Model Projections of COVID-19 Healthcare Demands in NYC: An Overview of Model Settings and Outputs

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Methods/Models

▶ **Data (model input & validation, weekly)**

- Cases: by age group, by neighborhood (from DOHMH)
- Deaths: by age group, by neighborhood (from DOHMH)
- Mobility: by neighborhood (from Safegraph.com)

▶ **Model-inference systems**

- Model V1: simple SEIR model trained on city-wide case data
- Model V2: SEIR by age-group trained on age-grouped case data
- Model V3/V4: network SEIR by age group, trained on age-grouped, neighborhood-level case (+ mortality) data
- **Model V5 (current)**: network SEIRS by age group, trained on age-grouped, neighborhood-level case data & mortality data
- **Account for:** infection-detection rate, seasonality, intervention, age-specific rates, time-lag from infection to detection/diff. health outcomes
- **Inference method**: ensemble adjustment Kalman filter (EAKF)
- For details: https://www.medrxiv.org/content/10.1101/2020.06.27.20141689v1

Key model assumptions and potential discrepancies

Parameter	Value (spring 20 wave)*	Potential changes (see updates)
Infection-detection rate	Estimated in the model	Age specific
Pr (Hospitalized | infection)	2.25 – 7.5%	Adjust by age
Time from infection to hospitalization	6 (SD=3) days	
Duration of hospitalization	24 (SD=5.2) days	Could change over time due to e.g. availability**
Pr (ICU adm | infection)	0.45 – 1.9%	Adjust by age
Time from infection to ICU adm	12 (SD=5) days	
Duration in ICU	21 (SD=5.9) days	Could change over time**
Pr (Incubated | ICU adm)	90 – 100%	Adjust by age
Duration of ventilator use	18 (SD=3) days	Could change over time**
Pr (Death | infection)	Estimated in the model	Age specific
Time from infection to death	9.36 (SD=9.76) days	NYC data; assume 2 days shorter for 65+ y/o

*these are distributions to account for uncertainty (i.e. not exact numbers);
**affect projected census count of in-patients, ICU patients, and intubated patients

Model Outputs

▸ **Key epidemiological parameter estimates (not included on Github)**

- o Rt: the effective reproductive number
- o Infection-detection rate, etc.

▸ **Key population/epidemiologic variable estimates (not included on Github)**

- o Susceptibility by age group, neighborhood
- o Cumulative infection rate (seroprevalence) by age group, neighborhood
- o Number of exposed, infectious individuals

▸ **Newly added numbers per week/day, under different scenarios**

- o Infections, cases, hospitalizations, ICU admissions, intubations, deaths

▸ **Demands to healthcare systems per week/day, under different scenarios**

- o Total hospital beds, non-ICU beds, ICU beds, ventilators

Uncertainty is Large

▶ **Model simplification/misspecification**

▶ **Delay in observations**
- From exposure/infection to symptom onset
- From symptom onset to seek treatment
- From admission to testing and reporting
- Total lag: ~2 weeks

▶ **Under-detection and variation over time and space**

▶ **Spatial heterogeneity**

▶ **Data revision/backfill**

▶ **Changing interventions & behavior over time - changing epidemic outcomes**

▶ **All results/projections are preliminary and will be updated continuously as the epidemic unfolds**

Model Validation: Weekly cases/deaths/hospitalizations

▶ **Ex: compared with observed # cases, # deaths, and # hospitalizations (out-of-fit, not used for model training)**
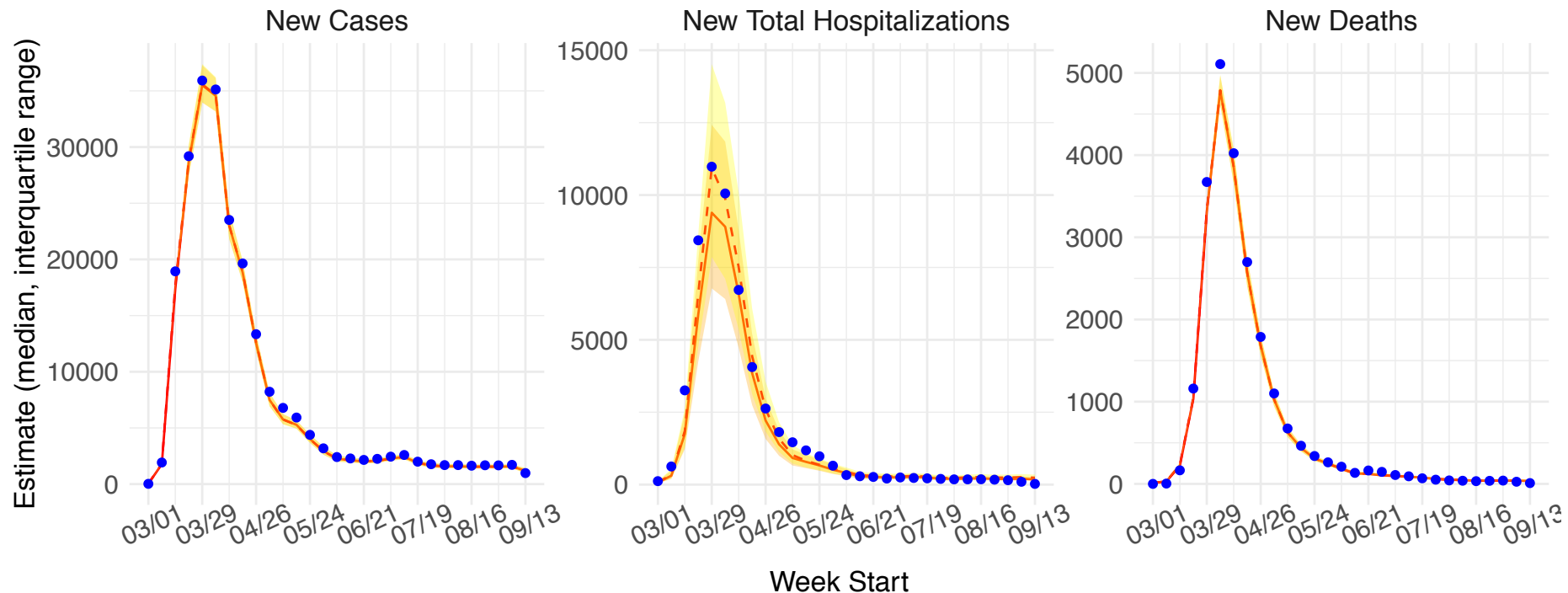
blue dots: observed; red lines: modeled

