ILINet Backfill:

Descriptive Analysis, Effects on Forecasts, and Approaches to Mitigation

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Outline and Work Discussed

1. Origins and descriptive analysis of backfill
   - Work from: CDC, Delphi Group (Logan Brooks, Roni Rosenfeld), FluSight Network, LANL (Dave Osthus)
2. Effects on forecast skill
   - Work from: Delphi Group, FluSight Network, Reich Lab (Casey Gibson)
3. Approaches to addressing
   A. without external data
      - Work from: Delphi Group (Logan Brooks, Roni Rosenfeld), Reich Lab (Casey Gibson)
   B. with external data (e.g., digital surveillance)
      - Work from: Delphi Group (David Farrow, Ryan Tibshirani), LANL (Dave Osthus), Machine Intelligence Lab (Fred Lu, Mauricio Santillana), Shaman Group (Sasikiran Kandula, Jeffrey Shaman)

Full citations on last slide

Source of Backfill in ILINet Data

Sun	Mon	Tue	Wed	Thu	Fri	Sat
Sick People Visit Doctor	Sick People Visit Doctor	Sick People Visit Doctor	Sick People Visit Doctor	Sick People Visit Doctor	Sick People Visit Doctor	Sick People Visit Doctor
		Health Care Providers Report to CDC			Initial ILINet Report	

Source of Backfill in ILINet Data

Sun	Mon	Tue	Wed	Thu	Fri	Sat
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		Additional or Revised Records			Revised ILINet Report	

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		Additional or Revised Records			Revised ILINet Report	
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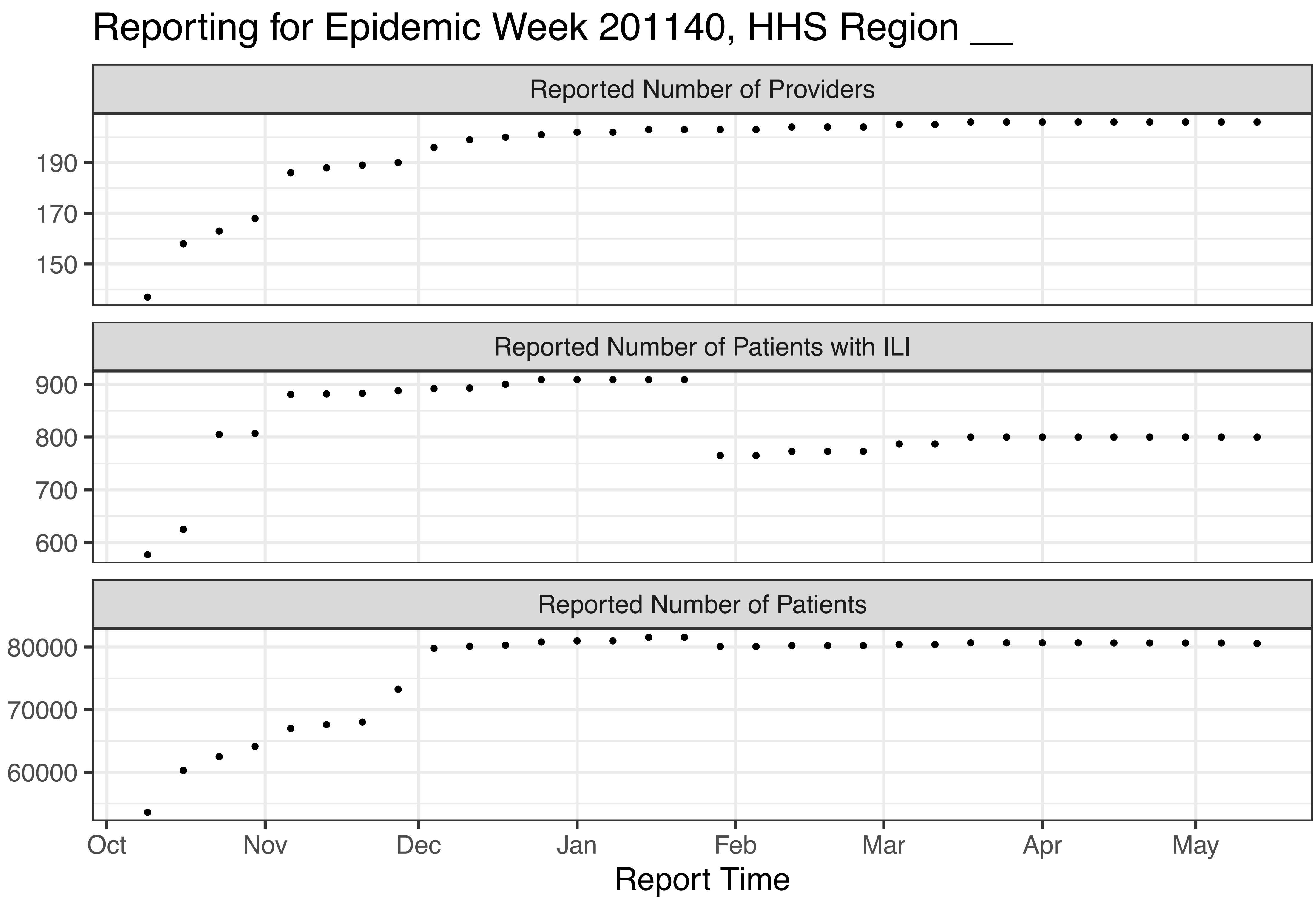
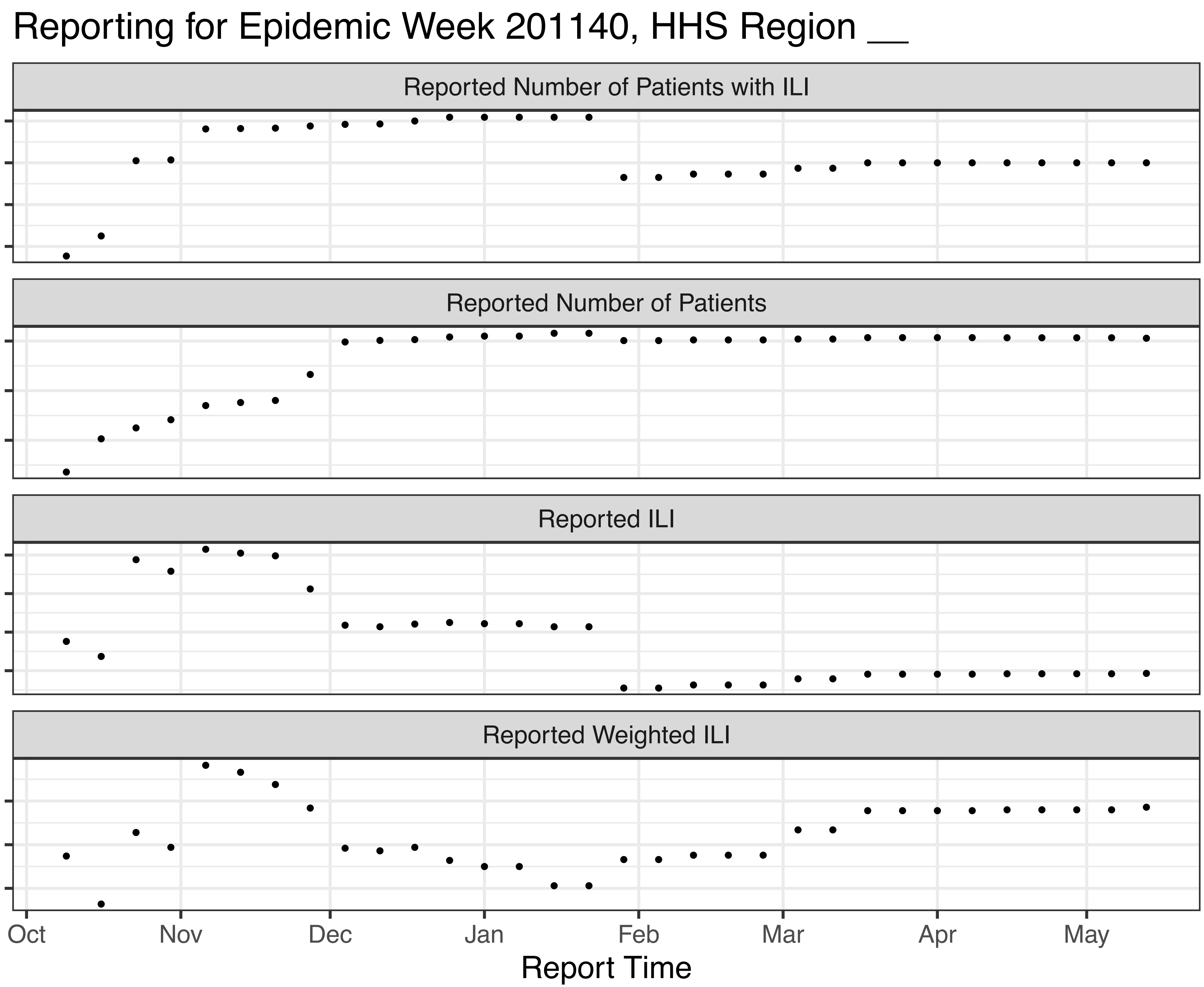
Illustration of Backfill



A later Report Time means more revisions have come in

Illustration of Backfill



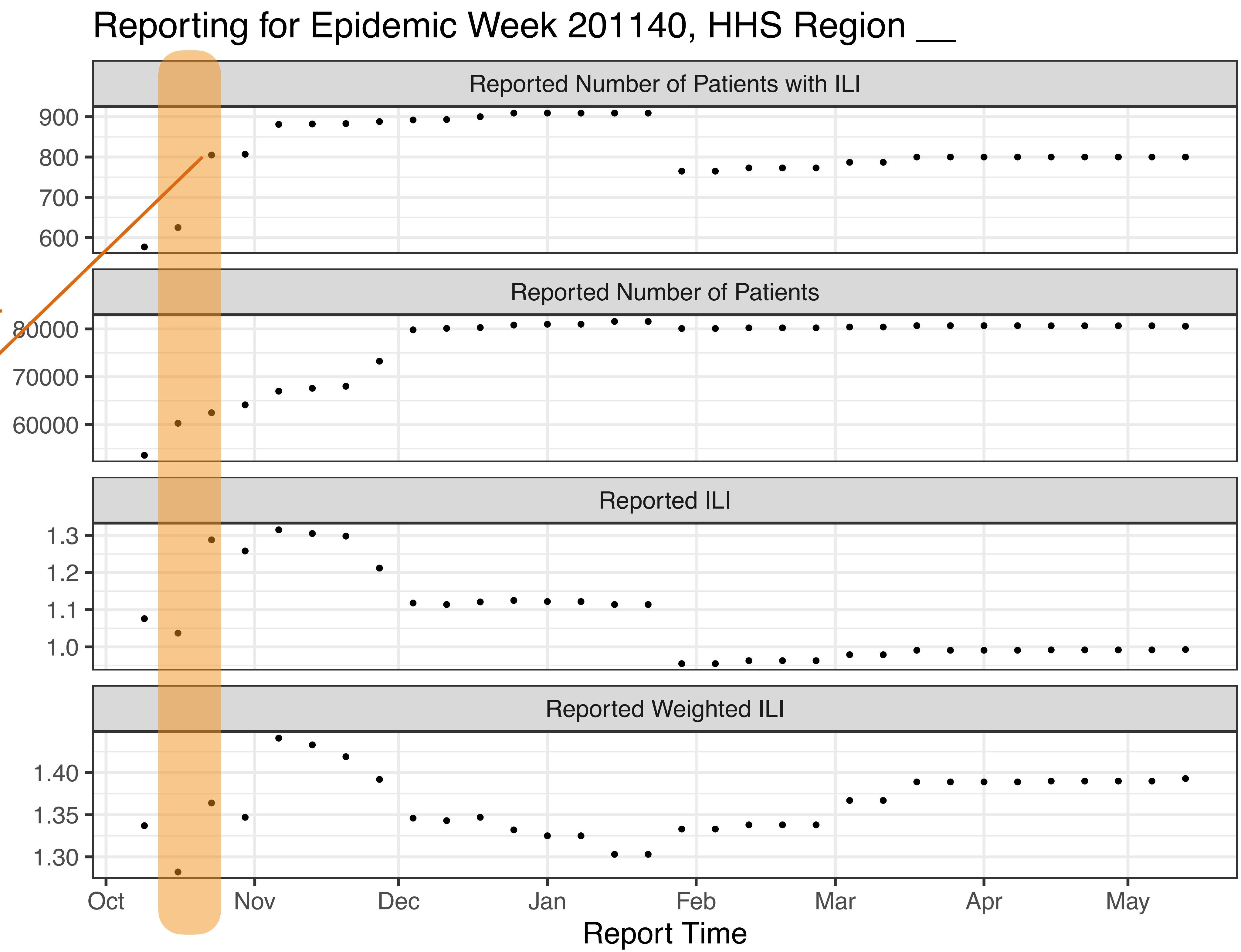
$$\text{ILI} = \frac{\text{Patients with ILI}}{\text{Patients}}$$

