Mask Use Mandates

Chris Troeger

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Summary of mandates

The mask mandate dataset includes 340 mandates from 217 locations. One of the challenges is defining the target population, as shown in the first table below. There is some inconsistency in the coding for the target population and there are a wide array of targeted groups in the mandates.

Types of targeted populations listed in mandate

One challenge is that there are a huge number of unique target populations in the extraction sheet. A full list is provided at the end of the document. Some of the inconsistency is from how the target populations are extracted and some is inherent in the many types. Some examples are *General public*, *Public spaces*, *All areas*, *Grocery shops*, *Indoor public spaces*, *Cafes*, *Churches*, *Maritime workers*, *Service personnel*, etc.

The current logic is that each location can only have a single mandate so I have implemented a way to rank the available mandates by location. If a location only has a single target population, that is kept. If a location has a mandate for 'General public' or some variation, that is kept. Finally, if a location has 'public' in the target population column, that is kept. After subsetting based on that, some locations still have multiple mandates so I keep the earliest implemented mandate. The resulting dataset is 189 location-mandates.

For example, in the table below, I am currently keeping rows 1, 4, and 5. Keeping row 1 because it is the most general of the target populations. Row 4 because it is the only mandate for Peru in this example. Row 5 because it is the earliest mandate for the general public. **These are examples**

Table 1: Example of the way that the mask mandates are extracted and saved

Row number	Location	Target population	Date implemented
1	Colorado	General public	2020-06-23
2	Colorado	Outdoor spaces	2020-06-23
3	Colorado	Transit	2020-06-20
4	Peru	Indoor business	2020-07-10
5	Ghana	General public	2020-07-01
6	Ghana	Public spaces	2020-07-12

Enforcement measures

The mask mandate dataset has a similar challenge in how enforcement policies are defined. The table below shows the count by enforcement type groupings. Currently these are defined as:

- If the enforcement column contains the expression 'fine' then the enforcement is a **Fine**
  - Unique enforcement types include *Fines | Fine: 20000 Kenyan shillings; or 6 month jail term | Fine | Fine: up to 30,000 PLN | Fine of £100, or £50 if you pay the fine within 14 days | £100 fine | Fine of £60 (which doubles for each subsequent offence up to a maximum of £1920 | Possible €100 to €600 fine | Fine of SR1,000 for individuals, SR10,000 for businesses | Fine of 3000 rupees (18 USD) | Fine between LE 300 and LE 5,000 | Fine of K5,000 | Fines of 500 to 1,000 euros | 5,000 RSD fine | Civil fine up to $1,000 and criminal prosecution for Reckless Endangerment (class A misdemeanor) | A person who knowingly and willfully violates this Order is guilty of a misdemeanor and on conviction is subject to imprisonment not exceeding one year or a fine not exceeding $5,000 or both. | $300 civil fine | Businesses or individuals can have their licenses revoked by state, Also Class C misdemeanor: punishable by up to 30 days in jail, a fine of up to $1,250, or both | fine up to $1,000 or confinement in jail for a term up to 180 days. | up to a year in jail and a $2,500 fine | Up to 90 days in jail / $100 fine | Misdemeanor and <$100 fine | Fined 2000 ALL.*
- If the enforcement column contains the expression 'detention' or 'arrest' then the enforcement is **Detention**
  - Unique enforcement types include *Up to detention | Arrest/Detention | Arrest.*
- If the enforcement column contains the expression 'legal', 'penalty', or 'misdemeanor' then the enforcement is **Penalty**
  - Unique enforcement types include *Legal action | Misdemeanor | Civil or criminal penalties | Criminal penalty | Civil, criminal, and administrative penalties | Businesses not enforcing: citation; Customer not complying: trespassing | (quote) A violation of this Order may be construed to be a violation of any such license, permit and other authorization to which pertinent penalties may be assessed. Pursuant to 37-B M.R.S.A. section 786, this Order may also be enforced by law enforcement as necessary. | Local public health agencies and law enforcement should focus their enforcement of this Directive on education, providing warnings and education about the risk of transmission, while reserving the imposition of penalties, trespass enforcement, and other formal enforcement mechanisms for only the most egregious, repeat violations that put the public at risk. | General "criminal prosecution and civil penalties" | Businesses: citation; Patrons: trespassing if won't leave | Citations or warnings.*
- If the enforcement column contains the expression 'none', 'not applicable', or 'no penalty' then the enforcement is **None**
  - Unique enforcement types include *Not applicable | None stated | Not stated | None Stated.*
- All other types are coded as **Other/unknown**
  - Unique enforcement types include *Not known | Other | Forced labor: cleaning | Police enforcement | No entry | NA | Denied entrance | Sanction | (quote) This Executive Order may be enforced by State and local law enforcement pursuant to, inter alia, Section 7, Section 15, Section 18, and Section 19 of the Illinois Emergency Management Agency Act, 20 ILCS 3305 | (quote) As currently permitted pursuant to state law, the Attorney General, county attorneys, and district attorneys enforcing this order should use their discretion and consider the totality of the circumstances as they determine appropriate enforcement actions | Loss of access to business' services | Decline entry.*

