

# The impact of COVID-19 on changes in community mobility and variation in transport modes<sup>^</sup>

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## Abstract

Using Google mobility data and Apple maps data we track changes in community mobility and transport modes during the COVID-19 Alert levels. Results show that Alert Level 4 – lockdown had a significant impact on the reduction in mobility and variation in transport mode. Mobility and transport mode progressively returned to pre-Alert Level 4 patterns with the exception of public transport. Regional heterogeneity in the variation of public transport use was evident in the data. Containment measures also had a significant negative effect on retail and recreation. Otago had a significantly delayed recovery in retail and recreation relative to other regions.

Keywords: COVID-19; Alert Level; community mobility; transport mode; public transport;

JEL Classifications: R11, R41, R48

## 1. Introduction

Many factors influence mobility choice. Location, infrastructure, transport costs and the availability of alternative recreation sites combine to determine the frequency of family outings to specific recreation sites. Similar factors influence travel patterns to supermarkets and retail outlets. Sheng and Sharp (2019) find that social networks play an important role in commuter transport choice, along with family size, income, location, availability of public transport and the price of petrol, and so on. The authors argue that Auckland transport users tend to adopt and mimic the behaviours of others living close to them, creating a behavioural feedback loop. In other words, holding other things constant, the likelihood that an individual chooses public

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transport increases when those in close proximity also use public transport. This result is important to policy aimed at increasing the use of public transport.

Due to external or self-imposed isolation measures, major regions in New Zealand experienced sharp reductions in traffic volumes during the COVID-19 pandemic. Government's decision to implement Alert Level 4 at 11:59pm 25 March 2020 had a dramatic impact on community mobility. The purpose of this paper is to quantify the impact of COVID-19 on changes in community mobility and variation in transport modes. We collect data from internet-based sources to analyse changes in the patterns of mobility relative to periods prior to Level 4 and during the phased return to Level 1 travel. The rest of the paper is organised as follows. Section 2 discusses community mobility changes and variation of transport modes, responding to Alert levels. Section 3 describes the empirical model and reports estimation results. Section 4 summarises with concluding remarks.

## 2. Data

The primary data source was obtained from Google Covid-19 Community Mobility Reports<sup>1</sup> and Apple Mobility Trends Reports.<sup>2</sup> Google Mobility and Apple maps data have been extensively used in literature for COVID-19 mobility research. For example, using Google Mobility data, Askitas *et al.* (2020) studied how lockdown policies affected the population mobility pattern across 135 countries. Abu-Rayash and Dincer (2020) compared mobility changes responding to COVID-19 in major cities in Canada, America and the UK. Tirachini *et al.* (2020) used Google mobility data to illustrate variations in the use of public transportation. Percy and Mountain (2020) found that the reduction in aggregate electricity demand was associated with the decline in mobility as measured at retail and recreation venues and workplaces. Using Google Mobility and Apple maps data, Falchetta and Noussan (2020) studied transport demand and modal choices in Europe and found public transport demand plunged due to containment policies. Carteni *et al.* (2020) estimated the Italian mobility trends on the basis of population, average daily mobility rate, and average percentage variation of daily mobility rate provided by the Italian Transport Ministry. They concluded that their estimation results were consistent with those obtained from both the Google mobility data and Apple driving data specific to the Italian case study.

Our sample period is divided into five sub-periods.<sup>3</sup> The pre-lockdown started on 15 February 2020 and ended on 25 March 2020. Alert Level 4 was from 26 March 2020 to 27 April 2020; Alert Level 3 from 28 April 2020 to 13 May 2020; and Alert Level 2 was from 14 May 2020 to 8 June. For Alert Level 1, 9 June 2020 – 7 July 2020, we use Google Covid-19 Community Mobility Report data and Apple Mobility Trends Reports data for 9 June 2020-11 July 2020.

