Supplementary Appendix

For paper titled *Stemming the flow: How much can the Australian smartphone app help to control COVID-19?*

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1. Model structure

The system dynamics model presented in this paper comprises a series of interconnected sub-models that include: 1) an infection sector that uses a modified susceptible – exposed – infected – recovered (SEIR) structure to capture population-level flow of people through the various disease states of COVID-19, 2) an overseas acquired cases sector that captures the inflow of infectious cases entering Australia from overseas, 3) a social distancing sector that captures individual and population-level social distancing measures, 4) a testing sector that captures the rate at which symptomatic infectious cases are identified through diagnostic testing, and 5) a contact tracing sector that captures the rate at which infectious cases are identified through standard and app-based contact tracing.

2. Infection sector

Figure 1 within the main text of the paper shows the modified SEIR structure used as the backbone of the infection sector of the model. The sector is represented using 17 stocks (state variables). The transition between stock variables is typically modelled using a first order delay in which people flow out of each stock at a rate *n(t)/d*, where *n(t)* is the number of people in the stock at time *t*, and *d* is the average duration of time people spend in that state. In situations where the flow of people leaving a stock is split into two categories, such as latent infectious people being divided between the undiagnosed early symptomatic [S1] state and the asymptomatic population [aS], people flow out of the stock at a rate of (*n(t)/d)*p* where *p* is the average proportion of the population expected to enter that state.

New community-acquired COVID-19 cases (i.e. those not related to overseas travel) were calculated using an basic reproduction number (R_0) of 2.53[1] and initial unrestricted contact rate of 20 contacts per day[2]. Flow between quarantined and non-quarantined stocks, as well as diagnosed and non-diagnosed stocks (with those in the diagnosed stocks considered to be in isolation), is controlled by mechanisms in the testing and contact tracing sectors (described in sections 5 and 6 of this Appendix respectively). As one of the key functions of the hospital sector is to diagnose and isolate infectious people, the model assumes that any undiagnosed symptomatic cases who require hospitalisation are tested and become diagnosed cases while in hospital.

The model also assumes that the entire Australian population is initially within the susceptible population sector. The population size is based on a 2020 demographic projection from the Australian Bureau of Statistics[3] using series B conditions. Because of a current lack of evidence of confirmed human reinfection with SARS-CoV2[4] and the short duration of the model period (one calendar year), the model assumes that individuals who have recovered do not return to the susceptible state. Due to the relatively low death count experienced in Australia to date, the model only accounts for COVID-19-related deaths that occur in a hospital setting. Parameter values for the infection sector are presented below in Table S1. Population estimates derived from the model of the daily rate of new notified COVID-19 infections (cases identified through testing, contact tracing or diagnosis upon arrival from overseas) and cumulative notified COVID-19 cases, plotted alongside publicly released figures (from www.covid19data.com.au) from 1 February 2020 to 5 June 2020 are presented in Figure S1.

Table S1: Select parameter values for the *Infection Sector* of the model

Parameter	**Value** [Reference]
Susceptibles	26,000,000 people[3]
Initial R_0 assumption	2.53[1]
Initial contacts per day	20[2]
Duration of non-infectious latent period	3.5 days[2]
Duration of infectious latent period	2 days[2]
Percent of infectious cases asymptomatic	17.9%[5]
Duration of early symptomatic period	5 days[6]
Average duration of late symptomatic period	3 days[2]
% Symptomatic cases requiring hospitalisation	20%[7]
% Hospitalised requiring ICU	25%
Average time to ICU admission	2.5 days[1]
Average remaining hospitalised period for patients	5 days[1]
Average remaining hospitalised period for patients	7.5 days[1]
Average duration of asymptomatic infectiousness period	8 days
Fatality rate - routine hospitalised cases	1%
Fatality rate – hospitalised cases requiring ICU	30%

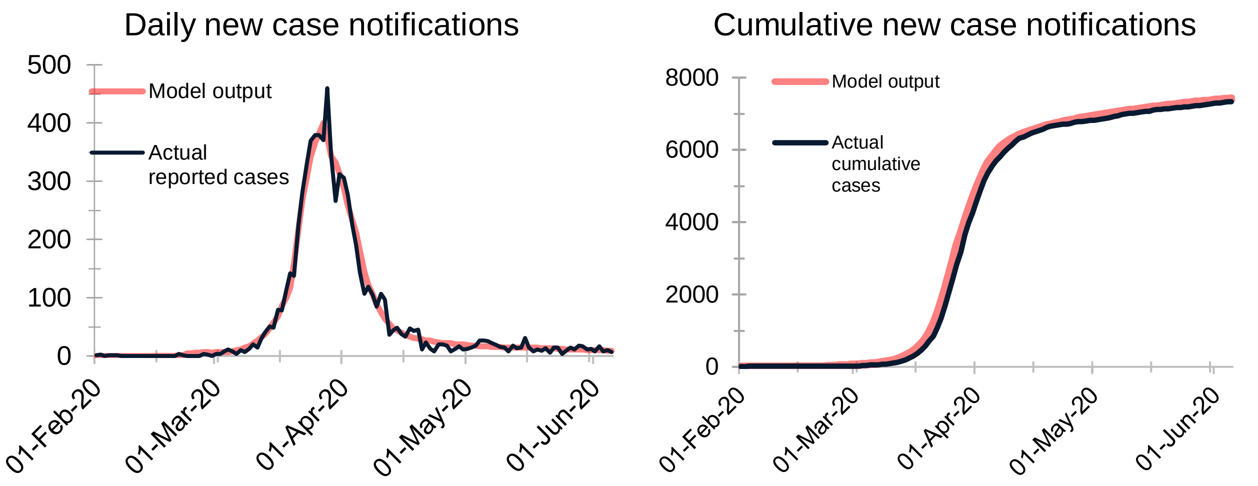

Figure S1: Estimated daily (left) and cumulative (right) new COVID-19 case counts in Australia derived from the system dynamics model and corresponding observed cases counts for the period of 1 February 2020 to 5 June 2020.

