

# BETS: The dangers of selection bias in early analyses of the COVID-19 pandemic

Nianqiao (Phyllis) Ju

5-th year Ph.D. student

Dept. of Statistics, Harvard University

joint work with Q. Zhao, S. Bacallado & R. Shah  
at Statistical Laboratory, University of Cambridge

December 21st, 2020 @ CMStatistics 2020

Manuscript: [arXiv:2004.07743](https://arxiv.org/abs/2004.07743)

(forthcoming in *The Annals of Applied Statistics*)

Slides: <https://nianqiaoju.github.io>

# A puzzling comparison

## THE LANCET

ARTICLES | [VOLUME 395, ISSUE 10225, P689-697, FEBRUARY 29, 2020](#)

### Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study

[Prof Joseph T Wu, PhD](#)  \*  • [Kathy Leung, PhD](#) \* • [Prof Gabriel M Leung, MD](#) • [Show footnotes](#)

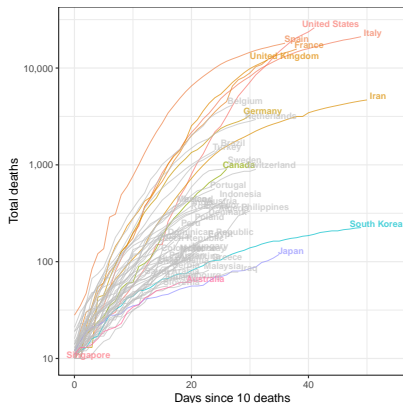
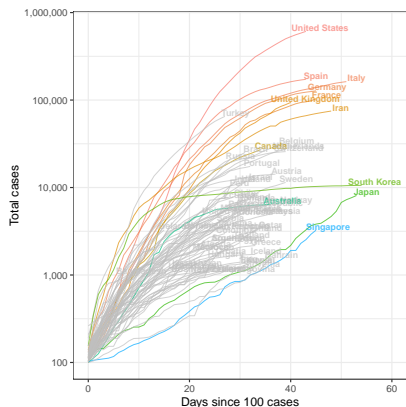
Published: January 31, 2020 DOI: [https://doi.org/10.1016/S0140-6736\(20\)30260-9](https://doi.org/10.1016/S0140-6736(20)30260-9)



**Methods** We used data from Dec 31, 2019, to Jan 28, 2020, on the number of cases exported from Wuhan internationally (known days of symptom onset from Dec 25, 2019, to Jan 19, 2020) to infer the number of infections in Wuhan from Dec 1, 2019, to Jan 25, 2020. Cases exported domestically were then estimated. We forecasted the national and global spread of 2019-nCoV, accounting for the effect of the metropolitan-wide quarantine of Wuhan

**Findings** In our baseline scenario, we estimated that the basic reproductive number for 2019-nCoV was 2.68 (95% CrI 2.47–2.86) and that 75 815 individuals (95% CrI 37 304–130 330) have been infected in Wuhan as of Jan 25, 2020. The epidemic doubling time was 6.4 days (95% CrI 5.8–7.1). We estimated that in the baseline scenario, Chongqing, Beijing, Shanghai, Guangzhou, and Shenzhen had imported 461 (95% CrI 227–805),

# Which one is correct?



In countries most hard hit by COVID-19, the total cases and deaths grew about 100 times in the first 20 days (doubling time:  $20 / \log_2(100) = 3.01$  days).

# Similar data, different inference?

The Lancet study ignored the lockdown of Wuhan on Jan. 23rd.



Figure: (left) before the lockdown (picture taken on Sept. 7, 2019) and (right) after the lockdown.

# Selection bias

- ① **under-ascertainment bias**: symptomatic patients did not seek healthcare or could not be diagnosed.
- ② **non-random selection bias**: cases included in the study are not representative of the population.
- ③ **travel ban**: ignoring the travel ban leads to under-estimation of epidemic growth.
- ④ **epidemic growth**: patients were more likely to be infected towards the end of their exposure period.
- ⑤ **right-truncation**: cases confirmed after a certain time are excluded from the dataset.