Model Validation: Weekly cases/deaths/hospitalizations

▶ **Compared with hospitalization, ICU, intubation <u>census</u> data from HERDS**

▶ **Potential discrepancies**
  - ○ HERDS tends to undercount
  - ○ The sojourn time in the hospital/ICU/on ventilator could change over time (eg, shorter if at capacity)
  - ○ Please adjust accordingly

FIGURES NOT SHOWN DUE TO DATA SHARING RESTRICTIONS

blue dots: observed; blue lines: modeled; red lines: projections

Real time projections

▶ **Projections under different scenarios:**
- Worst case: back to no interventions at all
- As Is: status quo
- Ctrl 1–5: further transmission reduction
- Rebound 1–2: relaxed social distancing – some increase in transmission

▶ **Seasonality assumptions:** Seasonality assumed v. no seasonality

▶ **Most likely:** As Is, Ctrl 1, Rebound 1, all with seasonality assumed

▶ **Time resolution:** daily for the next 2 weeks; weekly for the next 8 weeks

▶ **Spatial granularity:**
- Citywide and United Hospital Fund (UHF) neighborhood level
- Note: UHF based on resident address (not hospital locations)

▶ **Generated in real time**
- since 3/16/20; updated ~twice per week (Fri/Sat, Wed/Thur)
- Fri/Sat projections based on incomplete data and may underestimate

▶ **Make publicly available**
- https://github.com/wan-yang/COLUMBIA-COVID19-PROJECTIONS-FOR-NYC

Projection format

▶ **Github folder for the most recent projection: latest_projections**
  - ○ Projected numbers are in the excel files
  - ○ DailyProjections*: projections by day for the coming 14 days
  - ○ WeeklyProjection*: projections by week for the coming 8 weeks
  - ○ *citywide*: combining all locations; otherwise by UHF

https://github.com/wan-yang/COLUMBIA-COVID19-PROJECTIONS-FOR-NYC

Projection format - Projected epid/health outcomes

▶ **Tab: Projections_NewlyAdded (new infections/cases/ICU admissions etc for each week or day)**

    ○ Multiple scenarios for seasonality and changes in transmission rate

    ○ Our default: seasonality assumed, intervention = 'As Is'

    ○ Round 1 and Ctrl 1 is also possible

    ○ Numbers are median (interquartile range)

	A	B	C	D	E	F	G	H	I	J	K
1	Seasonality	interven	location	date	New Infections	New Cases	New Total H	New Non-ICU H	New ICU adm	New Intubation	New Deaths
346	Seasonality assume	As Is	city	10/11/20	15157 (9498, 2545	1790 (1287, 2	368 (240, 566	293 (174, 476)	73 (49, 105)	70 (46, 100)	55 (40, 80)
347	Seasonality assume	As Is	city	10/18/20	14382 (6839, 3009	1584 (947, 26	316 (176, 573	251 (127, 481)	61 (38, 98)	57 (36, 93)	50 (33, 79)
348	Seasonality assume	As Is	city	10/25/20	14621 (5386, 3652	1512 (715, 29	290 (128, 626	231 (93, 524)	52 (27, 101)	50 (26, 96)	44 (25, 82)
349	Seasonality assume	As Is	city	11/01/20	15614 (4557, 4511	1548 (580, 35	286 (101, 723	229 (75, 604)	49 (21, 114)	46 (20, 108)	41 (19, 90)
350	Seasonality assume	As Is	city	11/08/20	17367 (4119, 5591	1683 (508, 45	299 (86, 874)	241 (65, 728)	49 (17, 136)	47 (16, 129)	41 (15, 104)
351	Seasonality assume	As Is	city	11/15/20	20264 (4014, 7025	1932 (479, 58	335 (79, 1093	270 (60, 904)	53 (15, 169)	51 (14, 160)	43 (13, 127)
352	Seasonality assume	As Is	city	11/22/20	25028 (4270, 8988	2367 (493, 77	400 (80, 1421	323 (62, 1168)	61 (14, 217)	58 (13, 206)	49 (12, 163)
353	Seasonality assume	As Is	city	11/29/20	31729 (4838, 1141	3063 (553, 10	508 (88, 1891	412 (70, 1547)	76 (14, 288)	72 (14, 273)	61 (12, 217)
354	Seasonality assume	As Is	101: Kingsbridg	10/11/20	96 (55, 171)	12 (8, 19)	4 (2, 6)	3 (2, 5)	1 (0, 1)	1 (0, 1)	1 (0, 1)
355	Seasonality assume	As Is	101: Kingsbridg	10/18/20	96 (42, 212)	12 (7, 21)	3 (2, 6)	3 (1, 5)	1 (0, 1)	0 (0, 1)	1 (0, 1)
356	Seasonality assume	As Is	101: Kingsbridg	10/25/20	102 (34, 266)	12 (5, 24)	3 (1, 7)	3 (1, 6)	0 (0, 1)	0 (0, 1)	0 (0, 1)
357	Seasonality assume	As Is	101: Kingsbridg	11/01/20	112 (30, 345)	12 (4, 30)	3 (1, 8)	2 (1, 6)	0 (0, 1)	0 (0, 1)	0 (0, 1)
358	Seasonality assume	As Is	101: Kingsbridg	11/08/20	127 (28, 454)	14 (4, 38)	3 (1, 9)	3 (1, 8)	0 (0, 1)	0 (0, 1)	0 (0, 1)
359	Seasonality assume	As Is	101: Kingsbridg	11/15/20	154 (28, 612)	16 (4, 50)	3 (1, 11)	3 (1, 9)	0 (0, 2)	0 (0, 1)	0 (0, 1)
360	Seasonality assume	As Is	101: Kingsbridg	11/22/20	201 (31, 848)	20 (4, 70)	4 (1, 14)	3 (1, 12)	1 (0, 2)	1 (0, 2)	1 (0, 2)