weighted ILI is weighted by state population

A later Report Time means more revisions have come in

Illustration of Backfill

Jump in reported ILI due to a larger numerator



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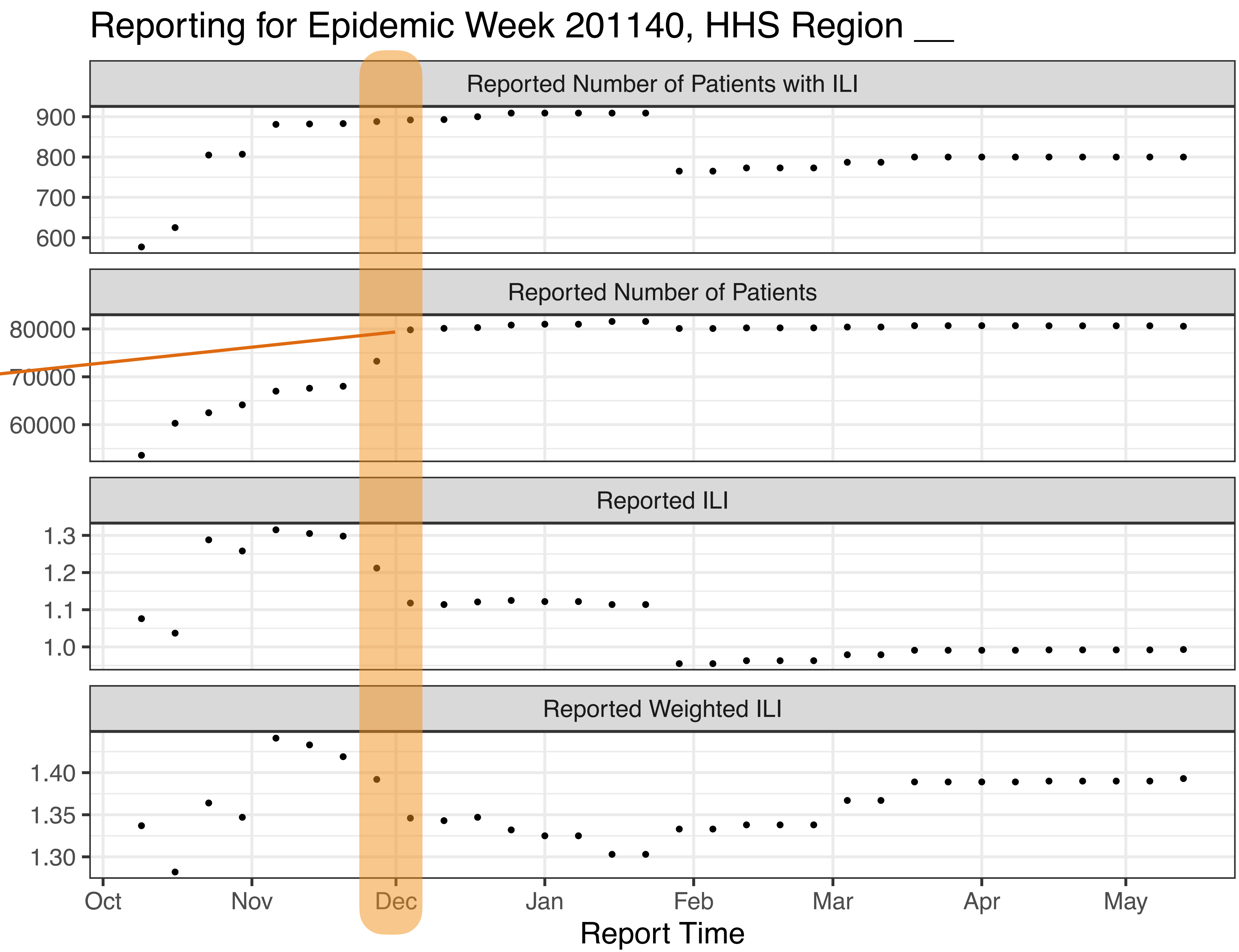


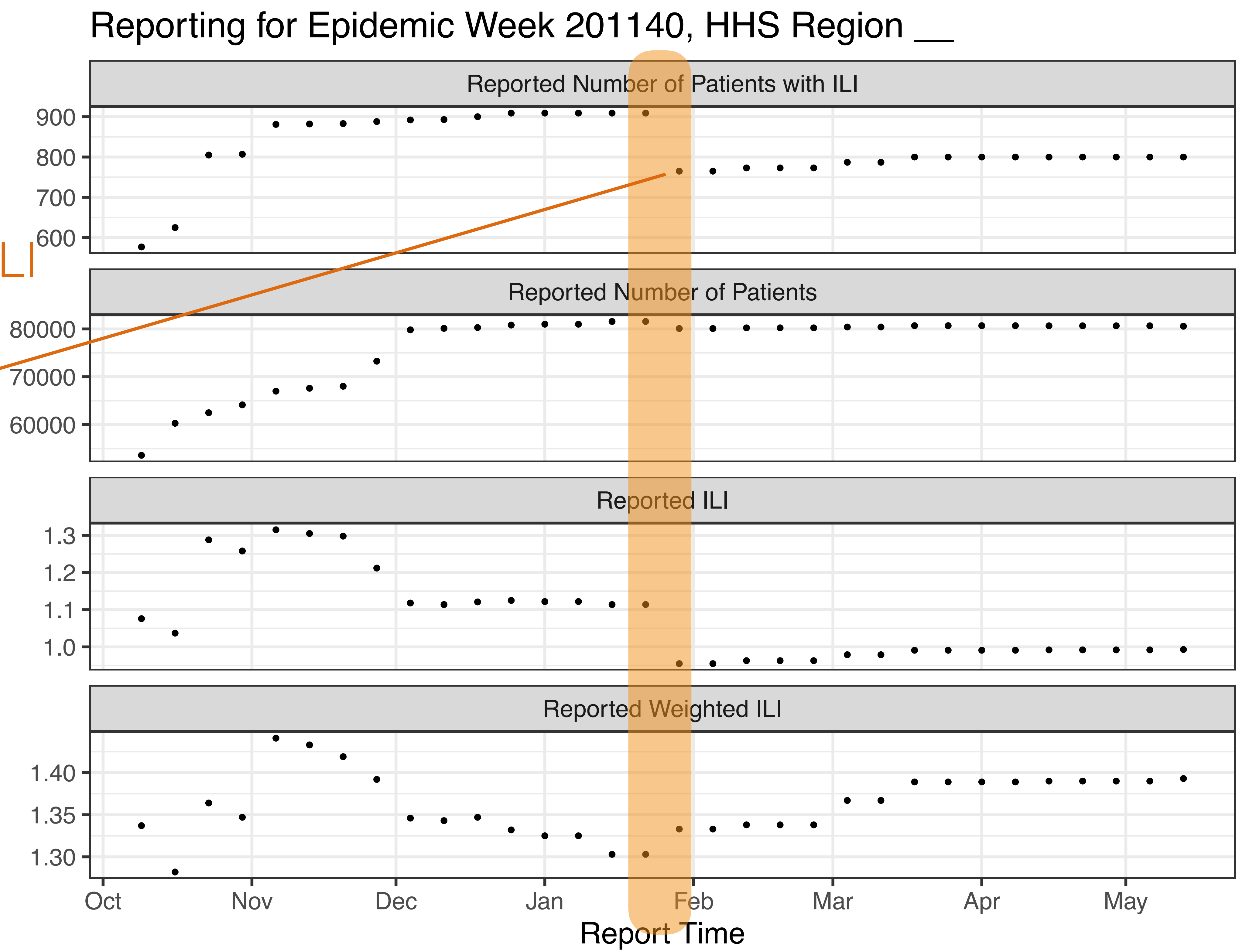
Drop in reported ILI due to a larger denominator

$$ILI = \frac{\text{Patients with ILI}}{\text{Patients}}$$

weighted ILI is weighted by state population

A later Report Time means more revisions have come in

Illustration of Backfill



Drop in reported ILI due to a smaller numerator

$$\text{ILI} = \frac{\text{Patients with ILI}}{\text{Patients}}$$

weighted ILI is weighted by state population

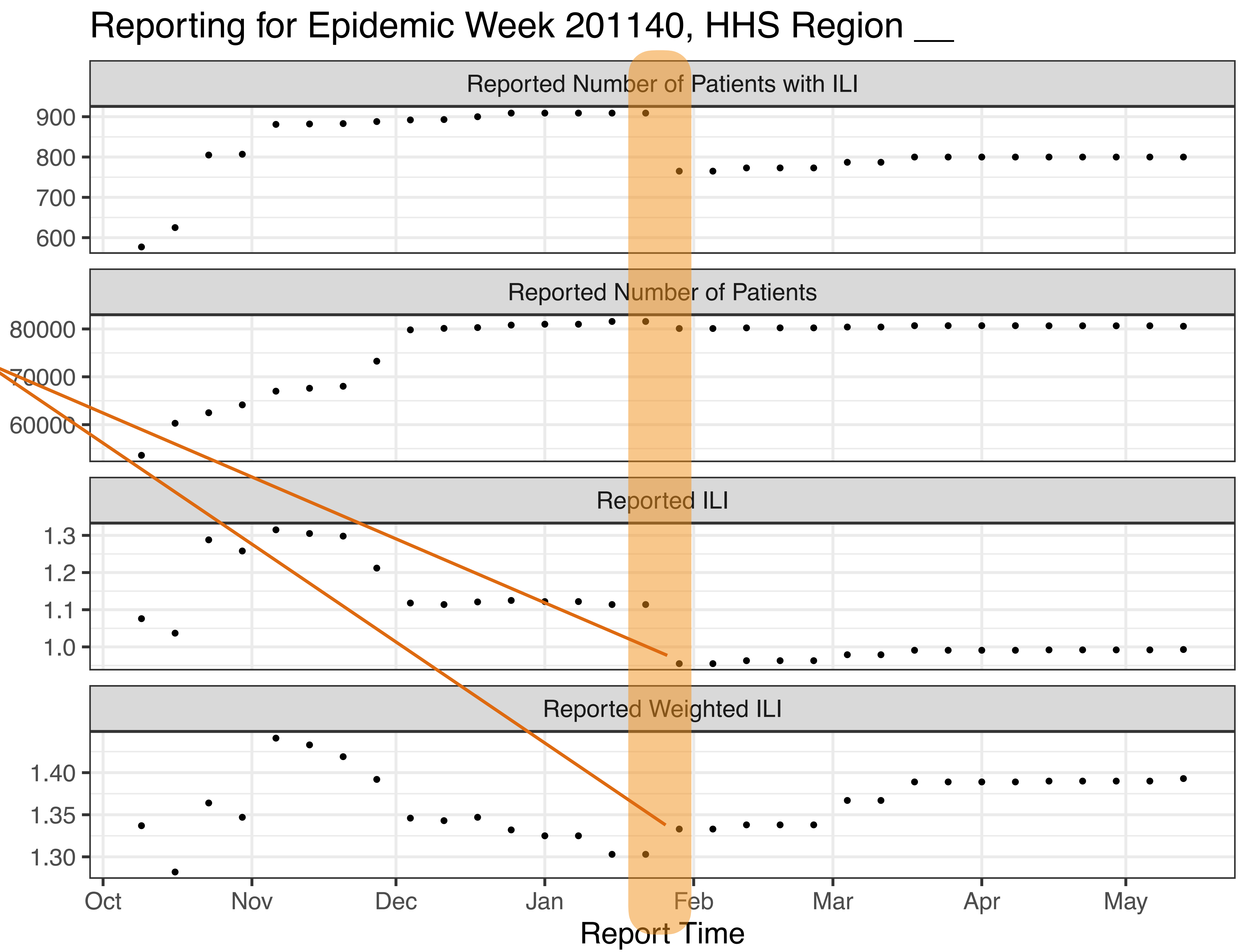
A later Report Time means more revisions have come in

Illustration of Backfill

ILI and weighted ILI don't always move the same direction

$$\text{ILI} = \frac{\text{Patients with ILI}}{\text{Patients}}$$

weighted ILI is weighted by state population



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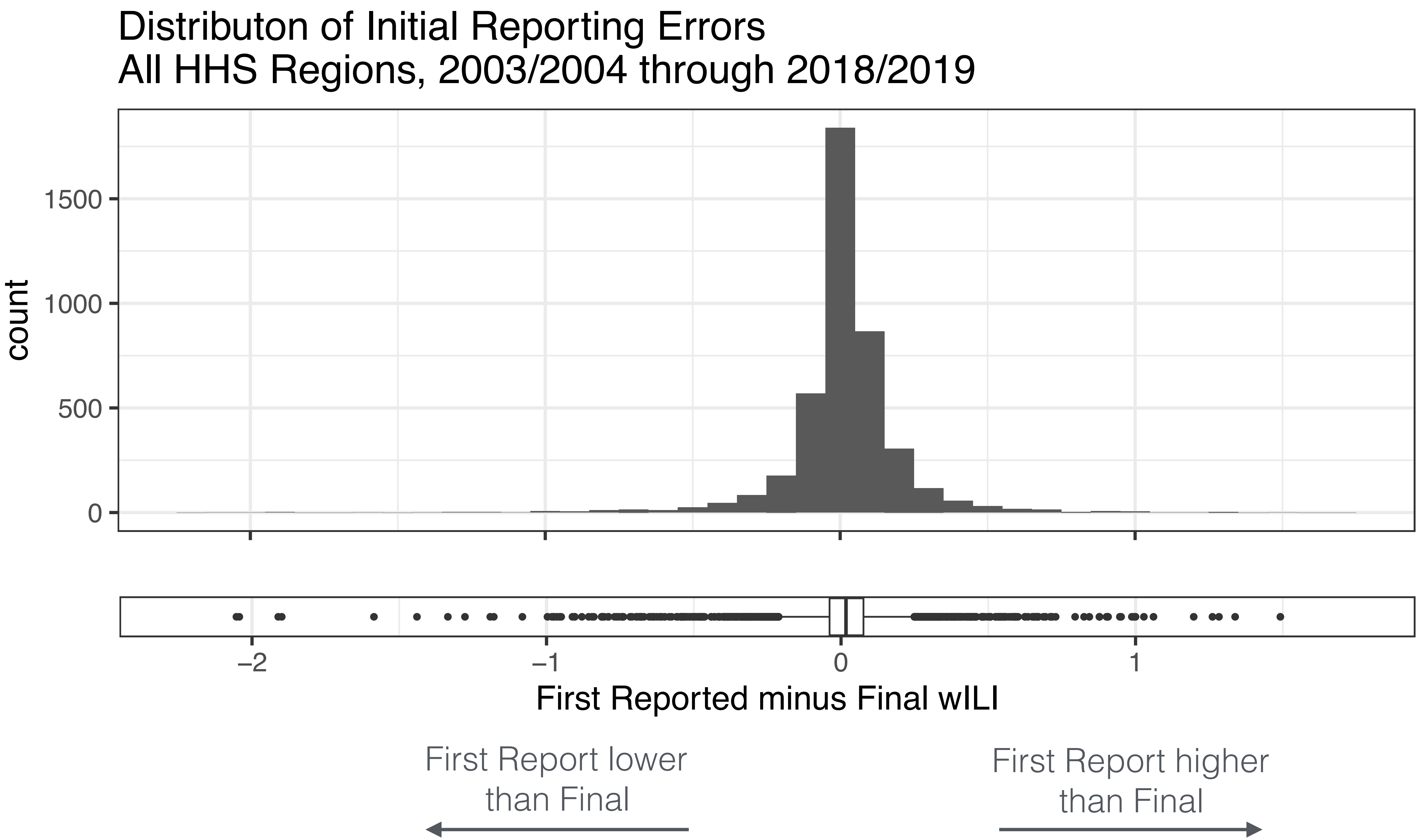
Prevalence and Severity of Backfill



