Estimating temporal variation in transmission of COVID-19 and adherence to social distancing measures in Australia

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Key messages

Estimating the effective reproduction number

- Analyses were performed to identify temporal changes in the *effective reproduction number* (R_{eff}) in each Australian state/territory (Figure 2). Due to very low case incidence, these estimates are becoming increasingly unstable, *i.e.*, based primarily on model assumptions rather than actual case data.
- We are currently developing new methods for assessing epidemic activity, which should be more informative when daily case incidence is very low. These new methods will incorporate data on population mobility and chains of transmission *e.g.*, from localised outbreaks.

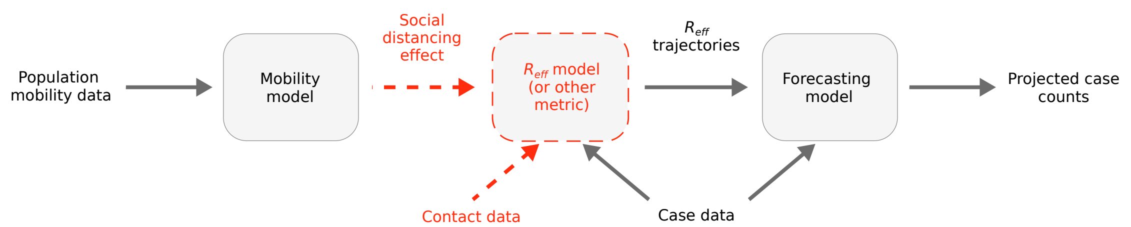
Forecasts of the daily number of new confirmed cases nationally

- Our most recent estimates of R_{eff} which were deemed reliable — estimated up to 11 April, based on data up to 20 April — were input into a mathematical model of disease dynamics which was projected forward to forecast the daily number of new confirmed cases.
- We report an Australia-wide forecast of the daily number of new confirmed cases up to 8 June (Figure 3), assuming that the effective reproduction number remains at its current estimated level (from 11 April).

Assessment of adherence to social distancing measures

- An analysis of trends in population mobility data streams up to 3 May was performed to assess adherence to social distancing policy. Relating changes in these data streams to changes in R_{eff} may enable the development of early indicators of increased transmission.
- This analysis suggests that adherence to social distancing measures may have decreased marginally in the past two to three weeks (Figure 4), although we note that the strongest signal of reduce adherence is for activities considered to be relatively low risk (driving and visiting parks).

Figure 1: Epidemic forecasting workflow. Red indicates components currently under development.



Estimating the temporal variation in the effective reproduction number in each jurisdiction

Background

The effective reproduction number at any point in time provides a data-informed model-based estimate of the rate of change in case incidence. If $R_{eff} < 1$, then the epidemic is estimated to be in decline. If $R_{eff} > 1$, the epidemic is estimated to be growing.

Data

We used line-lists of reported COVID-19 cases from the Australian national COVID-19 database, accessed via an agreement with the Commonwealth of Australia, Department of Health. We included data stratified by import status (imported from overseas or locally acquired) for each Australian state/territory up to and including 26 April, to estimate R_{eff} over time from 1 March up to mid-April (Figure 2).

Overview of methodology

We used a statistical method developed by colleagues at the London School of Hygiene and Tropical Medicine (LSHTM), recently adapted for COVID-19, which builds on their extensive experience and peer-reviewed work in this area.

This method estimates R_{eff} by using an optimally selected moving average window to smooth the curve and reduce the impact of localised events (*e.g.*, local outbreaks) that may cause large fluctuations. Importantly, the method accounts for delays in reporting (*i.e.*, the time from symptom onset to reporting) which is critical for incorporating the most recent data in the analysis (*i.e.*, for inferring when an observed drop in the number of reported cases reflects an actual drop in case numbers). See Appendix for further details.

Note that approximately 10% of reported cases in the national database currently do not have a reported import status. For the purpose of this analysis, we have assumed that all cases with an unknown source of acquisition are locally acquired.

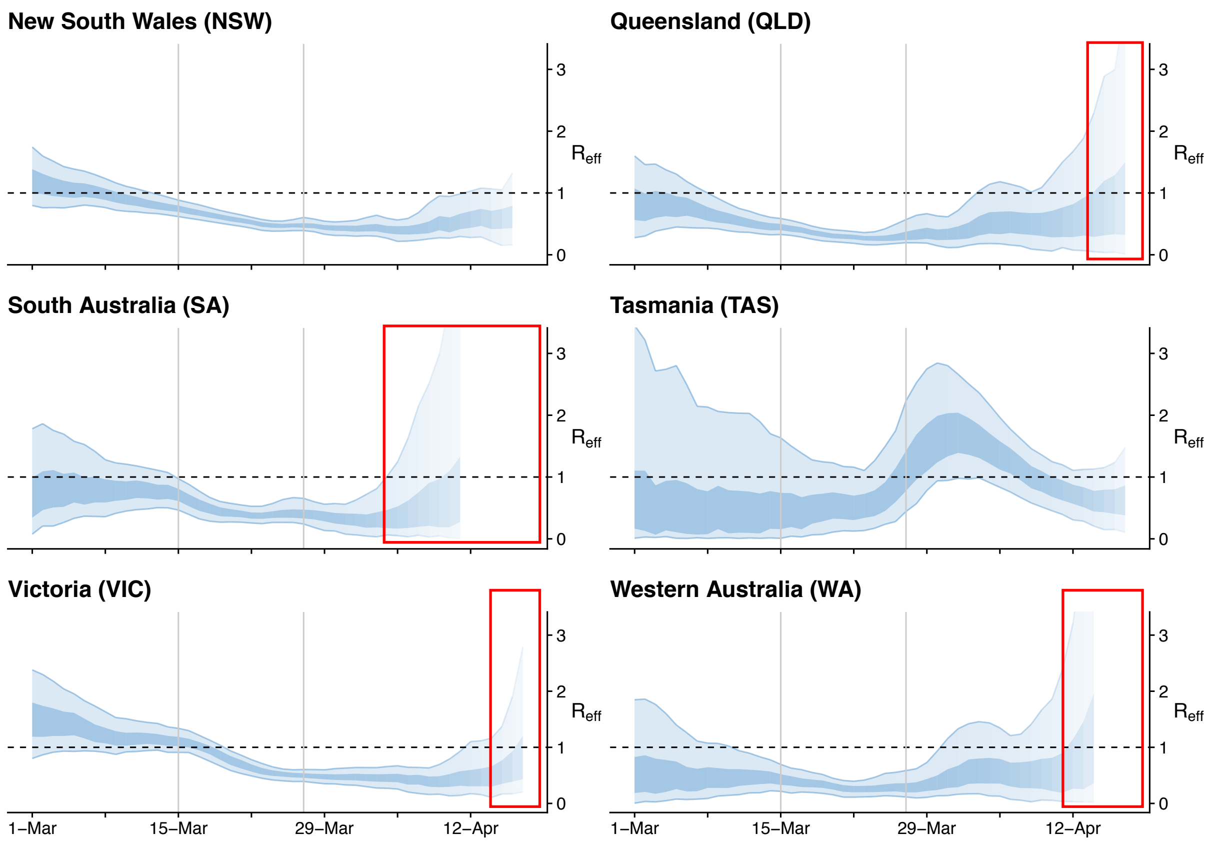
Accounting for quarantining of overseas arrivals

Results were produced assuming stepwise changes in the relative infectiousness of locally acquired to imported cases according to quarantine requirements for returning travellers. We assumed that 20%, 50%, and 99% of imported cases did not contribute to transmission prior to 15 March, between 15 and 27 March (inclusive), and after 27 March, respectively.

