The Medical Journal of Australia

Supporting Information

Supplementary methods and results

This appendix was part of the submitted manuscript and has been peer reviewed. It is posted as supplied by the authors.

Appendix to: Tran TH, Sasikumar SN, Hennessy A, et al. Associations between restrictions on public mobility and slowing of new COVID-19 case rates in three countries. *Med J Aust* 2020; doi: 10.5694/mja2.50822.

1. Google COVID-19 Community Mobility Dataset

The Google COVID-19 Community Mobility dataset was used with expressed permission from Professor Karen DeSalvo (Chief Health Officer at Google Health, personal correspondence 21 Sept 2020)

The Community Mobility data is publicly available from https://www.google.com/covid19/mobility/ and may be downloaded as CSV (comma separated values) files that was periodically updated by the Google Health team. The dataset consisted of aggregated and anonymised data (data from users of products such as Google Maps who have turned on Location History, which can be toggled to off by the user) that chart movement trends over time by geography across different categories of places such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. The 'Global CSV' dataset was downloaded on 23 July 2020 for the visualisation in this article.

This article visualised and juxtaposed the the specific categories of 'residential' versus 'workplaces' as the authors anticipated that these place categories would intuitively yield the most significant changes in mobility trends from restrictions to public mobility.

The aggregated data anonymously estimated the percentage change in the time spent (for residential category) or total number of visitors (for workplace category) compared to baseline days. The baseline day was defined at the median value from the 5 week period Jan 3 - Feb 3, 2020 (an arbitrary period that was deemed prior to most formal societal mobility restrictions being implemented during the COVID-19 pandemic). The Google Health team acknowledge that this arbitrary period may not reflect 'perfectly normal baseline days' for every region on the planet. A calibration list is offered within the website as a means to consider likely confounders of mobility trends for any given population. These confounders for the period of Jan 3 - Feb 3, 2020 included:

- Local events and seasonal changes that might bias the baseline
- Day-to-day and seasonal weather effects on visitors to parks
- Weekly, seasonal and academic term related variations to time spent in residential places
- Effect of types of work on mobility changes e.g. how might COVID-19 responses affect different jobs (weekend v weekday jobs)?
- Representation of data in the region i.e. regions that do not allow mobile devices and access to Google Maps such as certain governmental building and military bases.

Accounting for regional country variations in school terms; Sweden is most likely to have its baseline day value overestimated for the residential category and underestimated for the workplace category as Sweden's end to Christmas vacations occurred at the beginning of January (compared to early February in Australia and late January in South Korea). Simply put, more people were at home for vacation holidays for the baseline period in Australia and South Korea compared to Sweden. This may have contributed to the reduced excursions from baseline in the data visualisation for Sweden.

Importantly, it should be explicitly noted that the percentage changes in the 'residential' and 'workplace' category are in different units. The residential category shows a change in time duration spent at home, whilst the workplace category (like all the other categories) quantifies the change in total visitors to the place category. Therefore, the residential category percentage change should not be directly compared with the workplace category percentage change in terms of absolute values but may be compared between countries in relative values.

The mobility data is imperfect in terms of units of measurement for the different categories (i.e. residential vs all other categories) and the use of an arbitrary baseline period. However, with consideration for these confounders, it is possible, with data transparency during interpretation to attain insight from the aggregated and anonymised data from the Google Health COVID-19 Community Mobility Reports Dataset.

2. Impact of effective lockdown date (ELD) + 14 days on the doubling time of COVID-19 cases, Interrupted Time Series analyses.

Australia – ITS analysis at ELD + 14d

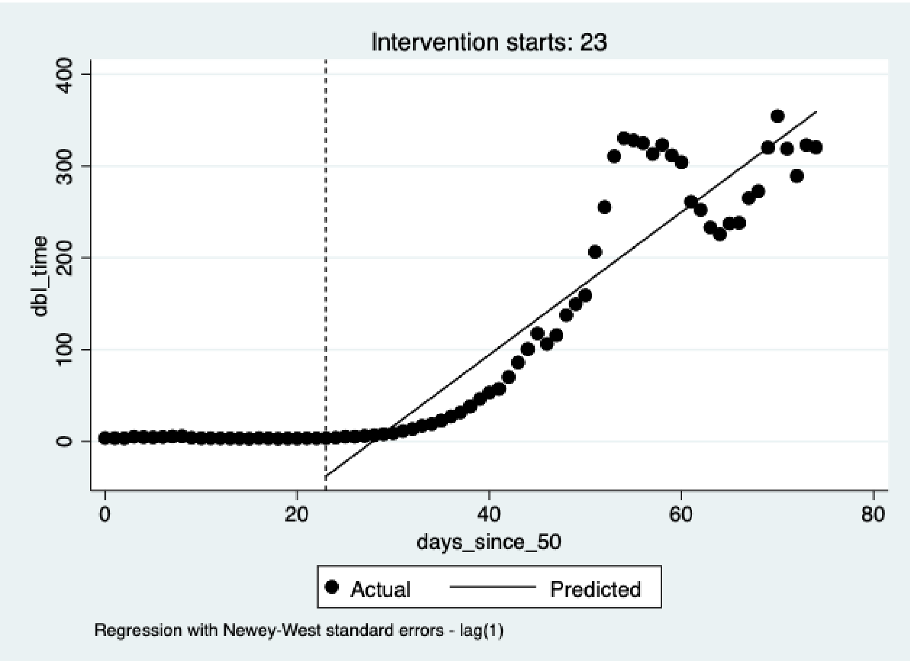
```
. itsa dbl_time, single trperiod(23) lag(1) posttrend figure

        time variable:  days_since_50, 0 to 74
                delta:  1 unit

Regression with Newey-West standard errors      Number of obs     =         75
maximum lag: 1                                  F(  3,        71) =     122.49
                                                Prob > F          =     0.0000
```