- Approximately 33% of initial reports are later revised by more than ± 0.1
- 3% are revised by more than ± 0.5
- 0.4% are revised by more than ± 1

Backfill Fairly Consistent Across Regions, Occurs Most Within about 10 Weeks

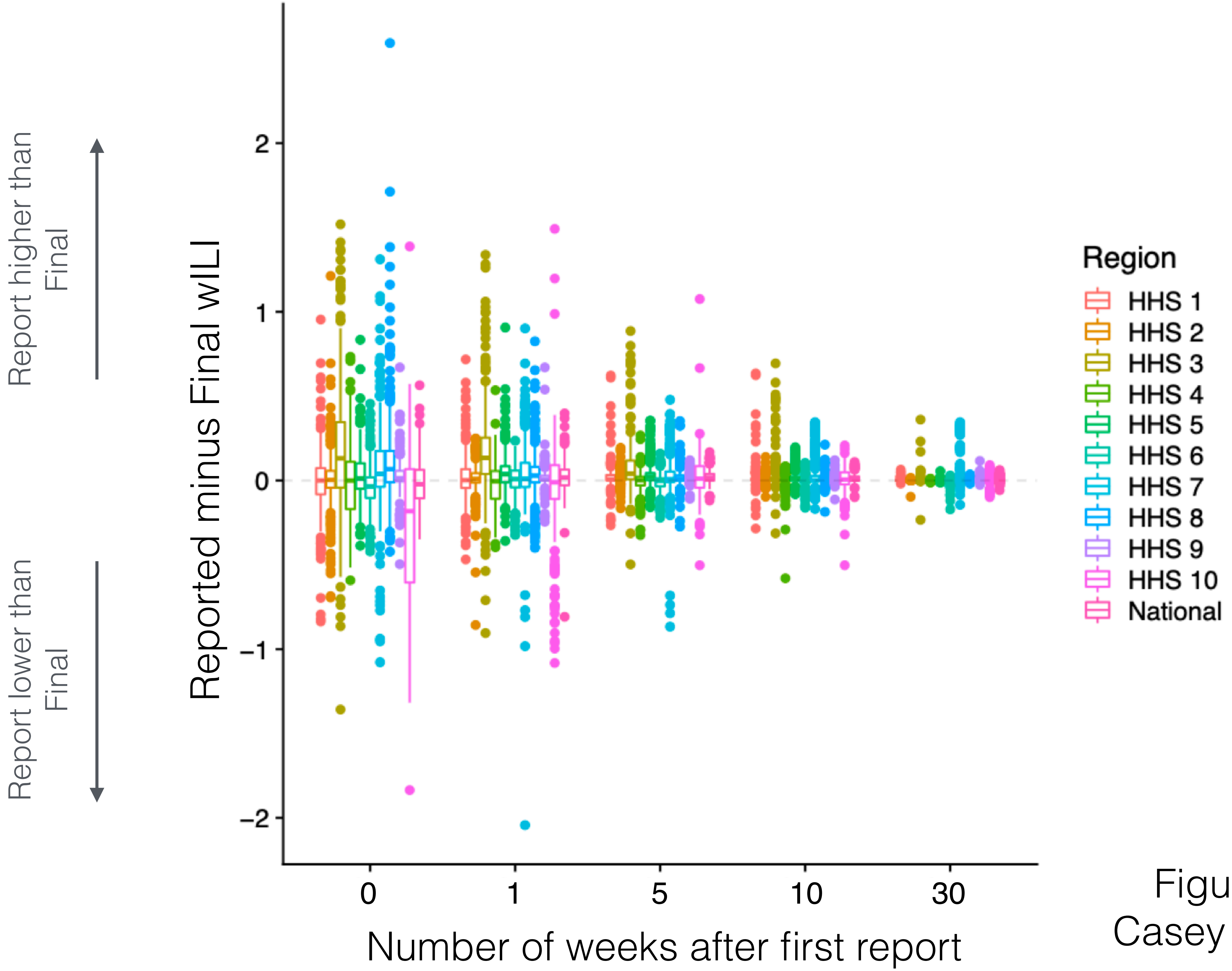
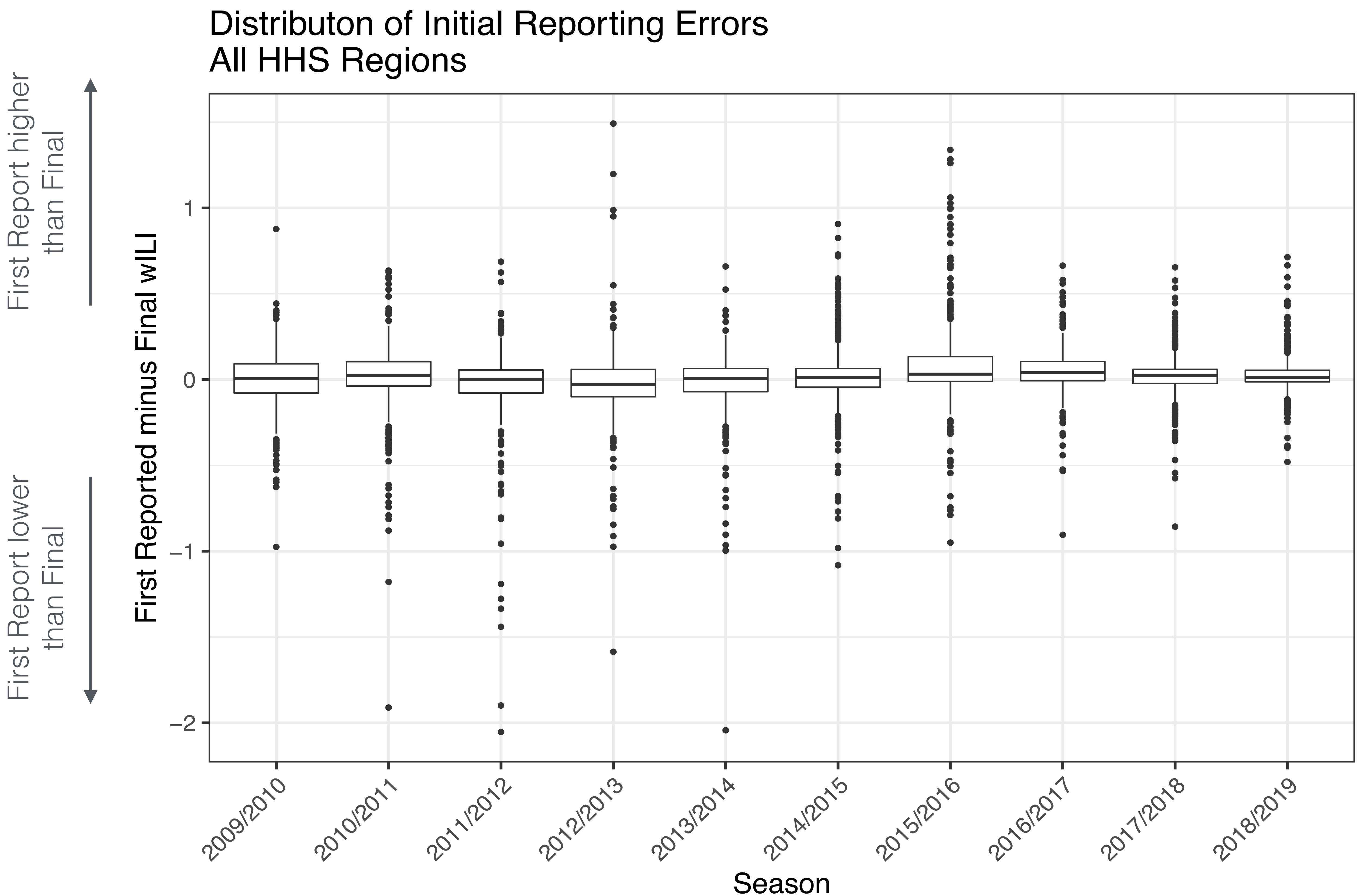
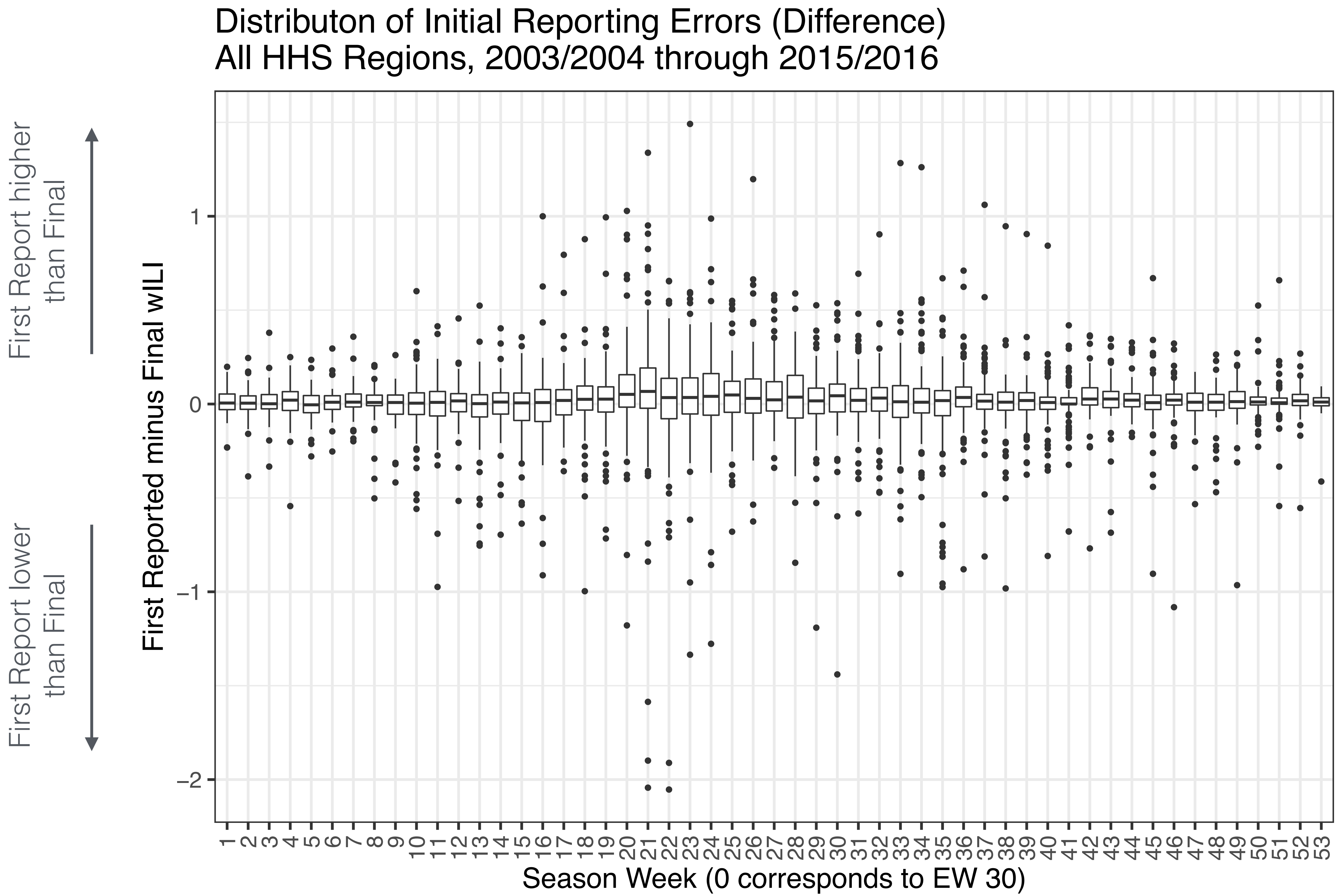