Overseas Acquired Cases Sector

The overseas acquired cases sector (pictured in figure S2) summarises the contribution of travellers with COVID-19 returning to Australia to local Australian outbreak dynamics. Overseas acquired cases are captured in the model in three ways, dependent on the time period in which they are occurring. The trend of publicly reported daily case counts attributed to overseas transmission demonstrates sustained growth beginning in the final week of February 2020. As such, the model assumes that overseas acquired COVID-19 cases arriving in Australia between the first reported case and this time were sporadic, and captures this effect by using a random number generator to seed between 0 and 10 cases per day into the overseas acquired cases structure.

Between the final week of February and the date when Australian announced ports were closed to all but citizens and residents (19 March 2020), the number of unconstrained overseas acquired COVID-19 cases arriving in Australia was modelled using a continuous exponential growth equation (with an initial value of 2 and a doubling time of 4 days). This curve represents the expected number of cases that would arrive in Australia had international travel restrictions not been put in place. The model then accounts for the effect of these restrictions using a graphical function with an accelerating trend that reduces the number of overseas arrivals from 0% to 70% less in the 15 days leading up to the closure of the borders are all but citizens and residents (shown in figure S2).

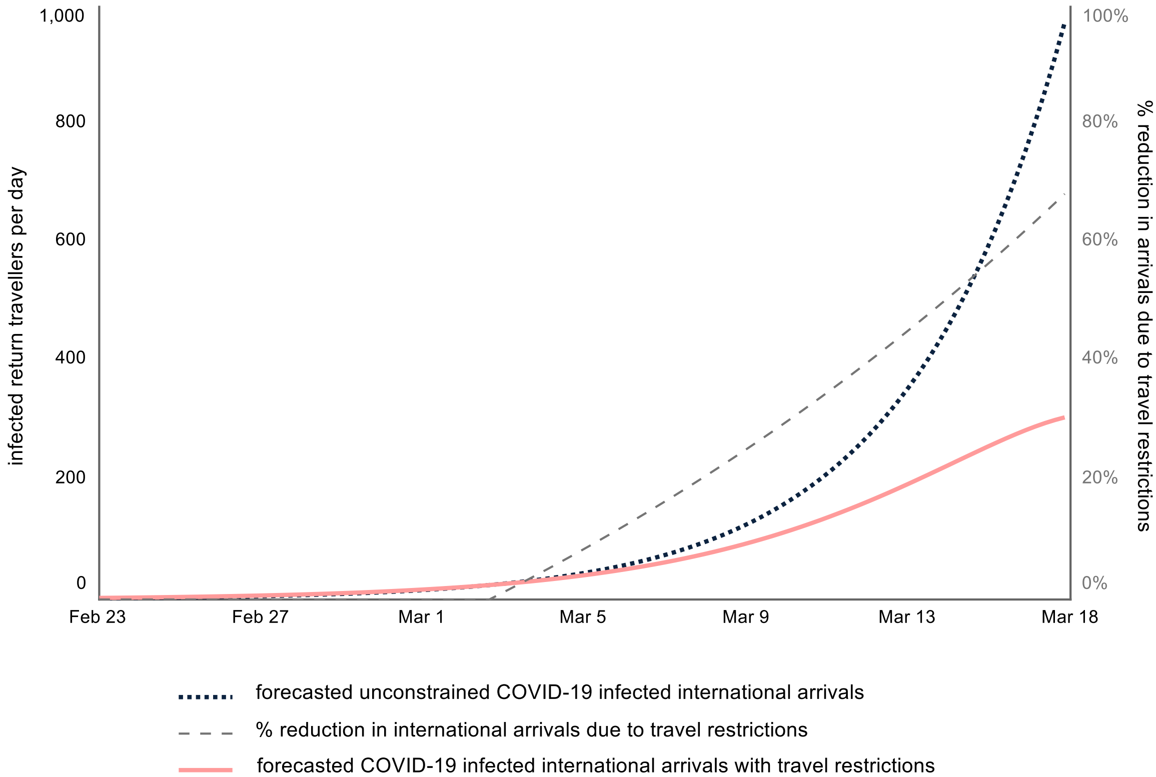

Figure S2: Modelled dampening effect of travel restrictions (dashed line) on the potential unconstrained number of infected incoming travellers (dotted line), resulting in diminished projected infected incoming travellers who arrived in Australia (solid line) prior to border closure measures.