◀ ▶   TotalNext8Weeks   TrainingEstimates   **Projections_NewlyAdded**   Projections_HealthcareNeeds   +

Ready   Filter Mode   100%

https://github.com/wan-yang/COLUMBIA-COVID19-PROJECTIONS-FOR-NYC

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Projection format: Projected healthcare demands

▶ **Tab: Projections_HealthcareNeeds (projected census counts, ICU beds etc)**
  - ○ Our default: seasonality assumed, intervention = 'As Is'
  - ○ Round 1 and Ctrl 1 is also possible
  - ○ ***mean: average count over the 7 days of the week
  - ○ ***max: maximal count over the 7 days of the week

	A	B	C	D	E	F	G	H	I	J
1	Seasona ▾	interve ▾	location ▾	date ▾	Total.Hospital.Bed.N ▾	Non.ICU.Hospital.Be ▾	ICU.Bed.Needs..prev ▾	Ventilator.Needs..p ▾	Total.Hospital.I ▾	Non.ICU.Hospi ▾
346	Seasonality	As Is	city	10/11/20	1494 (1036, 2098)	1278 (831, 1854)	214 (142, 305)	185 (125, 259)	1397 (965, 1960)	1190 (768, 1730)
347	Seasonality	As Is	city	10/18/20	1473 (987, 2180)	1248 (780, 1915)	221 (144, 325)	189 (126, 273)	1366 (906, 2028)	1150 (707, 1779)
348	Seasonality	As Is	city	10/25/20	1364 (846, 2220)	1146 (658, 1938)	211 (131, 331)	173 (110, 272)	1247 (754, 2052)	1042 (580, 1789)
349	Seasonality	As Is	city	11/01/20	1222 (663, 2307)	1023 (512, 1999)	189 (107, 337)	150 (86, 274)	1115 (582, 2129)	928 (446, 1839)
350	Seasonality	As Is	city	11/08/20	1124 (504, 2554)	940 (390, 2195)	169 (82, 360)	134 (64, 301)	1036 (442, 2345)	860 (341, 2013)
351	Seasonality	As Is	city	11/15/20	1107 (393, 3004)	920 (307, 2565)	160 (63, 417)	131 (49, 356)	1027 (351, 2737)	851 (273, 2337)
352	Seasonality	As Is	city	11/22/20	1187 (331, 3729)	984 (262, 3164)	166 (52, 513)	140 (41, 444)	1097 (302, 3360)	907 (237, 2851)
353	Seasonality	As Is	city	11/29/20	1390 (311, 4834)	1150 (249, 4067)	189 (46, 660)	162 (38, 579)	1266 (287, 4295)	1045 (228, 3618)
354	Seasonality	As Is	101: Kingsbridg	10/11/20	16 (11, 24)	14 (9, 21)	2 (1, 3)	2 (1, 3)	15 (10, 22)	13 (8, 20)
355	Seasonality	As Is	101: Kingsbridg	10/18/20	15 (10, 24)	13 (8, 21)	2 (1, 3)	2 (1, 3)	14 (9, 22)	12 (7, 20)
356	Seasonality	As Is	101: Kingsbridg	10/25/20	14 (8, 24)	12 (7, 21)	2 (1, 3)	2 (1, 2)	13 (7, 22)	11 (6, 19)
357	Seasonality	As Is	101: Kingsbridg	11/01/20	13 (7, 24)	11 (5, 21)	2 (1, 3)	1 (1, 3)	12 (6, 22)	10 (5, 20)
358	Seasonality	As Is	101: Kingsbridg	11/08/20	12 (5, 27)	10 (4, 23)	2 (1, 3)	1 (1, 3)	11 (4, 25)	9 (4, 21)
359	Seasonality	As Is	101: Kingsbridg	11/15/20	12 (4, 31)	10 (3, 26)	1 (1, 4)	1 (0, 3)	11 (4, 28)	9 (3, 24)
360	Seasonality	As Is	101: Kingsbridg	11/22/20	12 (3, 38)	10 (3, 32)	2 (0, 5)	1 (0, 4)	11 (3, 34)	10 (2, 29)

◄ ►   TotalNext8Weeks   TrainingEstimates   Projections_NewlyAdded   **Projections_HealthcareNeeds**   +

Ready   688 of 4128 records found   ⊞   回   ⊟   — ●——— +   100%

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Example projections

▶ **New Infections: under different ctrl scenarios**

○ Worst case: back to no interventions at all – transmission/infection would increase quickly

