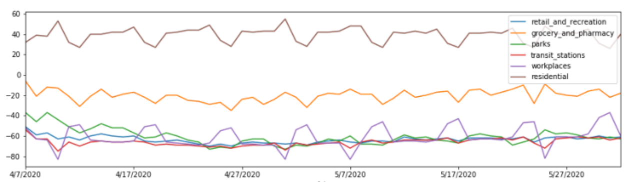


Figure 6. Line graph of Mobility change for six sectors during CB

**Phase One (2 - 18 June 2020)**

For Phase One (Figure 7), like CB, seasonality for Residential and Workplaces can be observed with higher changes during weekdays and lower changes during weekends. The peak mobility change for both sectors can be observed on 6-7 June (Saturday and Sunday) and 13-14 June 2020 (Saturday and Sunday). Transit Stations, Parks and Retail and Recreation continued to have high mobility decreases up to 60%. Meanwhile, Grocery and Pharmacy fluctuated around 0% to -20%. Even though CB had ended, since Phase One only lasted for 17 days and only a few restrictions had been lifted due to close monitoring, similar movement behavior to that during CB would be seen.

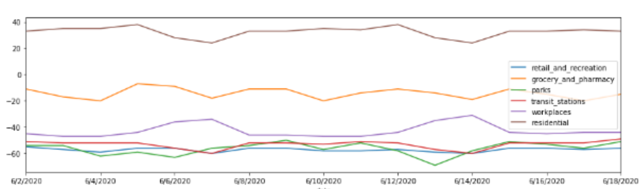


Figure 7. Line graph of Mobility change for six sectors during Phase One

**Phase Two (19 June - 27 December 2020)**

The line graph of mobility trends during Phase Two (Figure 8) shows a common convergence towards 0% for all sectors. The Residential sector had a steady decrease in the mobility change from 31% on 18 June to 9% on 27 Dec 2020. Meanwhile, the other sectors had a slow increase in mobility, such as Transit Stations, slowly increasing from -40% to only -23%. The seasonality can be seen clearly across the sectors during this period: with decreased mobility change on weekends and higher mobility change during weekdays. For example, on weekend periods such that 2-3 August or 9-20 August, we observe a peak in Retail and Recreation, Parks, Workplaces, Transit Stations and Grocery and Pharmacy while a trough is seen for Residential. Exceptions can be noted on dates such as 5 July 2020 where troughs can be spotted for Grocery and Pharmacy, Retail and Recreation and Transit Stations. This could be due to consumers' behavioral changes.

According to Accenture (Joon and Kumar, 2020), a significant increase in online revenue and transactions were found in industries such as Groceries, Restaurant and Delivery as well as Beauty and Cosmetics. This would mean a new normal for Singapore residents where e-commerce is the new norm and there is a lesser demand to travel and get groceries or food. This can explain the drop in mobility in Grocery and Pharmacy, Retail and Recreation and Transit Stations when CB was over, and business were slowly resuming their activities. Moreover, there are 4 public holidays worth noting: 10 July, 31 July, 10 August, and 25 December 2020. During these dates, significant drops were seen in Workplaces and Transit Stations, while the opposite can be said to the new peaks seen in Residential, Grocery and Pharmacy, Retail and Recreation and Parks. Interestingly, 10 July 2020 was Singapore Polling Day which was considered as a public holiday and employees were allowed to take a day off (Ministry of Manpower, 2021). During these dates, people would naturally not go to work at all, which explains the sudden drop in Workplaces' and Transit Stations' mobility. They were more likely to stay at home, stock up on grocery or spend their day out with families and friends. This accounts for the increase in mobility for Residential, Grocery and Pharmacy, Retail and Recreation and Parks.