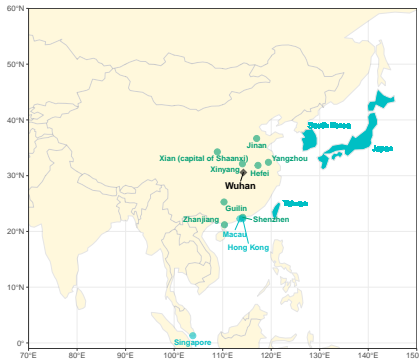
## Selection bias recap

selection bias	epidemic growth	incubation period
under-ascertainment bias non-random selection bias travel ban epidemic growth right-truncation	under-estimation	over-estimation under-estimation

### Keys to avoid the selection bias:

- ① Carefully design the study and adhere to the sample inclusion criterion.
- ② Start from a generative model and derive likelihood functions that adjust for sample selection.

# Data collection



- 14 locations where the local health agencies published full case reports.
- 1,460 COVID-19 cases that were confirmed by February 29 for locations in mainland China (February 15 for international locations).

# Overview of the dataset

available at <https://github.com/qingyuanzhao/bets.covid19>

Column name	Description	Example	Summary statistics
Case Residence Gender Age	Unique identifier for each case Nationality or residence of the case Gender Age	HongKong-05 Wuhan <input type="checkbox"/> Male / <input type="checkbox"/> Female 63	1460 in total 21.5% reside in Wuhan 52.1%/47.7% (0.2% NA) Mean=45.6, IQR=[34, 57]
Known Contact Cluster	Known epidemiological contact? Relationship with other cases	<input type="checkbox"/> Yes / <input type="checkbox"/> No Husband of HongKong-04	84.7%/15.3% 32.1% known
<b>Outside</b>	<b>Transmitted outside Wuhan?</b>	Yes/ <input type="checkbox"/> Likely / No	58.5%/7.7%/33.8%
<b>Begin Wuhan</b> <b>End Wuhan</b> Exposure	<b>Begin of stay in Wuhan (B)</b> <b>End of stay in Wuhan (E)</b> Period of exposure	30-Nov 22-Jan 1-Dec to 22-Jan	58.9% known period/date 8.2% known date
Arrived  <b>Symptom</b> Initial Confirmed	Final arrival date at the location where confirmed a COVID-19 case  <b>Date of symptom onset (S)</b> Date of first medical visit Date confirmed	22-Jan  23-Jan 23-Jan 24-Jan	40.6% did not travel  9.0% NA 6.5% NA



## Discerning Wuhan-exported cases

We obtained 378 cases exported from Wuhan that satisfy the following criteria:

- The case had stayed in Wuhan before January 23.
- The case had no recorded contact with other confirmed cases, or had the earliest symptom onset in their (family) cluster, or showed symptoms before they left Wuhan.
- The case did not have missing symptom onset.
- The case arrived at the location where they were diagnosed before January 24.

The principle is to only include cases as [Wuhan-exported](#) that pass a **“beyond a reasonable doubt”** test.

# A generative model

## Four crucial epidemiological events

- $B$ : Beginning of stay in Wuhan;
- $E$ : End of stay in Wuhan;
- $T$ : Time of transmission (unobserved);
- $S$ : Time of symptom onset.

Below we will:

- Define the support  $\mathcal{P}$  of  $(B, E, T, S)$  for the **Wuhan-exposed** population;
- Construct a generative model for  $(B, E, T, S)$ ;
- Define the sample selection set  $\mathcal{D}$  corresponds to **Wuhan-exported** cases;
- Derive likelihood functions to adjust for the sample selection.

# Wuhan-exposed population $\mathcal{P}$

Intuitively,  $\mathcal{P}$  = All people who stayed in Wuhan between December 1, 2019 (time 0) and January 24, 2020 (time  $L$ , the lockdown).

$$\mathcal{P} = \left\{ (b, e, t, s) \mid b \in [0, L], e \in [b, L] \cup \{\infty\}, t \in [b, e] \cup \{\infty\}, s \in [t, \infty] \right\}.$$

Under the following conventions.