Table 2: Summary of how I have defined enforcement/penalties for non-compliance

Enforcement type	Mandates (n)
Detention	9
Fine	43
None	133
Other/unknown	128
Penalty	27

Regressions

The mandate data are merged onto the Facebook, Yougov, and Premise mask use survey data by location and date. Mandates are a binary indicator for if a mandate is in effect by location-date. I assume that after a mandate is implemented, it is not lifted.

I am running these as mixed effects (ME) models with a random intercept by location_id.

There are 24229 location-days of mask use data, among which 7290 are days with a mask mandate in effect for this analysis.

Mixed-effects regression where (1-maskuse) is the dependent variable

Table 3: Mixed-effects

	Estimate	Std. Error	t value
Intercept	0.463	0.013	35.565
Mandate	-0.070	0.003	-23.520

Table 4: Date covariate

	Estimate	Std. Error	t value
Intercept	-0.440	0.392	-1.122
Mandate	-0.073	0.003	-22.935
Date	0.000	0.000	2.305

Table 5: Location-day variable

	Estimate	Std. Error	t value
Intercept	0.459	0.013	35.091
Mandate	-0.078	0.003	-24.732
Location days (1:n)	0.000	0.000	7.556

Table 6: Time measured as days since first case by location

	Estimate	Std. Error	t value
Intercept	0.459	0.013	34.846
Mandate	-0.073	0.003	-22.962
Days since 1st case	0.000	0.000	2.379

Table 7: Interaction with penalty

	Estimate	Std. Error	t value
Intercept	0.533	0.020	26.590
Detention	-0.074	0.020	-3.715
Fine	-0.131	0.009	-14.320
None	-0.073	0.005	-15.977
Other/unknown	-0.023	0.007	-3.148
Penalty	-0.159	0.024	-6.689

Table 8: More narrowly defined penalty. Criminal/civil penalties is the combination of the 'Detention' and 'Penalty' categories above

	Estimate	Std. Error	t value
Intercept	0.532	0.020	26.701
Criminal/civil penalty	-0.109	0.015	-7.135

	Estimate	Std. Error	t value
Fine	-0.131	0.009	-14.314
None	-0.073	0.005	-15.970
Other/unknown	-0.023	0.007	-3.154

Table 9: Civil or criminal penalty, Fines, anything else. Criminal and civil penalties combine 'Detention' and 'Penalty' above and None or other is a combination of 'None' and 'Other/unknown' above.