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1. Google Covid-19 Community Mobility Reports. <https://www.google.com/covid19/mobility/>. The baseline is the median value for the corresponding day of the week during 3 January-6 February 2020. The sample period is 15 February 2020 – 7 July 2020.

2. Apple Mobility Trends Reports. <https://www.apple.com/covid19/mobility>. The baseline volume is on 13 January 2020. The sample period is 15 February 2020 – 11 July 2020 (11, 12 May are missing).

3. Containment measures refer to <https://covid19.govt.nz/covid-19/restrictions/alert-system-overview/#:~:text=Dates%20when%20different%20Alert%20Levels%20came%20into%20force&text=COVID%2D19%20Alert%20Level%203,59pm%20Monday%208%20June%202020>.

## 2.1 Community mobility changes: Retail and recreation, workplace and public transport

Figure 1(a) shows the percentage change in mobility to retail and recreation, workplaces and transit stations from Google mobile phone location data. It is clear that Alert levels dramatically affected people's mobility behaviour and businesses activities. On average, the lockdown reduced mobility by 69% to 89% relative to the baseline levels. The blue line shows a substantial reduction in mobility for places of work as businesses closed except for essential services and people worked from home (WFH). At Alert Level 3, businesses opened but with strong restrictions and people were requested to WFH if possible. Mobility to workplaces increased but still remained at 40% less compared to the baseline level. Along with the more relaxed rules, travelling to workplaces trended to the pre-lockdown level, with about a 2% reduction due to WFH. The red line shows mobility trends for places such as restaurants, cafes, shopping centres, theme parks, museums, libraries and cinemas. Travel to those locations dropped significantly by 89% at Alert Level 4, by 75% at Alert Level 3, by 25% at Alert Level 2, and by 10% at Alert Level 1. This may reflect people's fear of infection, and avoidance of non-essential activities, such as eating or dining outside and outdoor public activity. A return to pre-COVID levels could also have been hampered by the closure of businesses unable to meet the financial challenge of the downturn. The green line shows mobility trends for places that are public transport hubs, such as bus, subway, train stations, sea port, or taxi stand. Public transport was hit the hardest and recovered the slowest relative to mobility associated with retail and recreation and workplaces. Even at Alert Level 1, there was 35% of reduction in public transport from the baseline level.

Figure 1(b) presents the recursive cumulative sum plots of changes in mobility trends to retail and recreation, workplaces and transit stations. The estimated parameters lie outside their corresponding 95% confidence intervals at 1 April 2020, showing structural changes for the time series of mobility trends to retail and recreation, workplaces and transit stations. The presence of structural breaks reflects the disruptive shift in mobility.

[Figure 1 here]

## 2.2 Variation in transport modes

Figure 2 illustrates the variation in transport modes relative to the baseline volume on 13 January 2020 based on Apple maps data. On the top graph of Figure 2, the blue line shows the change in driving pattern, the orange line shows the walking trend, and the green line shows the public transport trend. All these transport modes plunged dramatically during the lockdown, ranging from a reduction of 75% to 88% on average below the baseline (see the bottom graph of Figure 2). Slow recoveries followed with relaxed containment rules. Among them, driving bounced back quickly and almost caught up the baseline volume. Walking was more active than driving and public transport during the lockdown due to the strictest containment rules. However, there still was a reduction of 20% during Alert Level 1 relative to the baseline volume on 13 January 2020. Among all the transport modes, public transport experienced the largest reduction. The average changes over different alert levels are consistent with those in Figure 1 obtained from Google mobility data. This evidence presents a challenge to the public transport sector because COVID-19 could result in persistent reduction in demand.