- $B = 0$ : Started their stay in Wuhan before time 0.
- $E = \infty$ : Did not arrive in the 14 locations we are considering before time  $L$ . (We do not differentiate between people who stayed in Wuhan or went to a different location).
- $T = \infty$ : Were not infected during their stay in Wuhan. (We do not differentiate between infection outside Wuhan and never infected.)
- $S = \infty$ : Did not show symptoms of COVID-19 (never infected or asymptomatic).

## Wuhan-exported cases

The event of observing **Wuhan-exported cases** can be written as

$$\mathcal{D} = \{(b, e, t, s) \in \mathcal{P} \mid b \leq t \leq e \leq L, t \leq s < \infty\}.$$

Recall that **Wuhan-exposed population** is

$$\mathcal{P} = \{(b, e, t, s) \mid b \in [0, L], e \in [b, L] \cup \{\infty\}, t \in [b, e] \cup \{\infty\}, s \in [t, \infty]\}.$$

The Wuhan-exported cases have

- ①  $B \leq T \leq E,$
- ②  $E \leq L,$
- ③  $S < \infty.$

# A generative BETS model

$$f(b, e, t, s) = \underbrace{f_B(b) \cdot f_E(e | b)}_{\text{travel}} \cdot \underbrace{f_T(t | b, e)}_{\text{disease transmission}} \cdot \underbrace{f_S(s | b, e, t)}_{\text{disease progression}} .$$

The BETS model makes two basic assumptions:

Assumption 1: Disease transmission independent of travel

$$f_T(t | b, e) = \begin{cases} g(t), & \text{if } b < t < e, \\ 1 - \int_b^e g(x) dx, & \text{if } t = \infty. \end{cases}$$

Here  $g(\cdot)$  models the **epidemic growth** in Wuhan before the lockdown.

## A generative BETS model

$$f(b, e, t, s) = \underbrace{f_B(b) \cdot f_E(e | b)}_{\text{travel}} \cdot \underbrace{f_T(t | b, e)}_{\text{disease transmission}} \cdot \underbrace{f_S(s | b, e, t)}_{\text{disease progression}} .$$

Assumption 2: Disease progression independent of travel

$$f_S(s | b, e, t) = \begin{cases} \nu \cdot h(s - t), & \text{if } t < s < \infty, \\ 1 - \nu, & \text{if } s = \infty. \end{cases}$$

Here  $h(\cdot)$  is the density of the **incubation period**  $S - T$  (for symptomatic cases).

# Parametric assumptions

To ease the interpretation and simplify the likelihood functions, we assume:

Assumption 3: Exponential growth

$$g(t) = g_{\kappa,r}(t) \triangleq \kappa \cdot \exp(rt), \quad t \leq L,$$

Assumption 4: Gamma-distributed incubation period

$$h(s-t) = h_{\alpha,\beta}(s-t) \triangleq \frac{\beta^\alpha}{\Gamma(\alpha)} (s-t)^{\alpha-1} \exp\{-\beta(s-t)\}.$$

## Which likelihood function?

For a moment, let's pretend the time of transmission  $T$  is observed.

✗ Sample from  $\mathcal{P}$

$$\prod_{i=1}^n f(B_i, E_i, T_i, S_i)$$

✓ Sample from  $\mathcal{D}$  (Unconditional likelihood)

$$\prod_{i=1}^n f(B_i, E_i, T_i, S_i | \mathcal{D}), \text{ where } f(b, e, t, s | \mathcal{D}) \triangleq \frac{f(b, e, t, s) \cdot \mathbf{1}_{\{(b,e,t,s) \in \mathcal{D}\}}}{\mathbb{P}((B, E, T, S) \in \mathcal{D})}.$$

✓ Sample from  $\mathcal{D}$  (Conditional likelihood)

$$\prod_{i=1}^n f(T_i, S_i | B_i, E_i, \mathcal{D}), \text{ where } f(t, s | b, e, \mathcal{D}) \triangleq \frac{f(t, s | B = b, E = e) \cdot \mathbf{1}_{\{(b,e,t,s) \in \mathcal{D}\}}}{\mathbb{P}((B, E, T, S) \in \mathcal{D} | B = b, E = e)}.$$