	Estimate	Std. Error	t value
Intercept	0.537	0.019	27.819
Criminal/civil penalty	-0.109	0.015	-7.126
Fine	-0.131	0.009	-14.293
None or other	-0.059	0.004	-15.180

Table 10: Location-day variable and penalty interaction

	Estimate	Std. Error	t value
Intercept	0.529	0.020	26.614
Location days (1:n)	0.001	0.000	16.110
Detention	-0.105	0.020	-5.359
Fine	-0.160	0.009	-17.334
None	-0.104	0.005	-21.233
Other/unknown	-0.056	0.007	-7.491
Penalty	-0.164	0.023	-7.023

Table 11: Location-day, daily infections, and penalty interaction

	Estimate	Std. Error	t value
Intercept	0.521	0.020	26.621
Location days (1:n)	0.001	0.000	19.131
Daily infections	0.000	0.000	-13.344
Detention	-0.113	0.020	-5.778
Fine	-0.149	0.009	-15.860
None	-0.108	0.005	-21.622
Other/unknown	-0.057	0.007	-7.685
Penalty	-0.163	0.023	-7.043

Table 12: Location-day, daily incidence, and penalty interaction

	Estimate	Std. Error	t value
Intercept	0.529	0.019	27.188
Location days (1:n)	0.001	0.000	19.498
Daily incidence	-87.447	5.802	-15.071
Detention	-0.113	0.019	-5.797
Fine	-0.146	0.009	-15.616

	Estimate	Std. Error	t value
None	-0.105	0.005	-20.995
Other/unknown	-0.064	0.007	-8.651
Penalty	-0.150	0.023	-6.470

Table 13: Location-day, daily infections, and narrow penalty definitions

	Estimate	Std. Error	t value
Intercept	0.526	0.019	27.906
Location days (1:n)	0.001	0.000	19.252
Daily infections	0.000	0.000	-13.148
Criminal or civil penalty	-0.134	0.015	-8.931
Fine	-0.149	0.009	-15.861
None or other	-0.094	0.004	-21.421

Table 14: Any penalty interaction

	Estimate	Std. Error	t value
Intercept	0.538	0.019	27.822
Mandate: any penalty	-0.125	0.008	-15.908
Mandate: no penalty	-0.059	0.004	-15.182

Table 15: Any penalty interaction and smoothed daily infections

	Estimate	Std. Error	t value
Intercept	0.527	0.019	27.868
Daily infections	0.000	0.000	-8.373
Mandate: any penalty	-0.113	0.008	-14.020
Mandate: no penalty	-0.055	0.004	-13.925

Table 16: Location-day variable and any penalty interaction

	Estimate	Std. Error	t value
Intercept	0.534	0.019	27.770
Location days (1:n)	0.001	0.000	16.250
Mandate: any penalty	-0.152	0.008	-19.144
Mandate: no penalty	-0.091	0.004	-21.105

Table 17: Location-day, daily infections, and any penalty interaction

	Estimate	Std. Error	t value
Intercept	0.526	0.019	27.907
Daily infections	0.000	0.000	-13.149
Location days (1:n)	0.001	0.000	19.236

	Estimate	Std. Error	t value
Mandate: any penalty	-0.145	0.008	-18.032
Mandate: no penalty	-0.094	0.004	-21.413

Table 18: Location-day, daily infections

	Estimate	Std. Error	t value
Intercept	0.455	0.013	34.390
Daily infections	-0.074	0.003	-22.360
Location days (1:n)	0.000	0.000	-7.324
Mandate	0.000	0.000	7.144

Table 19: Sensitivity analysis, use earliest imposed mandate, even if it is not general public

	Estimate	Std. Error	t value
Intercept	0.467	0.013	35.767
Mandate	-0.083	0.003	-26.090

Table 20: Sensitivity analysis, linear regression (fixed effects only), narrow penalty definition

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.653	0.005	125.881	0
Civil or criminal	-0.180	0.012	-14.507	0
Fine	-0.233	0.010	-22.745	0
None or other	-0.264	0.006	-44.264	0

Table 21: Sensitivity analysis, linear regression (fixed effects only), any penalty

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.653	0.005	125.796	0
Any penalty	-0.213	0.009	-24.518	0
No penalty	-0.264	0.006	-44.234	0

Mixed-effects regression where mask use always is the dependent variable

$maskuse \sim mandate + (1|location)$

Mask use is the proportion of people that self-report always wearing a mask while outside their home.