Handling of low case incidence

We perform inference in a Bayesian framework that uses a combination of our prior knowledge of the reproduction number and the case notification data to estimate the effective reproduction number over time. We incorporate prior knowledge of the reproduction number by specifying a prior distribution on R_{eff}. This distribution was informed by early data on R_0 from Wuhan [1], China (≈2.6). In the absence of data (*i.e.*, when case incidence numbers are low or zero), R_{eff} will tend towards the prior distribution for R_{eff}, thereby obscuring our ability to detect any changes in the actual underlying effective reproduction number.

Figure 2: Time-varying estimate of the effective reproduction number of COVID-19 (light blue ribbon = 90% credible interval; dark blue ribbon = 50% credible interval) up to mid-April (17 April for QLD, TAS, and VIC; 16 April for NSW; 14 April for WA; and 11 April for SA) based on data up to and including 26 April, for each Australian state/territory with sufficient local transmission (excludes ACT and NT). Confidence in the estimated values is indicated by shading with reduced shading corresponding to reduced confidence. Results are produced assuming stepwise changes in the relative infectiousness of locally acquired to imported cases according to quarantine requirements for returning travellers introduced on 15 and 27 March (indicated by vertical grey lines). We assumed 20%, 50%, and 99% of imported cases did not contribute to transmission prior to 15 March, between 15 and 27 March (inclusive), and after 27 March, respectively. The broadening credible intervals reflect low incident case numbers (indicated by red boxes). In the absence of data (*i.e.*, when incident case numbers are low or zero), R_{eff} will tend towards the prior distribution for R_{eff} (95% prior CrI [0.24-7.73]), thereby obscuring our ability to detect any changes in the actual underlying effective reproduction number. The black dotted line indicates the target value of 1 for the effective reproduction number required for control.

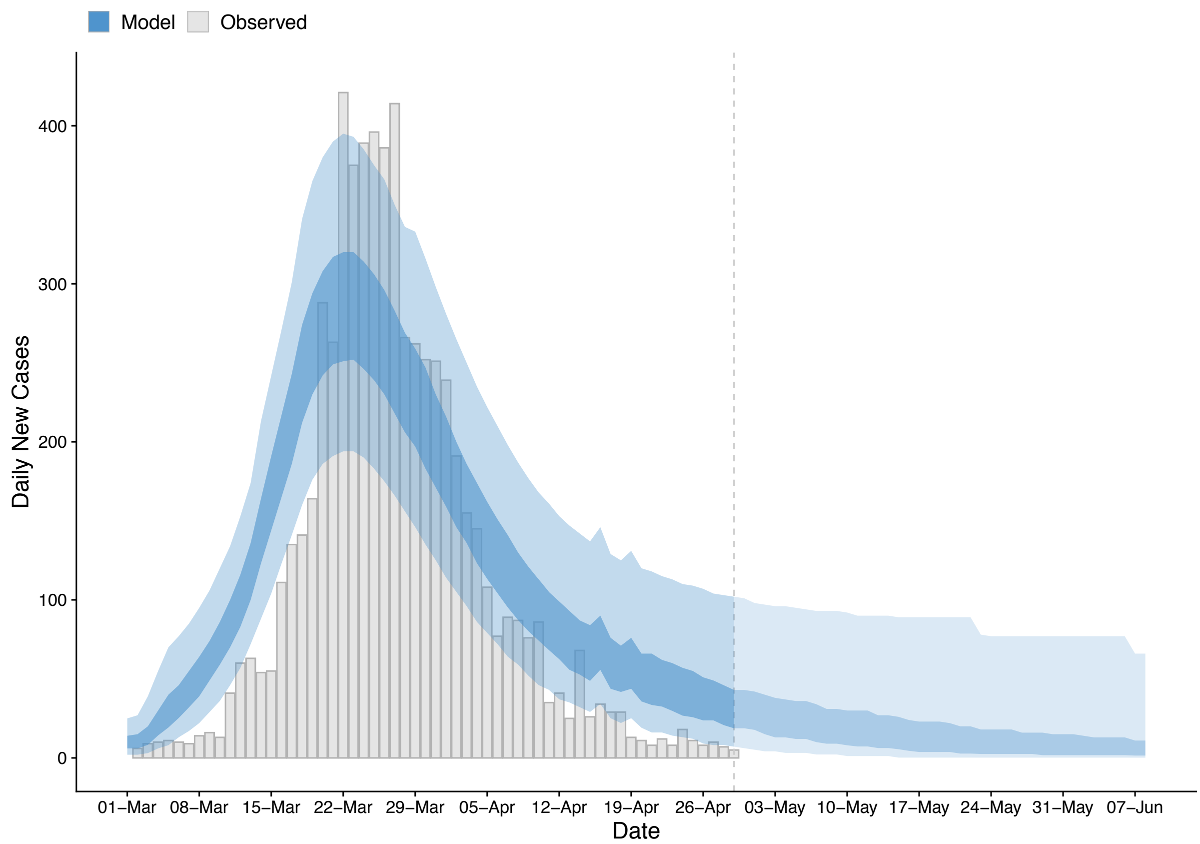


Forecasts of the daily number of new confirmed cases nationally

We used our estimates of time-varying R_{eff} and observed cases to generate preliminary forecasts of the daily number of new confirmed cases nationally (Figure 3). R_{eff} estimates were input into a mathematical model of disease dynamics that was extended to account for imported cases. A sequential Monte Carlo method was used to infer the model parameters and appropriately capture the uncertainty, conditional on each of a number of sampled R_{eff} trajectories up to 11 April, from which point they were assumed to be constant. The model was subsequently projected forward from 29 April to 8 June, to forecast the number of reported cases, assuming a case detection probability of 80%.

Note: These forecasts incorporate our most recent estimates of the effective reproduction number which we deemed reliable — those estimated using the Abbott et al (2020) method up to 11 April.

Figure 3: Time series of new daily confirmed cases of COVID-19 in Australia from 1 March to 29 April 2020 (grey bars) overlaid by daily case counts estimated from the forecasting model up to 28 April and projected forward from 29 April to 8 June. Inner shading = 50% confidence intervals. Outer shading = 95% confidence intervals. Note that forecasting model estimates prior to 29 April — the last recorded data point at the time of analysis (indicated by the dashed grey line) — use data up to and including the previous day. Projections were made from 29 April to 8 June inclusive.



Assessment of adherence to social distancing measures through the analysis of trends in population mobility data streams

Summary:

A number of data streams provide information on mobility before and in response to COVID-19 across Australian states/territories. Each of these data streams represents a different aspect of population mobility, but they show some common trends — reflecting underlying changes in behaviour. We use a latent variable statistical model to simultaneously analyse these data streams and quantify these underlying behavioural variables.