## Unobserved $T$

In reality, the time of transmission  $T$  is unobserved. We can use the **marginal likelihood**:

Unconditional likelihood

$$L_{\text{uncond}}(\theta) = \prod_{i=1}^n \int f(B_i, E_i, t, S_i | \mathcal{D}) dt,$$

where  $\theta = (f_B(\cdot), f_E(\cdot | \cdot), g(\cdot), h(\cdot))$ .

Conditional likelihood

$$L_{\text{cond}}(\theta) = \prod_{i=1}^n \int f(t, S_i | B_i, E_i, \mathcal{D}) dt,$$

where  $\theta = (g(\cdot), h(\cdot))$ .

# Results

Location	Sample size	Doubling time (in days)	Incubation period	
			Median	95% quantile
<b>Conditional likelihood</b>				
China - Hefei	34	2.1 (1.2–3.7)	4.3 (2.9–6.0)	12.0 (9.1–17.3)
China - Shaanxi	53	1.7 (1.0–2.8)	4.5 (3.1–6.2)	14.6 (11.5–19.8)
China - Shenzhen	129	2.2 (1.7–3.0)	3.5 (2.8–4.3)	11.2 (9.5–13.6)
China - Xinyang	74	2.3 (1.5–3.5)	6.8 (5.4–8.2)	16.4 (13.8–20.1)
China - Other	42	2.0 (1.1–3.4)	5.1 (3.6–6.7)	12.3 (9.8–16.4)
International	46	2.1 (1.4–3.4)	3.8 (2.5–5.3)	10.9 (8.4–15.1)
<b>All locations</b>	<b>378</b>	<b>2.1 (1.8–2.5)</b>	<b>4.5 (4.0–5.0)</b>	<b>13.4 (12.2–14.8)</b>
<b>Unconditional likelihood</b>				
China - Hefei	34	1.8 (1.4–2.4)	4.1 (2.8–5.5)	11.9 (9.0–17.2)
China - Shaanxi	53	2.5 (2.0–3.1)	5.3 (3.9–6.8)	15.0 (12.0–20.0)
China - Shenzhen	129	2.4 (2.1–2.8)	3.6 (2.9–4.3)	11.3 (9.6–13.7)
China - Xinyang	74	2.4 (2.0–2.9)	6.8 (5.6–8.1)	16.4 (13.9–20.2)
China - Other	42	2.1 (1.7–2.8)	5.3 (4.0–6.6)	12.4 (10.0–16.4)
International	46	2.0 (1.6–2.6)	3.7 (2.5–5.0)	10.8 (8.4–15.1)
<b>All locations</b>	<b>378</b>	<b>2.3 (2.1–2.5)</b>	<b>4.6 (4.1–5.1)</b>	<b>13.5 (12.3–14.9)</b>

(Point estimates obtained by MLE. Confidence intervals obtained by inverting LRT.)

## What happened in the Lancet study?

Wu et al. uses SEIR model and assumes density of  $S$  in  $\mathcal{P}$  is

$$f(s | \mathcal{P}) \propto \exp(rs), \text{ for } s \leq L.$$

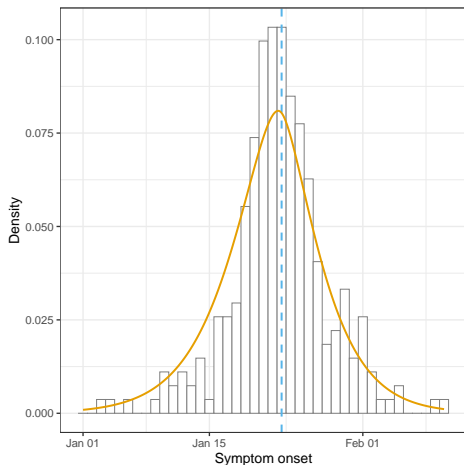
Under our model and some reasonable assumptions, density of  $S$  in  $\mathcal{D}$  is

$$f(t | \mathcal{D}, B = 0) \propto \exp(rt) (L - t) \mathbf{1}_{\{t \leq L\}},$$

and

$$f_S(s | \mathcal{D}, B = 0) \propto \exp(rs) \left( L + \frac{\alpha}{\beta + r} - s \right), \text{ for } s \leq L.$$