○ As Is: status quo

○ Ctrl 1–5: further transmission reduction

○ Rebound 1–2: relaxed social distancing – some increase in transmission

blue: model training; red: projections

New Infections (city)

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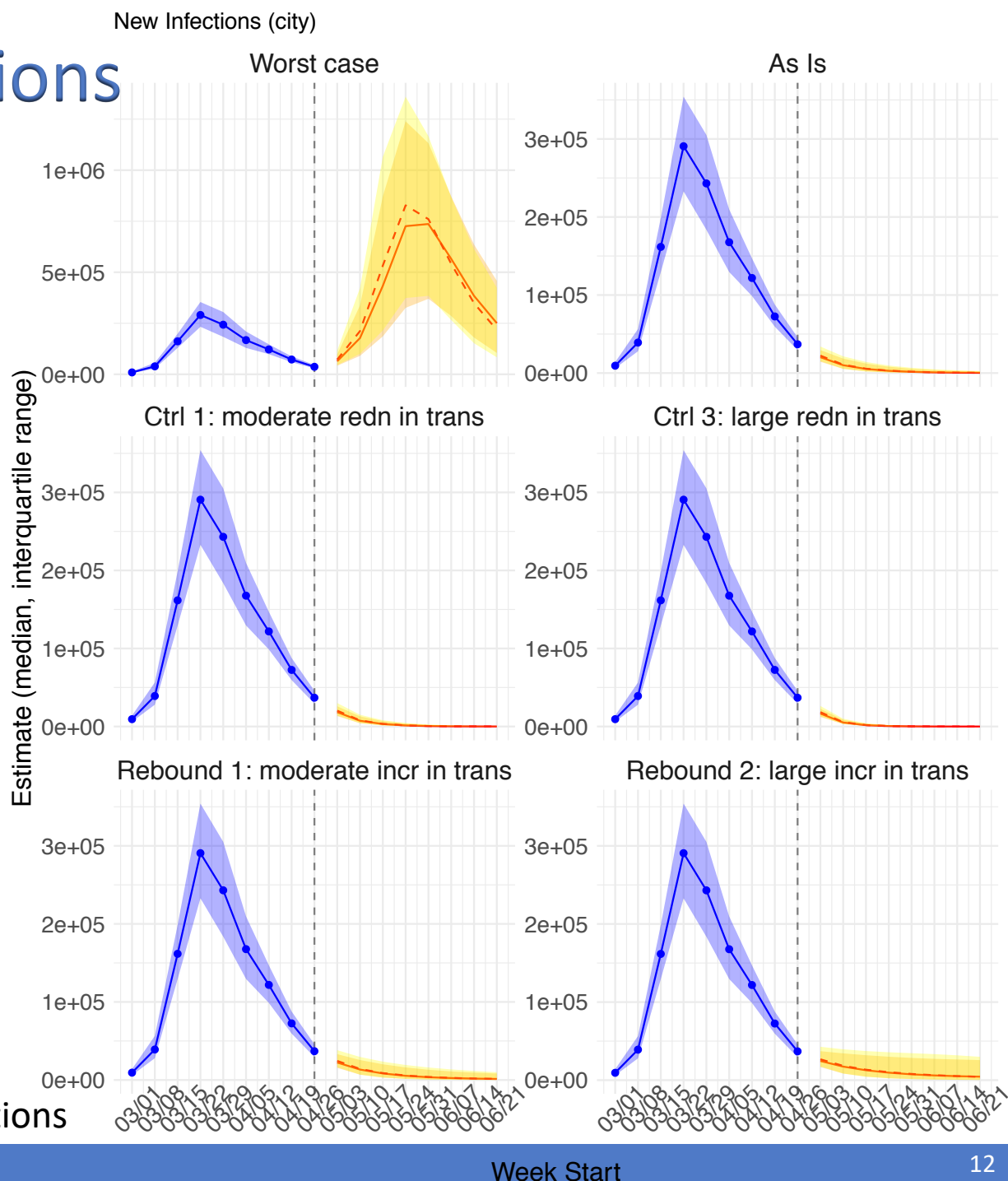
Example projections