dbl_time	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
_t	-.0613898	.0242513	-2.53	0.014	-.1097454	-.0130342
_x23	-40.79371	11.29262	-3.61	0.001	-63.31056	-18.27686
_x_t23	7.837658	.4718061	16.61	0.000	6.896904	8.778413
_cons	4.408395	.4095504	10.76	0.000	3.591775	5.225016

Postintervention Linear Trend: 23

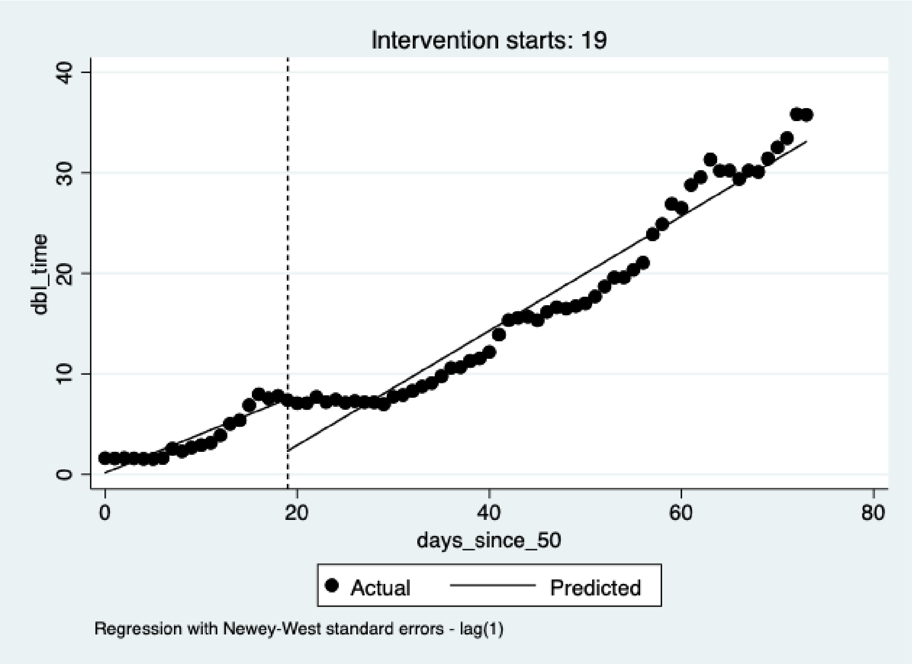
Treated: _b[_t]+_b[_x_t23]

Linear Trend	Coeff	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Treated	7.7763	0.4709	16.5150	0.0000	6.8374	8.7151



Sweden – ITS analysis at ELD + 14d

```
. itsa dbl_time, single trperiod(19) lag(1) posttrend figure


        time variable:  days_since_50, 0 to 73
                delta:  1 unit

Regression with Newey-West standard errors      Number of obs     =         74
maximum lag: 1                                  F(  3,        70) =     491.60
                                                Prob > F          =     0.0000

------------------------------------------------------------------------------
             |             Newey-West
    dbl_time |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          _t |   .3878885   .0538691     7.20   0.000       .28045     .495327
        _x19 |  -5.196617   1.114157    -4.66   0.000    -7.418734     -2.9745
      _x_t19 |   .1819178   .0621997     2.92   0.005     .0578645    .3059711
       _cons |   .1643351   .5457298     0.30   0.764    -.9240887    1.252759
------------------------------------------------------------------------------


                      Postintervention Linear Trend: 19

Treated: _b[_t]+_b[_x_t19]
------------------------------------------------------------------------------
Linear Trend |      Coeff   Std. Err.      t        P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |     0.5698    0.0292    19.4874     0.0000     0.5115     0.6281
------------------------------------------------------------------------------
```



South Korea – ITS analysis at ELD + 14d

```
. itsa dbl_time, single trperiod(14) lag(1) posttrend figure

        time variable:  days_since_50, 0 to 87
                delta:  1 unit

Regression with Newey-West standard errors      Number of obs     =         88
maximum lag: 1                                  F(  3,        84) =      28.66
                                                Prob > F          =     0.0000
```

dbl_time	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf. Interval]	
_t	.1221178	.0441576	2.77	0.007	.0343055	.20993
_x14	-118.2359	46.42916	-2.55	0.013	-210.5653	-25.90637
_x_t14	11.1734	1.944765	5.75	0.000	7.306026	15.04078
_cons	1.201498	.3959712	3.03	0.003	.4140663	1.988931

Postintervention Linear Trend: 14

Treated: _b[_t]+_b[_x_t14]

Linear Trend	Coeff	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Treated	11.2955	1.9439	5.8109	0.0000	7.4299	15.1611

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