Figure by Casey Gibson

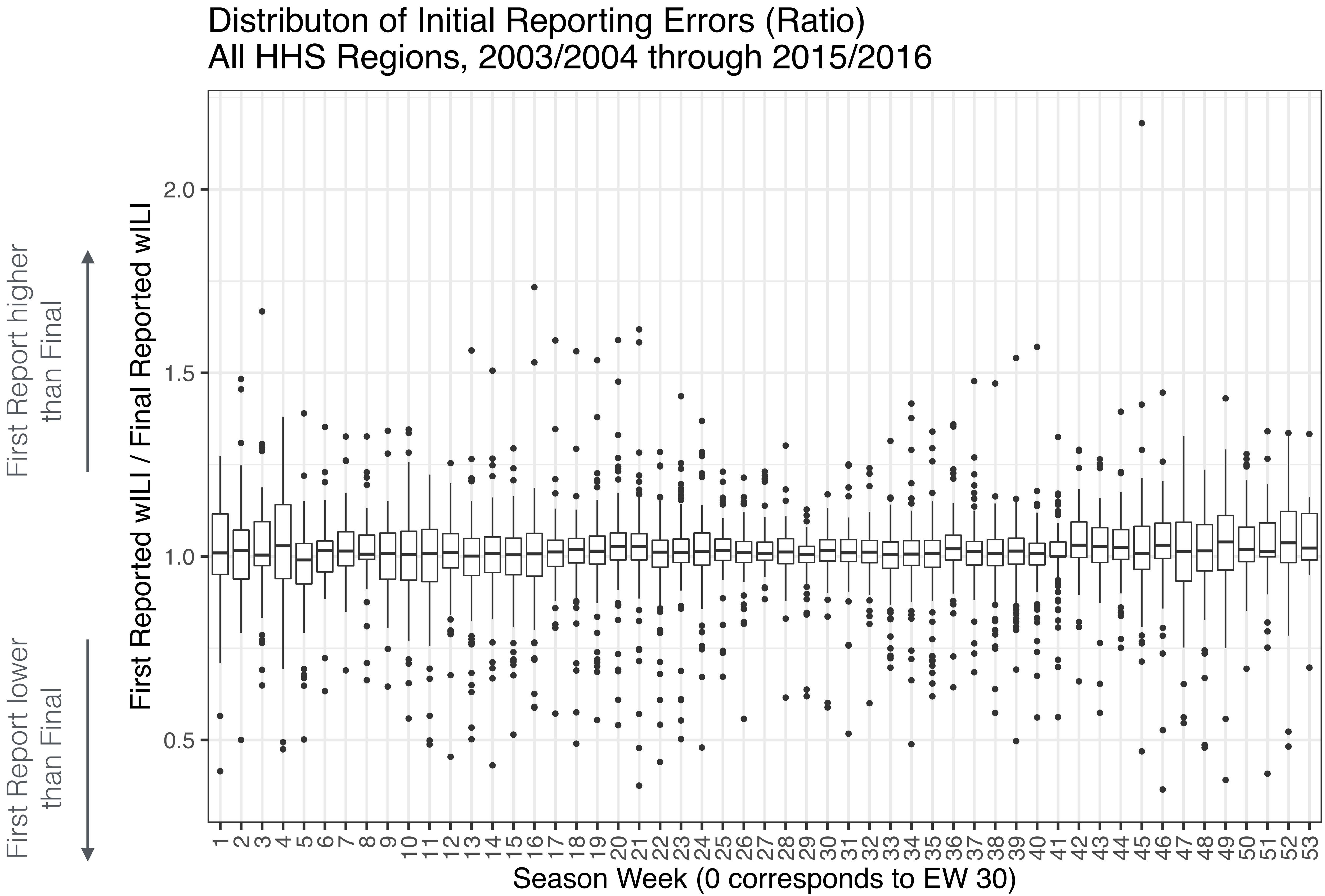
Initial Reporting Errors Slightly Smaller in Recent Seasons



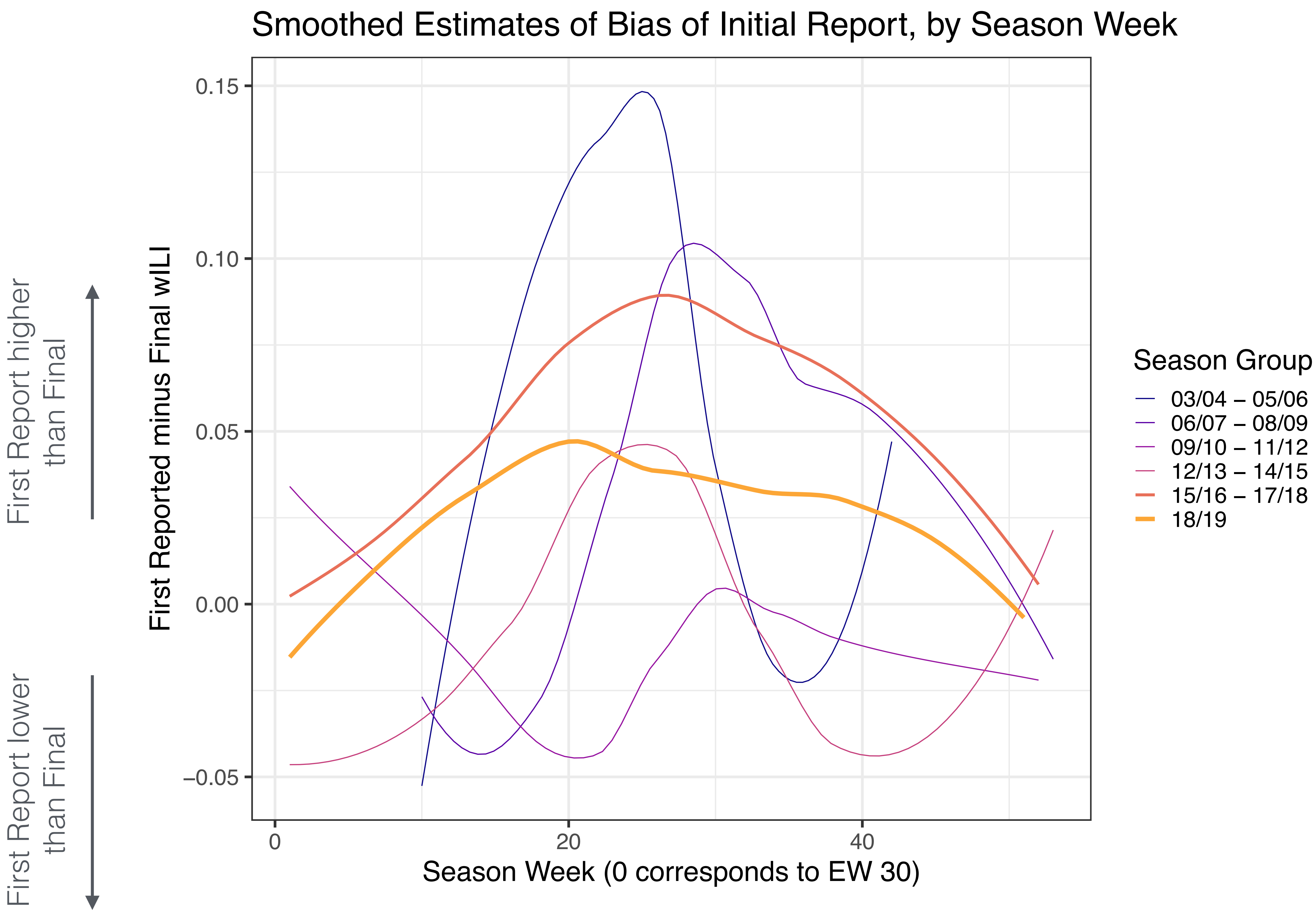
More Variability in Absolute Revisions Near Middle of Season



Relative Revisions More Consistent



Initial Report Bias Larger in Middle of Season, Reduced in Recent Seasons



Brooks et al. (2018): Large Effect on Forecast Skill for Seasonal Targets

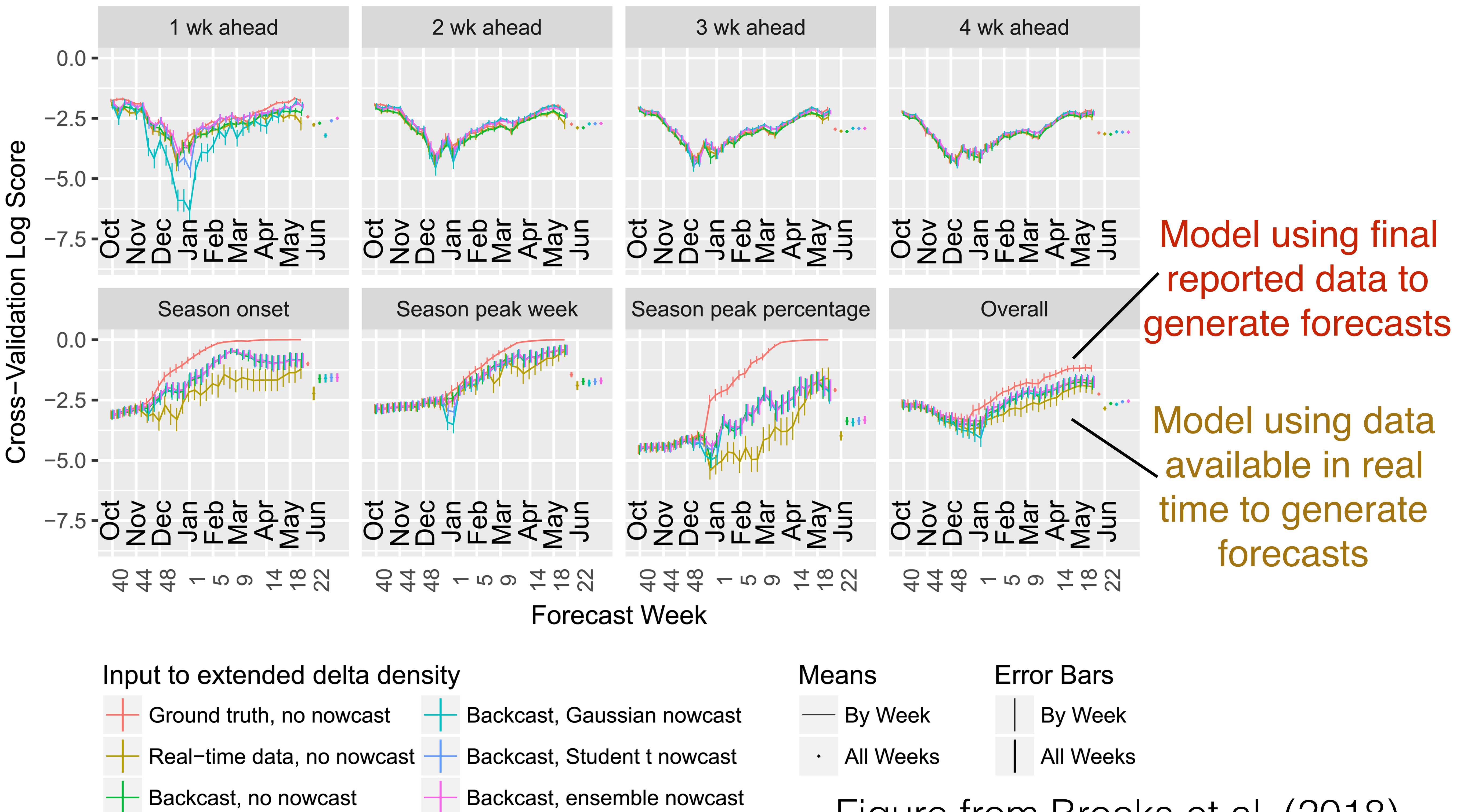


Figure from Brooks et al. (2018)

Relevance to Seasonal Targets

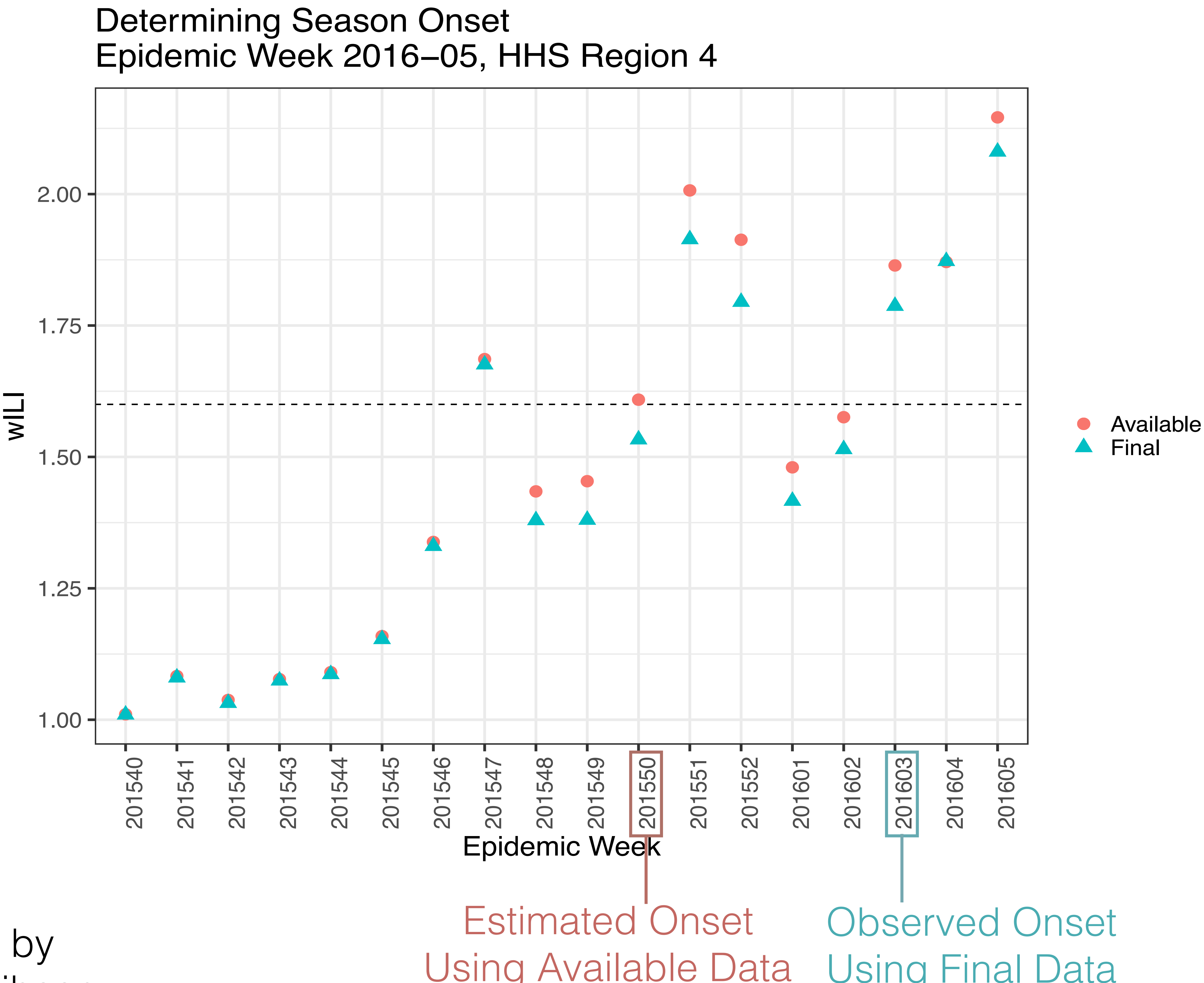
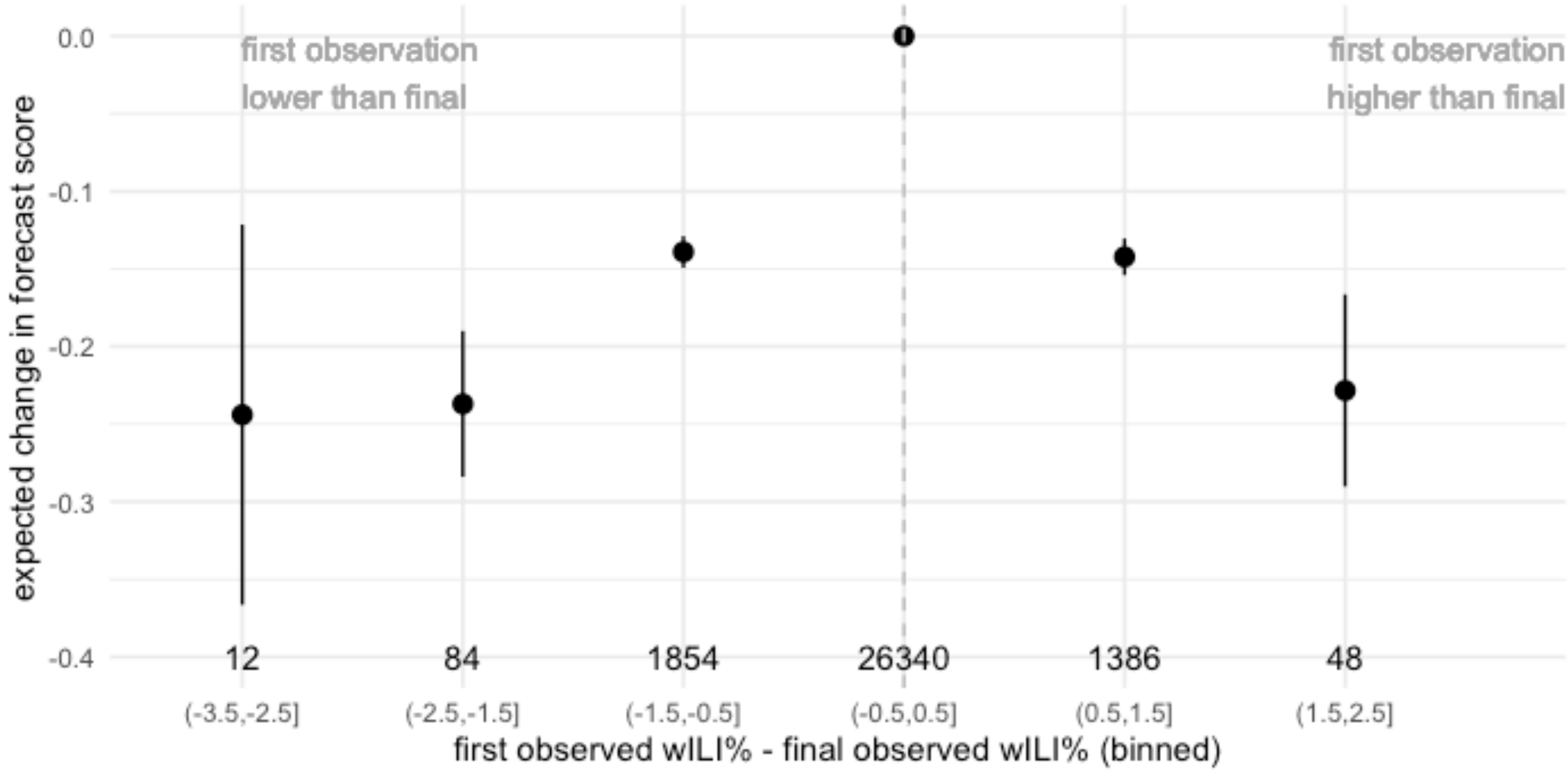