# Effect of travel ban



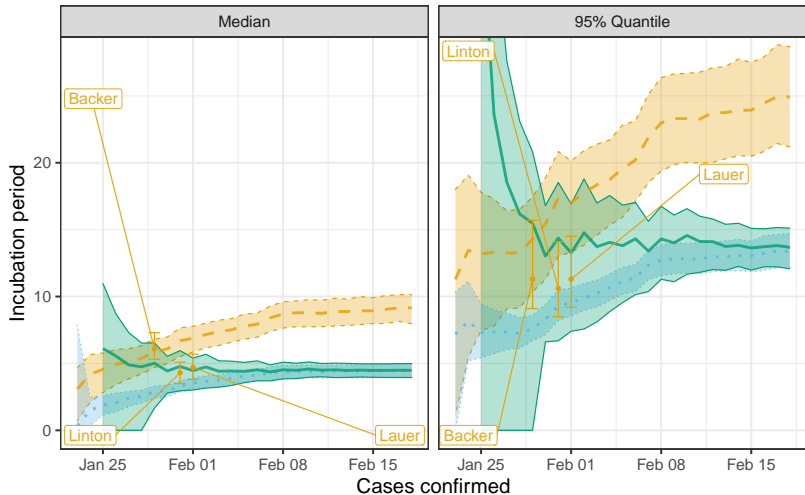
- Histogram: Density of the symptom onset of the Wuhan-resident cases;
- Orange curve: Theoretical fit  $f_S(s \mid \mathcal{D}, B = 0)$  using MLE of  $(r, \alpha, \beta)$ .
- Blue dashed line: January 23, 2020 (time  $L$ ).

## Selection bias recap

bias	remedy
under-ascertainment bias	
non-random selection bias	$\mathcal{D}$ v.s. $\mathcal{P}$
travel ban	$f(\cdot   \cdot, \mathcal{D})$
epidemic growth	$L_{cond}(r, \alpha, \beta)$
right-truncation	$L_{cond}(r, \alpha, \beta; M)$

### Keys to avoid the selection bias:

- ① Carefully design the study and adhere to the sample inclusion criterion.
- ② Start from a generative model and derive likelihood functions that adjust for sample selection.



Likelihood adjusted for a Nothing a Growth a Growth and truncation

Ignore epidemic growth  $\implies$  Overestimate incubation period.  
 Ignore right-truncation  $\implies$  Underestimate incubation period.

# Conclusions

## Conclusions about COVID-19

- Initial doubling time in Wuhan: 2–2.5 days.
- Median incubation period: about 4 days.
- Proportion of incubation period at least 14 days: about 5%.

## Our study has many limitations:

- Reported symptom onset could be inaccurate.
- Some degree of under-ascertainment is perhaps inevitable.
- Discerning Wuhan-exported cases is not black-and-white.
- Assumptions 1 & 2 (independence of travel and disease) could be violated.

# Conclusions

## Compelling evidence for selection bias in early studies

- (i) Under-ascertainment.
- (ii) Non-random sample selection.
- (iii) Travel ban.
- (iv) Epidemic growth.
- (v) Right-truncation.

## Don't make uncalculated BETS

- ① Carefully design the study and adhere to the sample inclusion criterion.
- ② Base statistical inference on first principles.



# Final lesson

As statisticians and data practitioners, we are blessed by the wealth of data in this digital age. But let's not forget an important lesson:

**Data Quality + Better Design**



**Data Quantity + Better Model**

Manuscript: [arXiv:2004.07743](https://arxiv.org/abs/2004.07743)

(forthcoming in *The Annals of Applied Statistics*)

Slides: <https://nianqiaoju.github.io>