Data streams:

We currently consider nine different data streams, provided by three different technology companies: Apple and Citymapper provide regularly updated data on direction requests, while Google provide less regularly updated data on different measures of mobility from users' GPS data.

Google provide GPS-derived indices of the amount of time spent (a combination of visits and lengths of stay) in locations of one of 6 types ('workplaces', 'residential', 'parks', 'grocery and pharmacy', 'retail and recreation', 'transit stations'). See Appendix for further details.

Each data stream is encoded as a percentage change in the mobility metric, relative to a pre-COVID-19 baseline.

Access and privacy:

The data streams provided by Apple, Citymapper and Google are all publicly available for the express purpose of supporting public heath bodies in their response to COVID-19. All of these datasets are fully anonymised and aggregated at the level of either states and territories or Australia's 4 largest cities, over each day. The large-scale aggregation of these datasets ensures the privacy of users - the smallest population is that of the Northern Territory: over 245,000.

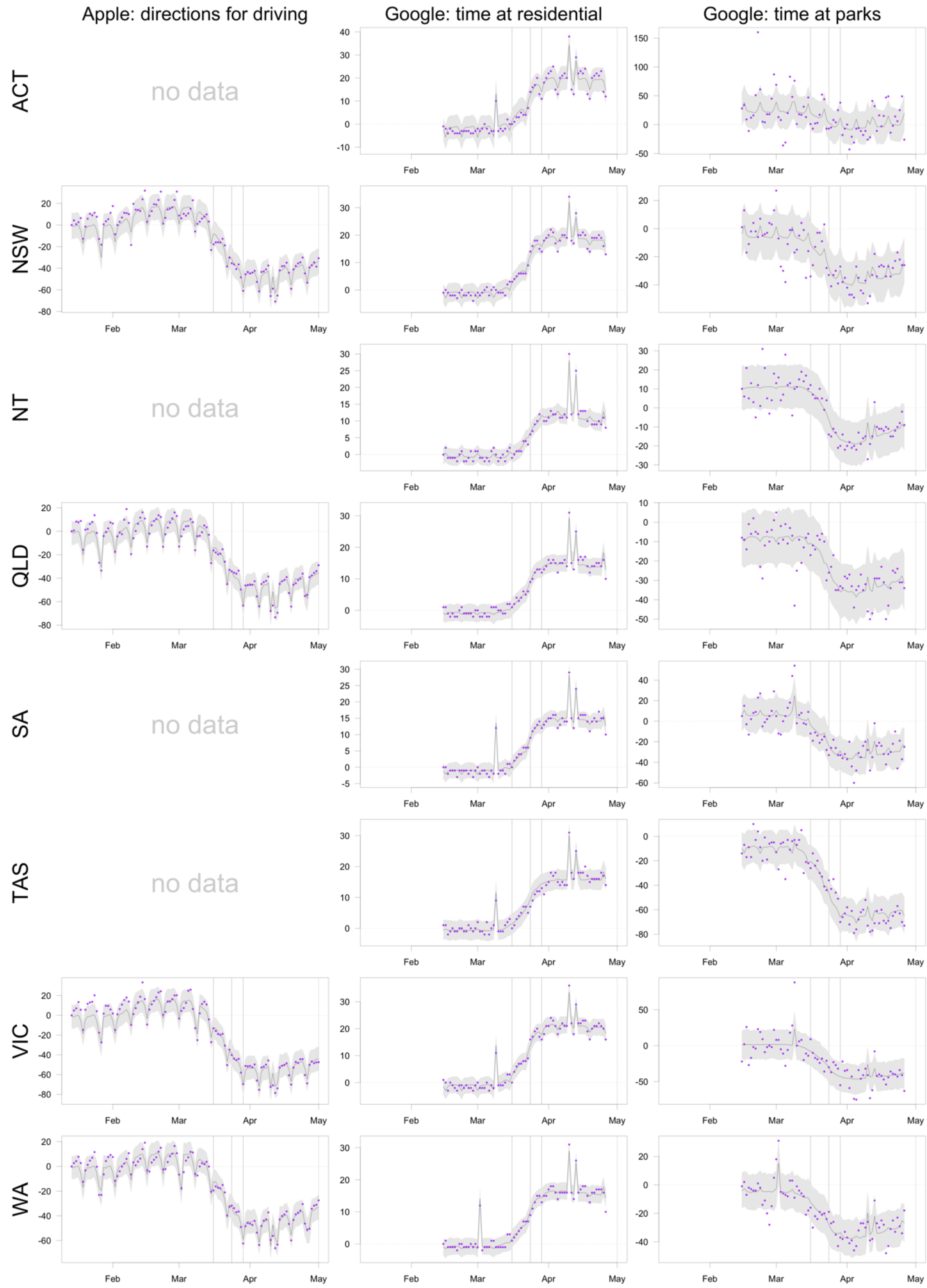
Interpretation:

The model identifies three COVID-19-related behavioural variables that explain the trends in all of these data streams. **The dominant behaviour in all data streams is a behavioural switch to increased social distancing occurring during the period when social distancing measures were implemented.** The switch to social distancing behaviour was most rapid around the date of the second social distancing measure we consider: closure of restaurants, bars, and cafes on 24 March. Also detected is a period of increased activity in some data streams in advance of this social distancing behaviour, apparently representing preparation for social distancing behaviour. This is most evident in Google's index of time spent at grocery stores and pharmacies (not shown in Figure 4). **The model also detects a very slight decline in the social distancing variable over time *i.e.*, increasing mixing (Figure 4).** Specifically, by 1 May, the impact of social distancing on time at parks is expected to have reduced by 30% on average across states (ranging from 13% to 41%), and the effect on requests for driving directions by 17% (13%–19%), and on time at residential addresses by 11% (1%–25%). However, it should be noted that these may represent an increase in low transmission risk activities, including activities encouraged by public health authorities *e.g.*, exercising.

Other behavioural variables driving the data streams but not related to COVID-19 are: a gradual increase in work- and school-related travel after the school holidays ended in February (evident in Apple's direction requests, and Google's time at transit stations and workplaces); reduced mobility on weekends (evident in weekly-cycles in most data streams); and reduced mobility on public holidays ('spikes' evident in most data streams).

Plots of each data stream and our model fits for each state and territory are shown in the Appendix, with annotation matching that in Figure 4.

Figure 4: Percentage change compared to a pre-COVID-19 baseline of three key mobility data streams in each Australian state and territory up to 1 May. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks 1 May, the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behaviours driving each data stream.



Acknowledgements
This report represents surveillance data reported through the Communicable Diseases Network Australia (CDNA) as part of the nationally coordinated response to COVID-19. We thank public health state from incident emergency operations centres in state and territory health departments, and the Australian Government Department of Health, along with state and territory public health laboratories. We thank members of CDNA for their feedback and perspectives on the results.

Technical Appendix

Estimating the effective reproduction number

Our analysis is based on the method developed by Abbott et al (2020) of the London School of Hygiene and Tropical Medicine, Centre for Mathematical Modelling of Infectious Diseases novel coronavirus working group. Full details of the statistical analysis and code base are available via their website (below) and described in the key references at the end of this document [2,3].

https://epiforecasts.io/covid/

Full details of the specific analysis described in this report are provided in [4].