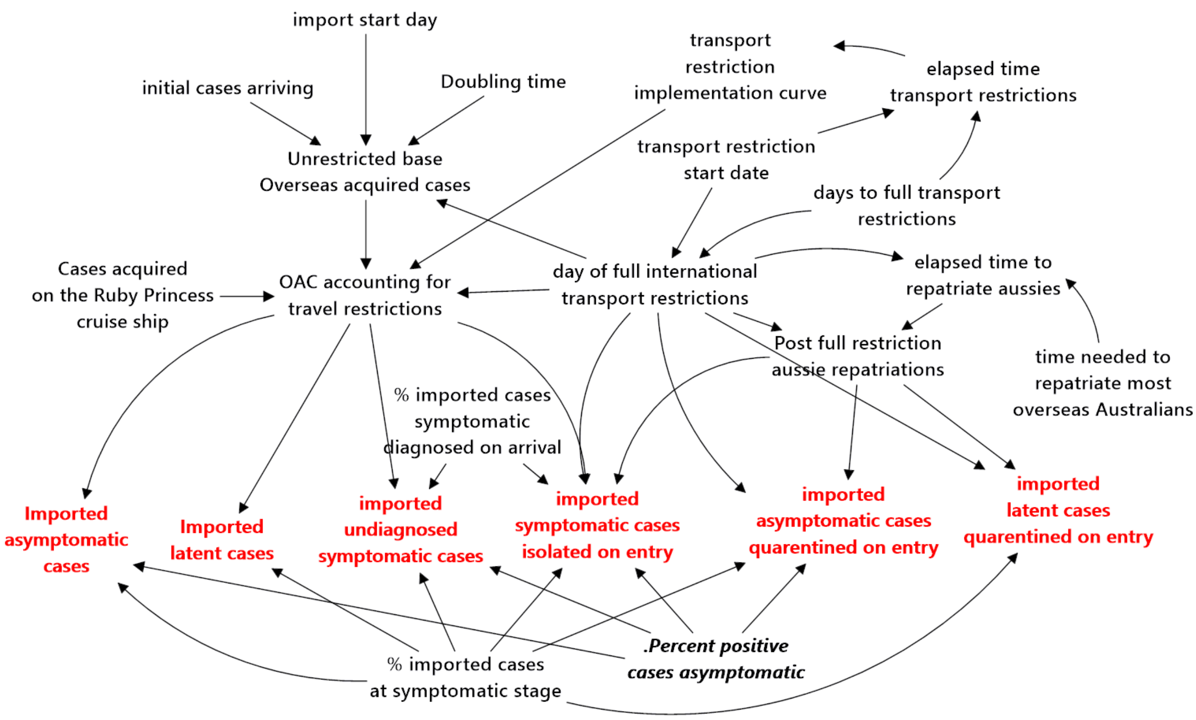

Figure S3: Model structure of the Overseas Acquired Cases Sector

The model captured the ongoing repatriation of Australian citizens and residents using a negative logit curve that returns the number of infected arrivals to pre-crisis conditions (i.e. before late February 2020) over the period of approximately one month. Additionally, to represent the inflow of infected individuals on 19 March 2020 when a cruise ship docked in Sydney and a considerable number of infected passengers disembarked[8], an additional 700 infected individuals were injected into the model on that day. A graph of the assumed number of overseas acquired COVID-19 cases entering Australia that was input into the model is shown in Figure S4.

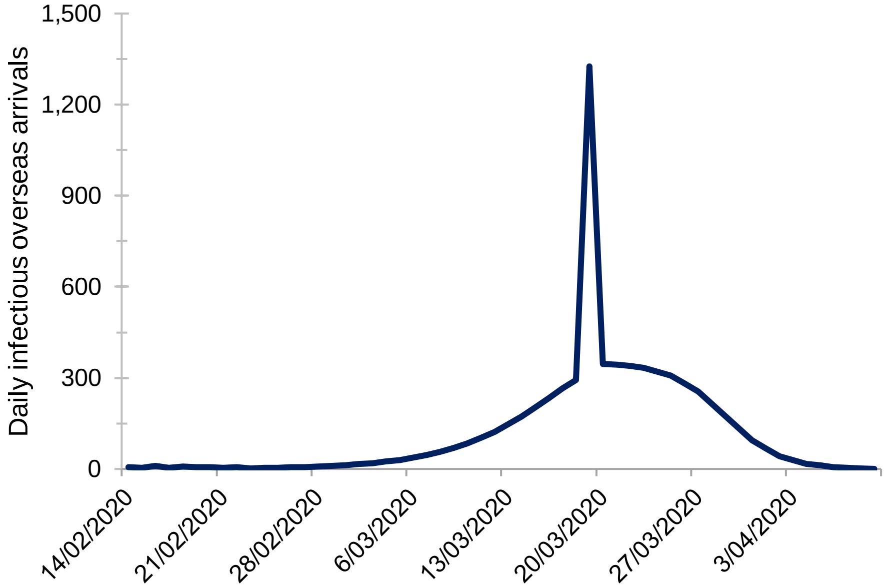

Figure S4: The assumed number of internationally acquired COVID-19 cases entering Australia from mid-February to mid-April

People arriving from overseas were divided amongst the different disease states using the ratios from the infection sector (described above), with the additional assumption that 5% of cases were symptomatic on arrival, and one-third of those were diagnosed upon arrival. On 29 March 2020 the Australian Government announced that Australians returning from overseas were required to spend 14 days in quarantine in designated sites such as hotels.[8] As such, overseas acquired cases arriving on or after this day were placed in the quarantined or diagnosed stocks corresponding to their disease state. As there still is significant uncertainty surrounding global COVID-19 transmission trends, particularly in how they might affect future international travel, the model assumes that existing restrictions on the arrival of international travellers will remain in place for the remainder of the year.

3. Social distancing sector

Two types of social distancing are captured within this sector of the model. The first is individual-level self-isolation or quarantine measures such as reductions in contact rates related to the natural tendency to stay home when sick, reduced contacts when hospitalised (coupled with high personal protective equipment usage by hospital staff), and compliance with individual-specific quarantine and isolation orders following diagnosis or confirmed contact with a diagnosed case (Figure S5). Specific relative mixing rates (listed in Table S2) for each of the self-isolation measures were multiplied by the number of people in the corresponding disease states to estimate the effective number of infective people within the population accounting for self-isolation. These mixing rates were based off of the assumption of a high level of compliance by those personally instructed to isolate or quarantine, extremely minimal transmission in hospital setting due to a death of publicly-reported hospital-acquired cases, and the tendency for those who are ill (such as those who are undiagnosed symptomatic cases) to stay home for a few days when they are ill. Additionally, a relative infectivity rate for true asymptomatic people, as well as those in the latter stages of their symptomatic period, was used to account for recent evidence that these individuals may be less infectious than those in the early stages of infectiousness.[9, 10] The resulting *adjusted effective infective population given reduced contacts* was then used as the total number of infective people when calculating the number of new community-acquired infections per day.