Figure by Casey Gibson

FluSight Network (Reich et al., 2019): Larger Effect on Forecast Skill for Larger Revisions

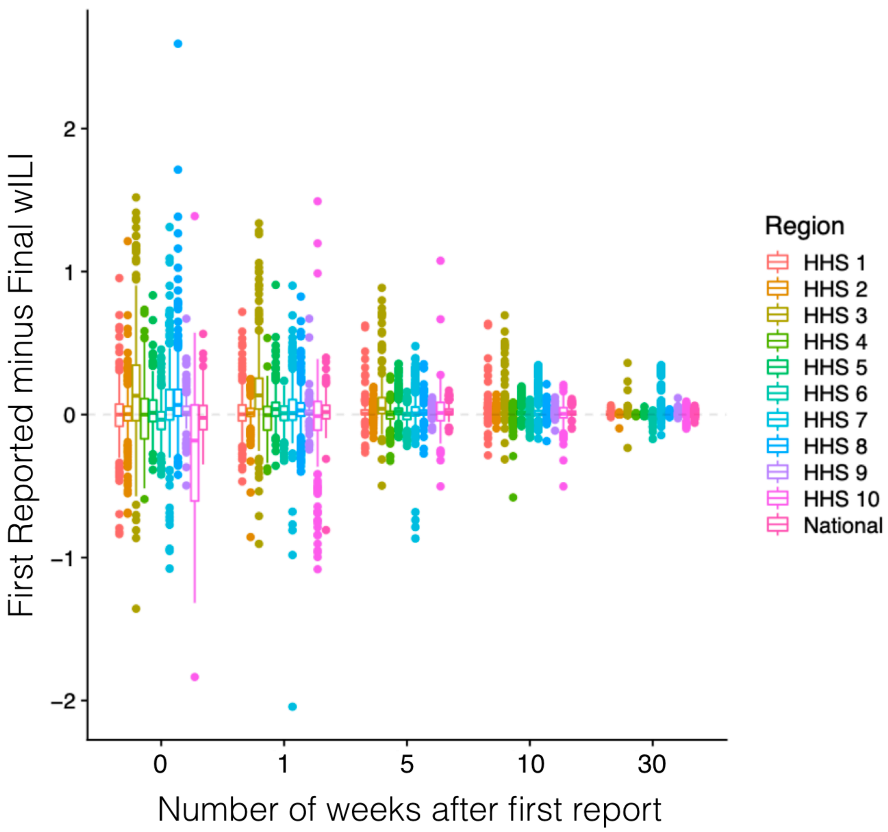


- "[T]here was an average change in forecast score of −0.29 (95% CI: −0.39, −0.19) when the first observed wILI measurement was between 2.5 and 3.5 percentage points lower than the final observed value, adjusting for model, week of year, and target."
- For a model with mean score of -1 (pretty good), this corresponds to a reduction of about 0.1 in probability assigned to the eventually observed outcome (or its neighbors).

Addressing without External Data

Basic Idea:

1. Estimate the distribution of reporting revisions based on past seasons
   - May be conditional on region, week of season, # of reporting providers …



Addressing without External Data

Basic Idea:

1. Estimate the distribution of reporting revisions based on past seasons
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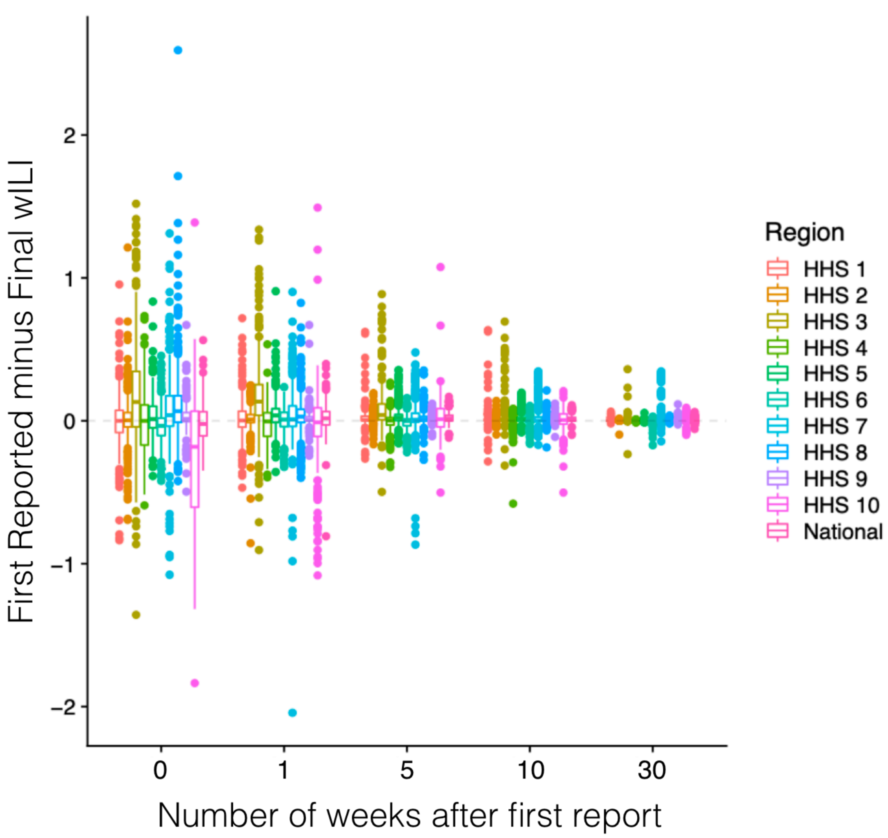
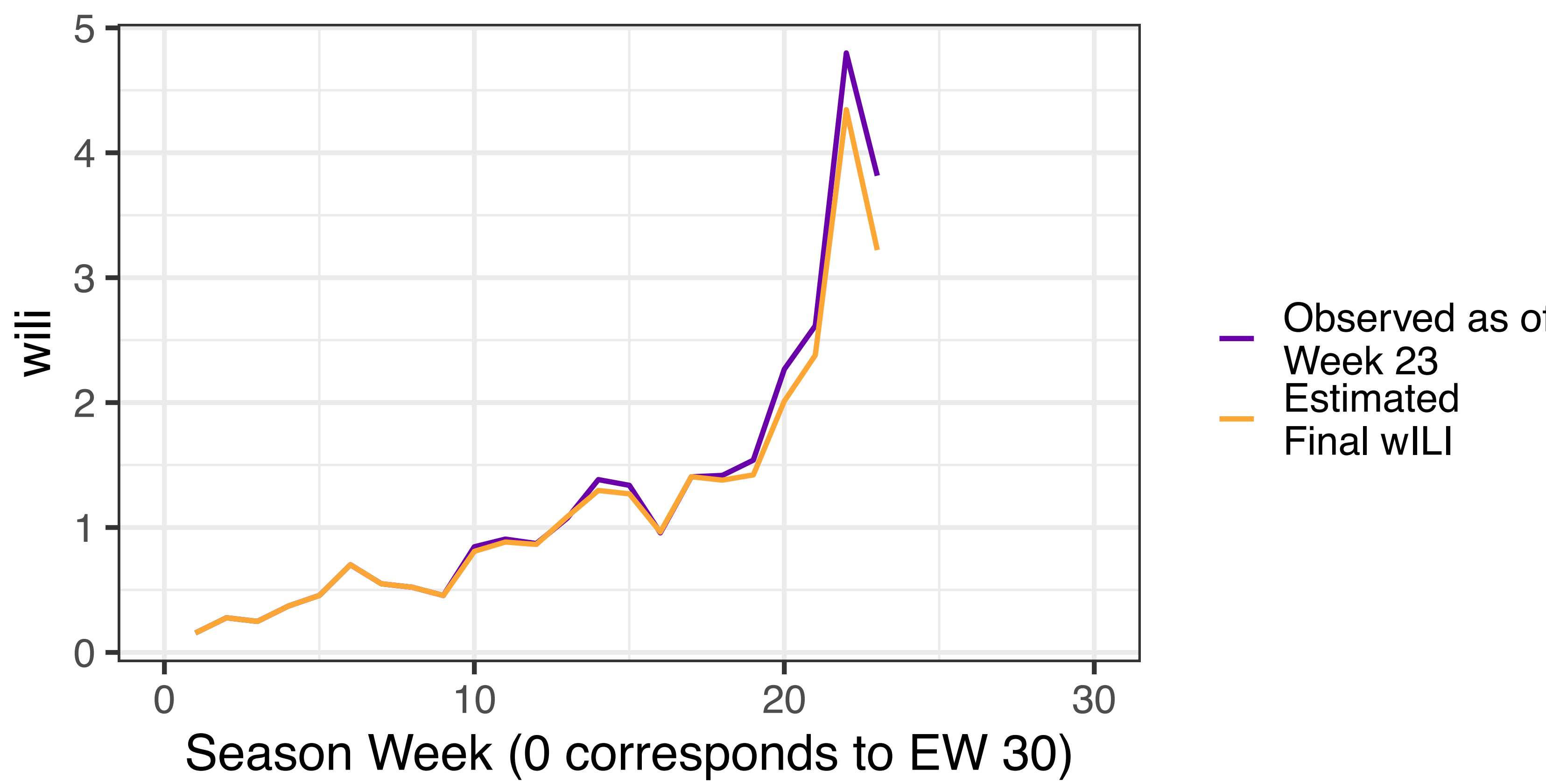
2. Estimate/impute final wILI in current season by adjusting early reports