Forecasts of the daily number of new confirmed cases nationally

A full description of the forecasting method is provided in [5] and details of the specific forecasts described in this report are provided in [4].

Assessment of adherence to social distancing measures through the analysis of trends in population mobility data streams

Summary:

A number of data streams provide information on mobility before and in response to COVID-19 across Australian states/territories. Each of these data streams represents a different aspect of population mobility, but they show some common trends — reflecting underlying changes in behaviour. We use a latent variable statistical model to simultaneously analyse these data streams and quantify these underlying behavious.

Data streams:

We currently consider nine different data streams, provided by three different technology companies: Apple and Citymapper provide regularly updated data on direction requests, whilst Google provides less regularly updated data on different measures of mobility from users' GPS data. Each data stream is encoded as a percentage change in the mobility metric, relative to a pre-COVID-19 baseline.

Apple

Apple provide three data streams from their Apple Maps app of the total number of user requests for directions, one each for driving, walking, and public transport. No further details are provided on the nature of these journeys. Separate versions of these data streams are provided for Sydney, Melbourne, Brisbane, Perth, and for all of Australia. We use the city-level data as representative of mobility within that state, and do not currently use the national composite data. Apple's proportional change data is relative to a baseline of the metric in each location on 13 January 2020. Daily counts are calculated using Pacific Standard Time (*i.e.*, the time in California), which largely but not entirely overlaps with the subsequent day in Australia. We therefore assign mobility data to the subsequent date. These data are updated daily and can be accessed at: https://www.apple.com/covid19/mobility.

Citymapper

Citymapper provide a composite index based on the numbers of requests for directions using the Citymapper app. This is a composite metric of requests for different transport mode, though Citymapper does not provide driving directions and is primarily used for public transport directions, with some use for walking, cycling, and cab directions. No further details are provided on the nature of these journeys. Separate versions of these data streams are provided for Sydney, Melbourne, and for all of Australia. We use the city-level data as representative of mobility within that state, and do not currently use the national composite data. Citymapper's proportional change data are relative to a baseline of the metric between 6 January and 2 February 2020. Daily counts are calculated using UTC (*i.e.,* the time in London), which largely but not entirely overlaps with the same day in Australia. We therefore assign mobility data to the date provided. These data are updated daily and can be accessed at: https://citymapper.com/CMI.

Google

Google provide GPS-derived indices of the amount of time spent (a combination of visits and lengths of stay) in locations of one of 6 types. The following are Google's descriptions of these places:

- retail and recreation: "places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters"
- grocery & pharmacy: "places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies"
- parks: "places like national parks, public beaches, marinas, dog parks, plazas, and public gardens"
- transit stations: "places like public transport hubs such as subway, bus, and train stations"
- workplaces: "places of work"
- residential: "places of residence"

This visitation information is derived from the aggregated GPS tracks of users with the Location History setting enabled (off by default). No further details are provided on the users or the nature of these visits. Separate versions of these data streams are provided for each state and territory, and for all of Australia. We do not currently use the national composite data. Google's proportional change data are relative to a baseline of the metric between 3 January and 6 February 2020. Daily counts are calculated using UTC (*i.e.,* the time in London), which largely but not entirely overlaps with the same day in Australia. We therefore assign mobility data to the date provided. These data are updated intermittently. Recently the data have been released every week but providing data only up to about a week before the release date so that data are typically between one and two weeks out of date. The data can be accessed at: https://www.google.com/covid19/mobility/.

Representativeness:

All of these data streams are derived from apps that are primarily smartphone-based. As such they overrepresent demographics that are more likely to own smartphones and have account with these technology companies. Data on the demographics of the users that contributed to these particular data streams are not available. Given that school-age children are underrepresented in COVID-19 cases in Australia, and that those over 65 are likely to be less mobile, these data may be unintentionally biased towards those contributing most strongly to transmission.

Apple's and Citymapper's direction requests likely represent deliberate visits to a specific location, and a location that the user either does not usually visit (and therefore requires directions) or would benefit from live traffic updates for. Whilst Google's index of the time spent in residential places is likely to be a good proxy for people staying at home, it does not exclude the possibility that this time is spent in another person's household.

Model description:

We simultaneously analyse all of these data streams using a statistical latent variable model [6]. A latent variable model is akin to fitting a linear regression model to each data stream using the same set of covariates, but where the covariates are learned from the datastreams rather than being specified in advance. These inferred covariates are termed latent variables. Latent variables are unitless quantities that summarise the patterns that are shared by some or all of the datastreams. Because all data streams share the same latent variables but have their own regression coefficients ('loadings'), the same latent variable can imply a percentage increase on one data stream, but a different percentage decrease in another.

In this analysis, we consider each latent variable to be an index of some underlying population-level behavioural pattern. This enables us to distill these multiple datastreams down into a smaller set of behavioural patterns we are most interested in. If a latent variable has a large influence on, and good statistical fit to multiple datastreams of different types of mobility, that gives us confidence that the pattern is reflective of general behaviours, rather than being a quirk of a single mobility index.

Traditional latent variable models are purely statistical – they make no initial assumptions about the structure of the underlying latent variables. We developed a semi-mechanistic Bayesian latent variable analysis that uses prior knowledge to define a parametric function (with unknown parameters) for each latent variable, so that the latent variables represent known or hypothesised patterns of population-level behaviour. Three of these latent variables are related to COVID-19, and three describe non-COVID-19-related trends. The three COVID-19 related latent variables considered are: 'preparation' — a surge of activity in preparation of social distancing, 'social distancing' — a switch to more socially-distant behaviour, and 'waning distancing' — a partial reversion to a non-social-distancing behavioural state. The three non-COVID-19-related latent variables are: 'back to work' — a behavioural switch associated with the start of school term one (and return to work for many parents), 'day of the week' — different behaviours on each day of the week, including weekday vs weekend behaviours, and 'public holidays' — different behaviours associated with public holidays in each state. The model fits for each data stream incorporate the impacts of all of these latent variables, though we are most interested in the COVID-19 related variables.

Because each data stream weights the different latent variables differently, these latent variables are considered only as relative effects — they have no absolute magnitude or sign. We therefore define each of them as functions with values constrained between 0 and 1. The following describes the parametric functions chosen for each latent variable to reflect prior knowledge of the behaviours they represent:

- Preparation — a smooth, symmetric unimodal peak representing behaviours in advance of anticipated social distancing behaviour. The date and width of the peak are estimated from the data.
- Social Distancing — a smooth monotone increasing function representing the population switching to a behavioural state of increased social distance. We assume that the switching happens in bursts around each of three major social distancing measures introduced at the national level: restriction of gatherings to 500 or fewer people on 16 March; closure of restaurants, bars, and cafes on 24 March; restriction of gatherings to 2 or fewer people (except South Australia) on 29 March. The relative magnitudes of the behavioural switches associated with each of these social distancing measures, as well as the rate of change around each, are estimated from the data.
- Waning Distancing — a smooth monotone increasing function representing a waning of social distancing behaviour as the population switches back to a socially non-distant

behavioural state. Currently the parameters of this latent variable are fixed — implying a linear increase starting one week after the last social distancing intervention (5 April). The relative impact of (and evidence for) this behaviour on each data stream is estimated from the data. As more up-to-date data become available for the Google data stream, the timing and slope of this effect will be estimated from the data.