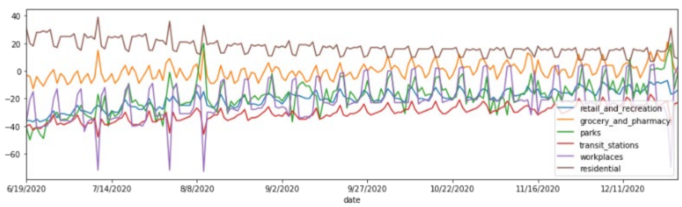


Figure 8. Line graph of Mobility change for six sectors during Phase Two

**Phase Three (28 December 2020 - 7 May 2021)**
From the line graph in Figure 9, we can detect a very gradual convergence towards 0 and three dates stand out of the trend: 1 January, 12 February, and 2 April 2021. Like Phase Two, all these dates are public holidays. In the case of 1 January, a mobility change increase from 31 December 2020 to 1 January 2021 can be represented by a trough in Retail and Recreation, Transit Stations and Workplaces sectors while the same increase is displayed by a peak in Residential. This is because the baseline is taken to be the mobility of a normal day of the week and not a normal holiday day, so naturally the mobility change would increase, as shown by a sudden decrease in mobility in Retail and Recreation (4% to 25%), Transit Stations (21% to 46%) and Workplaces (35% to 72%) and a sudden increase in mobility in Residential (15% to 35%). The mobility change for Grocery and Pharmacy for public holidays generally decreased, significantly increases in the previous days. On 31 December 2020, Grocery and Pharmacy reached a peak of 23% increase from its previous 6% increase, likely to be a result of residents stocking up before shops closing during these dates. Interestingly, Parks' mobility hit the lowest (local minima) on 1 Jan (35% increase to 36% decrease) but it reached a peak on 12 Feb (19% increase to 1% increase). This maybe because for those in Singapore who do not celebrate CNY, they chose to use this day as a day out instead of visiting relatives.


Figure 9. Line graph of Mobility change for six sectors during Phase Three

After analyzing each phase, we would like to give an overall trend analysis for the most prominent sector across different phases: **Retail and Recreation**. Retail and Recreation's lowest median is during CB (a decrease of 63.5%) and its highest one is during Pre CB (a decrease of 13.0%), as seen from Figure 10. Even though movement had been reduced during Pre CB as compared to the baseline, a drastic drop of 50.5% change from a median of -13.0% to a median of -63.5%. This meaningful change can be explained by the closure of recreational activities as well as restaurants only allowing takeaways and deliveries. Consequently, the main demographics for footfall in this sector would be delivery couriers and people taking away food and beverages to consume at home, decreasing the mobility in Retail and Recreation. Over the reopening phases, Phase One only saw a median change of 57% decrease, higher but not much different from that of CB. Interestingly, the mobility change median suddenly increased with Phase Two having a much higher median change at 20% decrease and Phase Three having a median change at 14% decrease from the baseline mobility. The sudden and rather drastic change in movement can be accounted for by the residual effect from CB and the short period for Phase One (only 16 days from 2nd to 17th June 2020), so movement change would not be so different. Phase Two allowed gathering of up to 5 people, so people would have reasons to go to restaurants and recreational facilities with friends and families.

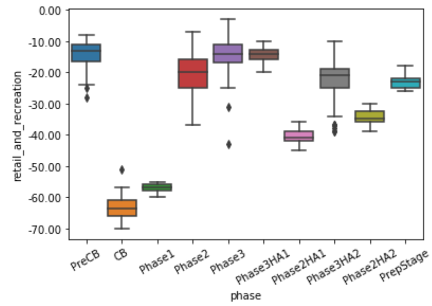


Figure 10. Box plots of Mobility change for Retail and Recreation over different phases

## 4.2 Correlation Analysis

From the data set, we created Figure 11 to analyze the correlation between sectors. The highest correlation coefficient is 0.96, which is between Retail and Recreation and Transit Stations. This coefficient indicates a strong positive linear relationship between the two sectors: when the mobility in Retail and Recreation decreases, the mobility in Transit Stations is also seen to be decreased and vice versa. When restrictions were implemented, a lot of recreational facilities were closed while dining businesses could only allow for takeaways. This service closure, together with the fear of community transmission, would lower the needs for commuting and utilizing public transportation platforms. On the other hand, when the social distancing measures were eased, more dine-in outlets and recreational places were re-opened. People could gather in small groups that increase the demand for commuting. Naturally, we would see an increase in mobility for Transit Stations as well.

The next highest correlation coefficient is Residential and Workplaces with a correlation coefficient of -0.95. This means that there is a strong negative linear relationship between both sectors: when there is an increase in movement for Residential, there would be a decrease in mobility for Workplaces. One of the measures used during Singapore's CB period was to move business online or Work from Home (WFH). Consequently, the movement in Workplaces would fall as people no longer go to their office. Most would opt to work from home instead, increasing the mobility in the Residential sector.