[Figure 2 here]

### 3. Model and Results

#### 3.1 Empirical model

The basic autoregressive conditional heteroscedasticity (ARCH) model (Engle, 1982) is

$$y_t = x_t\beta + \varepsilon_t \quad (1)$$

Where  $\varepsilon_t = \sigma_t e_t$ ,  $e_t \sim$  white noise (0,1).  $y_t$  is the dependent variable at t.  $x_t$  is a 1 x k vector, representing alert levels.  $\beta$  is a k x 1 coefficient vector, estimating the impact of Alert levels on the dependent variable.

$$Var(\varepsilon_t) = \sigma_t^2 = \gamma_0 + A(\sigma, \varepsilon) \quad (2)$$

If  $A(\sigma, \varepsilon)$  in Equation (2) is equal to zero, the model in Equation (1) collapses to linear regression. The option for ARCH ( ) depends on terms added to  $A(\sigma, \varepsilon)$ .

$$A(\sigma, \varepsilon) = A(\sigma, \varepsilon) + \alpha_{1,1}\varepsilon_{t-1}^2 + \alpha_{1,2}\varepsilon_{t-2}^2 + \dots \quad (3)$$

For example, ARCH (1) includes the first lagged term in Equation (3), indicating variance at t depends on the variance at t-1. ARCH (1/3) includes terms with lags 1, 2 and 3. So  $\sigma_t^2$  represents the conditional variance, which by definition is a function of variances in the past. We have checked ARCH options and selected models that meet convergence for the algorithm and stationarity for the squared series.

#### 3.2 Results

Estimation results are reported in Table 1. There are six columns for the six specific subsamples. Columns (1) to (3) report results for retail and recreation, workplaces and public transport based on Google mobility data. Columns (4) to (6) present results for driving, walking and public transport from Apple maps data. Table 1 gives the following findings.

[Table 1 here]

First, the impact of Alert Level 4 on mobility and transport modes is larger than those of other alert levels, ranging from -82% for workplaces to -94% for public transport based on Google mobility data and from -80% for walking to -90% for driving based on Apple maps data.

Second, containment measures have significant and negative effects on retail and recreation. The magnitude varies with alert levels. This empirical evidence implies that businesses in the retail and recreation sector faced financial hardship from uncertainty and reduced customers.

Third, the impact of Alert levels on public transport based on Google mobility data is consistent with that from Apple maps data, implying the estimation results are robust. More importantly, we find that the negative and significant impact of COVID-19 on public transport may be long-lasting and persistent.

#### 4. Regional investigation

We further investigate regional heterogeneity in terms of mobility and transport modes in four major regions, Auckland, Wellington, Canterbury, and Otago. Figure 3 shows the percentage change in mobility and driving for those major regions.

[Figure 3 here]

In Figure 3 (a), reductions in mobility to retail and recreation are evident in all regions, with the largest reduction at Level 4 and the smallest at Level 1. Even at Level 1, there was still 10% less travel activity to retail and recreation. Data show delayed recovery in retail and recreation in Otago.

As expected, similar trends to workplaces are observed for those major regions. Mobility to workplaces recovered to the baseline level at Level 1.

In general, the public transport sector experienced a significant reduction in mobility. For example, even at Level 1, mobility was 35% down from the baseline is observed. Regional heterogeneity in percentage change in movement for public transport is also evident. In Wellington, public transport was more active than other areas but still didn't return to pre-COVID levels.

Figure 3(b) shows the variation of driving in major regions. Otago experienced the most significant change in driving than the other regions. Before the lockdown, driving activity in Otago was above the average level. However, for most of the time since the lockdown, driving in Otago was less active than the other regions. Combining the information from Figure 3(a) on mobility to workplaces and transit stations, we find similarities for Auckland, Wellington, Canterbury, and Otago, and infer that the reduced driving activity may come from the less mobility to retail and recreation (see the red line for Otago in Figure (a)). Economic recovery in the Otago region may be prolonged if the low mobility to retail and recreation continues.