- **Hospitalization: under different ctrl scenarios**
  - Dynamics similar to infections
  - With some delay
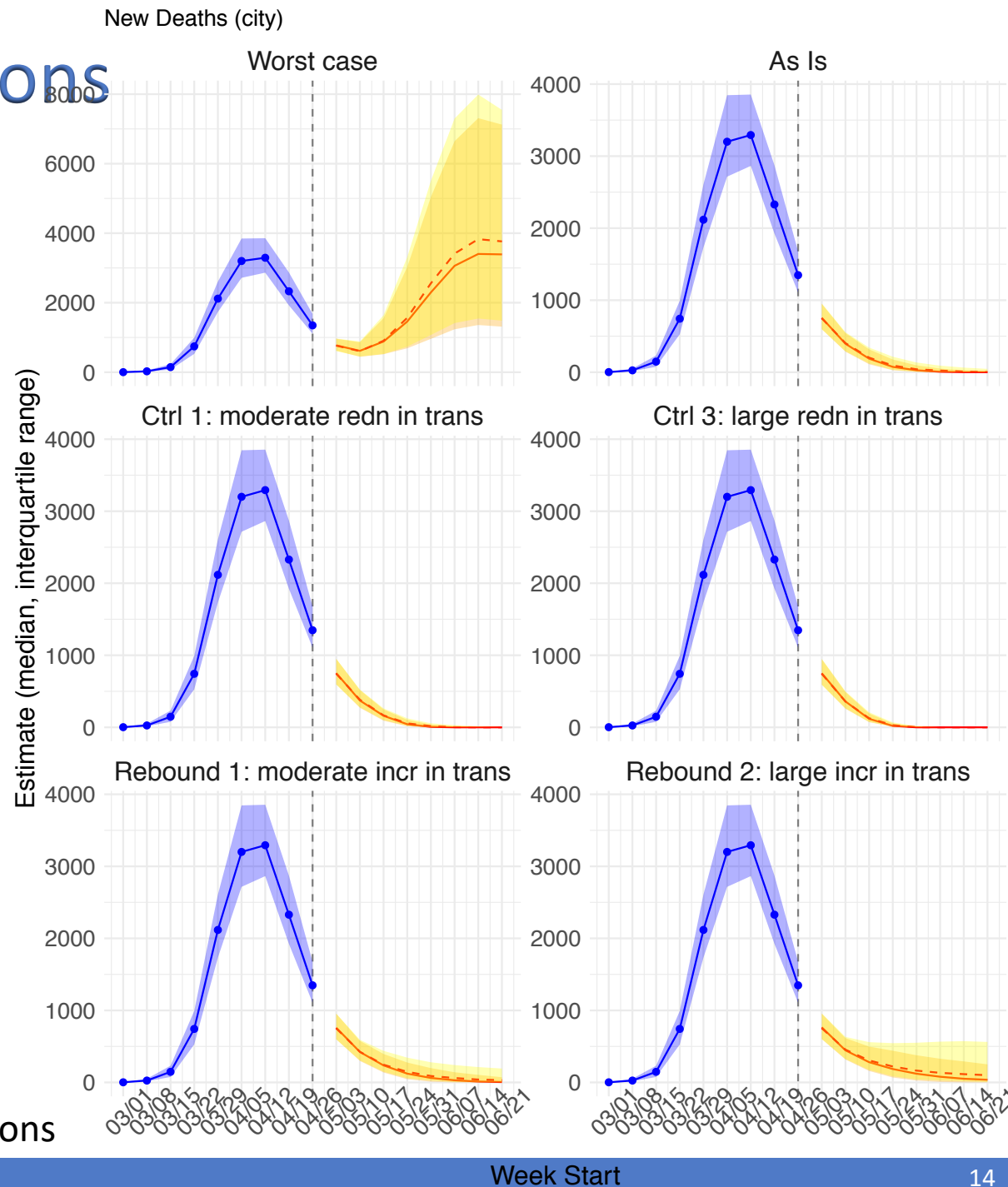
- **Spatial granularity:**
  - Citywide
  - Neighborhood

blue: model training; red: projections

New Total Hospitalizations (city)
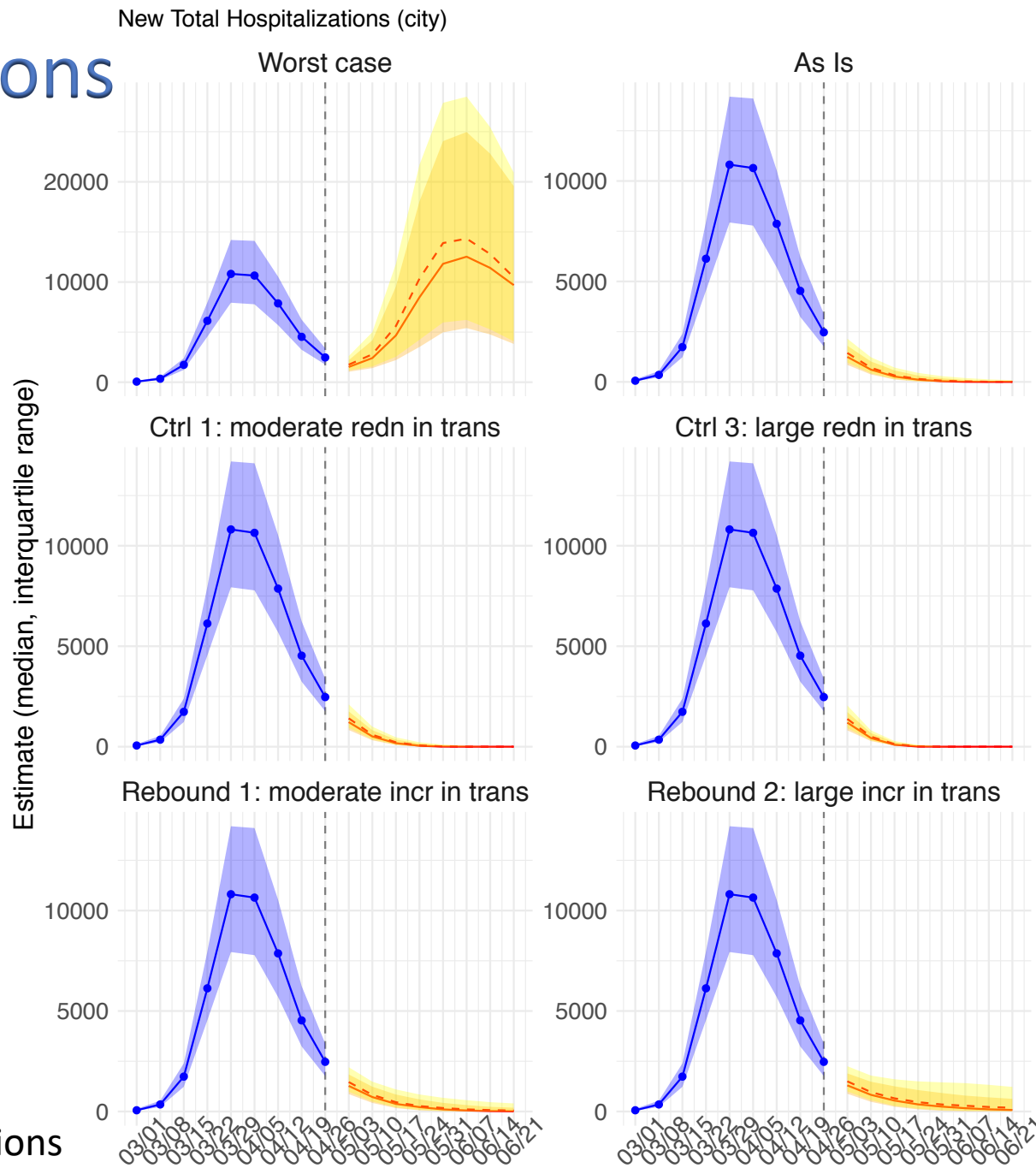
Example projections