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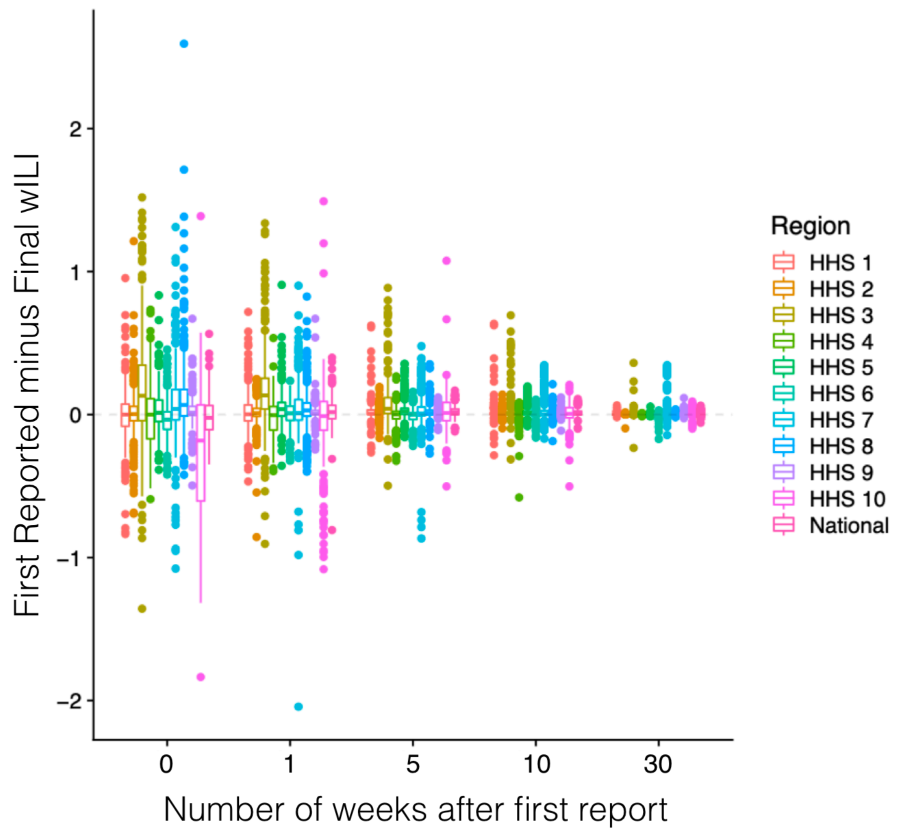
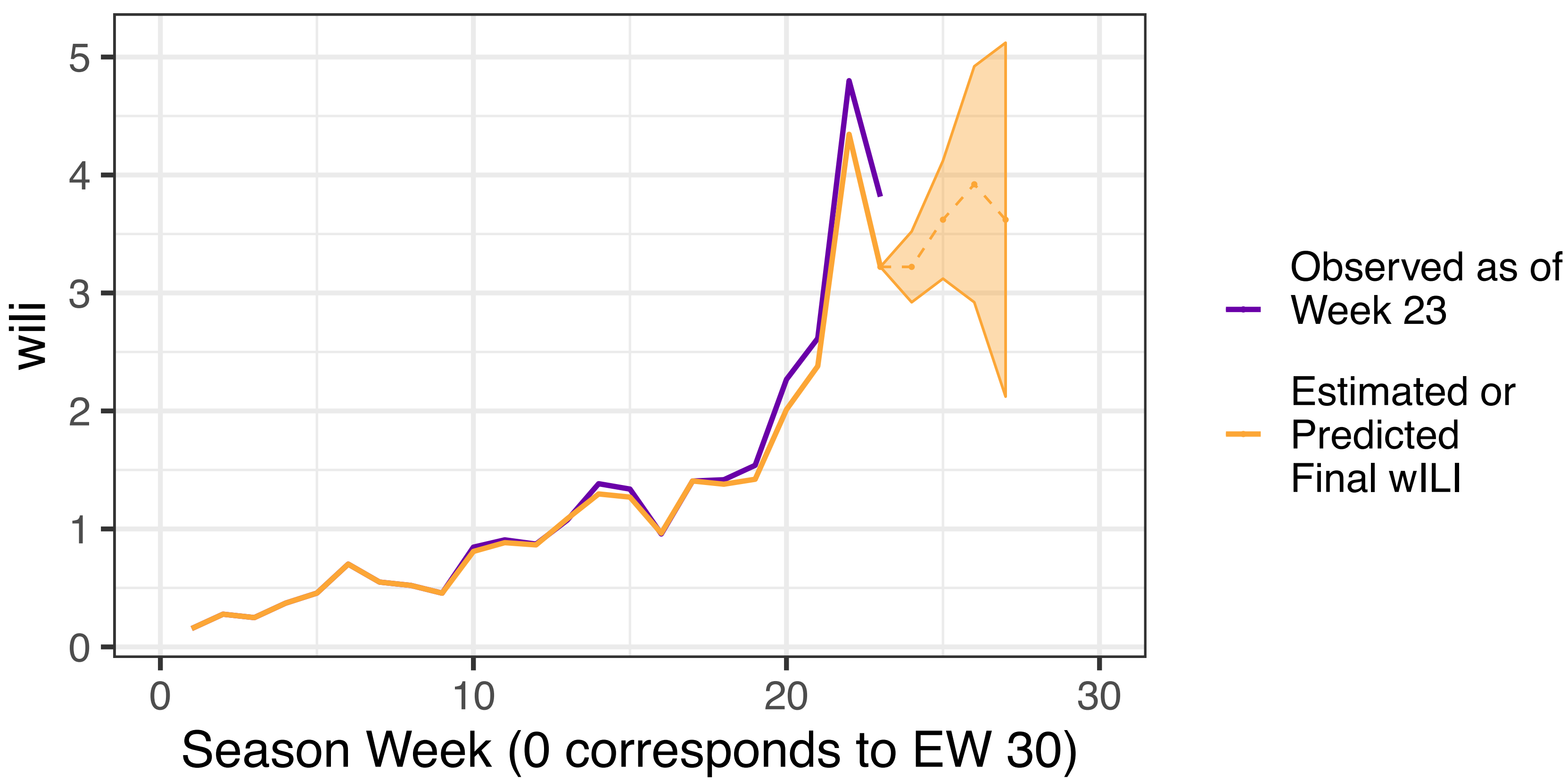
3. Use estimated final wILI as inputs to forecasting





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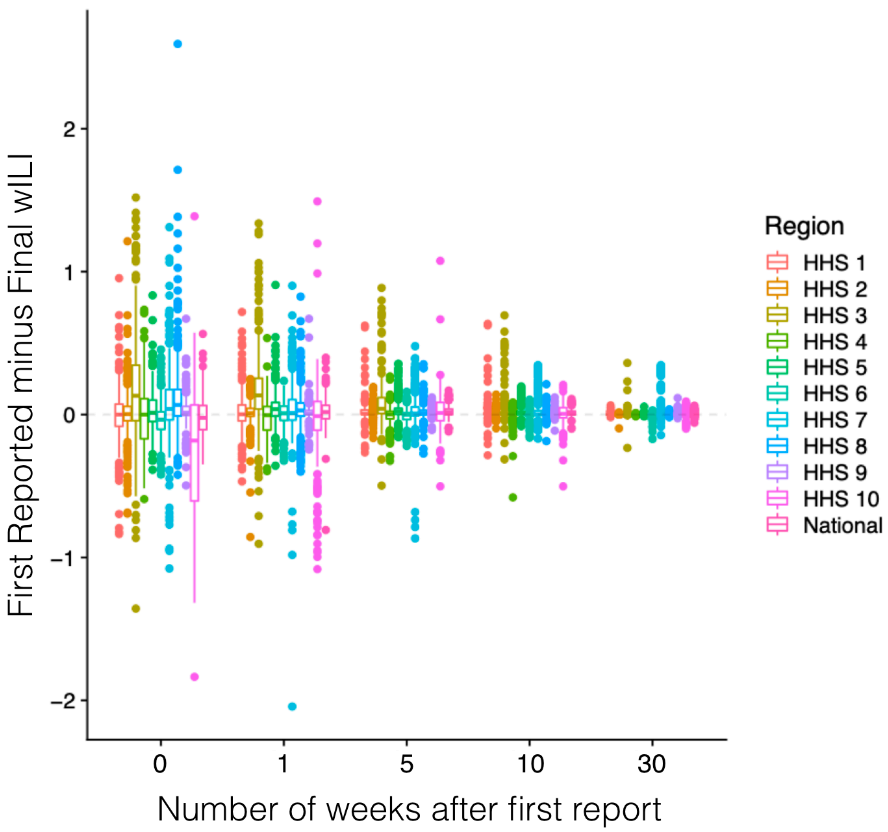
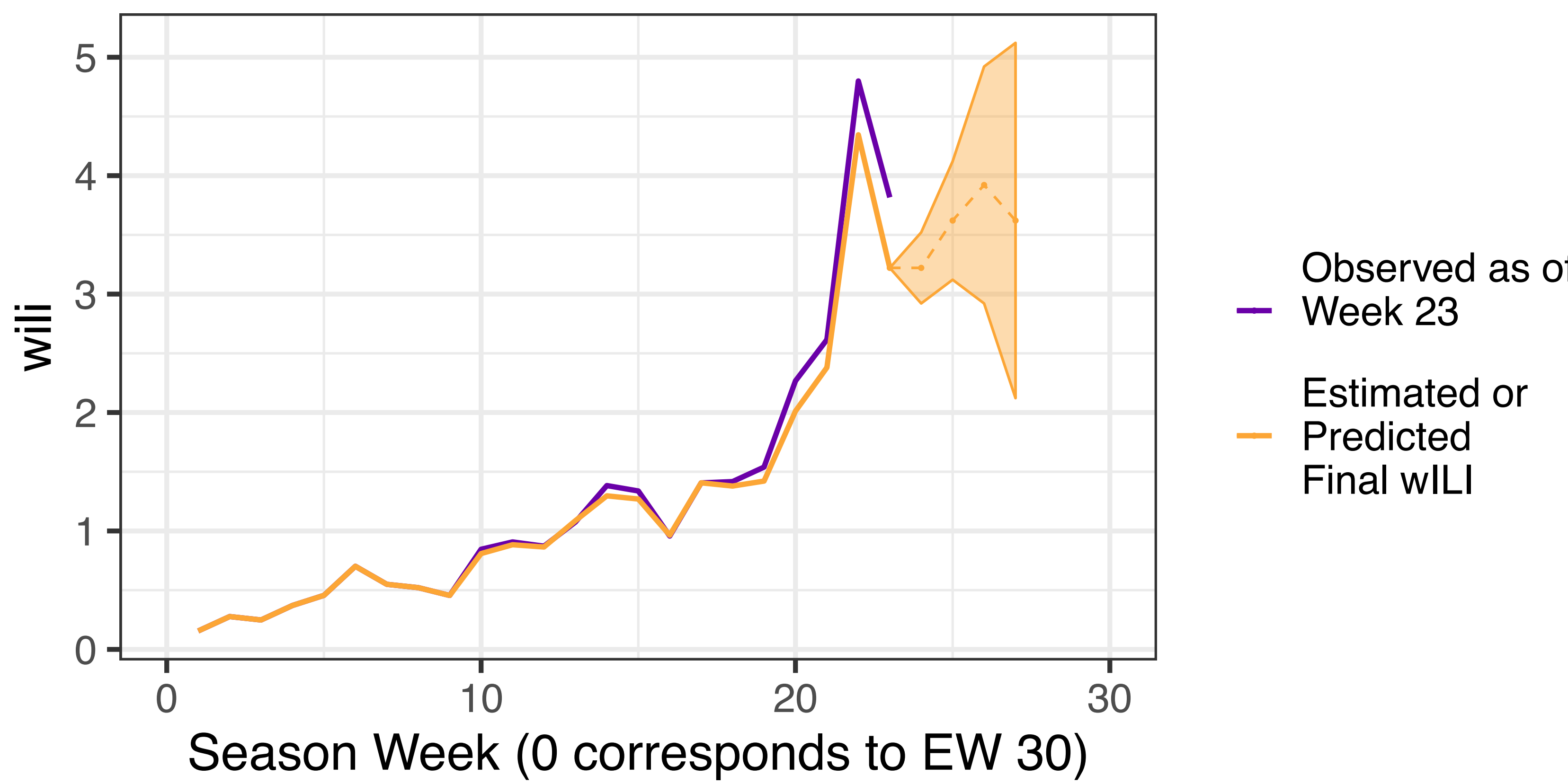
- We might sample many possible values for final wILI and repeat steps 2-3