Table S2: Select parameter values for the *Social Distancing* sector of the model

Parameter	**Value** [Reference]
Relative mixing rate of diagnosed or quarantined cases	0.1
Relative mixing rate of hospitalised cases	0.02
Relative mixing rate of undiagnosed symptomatic	0.75
Relative infectivity of true asymptomatic	0.7
Average contacts per day under perfect total lockdown	1.6[11]
Maximum % of total population able to social distance	75%
Maximum % compliance with social distancing	90%

The second type of social distancing captured by the model is population-wide government-ordered and -enforced social distancing measures (Figure S65). The model characterises the effect of this type of social distancing by scaling the average number of contacts per day (using the *social distancing effect* variable) from the unconstrained average number of contacts per day (20/day)[2] to a hypothetical minimum of 1.6/day[11], which represents the number of people in the average household size in Australia minus one (the index person). The model assumes that the overall effectiveness of social distancing measures is constrained by the proportion of the population who have employment and housing situations that allow them to comply with social distancing, and the average proportion of person-time that the population is compliant with social distancing measures.

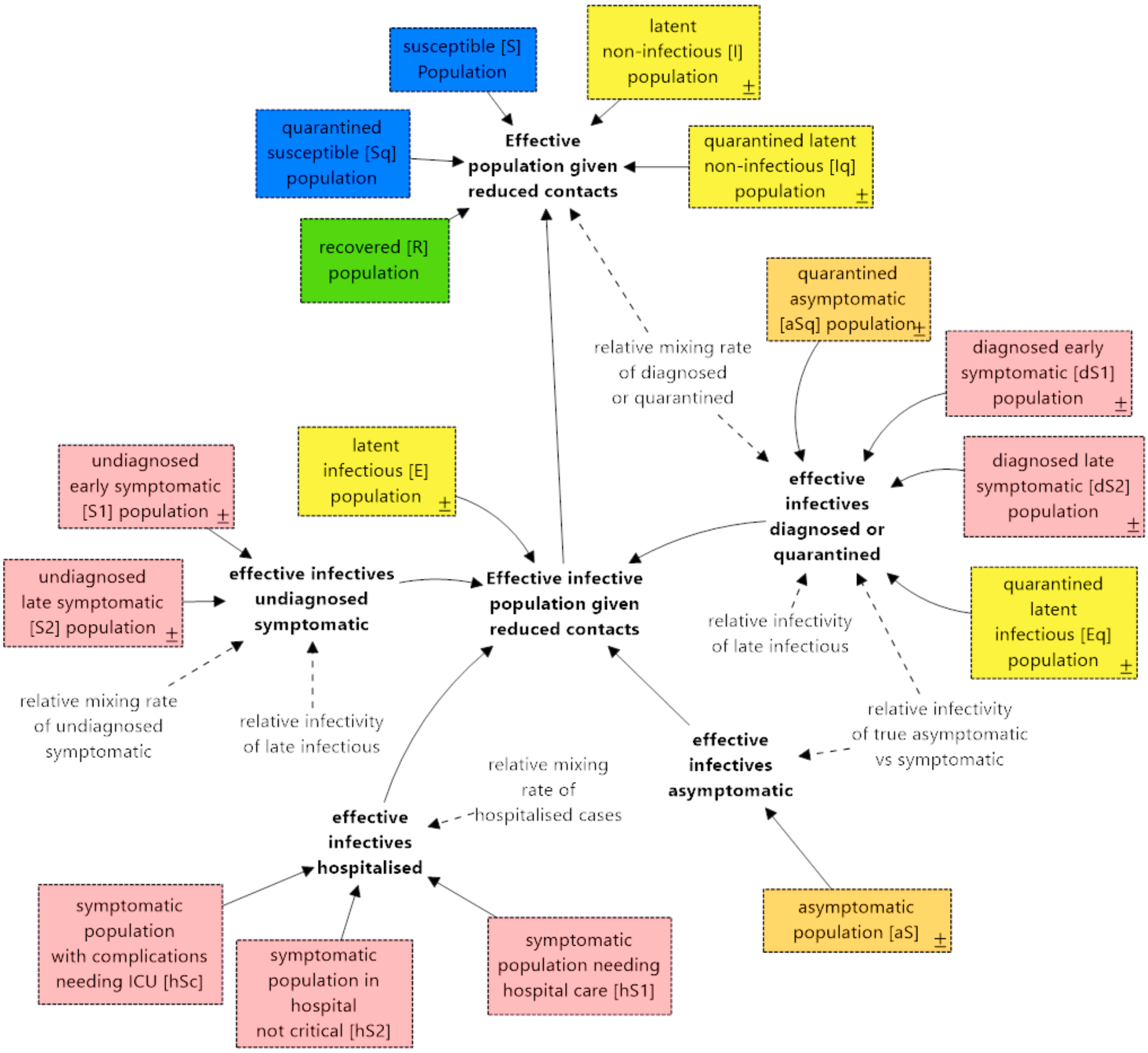

Figure S5: Model structure of the individual-level self-isolation/quarantine measures within the Social Distancing Sector

The effect of this form of social distancing is applied in addition to the individual-level self-isolation measures. The model assumes that population-wide measures began on 13 March 2020 when the Australian Government announced a ban on non-essential outdoor gatherings of more than 500 people, rapidly increased in intensity following a sigmoid-shaped curve, and reached full intensity by early April when States and Territories began closing their borders.8 The strengthening and easing of social distancing measures are shown in Figure 2a-b in the main text of the paper. The model makes no assumptions about future reinstatement of social distancing measure.