▶ **Deaths: under different ctrl scenarios**
- o Dynamics similar to infections
- o With more delay

▶ **Spatial granularity:**
- o Citywide
- o Neighborhood

New Deaths (city)

blue: model training; red: projections
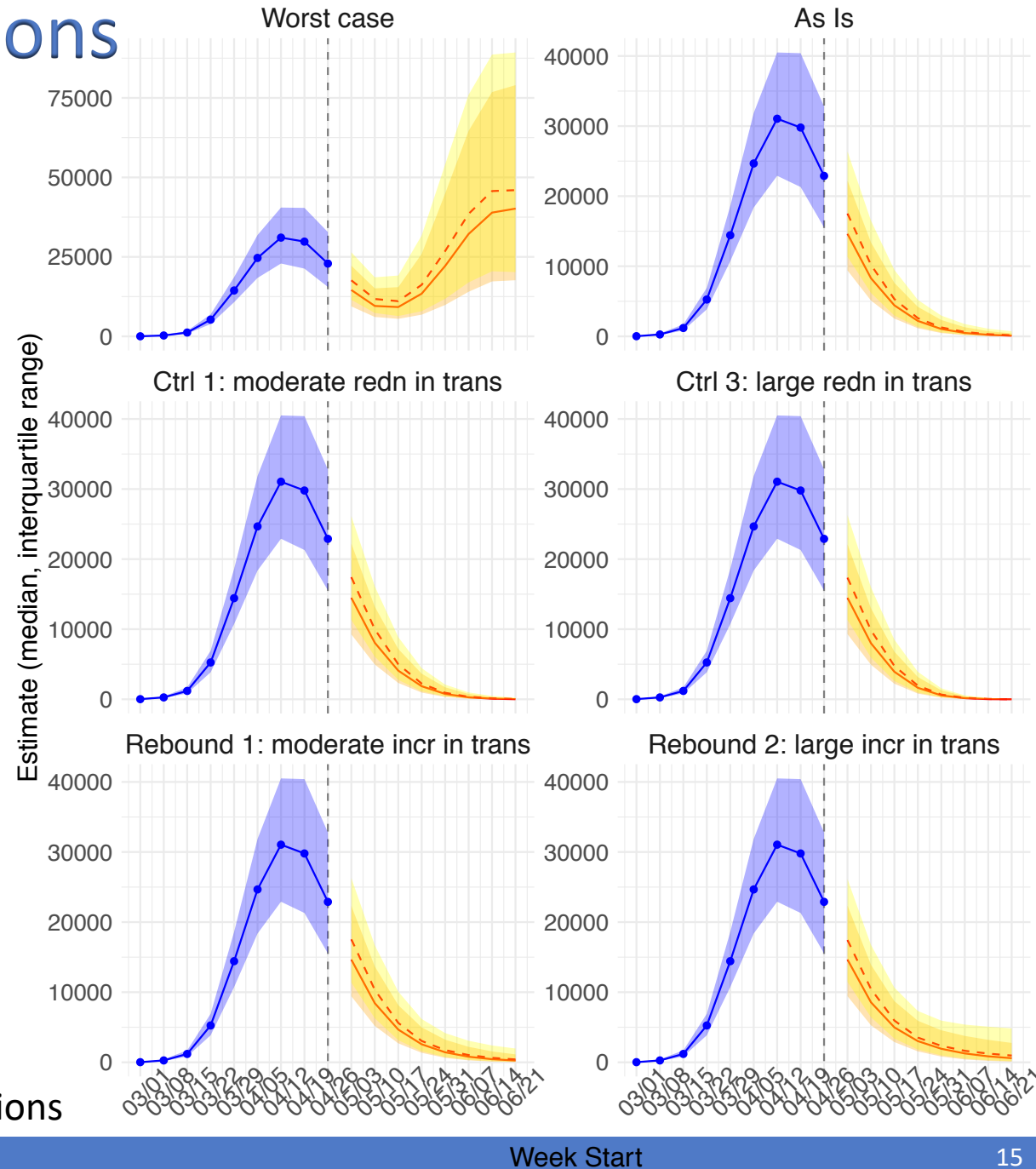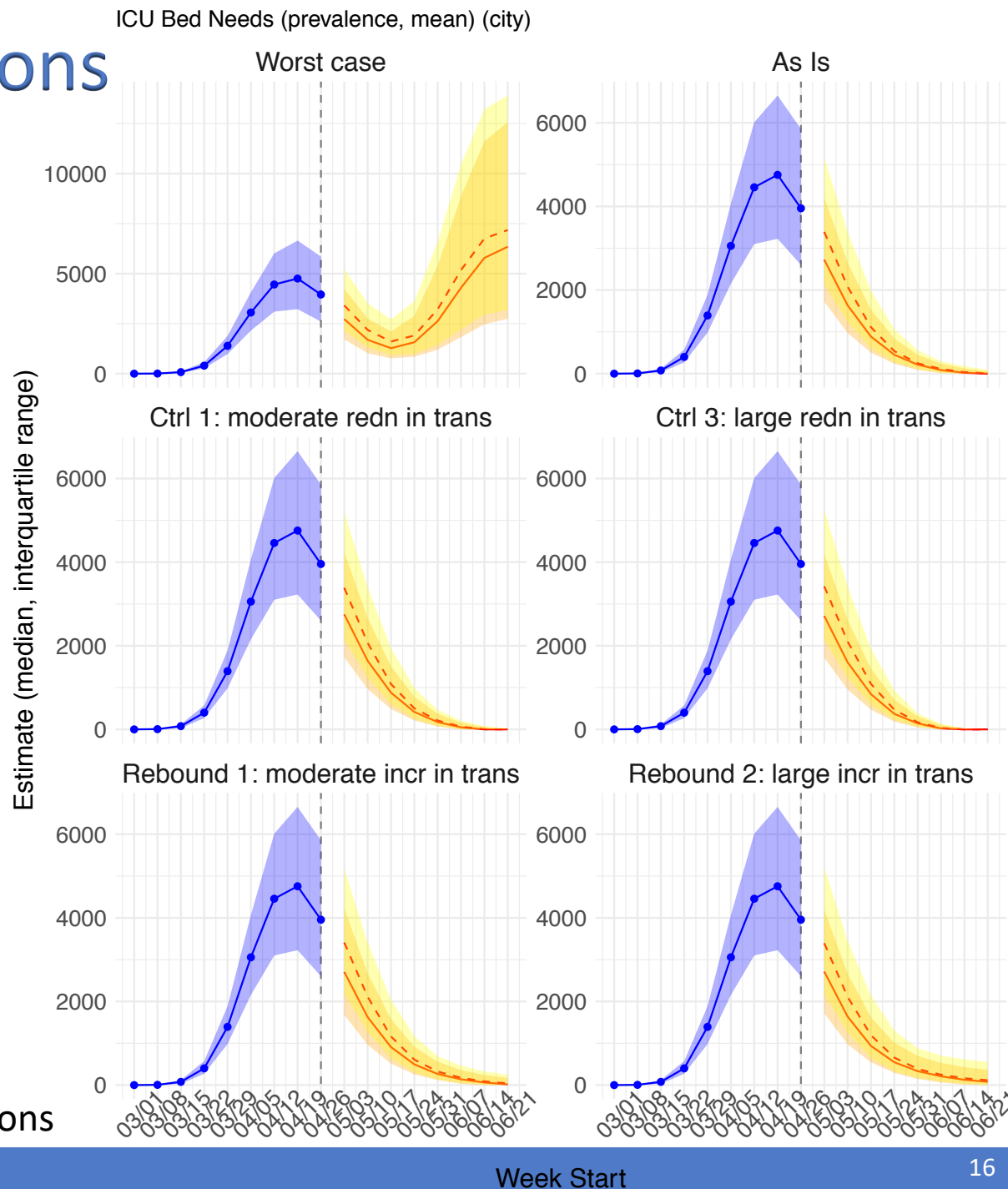
Example projections