#### 5. Concluding remarks

COVID-19 and the Government alert system reduced mobility due to fear about community transmission, widespread WFH arrangements and cancellations of major events. We use ARCH models to examine the impact of Alert levels on mobility and transport modes. Our results show that the impact of Alert Level 4 – lockdown on mobility and transport modes is greater than those of other alert levels. Containment measures had a significant and negative effect on retail and recreation. The public transport sector also experienced a significant reduction. The negative and significant impact of COVID-19 on public transport may be long-lasting and persistent, as one could speculate COVID-19 measures, such as physical distancing on public transport, would possibly dampen social network effects. Moreover, regional heterogeneity in the variation for using public transport was evident. The utilisation of public transport in Wellington was more active than other areas. Recovery in retail and recreation in Otago lagged behind other regions.

COVID-19 caused the disruptive change in many ways. The concept of “Business as usual” may need to incorporate WFH. Anxiety, fear and uncertainty discouraged people from travelling by public transport or by mobility-as-a-service (Maas), such as Uber, taxi. Meanwhile, public transport operators will face major financial challenges associated with changes to operational procedures and enhanced cleaning protocols. They will need to consider

niche innovations aimed at minimising health risks and making people feel safe as many people still depend on public transport as their only transport option. In such cases, approaches to public transport policy that focus on encouraging and supporting alternative strategies like mandatory mask-wearing on public transport from 31 August 2020, combined with frequent promotional campaigns on TVs and radio regarding safe commuting on buses, trains and ferries, would help to reshape the behavioural change needed to foster transport use and rebuild positive social networks.

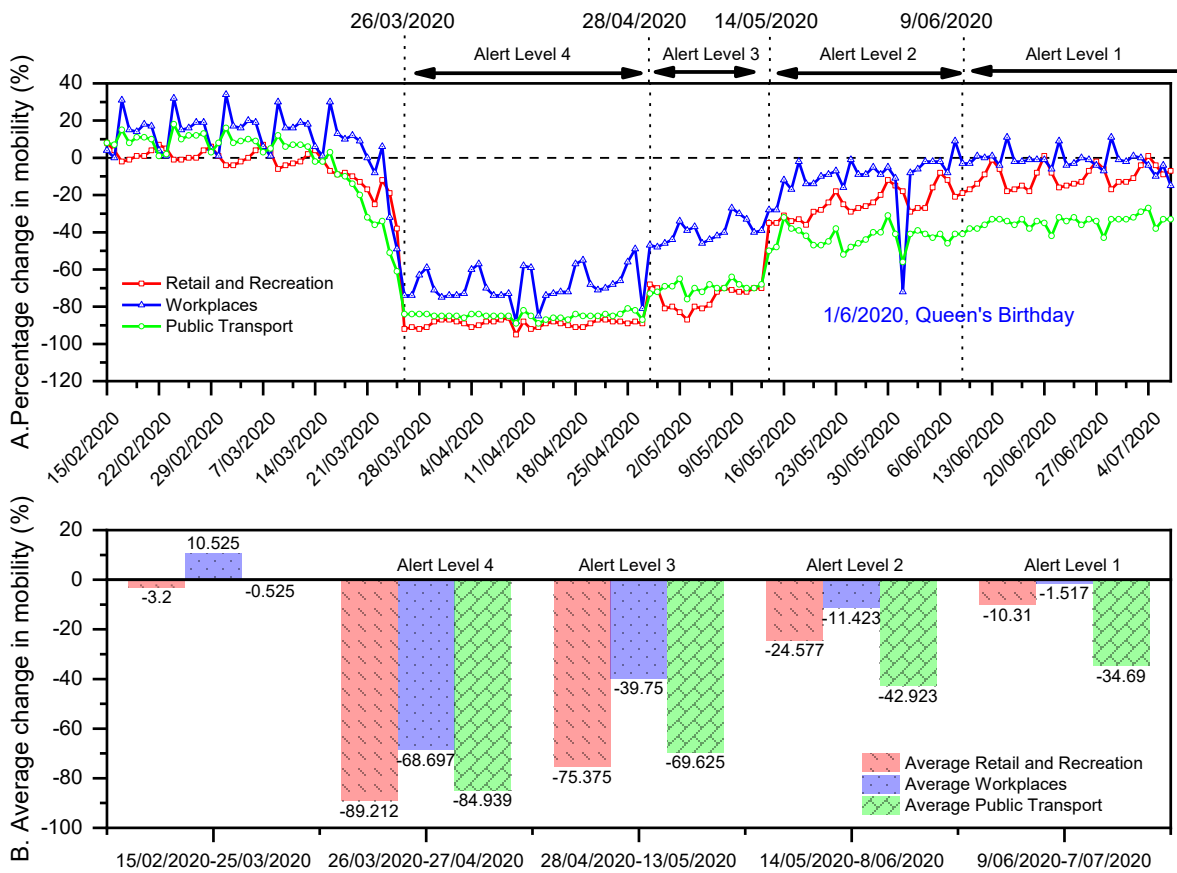
It is worth noting that the data obtained from Google Covid-19 Community Mobility Reports and Apple Mobility Trends Reports represents a sample of users. It may not represent the exact behaviour of the population. The consistency with results from NZTA verifies the validity of this research.<sup>4</sup>