Table 22: Mixed effects

	Estimate	Std. Error	t value
Intercept	0.537	0.013	41.225
Mandate	0.070	0.003	23.520

Table 23: Date covariate

	Estimate	Std. Error	t value
Intercept	1.440	0.392	3.673
Mandate	0.073	0.003	22.935
Date	0.000	0.000	-2.305

Table 24: Location-day variable

	Estimate	Std. Error	t value
Intercept	0.541	0.013	41.366
Mandate	0.078	0.003	24.732
Location days (1:n)	0.000	0.000	-7.556

Table 25: Interaction with penalty

	Estimate	Std. Error	t value
Intercept	0.467	0.020	23.324
Detention	0.074	0.020	3.715
Fine	0.131	0.009	14.320
None	0.073	0.005	15.977
Other/unknown	0.023	0.007	3.148
Penalty	0.159	0.024	6.689

Table 26: Interaction with penalty and location-day days

	Estimate	Std. Error	t value
Intercept	0.471	0.020	23.693
Location days (1:n)	-0.001	0.000	-16.110
Detention	0.105	0.020	5.359
Fine	0.160	0.009	17.334
None	0.104	0.005	21.233
Other/unknown	0.056	0.007	7.491
Penalty	0.164	0.023	7.023

I also wanted to run the analysis as a panel to account for the time series in a different way. To do so, I had to create a new variable for the index because we have different sources of mask use data that sometimes had the same location-date. This new variable is location_source. Sources include Facebook, Yougov, Premise, etc.

The panel set up is a random effects model with an index by (date, loc source).

Including this location_source in the mixed effects model does not seem to meaningfully affect the coefficient on mandates ($maskuse \sim mandate + (1|locsource)$). However, the panel regression set up does seem to affect the coefficient on mask mandates, decreasing it pretty substantially.

Tables for coefficients in panel regression

Table 27: Panel model, indexed by date and location-source

	Estimate	Std. Error	z-value	Pr(>|z|)
Intercept	0.563	0.003	162.243	0
Mandate	0.037	0.004	10.324	0

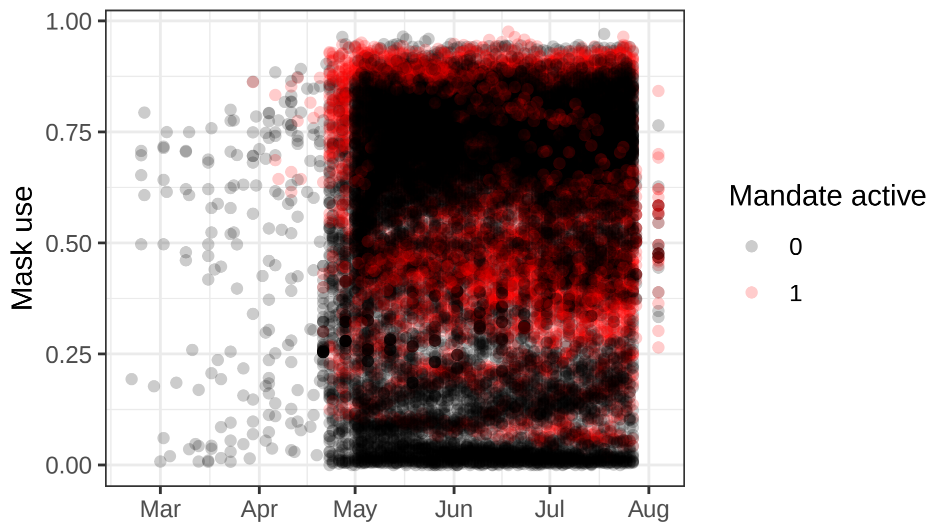
And really changing the values for the coefficients on the penalties