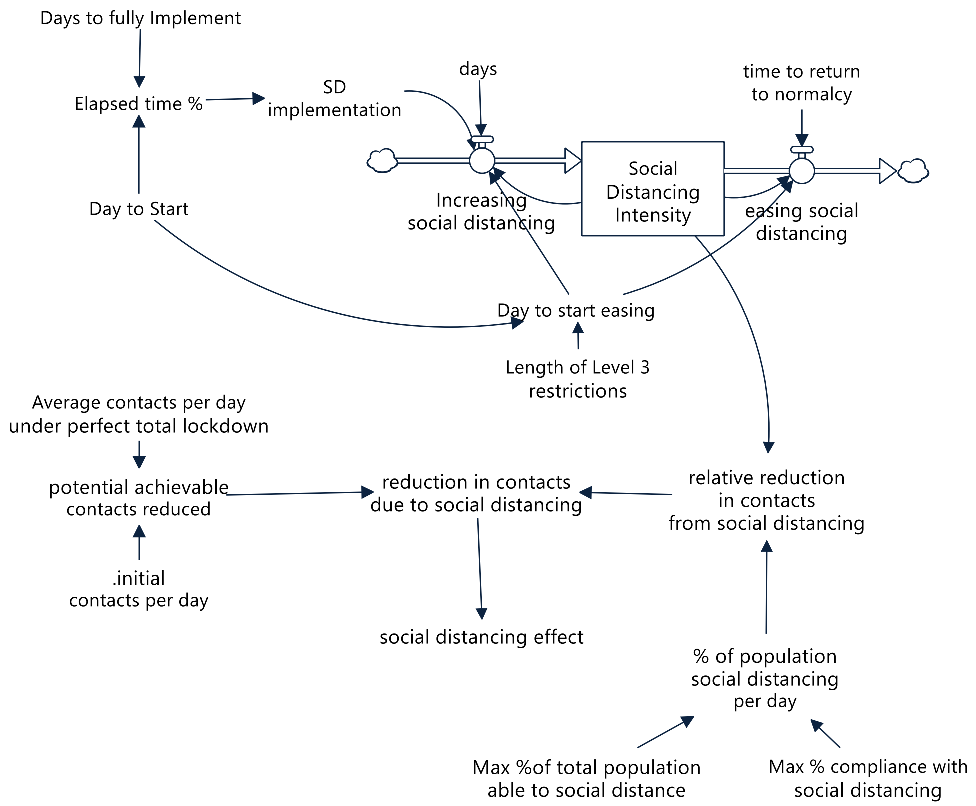

Figure S5: Model structure of the population-wide social distancing measures, ordered and enforced by the Australian Government, within the *Social Distancing Sector*

4. Testing Sector

The testing sector captures the number of diagnostic COVID-19 screening tests being conducted, and the percentage of those done on infected individuals .Like the implementation of population-wide social distancing measures, the intensity of testing increases rapidly (shown in Figure S7) until it reaches the maximum number of tests per day (30,000 tests/day). The model assumes that testing occurs 48 hours after symptom onset [2]

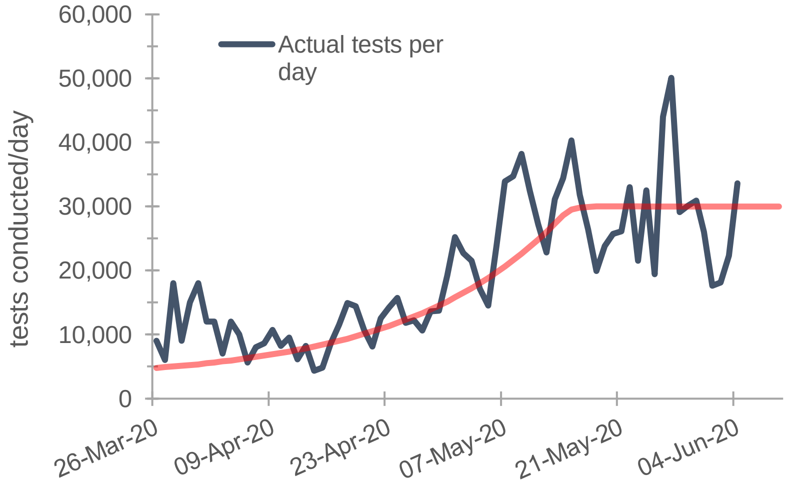

Figure S6: Modelled daily COVID-19 diagnostic tests conducted in Australia and corresponding reported tests conducted per day for the period of 26 March 2020 to 4 June 2020.

(*awareness delay*), and that diagnosis, case notification, and case isolation occurs 24 hours after testing (*test processing delay*).[12]