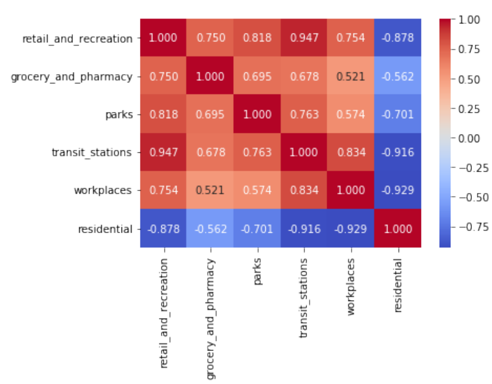


Figure 11. Correlation table for all sectors during the whole study duration

Table 2. Rank correlation coefficient by row for the whole study duration

| Sector | Retail and Recreation | Grocery and Pharmacy | Parks | Transit Stations | Workplaces | Residential |
|---|---|---|---|---|---|---|
| Retail and Recreation | - | 5 | 3 | 1 | 4 | 2 |
| Grocery and Pharmacy | 1 | - | 2 | 3 | 5 | 4 |
| Parks | 1 | 4 | - | 2 | 5 | 3 |
| Transit Stations | 1 | 5 | 4 | - | 3 | 2 |
| Workplaces | 3 | 5 | 4 | 2 | - | 1 |
| Residential | 3 | 5 | 4 | 2 | 1 | - |
| **Total** | **9** | **24** | **17** | **10** | **18** | **12** |

Moreover, we also rank the correlation coefficients from 1 (the highest) to 5 (the lowest) for each row (Table 2). Looking at each column, we have an idea of how correlated one particular sector is to other remaining sectors. The lower the numerical value, the more correlated the sector is to other sectors. In Table 2, Retail and Recreation and Transit Stations columns have mostly ranks of 1s, 2s and 3s, which means that they are the most correlated sectors to other sectors during the study duration. To quantify this ranking across sectors, we sum up the rank value for each column. Retail and Recreation and Transit Stations both have a total of 9 and 10, respectively. They are considered as the top two most highly correlated sectors to the others.

Figure 11 also shows a rather strong correlation between certain sectors, for example, between Retail and Recreation -Transit Stations and Residential-Workplaces, being the two strongest. Moreover, the most highly correlated sectors to their remaining sectors are Retail and Recreation and Transit Stations. We are interested to find out whether this correlation pattern would hold for each of the identified timeline phases. We would focus more on the sectors' mobility correlations during **CB** and **Phase Three**.

Referring to **CB**, a different pattern occurs: the highest correlation coefficient is -0.92 between Workplaces and Residential and the second highest is 0.81 between Parks and Retail and Recreation. This can be seen clearly in Figure 12. Workplaces and Residential is still the one with the most highly correlated pair. For Parks and Retail and Recreation, the coefficient of 0.81 indicates a strong positive correlation between these two sectors, meaning that when the mobility in Parks decreases, that in Retail and Recreation will also decrease. This correlation might be accounted for since both are considered recreational and necessary to be limited in terms of movement. Thus, tighter social distancing measures would affect both movements in Parks and Retail and Recreation. Looking at Table 3, Grocery and Pharmacy and Transit Station have values of 12 and 13 as their total, respectively, making them the most highly correlated sectors to the others. It is interesting to find Grocery and Pharmacy as the most correlated sector during CB, given that it is the least correlated one in Table 2.