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4.[https://www.nzta.govt.nz/assets/resources/covid-19-impacts-on-transport/Waka-Kotahi-NZTA-COVID-19-200630-Deep-dive-Wave-13-impact-of-fares-on-public-transport\\_20206030.pdf](https://www.nzta.govt.nz/assets/resources/covid-19-impacts-on-transport/Waka-Kotahi-NZTA-COVID-19-200630-Deep-dive-Wave-13-impact-of-fares-on-public-transport_20206030.pdf)

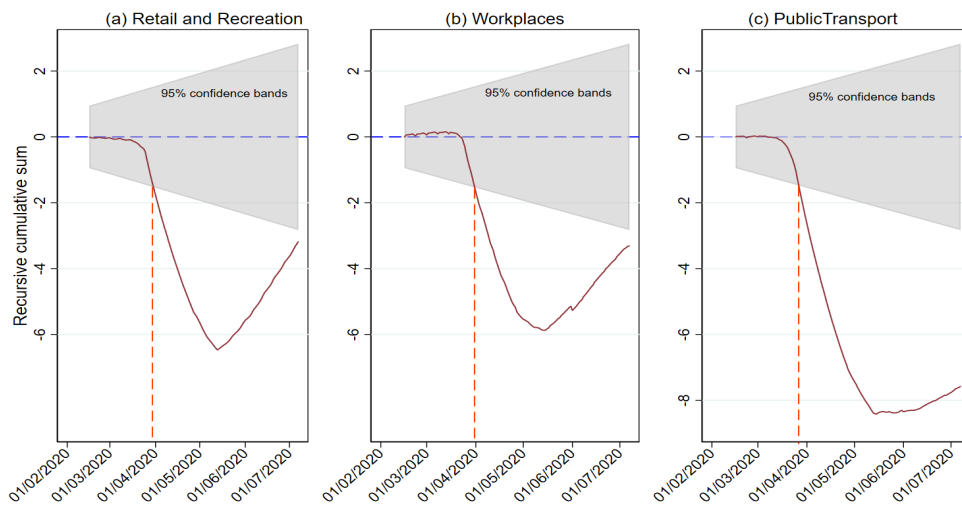
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Notes: Authors' elaboration based on Google Covid-19 Community Mobility Report. <https://www.google.com/covid19/mobility/>. The baseline is the median value for the corresponding day of the week during 3 Jan-6 Feb 2020.