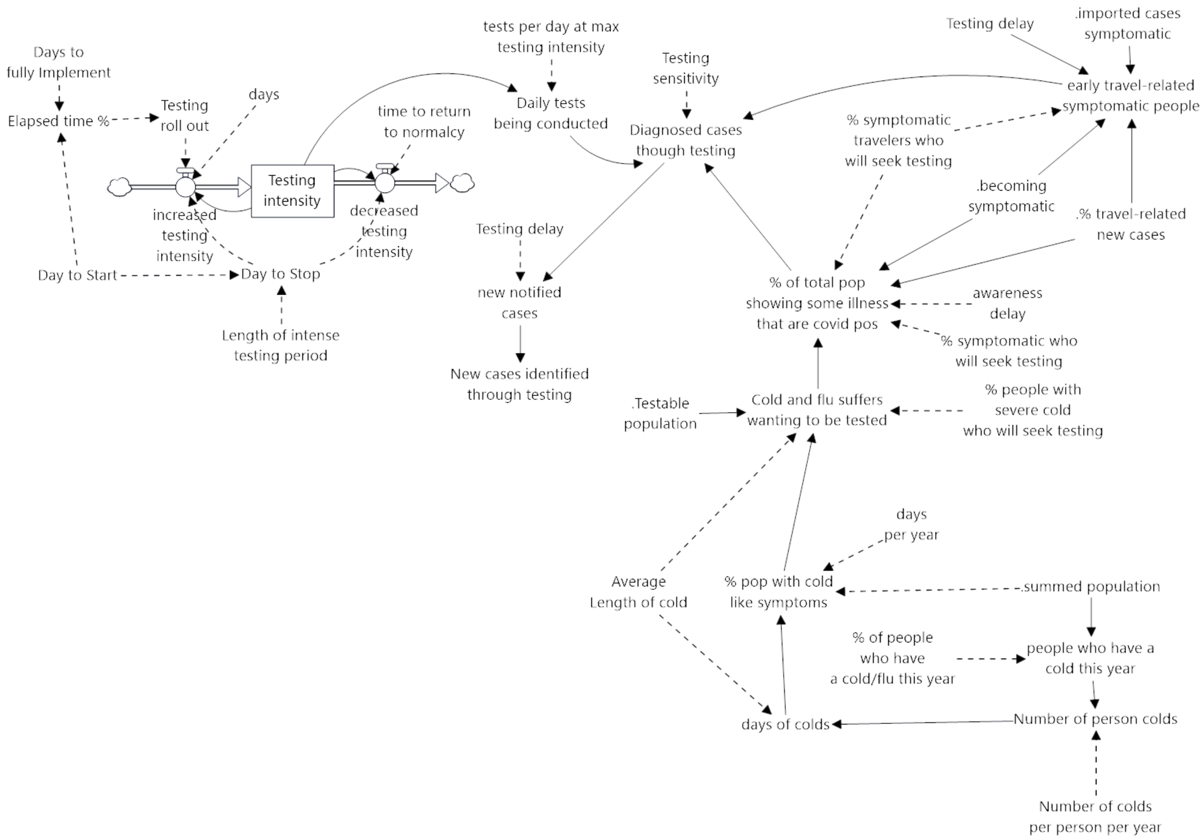

Figure S7: Model structure of the *Testing Sector*

Those tested are divided into 3 categories: 1) overseas travel-related symptomatic COVID-19 cases, 2) non-travel related symptomatic COVID-19 cases and 3) (non COVID-19 infected) cold/flu suffers presenting to be tested (the model structure is presented in Figure S8). Testing-related model parameters are presented in Table S3. The model assumes that individuals who have travelled overseas are both given priority for available tests due to testing criteria, and seek testing at a higher rate than those who have not travelled recently, due to heavy early media attention in Australia of the linkage between overseas travel and becoming infected with COVID-19. Of those without a travel history, the model assumes that most people presenting to be tested are suffering from a non-COVID-19 cold or influenza-like illness. This is because the peak proportion of tests returning a positive result was only slightly above 3%[13], and because, except under in a few other circumstances, testing criteria to date have required that individuals must have COVID-19-like symptoms to be eligible for testing[7]. The model therefore calculates the number of positive tests by calculating the proportion of individuals who are infected with COVID-19 among the total number of individuals who are displaying COVID-19 symptoms (i.e. those with COVID-19 plus those with a cold or influenza-like symptoms) and applying that proportion to the total number of tests conducted on a given day.

Upon diagnosis, the model accounts for targeted isolation of diagnosed individuals by flowing these people from the *undiagnosed early symptomatic[S1] population* stock to the *diagnosed early symptomatic [dS1] population* stock.

Table S3: Select parameter values for the Testing Sector of the model

Parameter	**Value** Reference
Average tests per day at peak of outbreak	30,000 tests
Testing sensitivity	0.9
Test processing delay	1 day[12]
Percent symptomatic travellers who will seek testing	85%
Awareness delay	2 days [2]
Percent symptomatic who will seek testing	50%
Percent people with cold/flu symptoms who will seek testing	35%
Average length of cold symptoms	10 days[14]
Percent of people who will have a cold/flu this year	60%[14]
Number of colds per person per year	2 events [14]

5. Contact Tracing Sector

The contact tracing sector captures the number of new contacts that are identified by contact tracers, either through traditional contact tracing where the newly identified positive cases supply contact tracers with information that can lead to known contacts, or through a digital contact tracing app where a smartphone digital app collects data on the the date, time, distance and duration of contact that infected users have with other app users. As the app collects this information without the need for any user input or awareness of who they are coming in contact with, the app has the potential to identify contacts that would otherwise be missed by traditional contact tracing (refered to as ‘unknown’ contacts in the model structure shown below in figure S9). The average number of contacts per day (scaled for population-wide social distancing) from the infection sector is used to calculate the total known and unknown contacts an infector has per day.

Under scenarios where the app is not in place, the model assumes that traditional contact tracing methods are able to identify an average of 50% of the people who the infector has come into contact with (i.e. known contacts). In scenarios where the app is in place, the app is able to identify a combination of both ‘known’ and ‘unknown’ contacts, scaled by the probability that both ‘infectors’ and their contacts (potential ‘infectees’) have the app on their respective smartphones. As the app is not treated as a replacement for traditional contact tracing, the model assumes that ‘known’ contacts who are not identified through the app would otherwise be identified through traditional contact tracing.