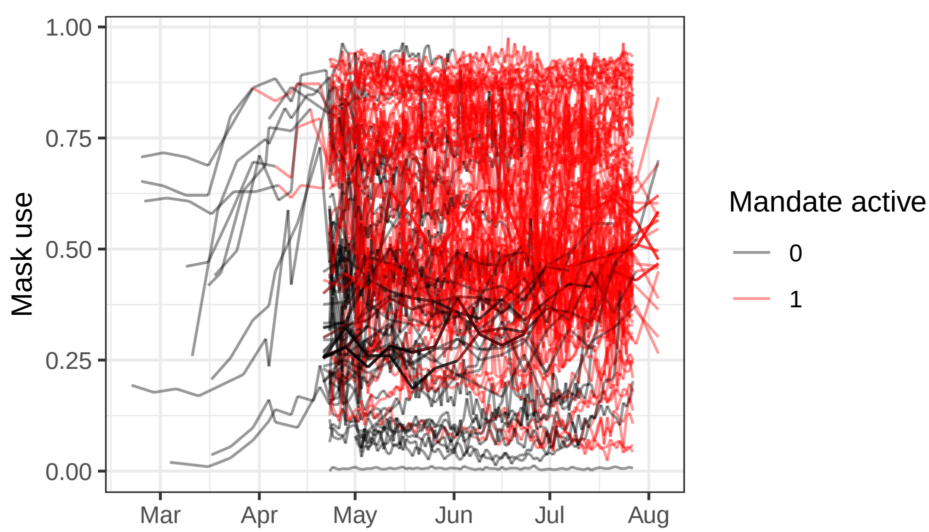
Table 28: Panel model, interaction with penalty type

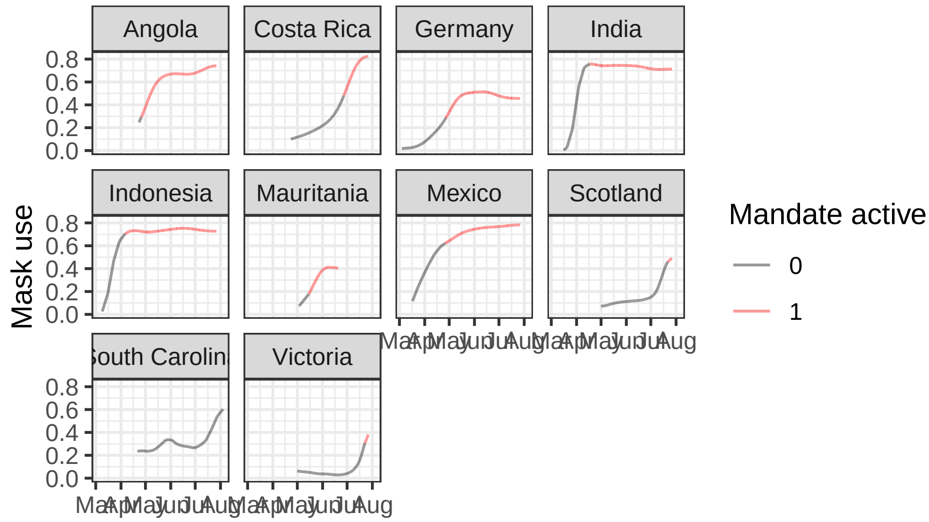
	Estimate	Std. Error	z-value	Pr(>|z|)
Intercept	0.347	0.005	68.834	0.000
Detention	0.244	0.014	17.332	0.000
Fine	0.233	0.010	23.380	0.000
None	0.206	0.006	32.100	0.000
Other/unknown	0.329	0.007	50.157	0.000
Penalty	0.032	0.021	1.578	0.115

Which is the better regression set up? Any alternatives?