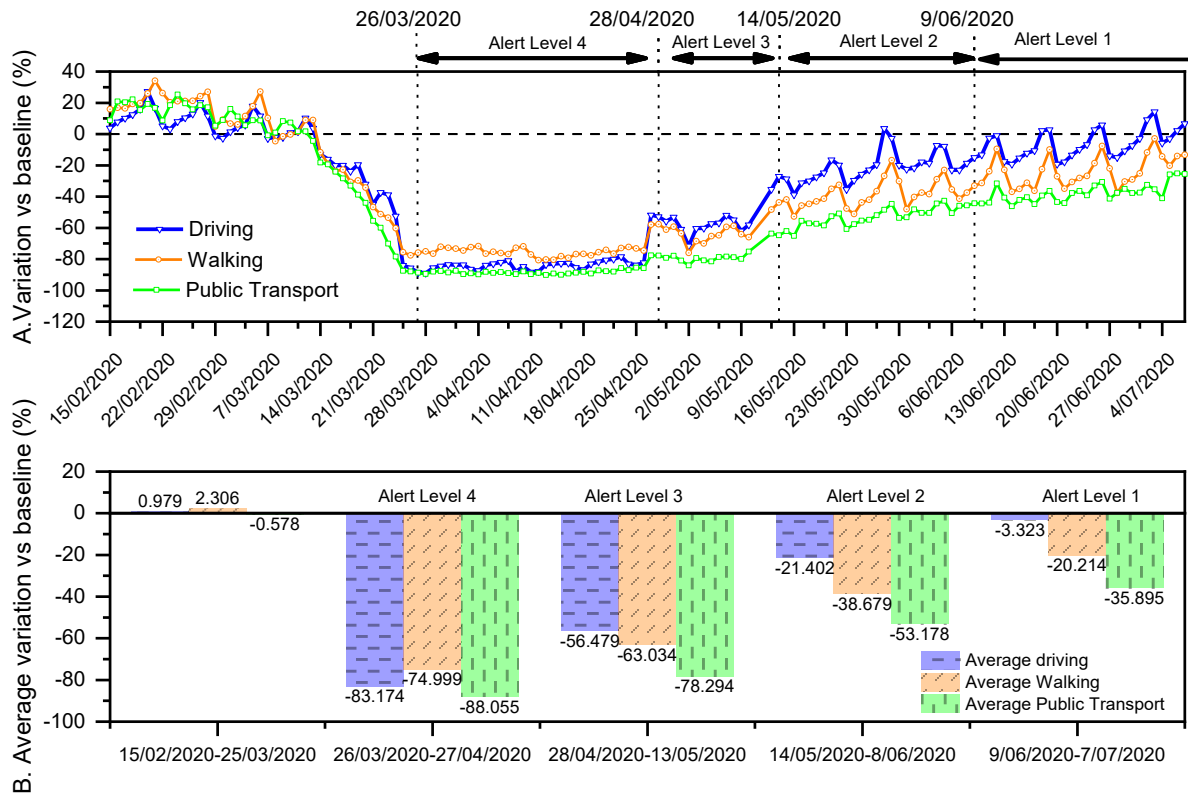
(a) Percentage change in mobility



(b) Structural break test

Figure 1. Percentage change in mobility and structural break test by journey destination





Notes: Authors' elaboration based on Apple Mobility Trends Reports.  
(a) Percentage change in requests for directions by transport mode in New Zealand  
(b) Average percentage change for (a).  
<https://www.apple.com/covid19/mobility>. The baseline volume is on 13 Jan 2020.

Figure 2. Variation of transport modes in New Zealand

Table 1. The impact of COVID-19 Alert levels on changes in mobility and transport mode