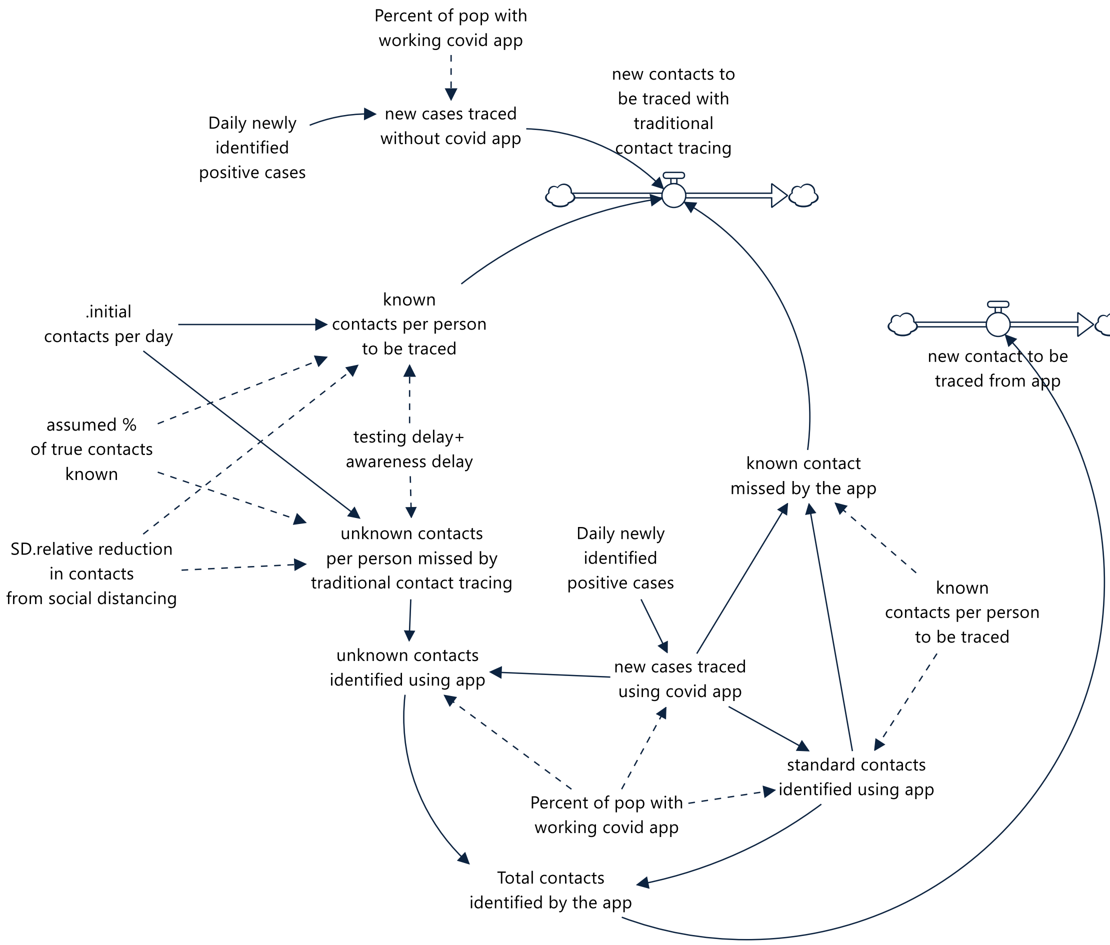

Figure S8: Structure used to model number of ‘known’ and ‘unknown’ contacts identified through contact tracing

The contact tracing process is modelled as a first-order delay process, where contact lists are first established, then contacts are placed on a waiting list to be contacted by contact tracers, and finally the contacts are contacted by the tracers. The model assumes that it takes 0.5-5 days (triangular distribution, mode = 1 day) to establish the contact list (figure S9). The number of contacts that can be called each day is constrained by the average number of contact tracers available (assumed to be 400) and the average number of calls per day they can make (assumed to be 10 calls). The model futher assumes that 50% of calls are unsuccessful at reaching the contact, and that 4% per day of contacts are deemed totally unreachable. The model also assumes that contacts identified by the contact tracing app skip the contact list stage and are immediately placed in the queue to be traced, thus reducing the amount of time needed for them to be successfully traced. In addition, the model also assumes that all app users who subsequently are diagnosed with COVID-19 will opt to have their contacts forwarded to their local public health authority.

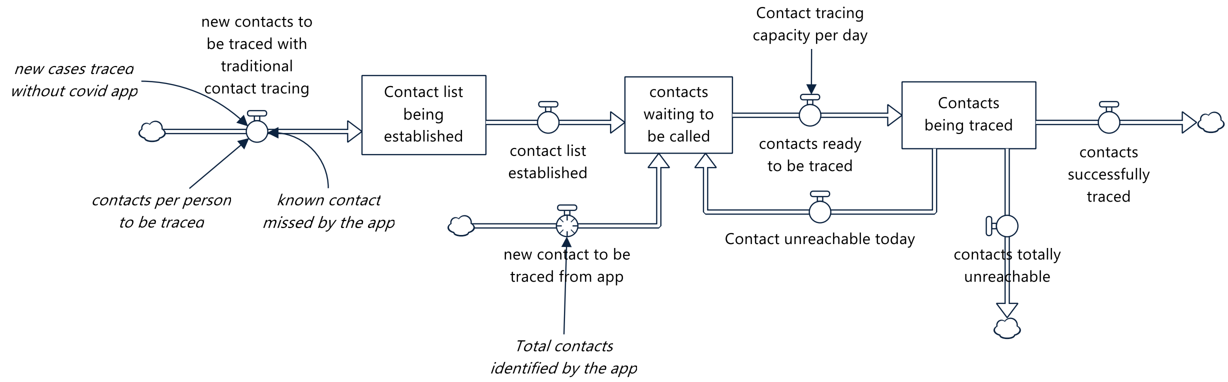

Figure S9: Simplified stock and flow structure used to model number of ‘known’ and ‘unknown’ contacts identified through contact tracing

To establish the number of traced contacts that have themselves become infected cases, the daily count of people passing through the *contacts successfully traced* flow was multiplied by the amount of time their infector was infectious in the community (a uniformly distributed random number of days between 2 and 5 days) and the probability of infection per contact as calculated in the *Infection Sector*. Furthermore, to establish where those who have become infected sit within their own disease progression pathway, the number of days their ‘infector’ was infectious in the community was summed with the average amount of time required for them to pass through the contact tracing process.