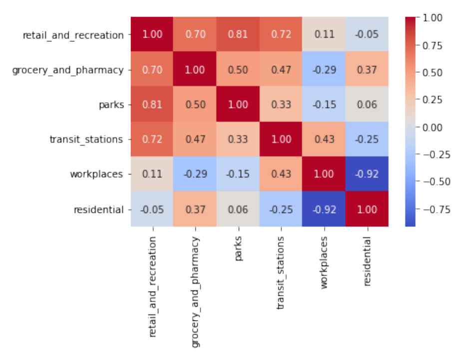


Figure 12. Correlation table for all sectors during CB

Table 3. Rank correlation coefficient by row during CB

| Sector | Retail and Recreation | Grocery and Pharmacy | Parks | Transit Stations | Workplaces | Residential |
|---|---|---|---|---|---|---|
| Retail and Recreation | - | 3 | 1 | 2 | 4 | 5 |
| Grocery and Pharmacy | 1 | - | 2 | 3 | 5 | 4 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Parks | 1 | 2 | - | 3 | 4 | 5 |
| Transit Stations | 1 | 2 | 4 | - | 3 | 5 |
| Workplaces | 5 | 3 | 4 | 2 | - | 1 |
| Residential | 5 | 2 | 4 | 3 | 1 | - |
| **Total** | **13** | **12** | **15** | **13** | **17** | **20** |

Finally, for **Phase Three**, from Figure 13, the highest correlation coefficient is the one between Workplaces and Residential, with the value being -0.91. The second highest is Grocery and Pharmacy and Retail and Recreation, being 0.77. The correlation between Grocery and Pharmacy and Retail and Recreation interests us since their correlation coefficient is not usually high compared to the other sector pairs. During Phase Three, both Grocery and Pharmacy and Retail and Recreation has a decrease in mobility, as seen in Figure 9. This is most likely because the capacity of malls increases during this phase (Sin 2020). As a result, people tend to go out more often, increasing both movements in the Retail and Recreation as well as Grocery and Pharmacy sectors. In Table 4, the most correlated sectors are shown to be Retail and Recreation and Transit Stations (with a total of 11 and 12, respectively). This pattern corresponds to that in Table 2, and this is further explained since Phase Three is one of the longest phases during this study.

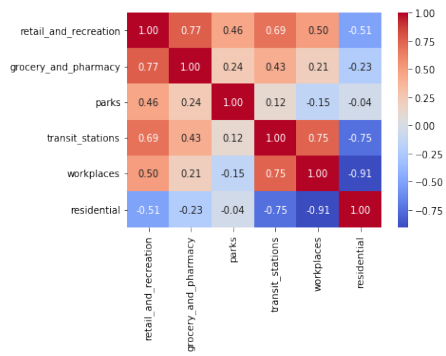


Figure 13. Correlation table for all sectors during Phase Three

Table 4. Rank correlation coefficient by row during Phase Three

| Sector | Retail and Recreation | Grocery and Pharmacy | Parks | Transit Stations | Workplaces | Residential |
|---|---|---|---|---|---|---|
| Retail and Recreation | - | 1 | 5 | 2 | 4 | 3 |
| Grocery and Pharmacy | 1 | - | 3 | 2 | 5 | 4 |
| Parks | 1 | 2 | - | 4 | 3 | 5 |
| Transit Stations | 3 | 4 | 5 | - | 2 | 1 |
| Workplaces | 3 | 4 | 5 | 2 | - | 1 |
| Residential | 3 | 4 | 5 | 2 | 1 | - |
| **Total** | **11** | **15** | **23** | **12** | **15** | **14** |

## 6. Conclusion

The paper has addressed its objectives of exploring, investigating and evaluating the impact of Covid-19 on mobility changes in six sectors in Singapore as well as their relationships from 15 February 2020 to 18 August 2021. With the peak mobility increase for Residential and peak mobility decrease for rest of the sectors during CB, evidence supports that Singapore residents are following social distancing measures. Moreover, the gradual mobility change, decreased towards 0 from Phase One to Phase Three, reflects the easing of COVID-19 measures as well as people resuming to the new normal mobility.

Correlation analysis is used to explore the linear relationship between different sectors over the pandemic period as well as their relationships within each phase. As observed over all phases, Transit Stations and Retail and Recreation are two of the most sensitive to mobility changes. This is because they have the highest correlation coefficient ranks, meaning that a mobility change in other sectors would result in an equally large change in these two sectors. On the other hand, Grocery and Pharmacy is the most unaffected sector as this sector is considered a necessity and would not be affected as much as the other sectors due to the pandemic.

A limitation for this research is that we only look at descriptive analysis for a limited data points up to 18 August 2021. Many research opportunities can be explored as part of our future work such as predictive analysis to forecast the changes in mobility with respect to each sector. Moreover, the current analysis can always be applied upon new data sets as well as other countries.

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