- Back to Work — an increasing sigmoid function representing a switch from one behavioural state during the school holidays to another during term one. The location (date by which 50% of people have switched) and slope of this sigmoid are estimated from the data.
- Day of the Week — a flexible curve over the day of the week, representing a gradient of behaviour between the peak of activity in the work week, and the trough at the weekend. The curve is constrained between 0 and 1, with a value of 1 constrained to fall on a Sunday. The three parameters describing the shape of the curve are estimated from the data.
- Public Holidays — a series of independent offsets applied to each public holiday in each state to represent different behavioural states on these days. The value offset for each holiday is estimated from the data and scaled to between 0 and 1.

References

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Supplementary figures to population mobility analysis

Figure S1: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in Western Australia. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

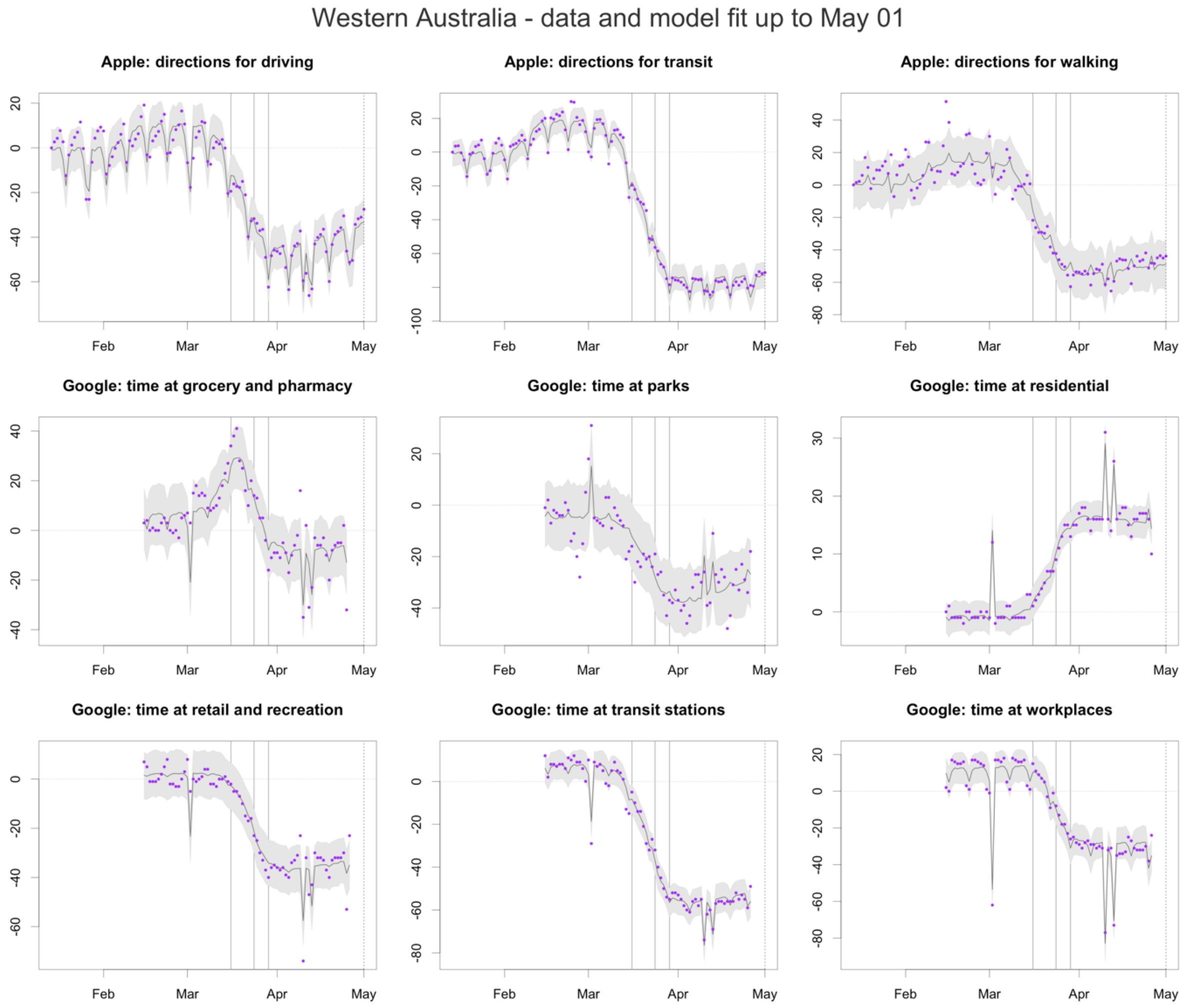

Figure S2: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in Victoria. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