To acomplish this, the two flows entering the contact tracing stock and flow structure (shown in Figure S10) were timestamped and the built-in cycle-time function of the software (Stella Architect v1.9.5) was used to calculate the mean and standard deviation cycle-time of contacts leaving the system through the contacts’ *sucessfully traced* flow. The mean and standard deviation were then used to build a normally distributed cumulative function, which was shifted (uniformly distributed random amount between 2 and 5 days) to account for the additional time between onset of infectiousness in their original ‘infector’ became infectious and the time of diagnosis and coming to the attention of the contact tracers. This shifted CDF was used to determine what proportion of these newly-identified positive cases fit into each stage of the disease progression (shown below in Figure S11). As all successfully identified contacts, regardless of whether or not they exhibit symptoms of COVID-19, are requested to self-quarantine for 14 days, individuals in non-symptomatic stages of the disease progression are shifted to their respective quarantined stock. Additionally, susceptible individuals identified through contact tracing are also placed in quarantine (in the quarantined susceptible [Sq] population stock) for a period of 14 days, thus removing them from the effective susceptible population for that period of time.

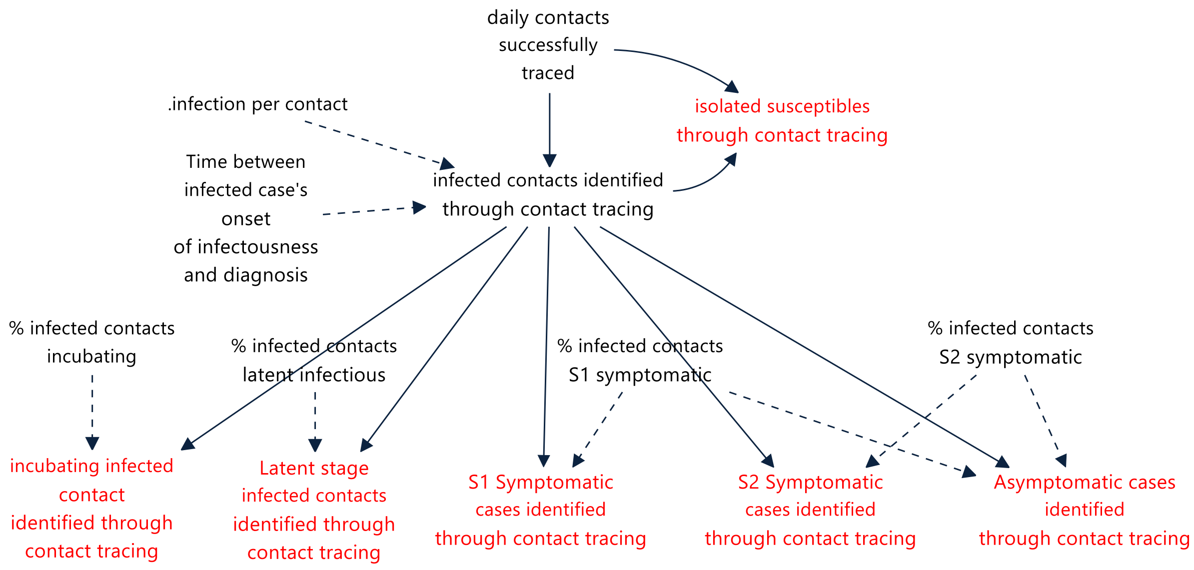

Figure S10: Structure used to model number contacts identified through contact tracing who themselves become infectious cases.

The implementation of the app was modelled using the structure shown in Figure S12. The model assumes the app was released on 26 April 2020 and the growth in uptake of the app is logarithmic over a 45-day period to reach the target (user-defined) app uptake level. Under normal conditions the model assumes that users of the app are limited to those over the age of 14 years (81% of the total Australian population[3]), those who own a smartphone (84% of the population aged >14 years[15]), and the fraction of those who are assumed to have sufficient digital literacy to download app (90% of the previous product). Additionally, despite being released in late April, the app was not initially actively collecting user data[16]. The model assumes that the app became operational on 10 May 2020.

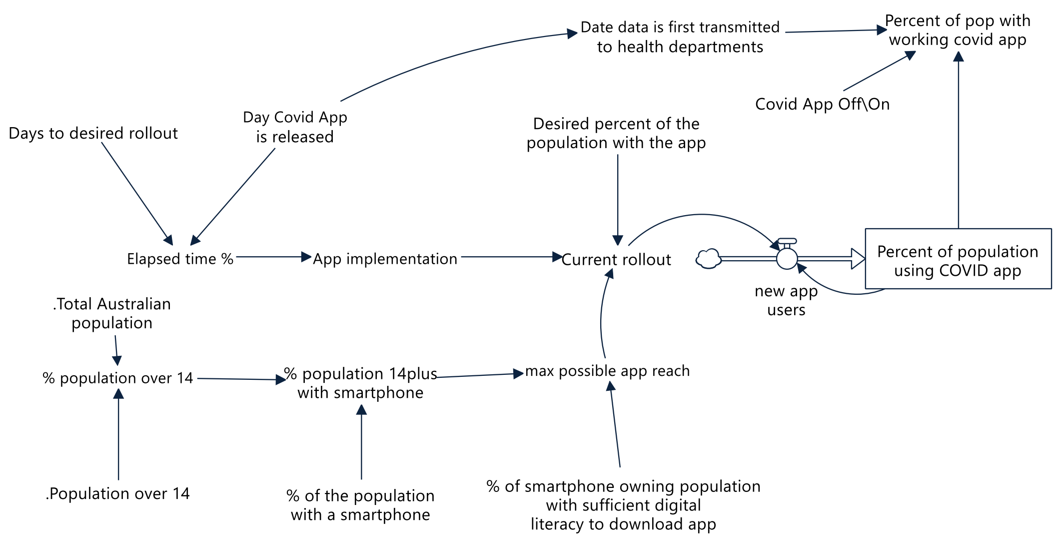

Figure S11: Structure used to model the implementation and uptake of the COVIDSafe mobile contact tracing App.

6. References

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