Here are a few plots showing the distribution of mask use data






Angola
Costa Rica
Germany
India
Indonesia
Mauritania
Mexico
Scotland
South Carolina
Victoria
Mask use
Mandate active
0
1
0.0
0.2
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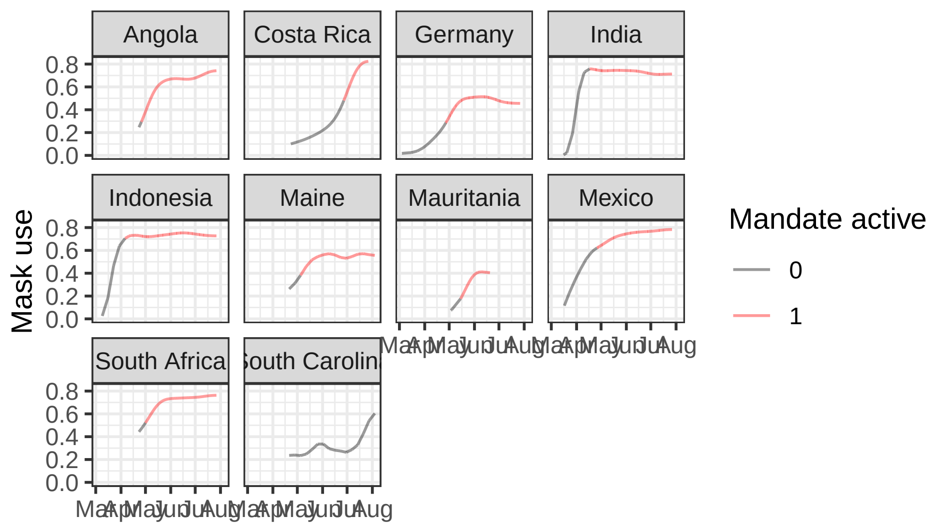
0.6
0.8
Mar Apr May Jun Jul Aug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Costa Rica
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India
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Maine
Mauritania
Mexico
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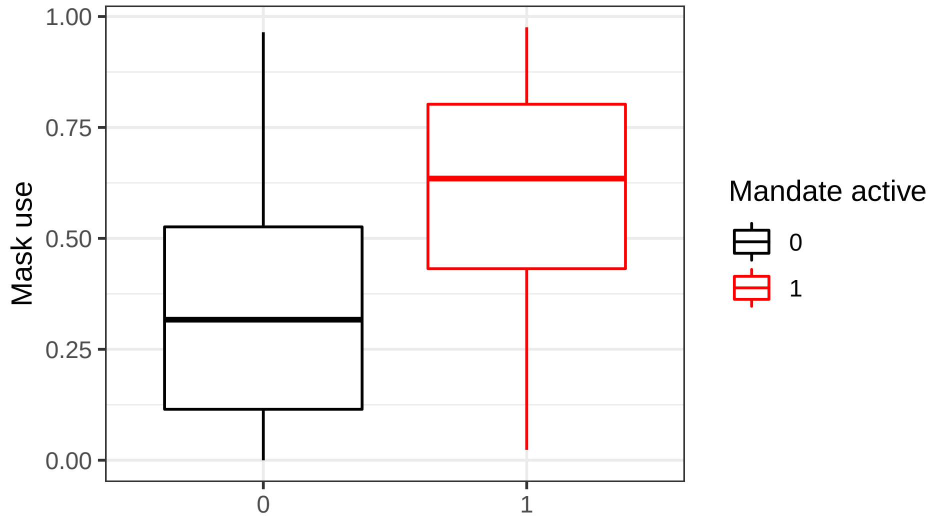