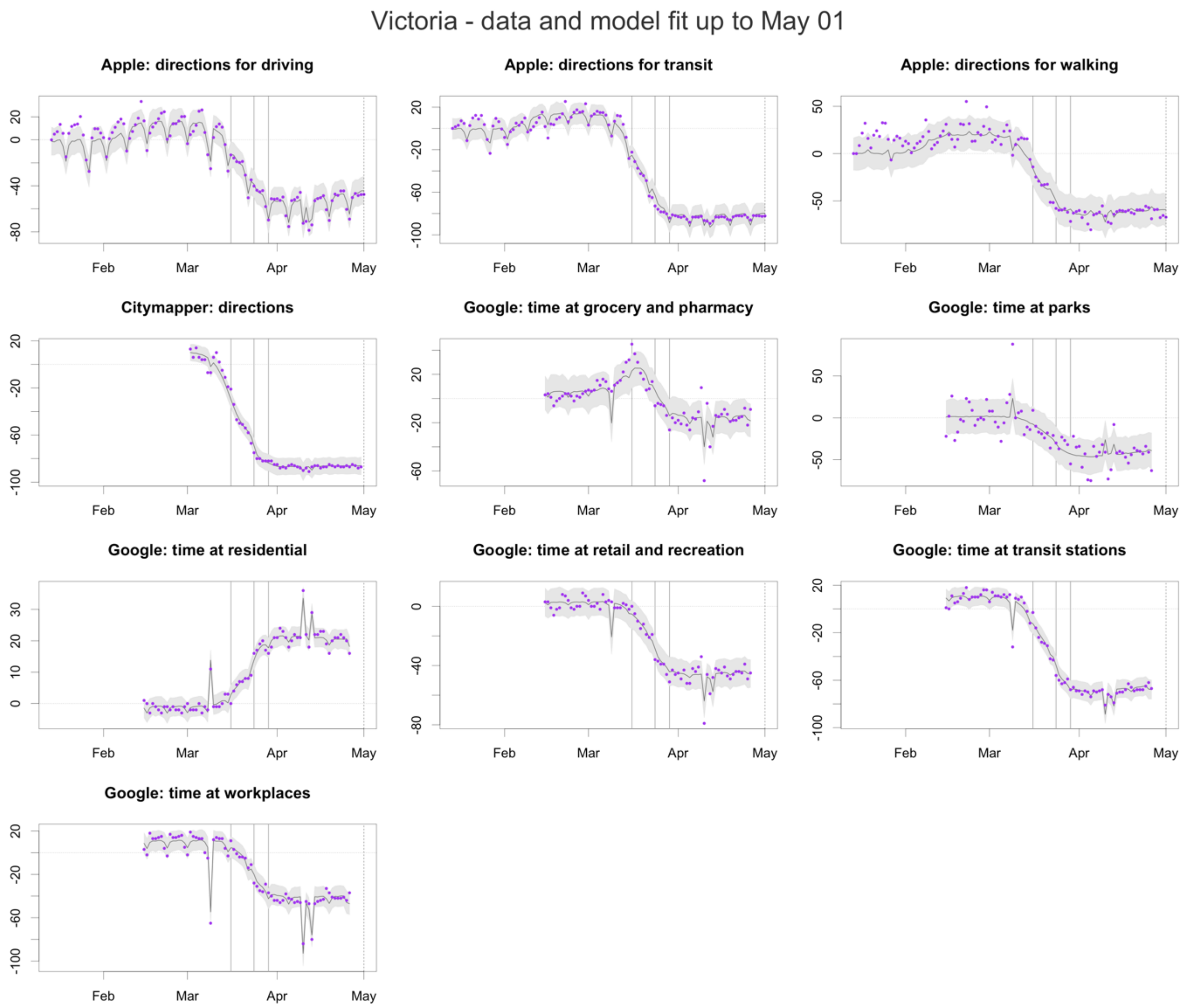

Figure S3: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in Tasmania. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

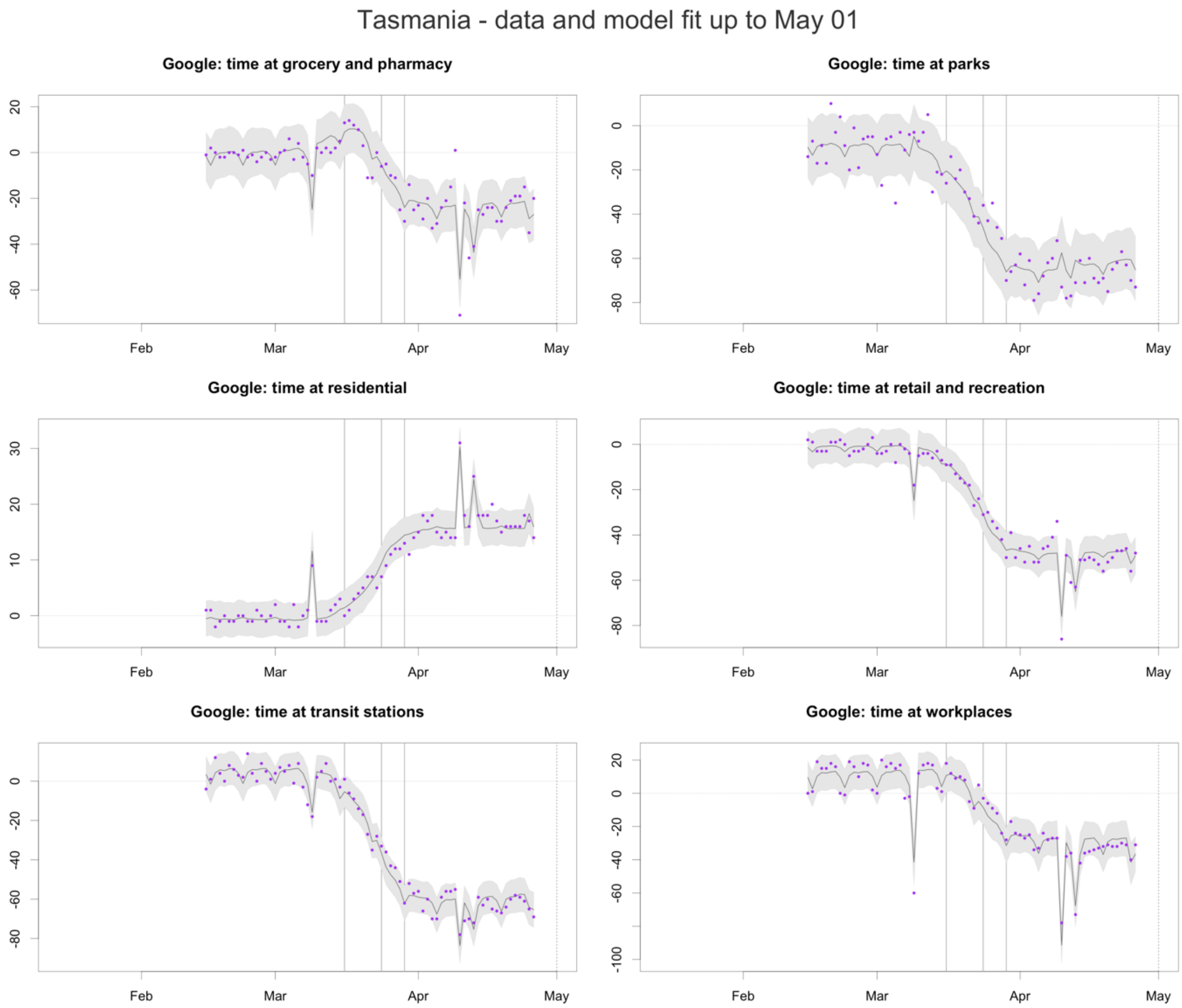

Figure S4: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in South Australia. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