VARIABLES	Panel A: Mobility			Panel B: Transport Mode		
	(1) Retail and Recreation	(2) Workplaces	(3) Public Transport	(4) Driving	(5) Walking	(6) Public Transport
<i>COVID-19 Alert Levels</i>						
Alert Level 4	-89.69*** (0.842)	-82.15*** (1.666)	-93.62*** (0.782)	-89.18*** (3.198)	-79.63*** (1.870)	-80.25*** (1.087)
Alert Level 3	-73.69*** (0.792)	-53.32*** (1.696)	-78.33*** (0.930)	-61.62*** (3.761)	-69.06*** (1.735)	-70.29*** (1.164)
Alert Level 2	-27.78*** (1.215)	-36.82*** (1.736)	-52.40*** (0.685)	-24.45*** (2.273)	-43.34*** (1.946)	-47.49*** (1.310)
Alert Level 1	-10.46*** (1.026)	-15.38*** (1.723)	-44.42*** (0.633)	-10.60*** (2.416)	-20.98*** (1.957)	-28.72*** (1.041)
Lagged arch terms	YES^	YES	YES	YES	YES	YES
Log likelihood	-440.858	-536.324	-422.411	-540.221	-541.763	-480.140
AIC	901.716	1090.647	862.822	1098.443	1097.525	974.279
BIC	931.414	1117.376	889.550	1125.295	1118.41	995.165
Observations	144	144	144	146	146	146

Notes: ^YES denotes variables are included in the model.

Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Panel A: Authors' elaboration based on Google Covid-19 Community Mobility Reports.

<https://www.google.com/covid19/mobility/>. The baseline is the median value for the corresponding day of the week during 3 January-6 February 2020. The sample period is 15 February 2020 – 7 July 2020.

Panel B: Authors' elaboration based on Apple Mobility Trends Reports.

<https://www.apple.com/covid19/mobility>. The baseline volume is on 13 January 2020. The sample period is 15 February 2020 – 11 July 2020 (11, 12 May are missing).

Reference category: the pre-lockdown period 15 February 2020 -25 March 2020.

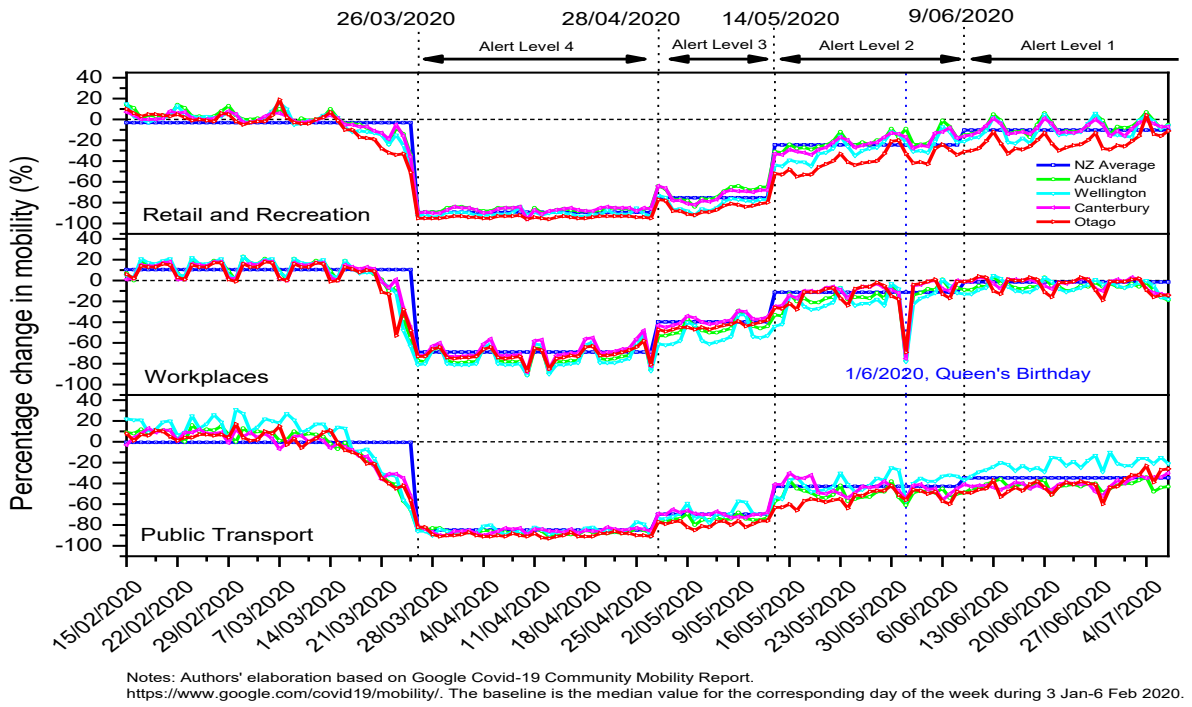
COVID-19 Alert Level 4 - 26 March 2020 -27 April 2020;