- **Hospital bed needs: under different ctrl scenarios**

  o Accounted for severity, admissions, length of stay, and discharges over time

- **Spatial granularity:**
  o Citywide
  o Neighborhood

blue: model training; red: projections

Total Hospital Bed Needs (prevalence, mean) (city)

Example projections

- **ICU bed needs: under different ctrl scenarios**
  - Accounted for severity, admissions, length of stay, and discharges over time

- **Spatial granularity:**
  - Citywide
  - Neighborhood

blue: model training; red: projections

ICU Bed Needs (prevalence, mean) (city)
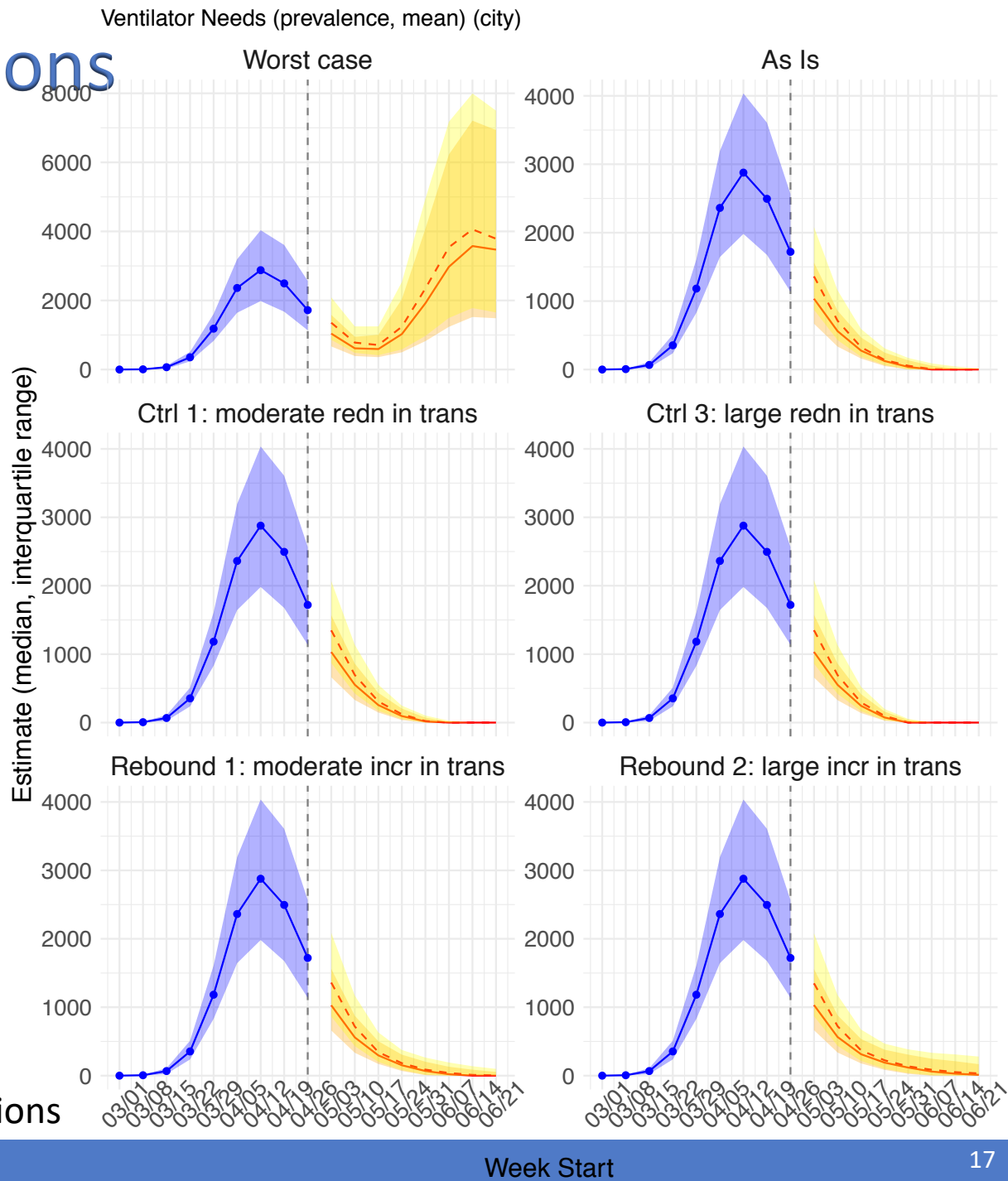
Example projections

- **Ventilator needs: under different ctrl scenarios**
  - Accounted for severity, intubations, length of use, and extubations over time

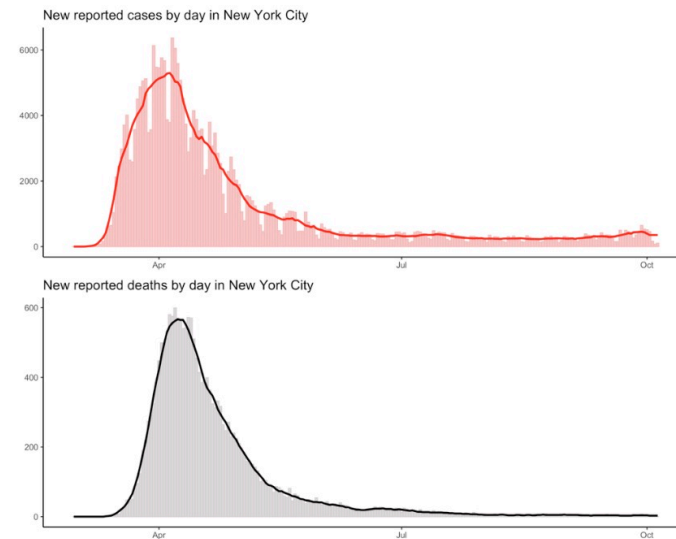- **Spatial granularity:**
  - Citywide
  - Neighborhood

Ventilator Needs (prevalence, mean) (city)

blue: model training; red: projections

For more visualization:

▶ **COVID-19 Dashboard by Chen et al. at Columbia**

  ○ https://msph.shinyapps.io/nyc-neighborhoods-covid/

The NYC Neighborhoods COVID-19 Dashboard is a tracker and data visualization tool to provide continuously updated sources of COVID-19 data in NYC for lay public, essential workers, policymakers, and researchers.

There are five tools available (located at the top navigation menu):
· **COVID-19 Tracker** provides daily tracking of the local development for COVID-19 cases, deaths, and tests in 177 NYC ZIP Code Tabulation Areas (ZCTAs).