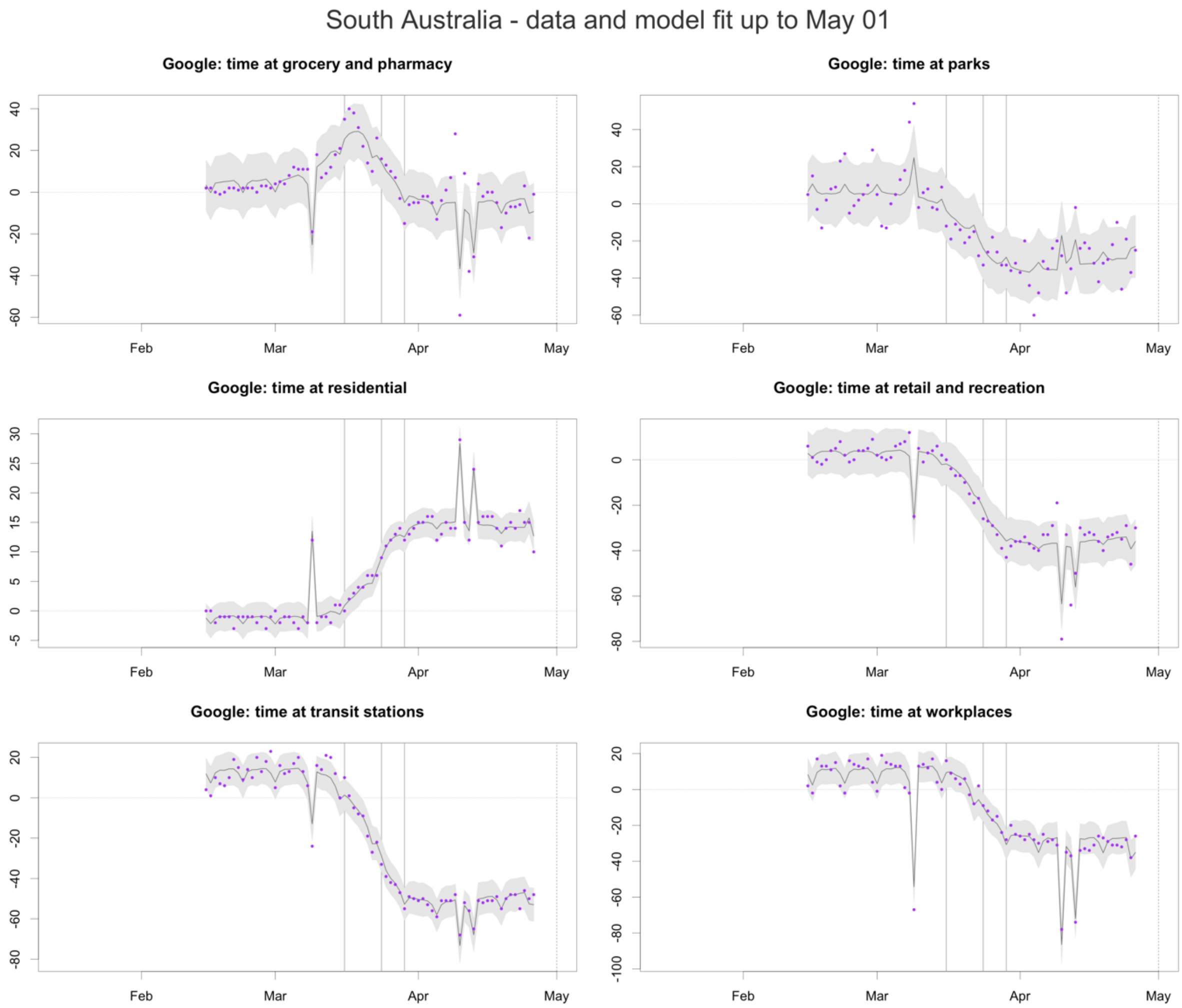

Figure S5: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in Queensland. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

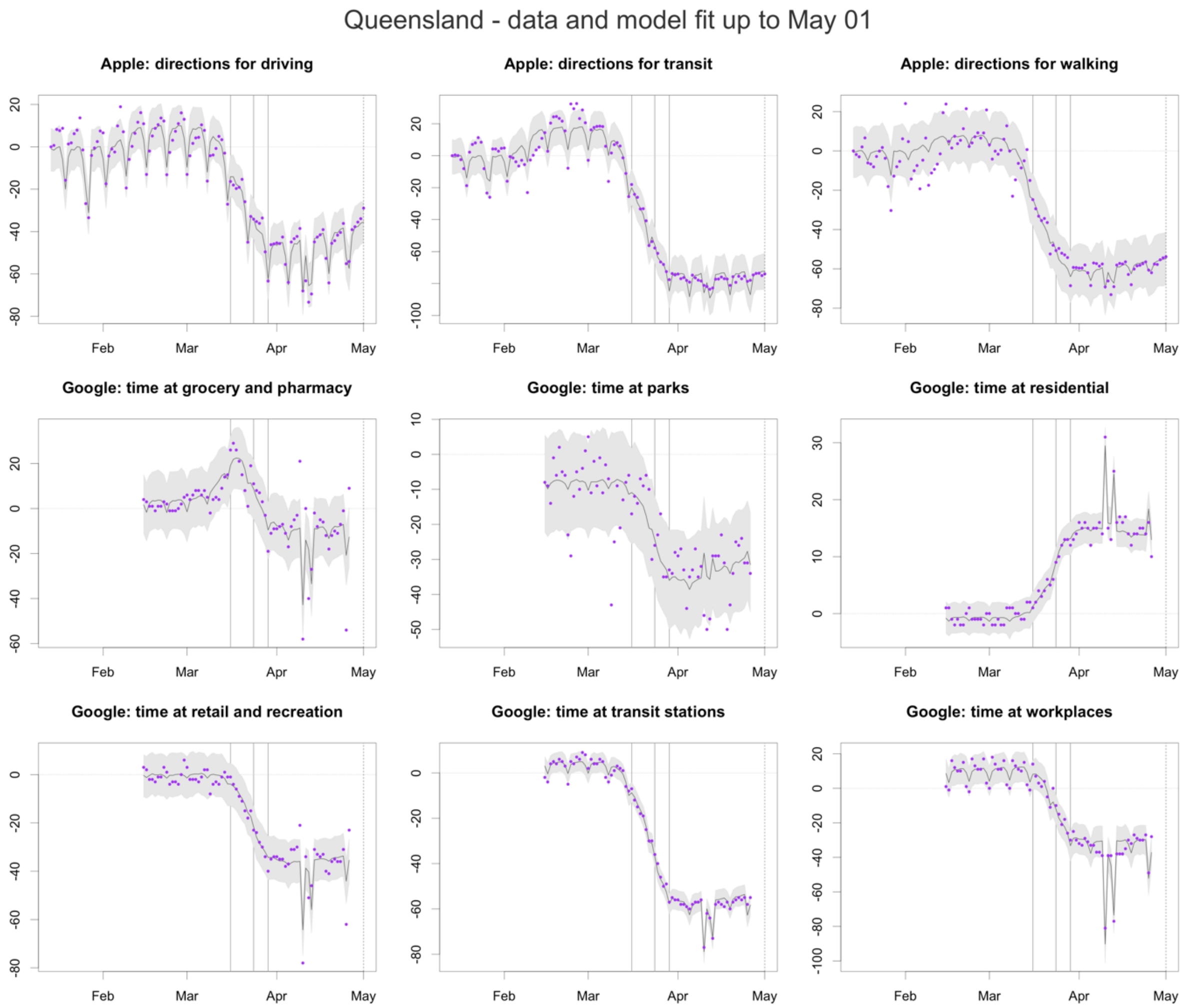

Figure S6: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in Northern Territory. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