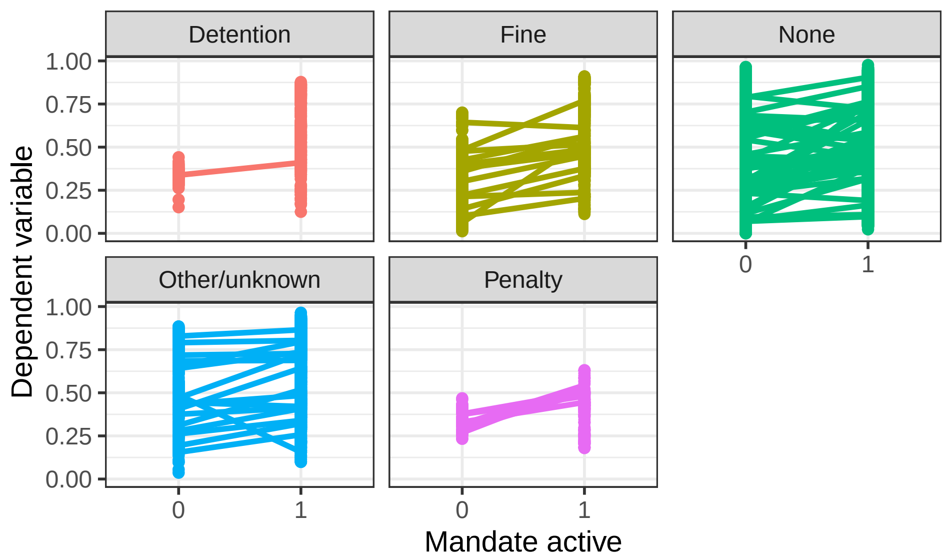

Results from the mixed-effects regression where dependent variable is $\Delta maskuse/(1 - maskuse)$ (not shown)

Full list of target populations in mask mandates

General public, All public spaces, on buses, Public transport, All areas, Grocery shops, All indoor public places, Indoor events, Demonstrations, Government buildings, Delivery persons, general public, Public transport, Over 12s, all offices, Public spaces, Public places, businesses and common areas of residential buildings, Mosques, Public places, public places, Outdoor spaces, Cafe, restaurant staff, pubic transport, hospitals, pharmacies, Indoor public spaces, all travellers, Transport and closed public spaces, Public, public transport, public transport, shopping, public transport, retail, markets, Public areas, Ferry, All citizens, Caregivers, any symptoms, vendors and shoppers, Public transport, Shops, Those without disabilities, over five, or not alone indoors, All persons, Markets, commercial businesses, Public/Private Transit, General Public; All public spaces; Public transit, Salon and Barbershop employees, General Public, Health care workers, Airport, Public transit; Businesses, Travelers (14 days), Employees in craft sector, Public transit, Events >20, Stores; Public transit; Sea voyages, Markets; Mosques, Stores; Public transit, General public; Public transit; Private transit; Religious institutions; Maritime transport, Public transit; Private transit; Gatherings, General public; Public transit; Private transit; Gatherings, Truck drivers, General public; Public transit; Businesses, General public; Public transit, Churches, School, Entertainment, Businesses, All travellers from high-risk countries, Agricultural workers, Some public spaces, Asthmatics, Caregivers, ill person or COVID-19 positive, Public places other than pools and restaurants, General public; businesses, public transport, and government, General public, transport staff, Food industry, Martitime workers, NLT staff, Service personnel, Restaurants, Taxis, Performing arts, Indoor public places and transportation, Airline and airport staff, Bus and car travel, Restaurant staff, Markets, Hospitals, Public Transport, Public transit; Businesses; Indoor public spaces, Public Transport, Airplanes, Visitors, General public; Businesses, Schools; Businesses; Public transit, Public transit; Private transit, Indoor public spaces; Public transit, General public; Public transit; Private transit, Air travel, Schools, Businesses; Indoor public spaces, Indoor public areas, Public transit; Indoor public spaces, Businesses; Public transit; Private transit, General public; Gatherings; Public transit, Genearl public, All indoor spaces, transportation, and outdoor spaces if group is 10 or more, Some businesses, and at gatherings with non-household members, All indoor spaces, Government offices and facilities, Indoor spaces and only applies to people 11 years or older, All businesses, transportation, and outdoor public spaces, Ride share programs, taxis, and private transportation vehicles (recommended for public transportation but not required), All public transportation and private transportation (e.g. rideshare, taxis), Essential businesses, Indoor public spaces; Ourdoor public spaces; Businesses; Public transit, Customers, All public spaces; Customers, All public spaces; Customers; Public transit, Customers; Public transit, Enclosed public spaces, Customers; Outdoor gatherings, Customers; Indoor gatherings, Customers; All indoor settings, All outdoor public spaces, All Public Spaces; Public transit; Businesses, All Public Spaces, State Buildings, Public transportation, All indoor spaces and transportation, All indoor public spaces, All Public Spaces; Public transit, Indoor public spaces; Businesses; Public transit, Indoor settings and retail, Indoors, public transport, Employees at outdoor arenas; Employees at pools, Massage; Tattoo; Salons, Businesses; Government Buildings, NA.