· **COVID-19 Distribution** provides a data visualization of COVID-19 cases, hospitalizations, and deaths in NYC ZCTAs and by age, gender, and race/ethnicity.
· **COVID-19 Trends** shows the time trends for COVID-19 cases, hospitalizations, and deaths by NYC boroughs, ZCTAs, and demographics.
· **COVID-19 Projection** provides projection of COVID-19 new cases, new hospitalizations, and new deaths in the next 8 weeks by NYC United Hospital Fund neighborhood.

Key takeaways

▶ **Large uncertainties – take multiple scenarios into account & be prepared**
  o Most likely: As Is, Ctrl 1, Rebound 1, all with seasonality assumed

▶ **Errors grow over time – projections farther in the future are less accurate**

▶ **Projected census counts may not match with HERDS data**
  o Could vary due to changing sojourn time in each category (e.g. duration of the ICU), which may not be updated timely
  o Adjust based on newly admitted in-patients/etc., sojourn times in your hospital, and your market share

▶ **UHF-level projections are based on patient resident location (i.e., not hospital location)**
  o Adjust based on your catchment population if needed

▶ **Projections are updated continuously and posted here:**
  o https://github.com/wan-yang/COLUMBIA-COVID19-PROJECTIONS-FOR-NYC

▶ **Visualization by Chen et al:**
  https://msph.shinyapps.io/nyc-neighborhoods-covid/

Acknowledgements

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- o Wan Yang, Sasikiran Kandula, Jeffrey Shaman

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▶ **Thank you!**