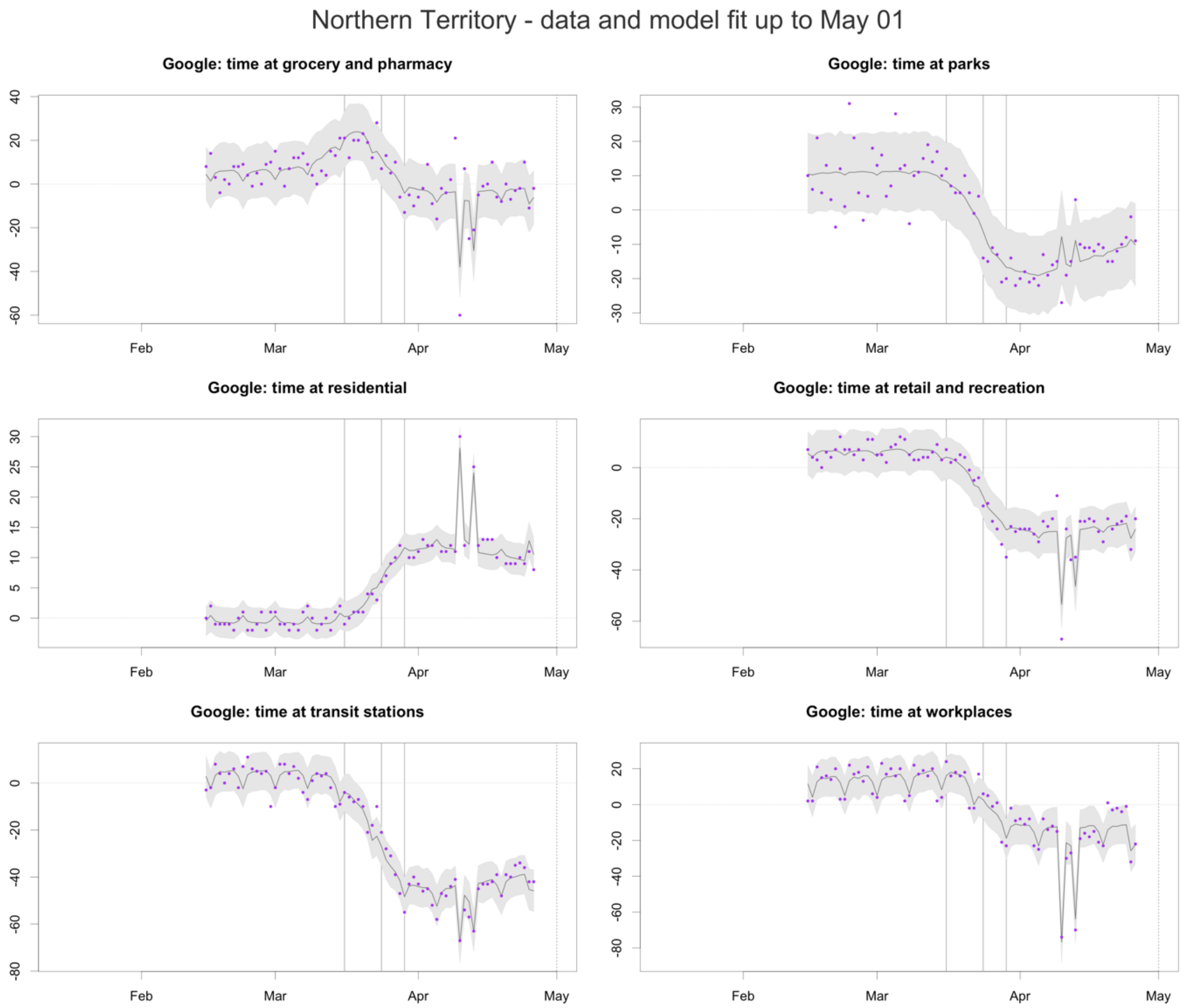

Figure S7: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in New South Wales. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.

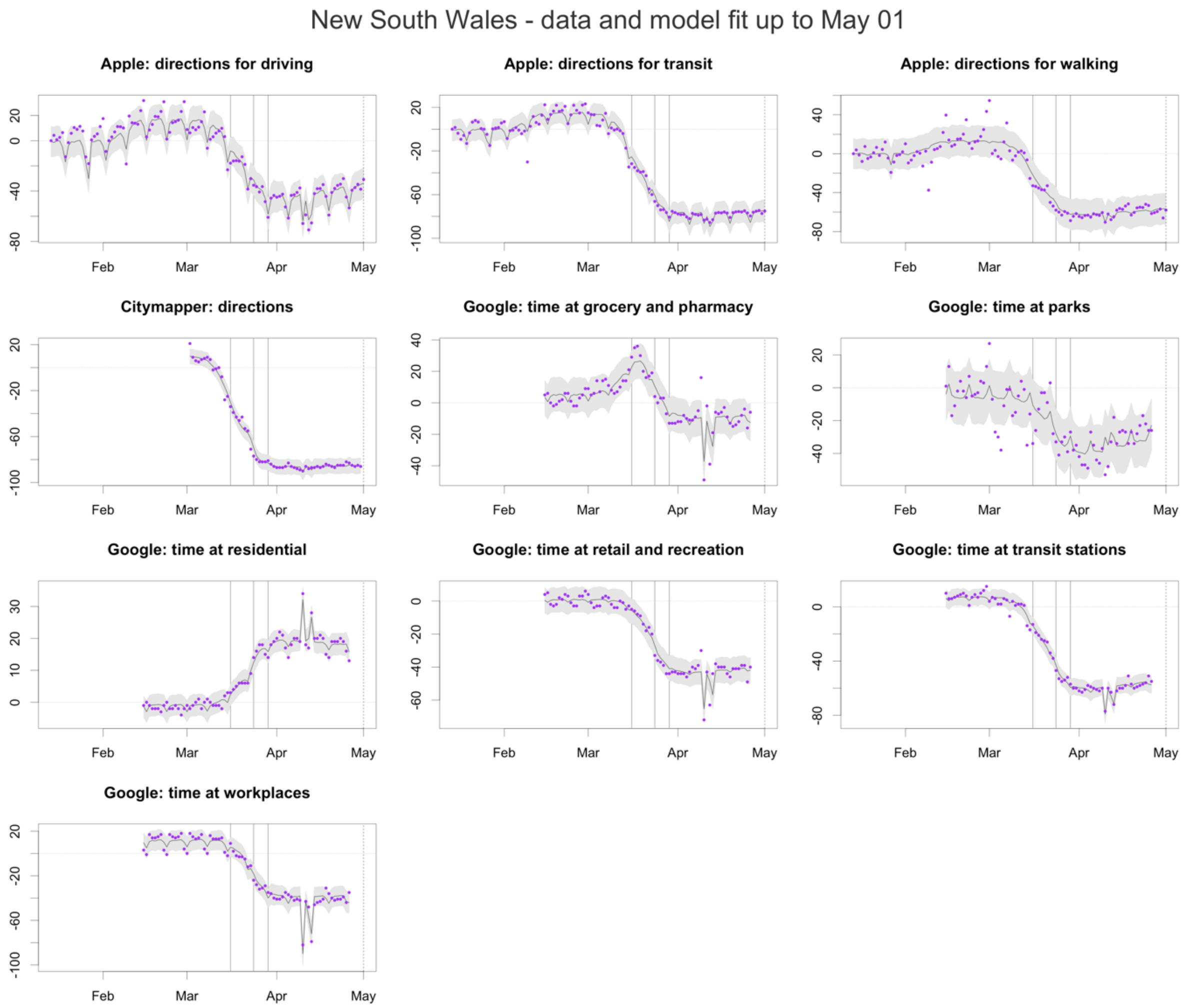

Figure S8: Percentage change compared to a pre-COVID-19 baseline of a number of key mobility data streams in the Australian Capital Territory. Solid vertical lines give the dates of three social distancing measures: restriction of gatherings to 500 people or fewer; closure of bars, restaurants, and cafes; restriction of gatherings to 2 people or fewer. The dashed vertical line marks the most recent date for which some mobility data are available. Blue dots in each panel are data stream values (percentage change on baseline). Solid lines and grey shaded regions are the posterior mean and 95% credible interval estimated by our model of the latent behavioural variables driving each data stream.