COVID-19 Alert Level 3 - 28 April 2020 – 13 May 2020;

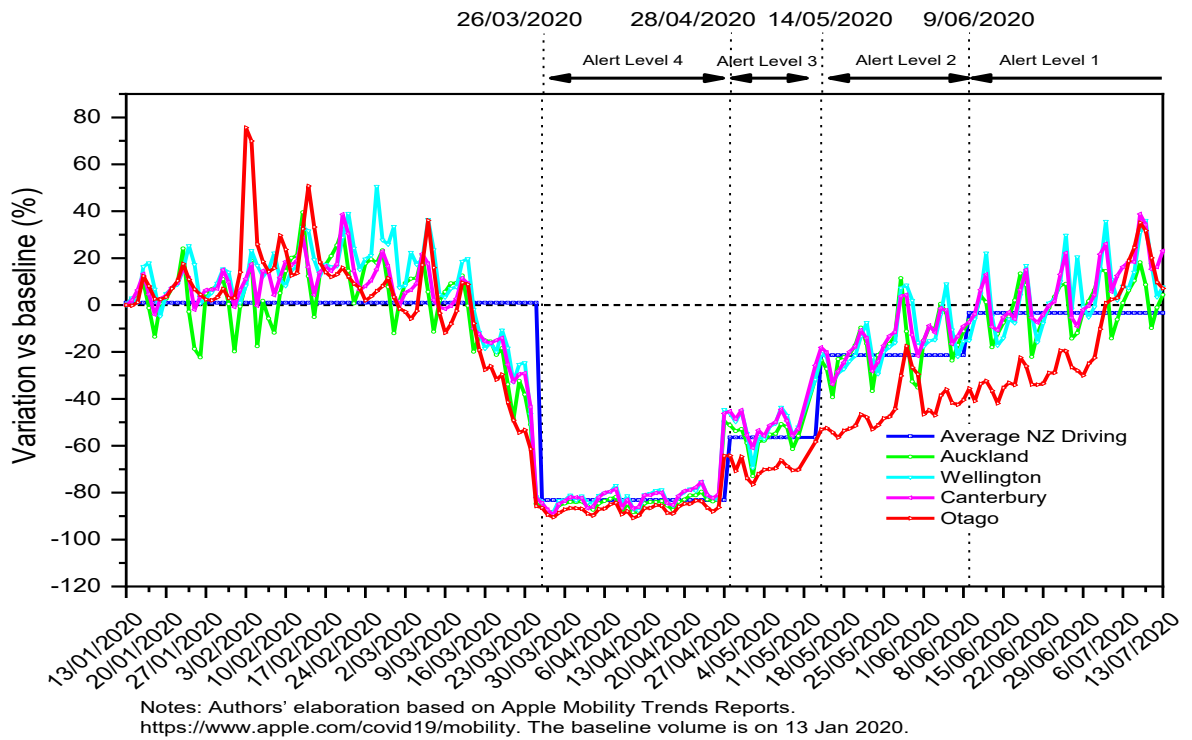
COVID-19 Alert Level 2 - 14 May 2020 – 8 June 2020;

COVID-19 Alert Level 1 - 9 June 2020 – 7 July 2020 in Panel A; 9 June 2020 – 11 July 2020 in Panel B.

The full results are available upon request.



(a) Regional heterogeneity in percentage change in mobility



(b) Variation of driving in major regions in New Zealand

Figure 3. Regional heterogeneity in percentage change in mobility and variation of driving in New Zealand