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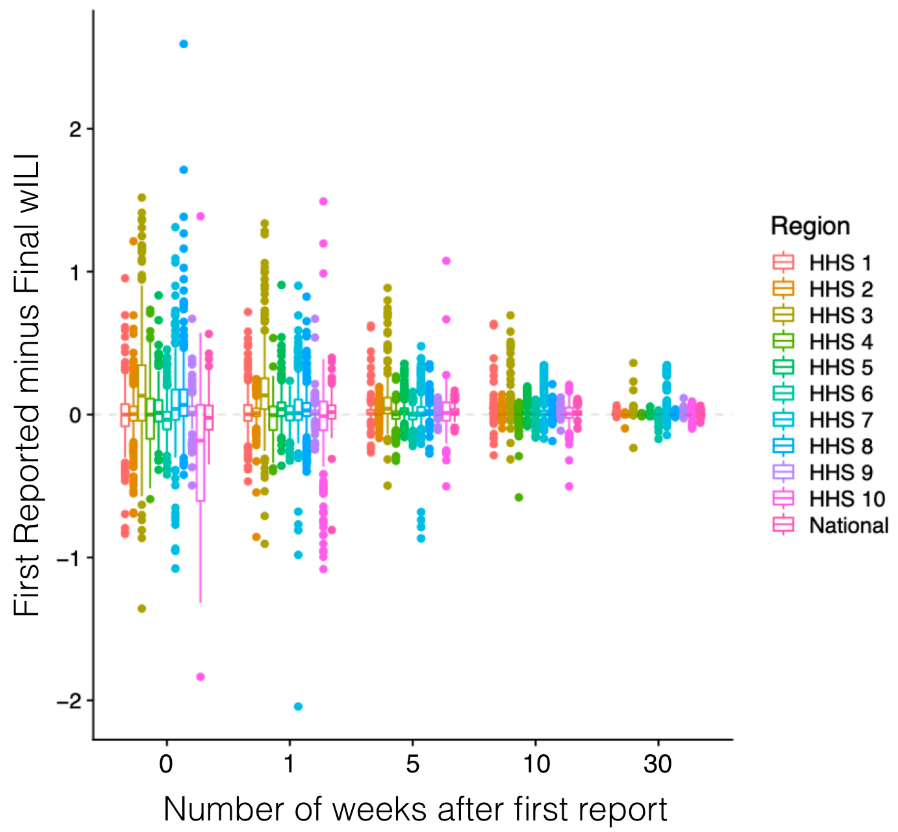
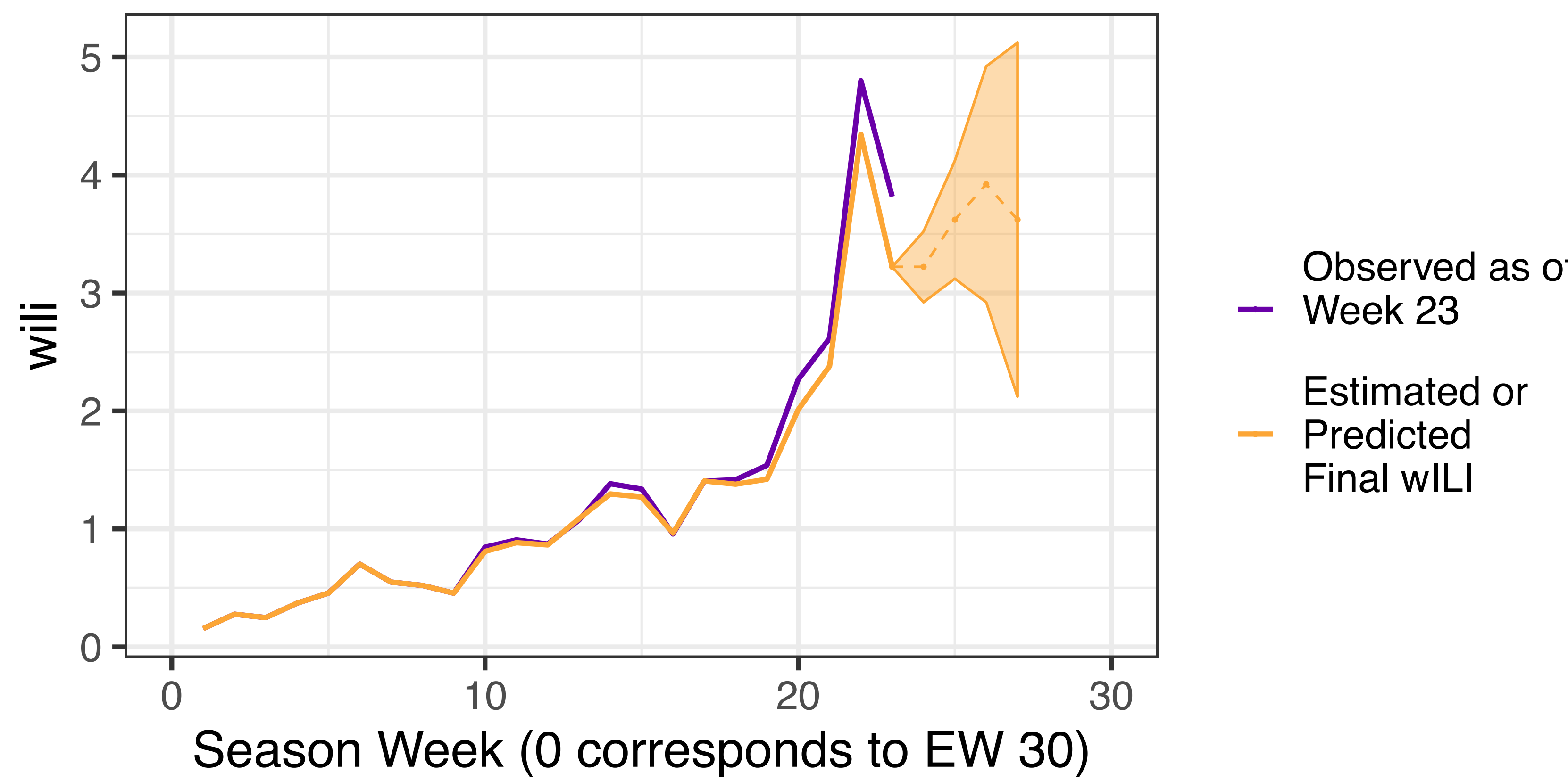




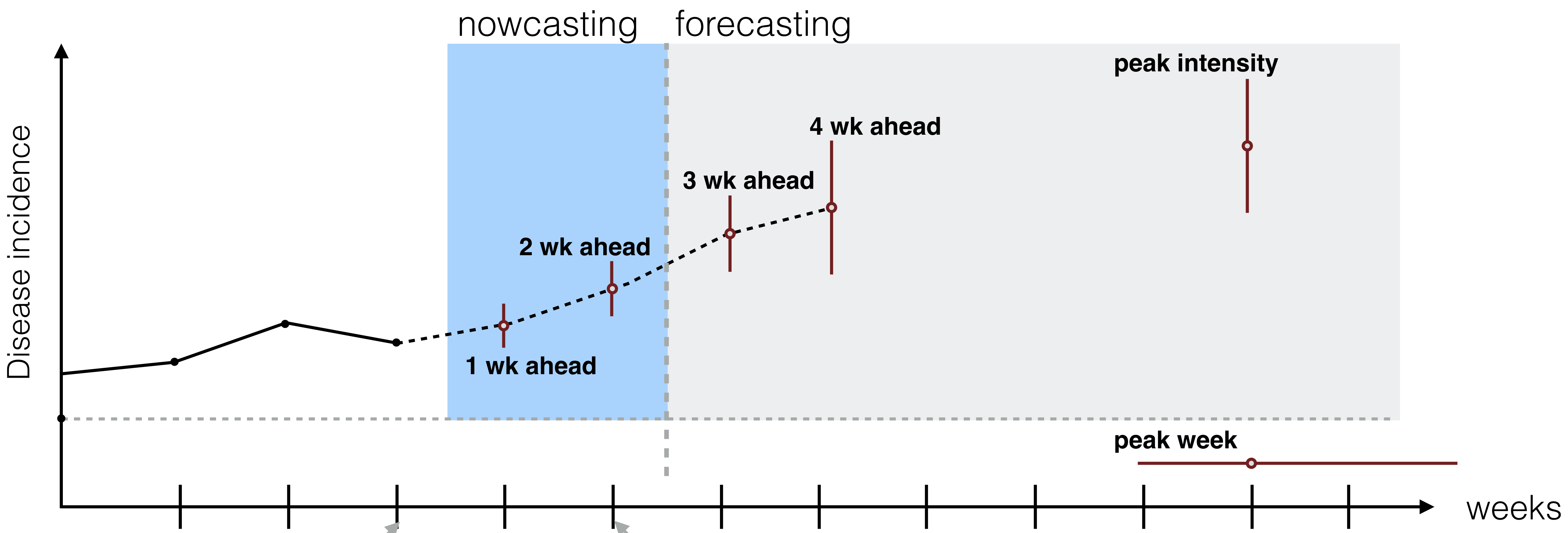
Examples in context of flu:

- Brooks et al. (2018)
- Work in progress by Casey Gibson

Examples in other contexts:

- Bastos et al. (2019) - dengue, ARI
- Höhle and an der Heiden (2014) - E. coli

Connection to "Nowcasting"

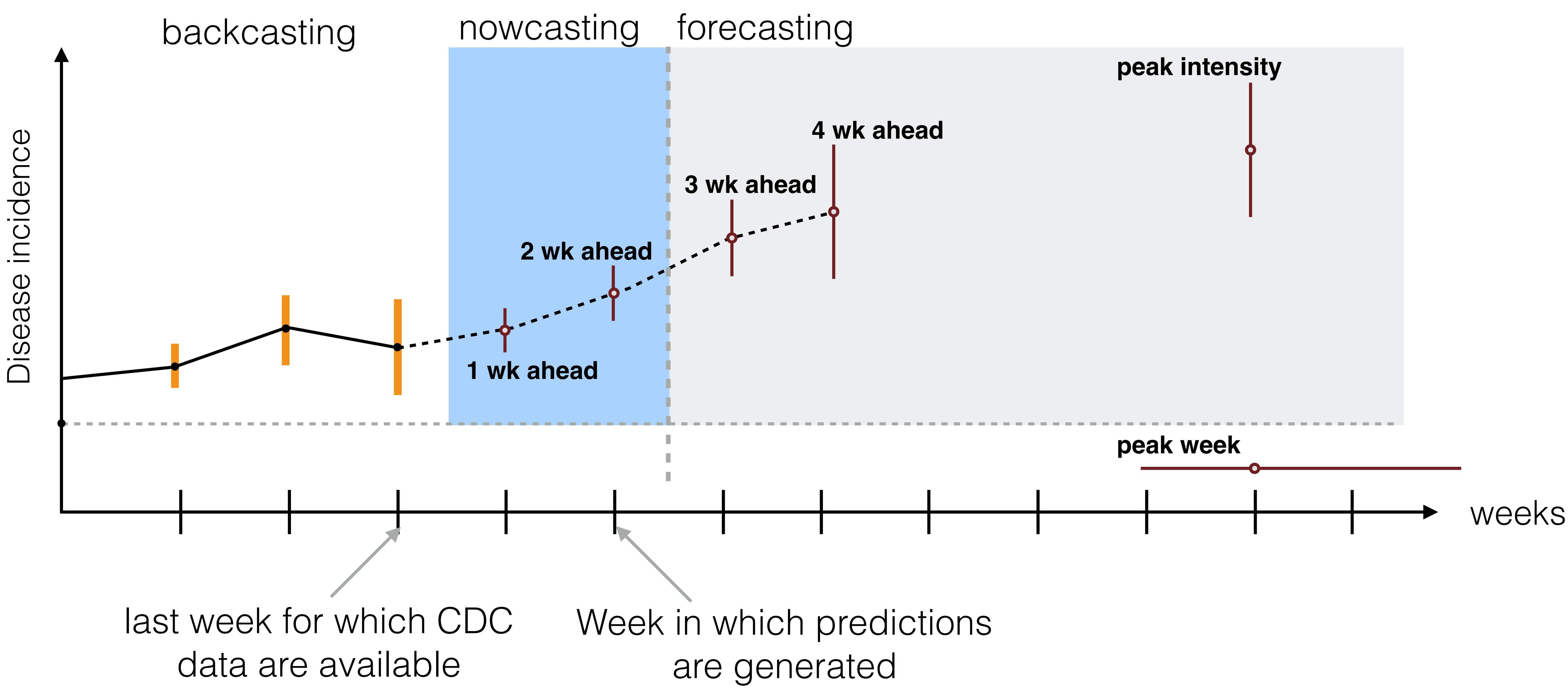


last week for which CDC data are available

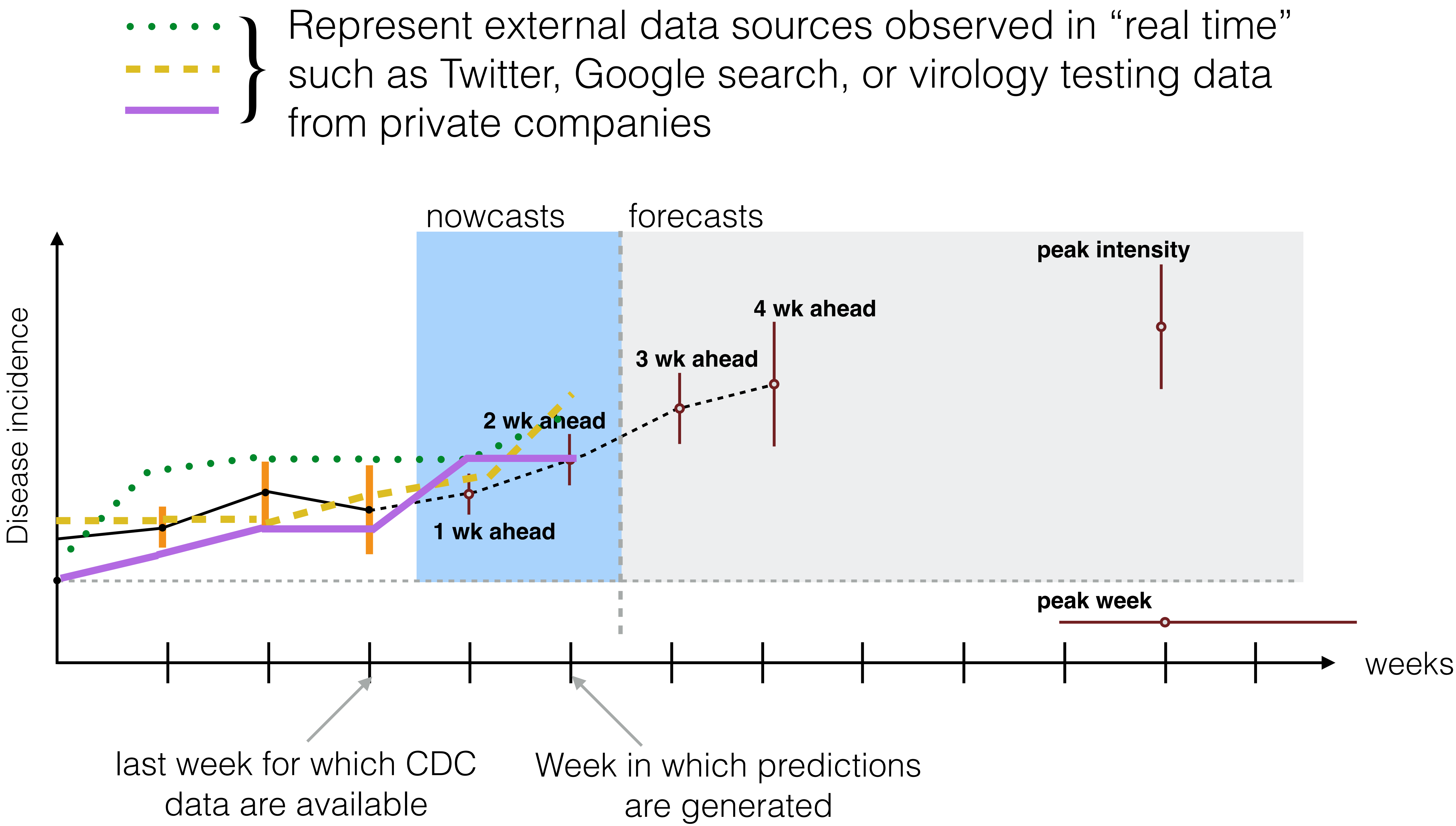
Week in which predictions are generated

Connection to “Nowcasting”

Bars represent uncertainty in observed wILI



Adding in External Data



Brooks et al. (2018): Backcasting and Nowcasting Are Helpful

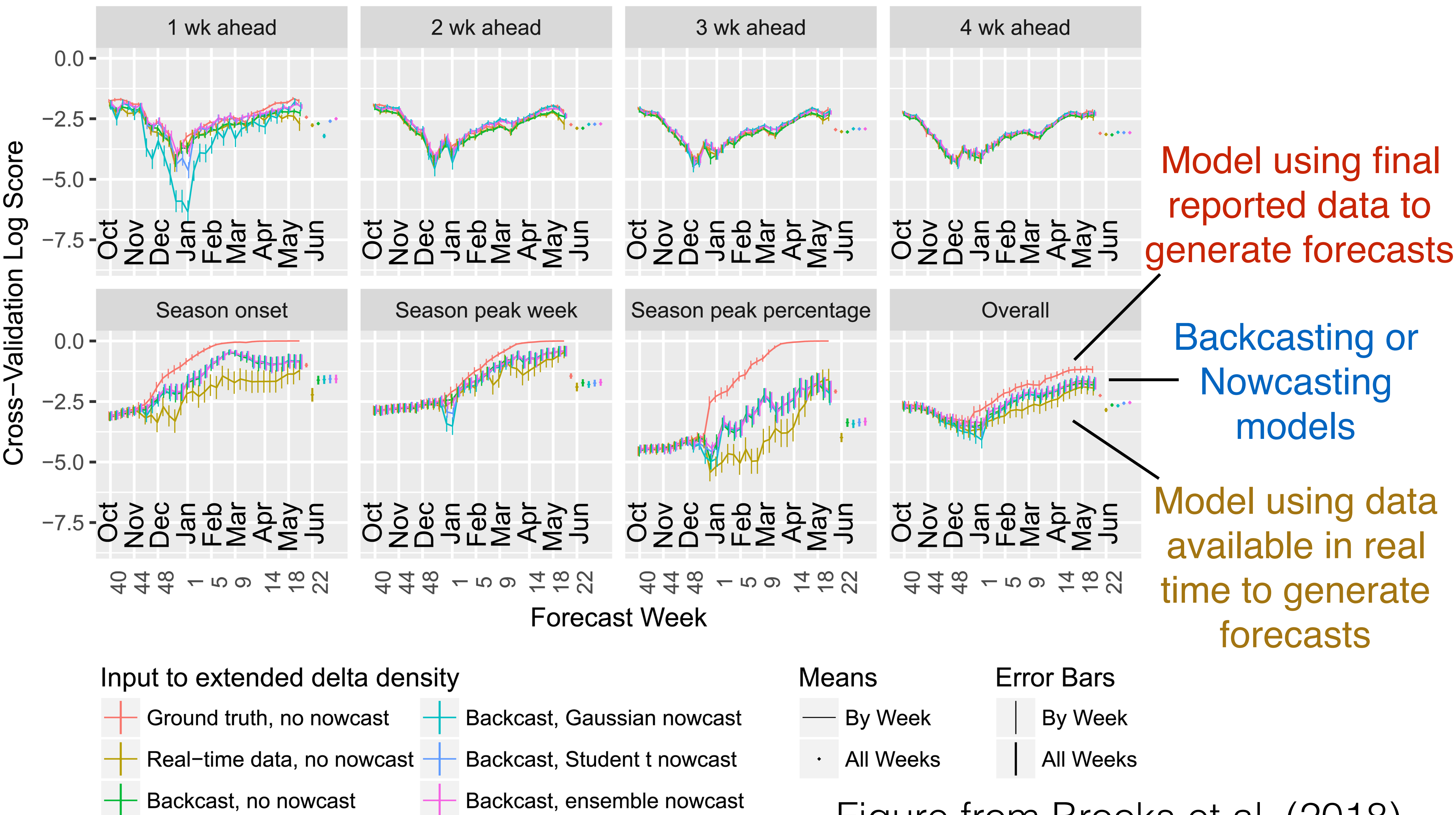
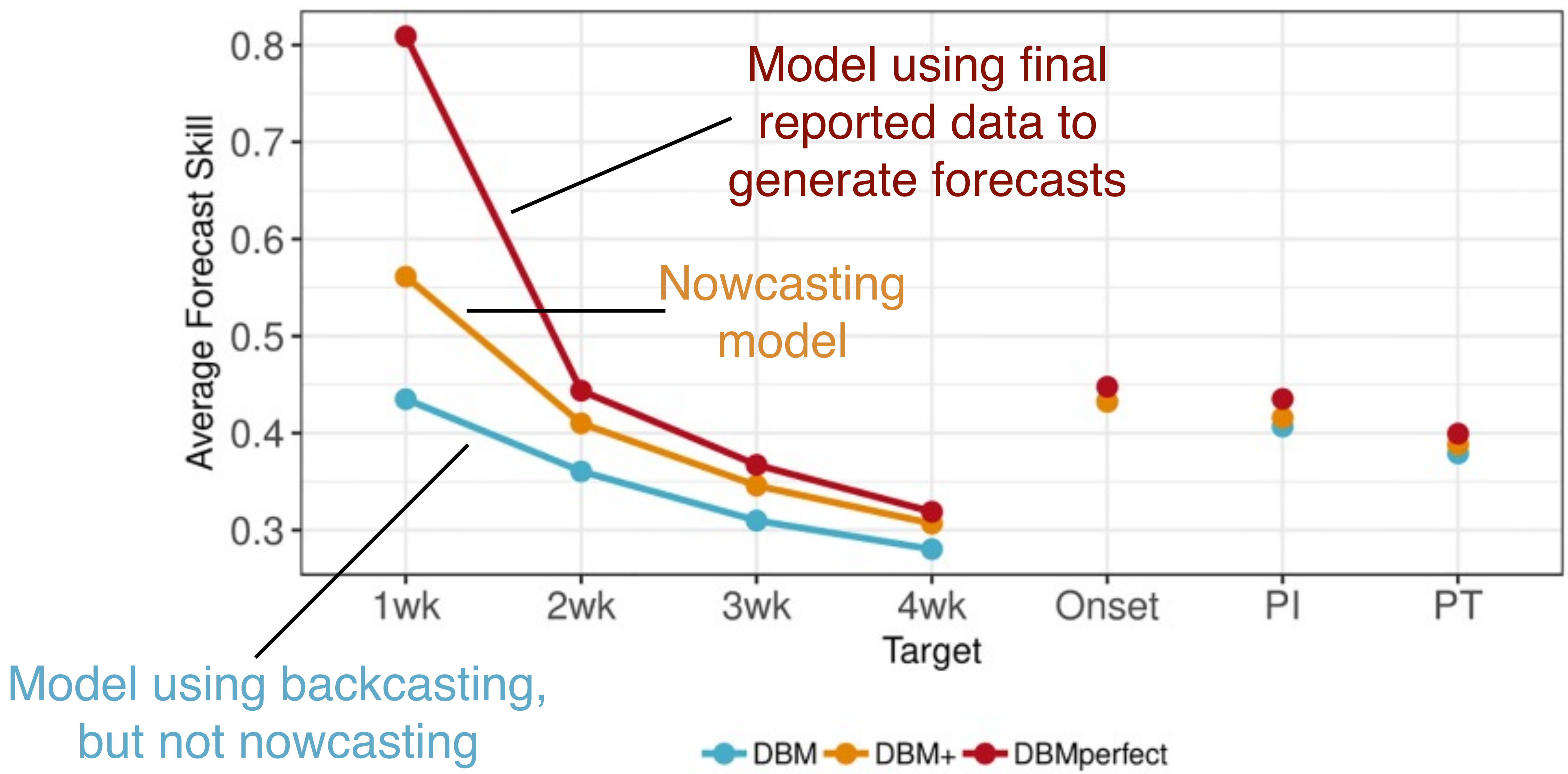


Figure from Brooks et al. (2018)

Osthus et al. (2018): Nowcasting is Helpful (all Models do Backcasting)



- Figure from Osthus et al. (2018)
- Additional examples in references: Brooks et al. (2018), Kandula et al. (2017), Kandula and Shaman (2019), Lu et al. (2019)

Summary

- Backfill is inevitable, but seems to be improving in recent seasons
- Backfill can have substantial impacts on forecast skill, especially for seasonal targets
- Statistical approaches to accounting for backfill can help, but don’t get us all the way to the forecast skill we would have in the absence of backfill
- Additionally, nowcasting with external data can be helpful.

References

1. Bastos LS, Economou T, Gomes MFC, Villela DAM, Coelho FC, Cruz OG, Stoner O, Bailey T, Codeço CT. A modelling approach for correcting reporting delays in disease surveillance data. *Statistics in Medicine*. 2019; 1-15.
2. Brooks LC, Farrow DC, Hyun S, Tibshirani RJ, Rosenfeld R. Nonmechanistic forecasts of seasonal influenza with iterative one-week-ahead distributions. *PLOS Computational Biology*. 2018; 14(6): e1006134.
3. Farrow DC, Jahja M, Rosenfeld R, Tibshirani RJ. Kalman filter, sensor fusion, and constrained regression: Equivalences and insights. arXiv. 2019; 1905.11436.
4. Höhle M, an der Heiden, M. Bayesian Nowcasting during the STEC O104:H4 Outbreak in Germany, 2011. *Biometrics*. 2014; 70, 993-1002.
5. Kandula S, Hsu D, Shaman J. Subregional Nowcasts of Seasonal Influenza Using Search Trends. *J Med Internet Res*. 2017;19(11):e370.
6. Kandula S and Shaman J. Reappraising the utility of Google Flu Trends. *PLOS Computational Biology*. 2019; 15(8):e1007258.
7. Lu FS, Hattab MW, Clemente CL, Biggerstaff M, Santillana M. Improved state-level influenza nowcasting in the United States leveraging Internet-based data and network approaches. *Nature Communications*. 2019; 10(147).
8. Osthus D, Daughton AR, Priedhorsky R. Even a good flu forecasting model can benefit from internet-based nowcasts, but those benefits are limited. *PLOS Computational Biology*. 2019; 15(2): e1006599.
9. Reich NG, Brooks LC, Fox SJ, Kandula S, McGowan CJ, Moore E, Osthus D, Ray EL, Tushar A, Yamana TK, Biggerstaff M, Johansson MA, Rosenfeld R, Shaman J. A collaborative multiyear, multimodel assessment of seasonal influenza forecasting in the United States. *Proceedings of the National Academy of Sciences*. 2019; 116(8), 3146-3154.
10. Unpublished work in progress by Casey Gibson (University of Massachusetts)

Source of Backfill in ILINet Data

Sick People Visit Doctor

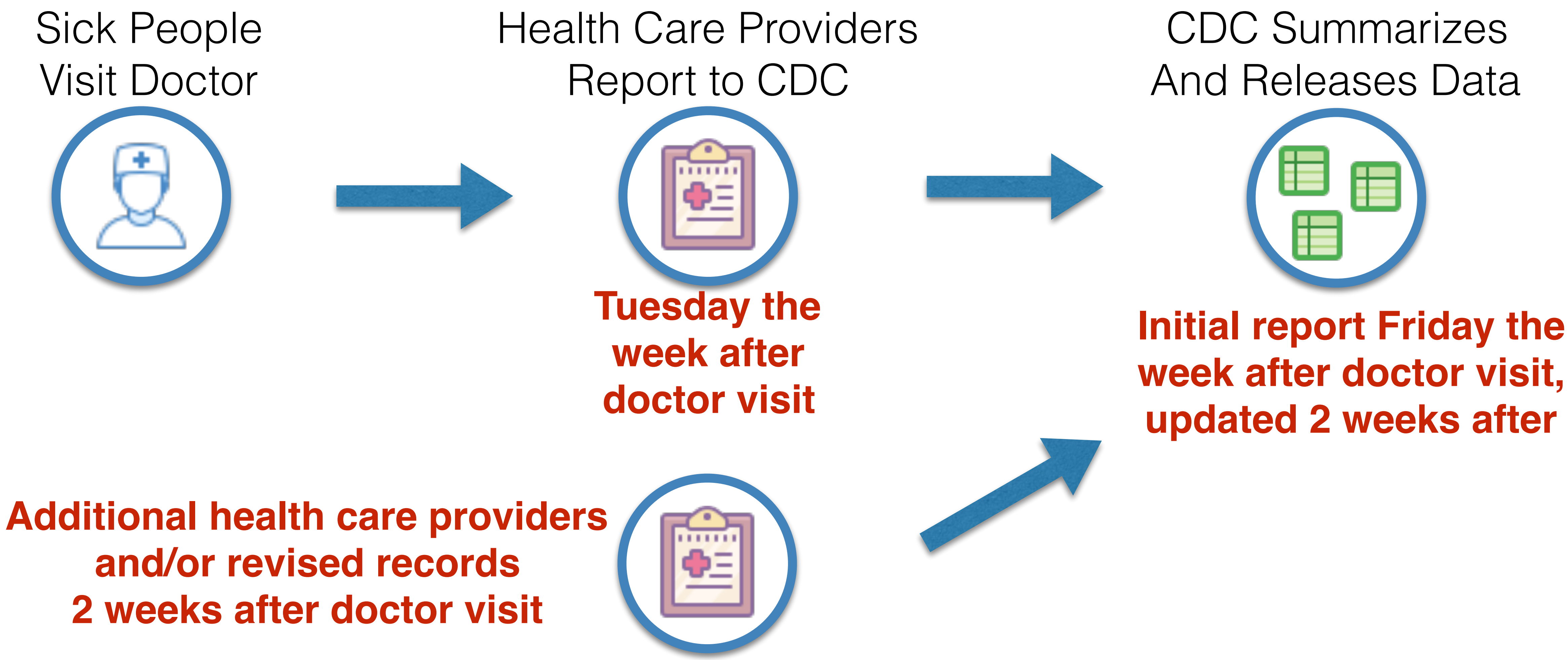
Health Care Providers Report to CDC

CDC Summarizes And Releases Data

Tuesday the week after doctor visit

Initial report Friday the week after doctor visit

Source of Backfill in ILINet Data



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