COVID-19 and Universities:

Report from the Higher Education working group at the Isaac Newton Institute

Version for SAGE: 13th January 2021

Authors in alphabetical order: Kirsty Bolton[1], Ellen Brooks-Pollock[2], Chris Budd[3], Louise Dyson[4], Jess Enright[5], Emma Fairbanks[1], Julia Gog[6], Jason Hilton[7], Ed Hill[4], Rebecca Hoyle[7], Matt Keeling[4], Emily Nixon[2], Lars Schewe[8], Helena Stage[9], Maria Tang[6], Michael Tildesley[4]

[1]University of Nottingham; [2]University of Bristol; [3]University of Bath; [4]University of Warwick; [5]University of Glasgow; [6]University of Cambridge; [7]University of Southampton; [8]University of Edinburgh; [9]University of Manchester

Executive Summary – Key Findings

- Reductions in adherence to NPIs (including case and household isolation) will have more impact than any marginal benefits generated from a staggered return of students to university.

- The emergence of more transmissible new variants results in impaired effectiveness of mass asymptomatic testing.

- We observe evidence of spillover transmission between higher education and the wider community in some, ***but not all***, settings.

Executive Summary (1)

1. Impact of staggering on student return

- We note there may be operational reasons why a staggered return at HE institutions is desired, such as testing capacity. This only considers the direct impact on transmission and isolation.
- However, under a staggered return, higher infection prevalence amongst returning students increases the prospect of repeated isolation of households.
- In absence of other controls, staggering can reduce and delay the size of the infection peak, though reductions in attack rate are slight (given the assumption that individuals do not “compensate” to replace contacts that were unable to occur due to everyone not having returned.)
- Strong adherence to isolation, test and trace guidance remains crucial in order to break chains of transmission and effectively reduce the likelihood of large scale outbreaks.

2. Asymptomatic testing

- Testing upon return: including a second LFT, with no contacts occurring between the two tests, is estimated to cause a minor decrease in attack rate.
- Regular mass testing/screening: in the presence of a more transmissible variant, testing has a decreased ability to control case numbers.
- Variants with increased transmissibility: Very large outbreaks are almost certain without any regular asymptomatic testing.

Executive Summary (2)

3. Infection risk in residential student halls

- Analysis of one HE institution found that students living in larger halls were at higher risk of SARS-CoV-2 infection in the autumn term
- We did not find evidence of a dependence on household secondary attack rate with household size, potentially suggesting household structures are less important than hall capacity.

4. Transmission to/from the community

- Importations into the student population from the community AND to the community from student populations do occur.
- We do not find a consistent indication of student-community transmission spillover across studied LTLAs.
- Where there is an indicative signal of transmission spillover, there is some correlation between the size of a university outbreak and the strength/robustness of the spillover signal.

General caveats

- **Readers should focus on the high-level, qualitative insights offered from these analyses rather than the specific findings or quantitative figures from individual modelling contributions.** A number of these analyses are based on insights from individual institutions, or parameterised using data from a specific HEI.
- Testing scenarios within HE and the potential implications of increased transmissibility of a new SARS-CoV-2 variant for HE are considered. However, these are initial insights and further work is needed (though not necessarily specific to the HE sector).
- Some of the data included in this slidepack have not yet been cleared for wider circulation or public release

1. Impact of staggering student return

We consider insights from:

A. Simple model of isolation *upon return only*

Three spread models considering the impact of staggering over time

B. Simple SIR model

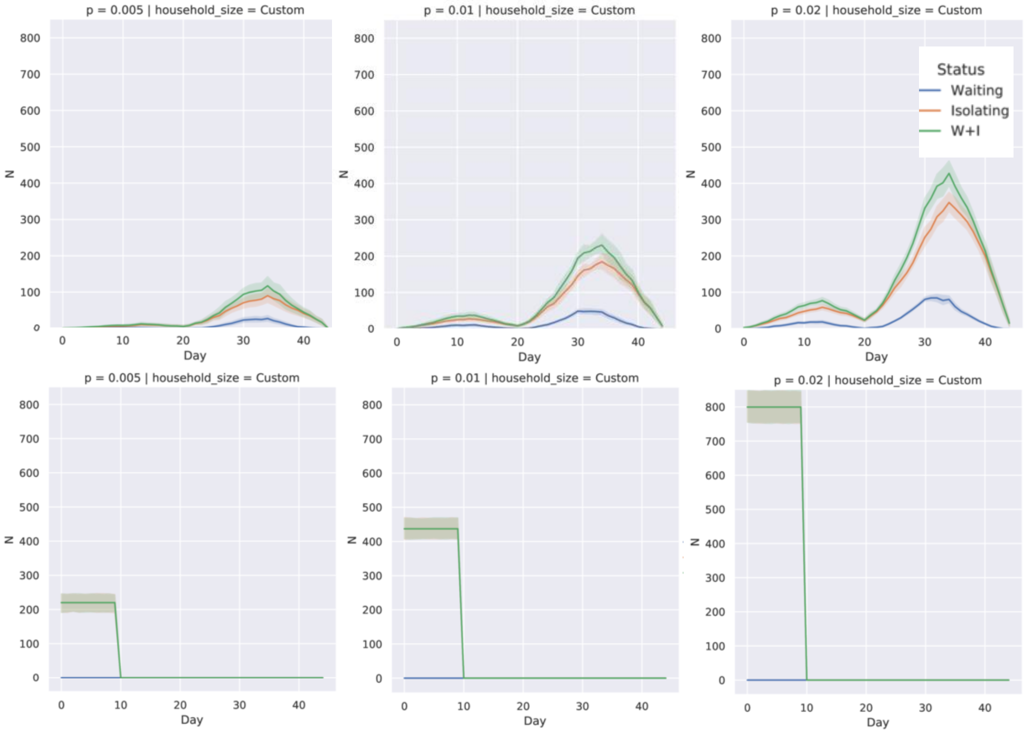
C. Network model

D. Stochastic compartmental model

Please note that the model C and D are parameterised using data on (different) individual HE institutions

1a. Impact of staggering on student isolation ***upon return***

We take the household distribution from one English HE institution. Students take one test and if +ve all students in the household that have arrived isolate, whilst all students that are planning to return to campus are delayed.



Stagger return distribution: 30% between days 0 and 13 (uniformly distributed), 7 days break, 70% between days 21 and 34 (uniformly distributed).

Only considering isolation on return - spread on campus not simulated here.

	w/ staggering		w/o staggering
p	Total days isolation	Total days waiting	Total days isolation
0.005	1251	278	2201
0.01	2717	596	4371
0.02	5204	1041	7997

For low rates of +ve tests, staggering reduces the total days spent in isolation on return. For higher rates, staggering leads to repeated isolation of households and to long waiting times for students whose household is isolating.

1b. Impact of staggering over time: ***Mean Field SIR Model***

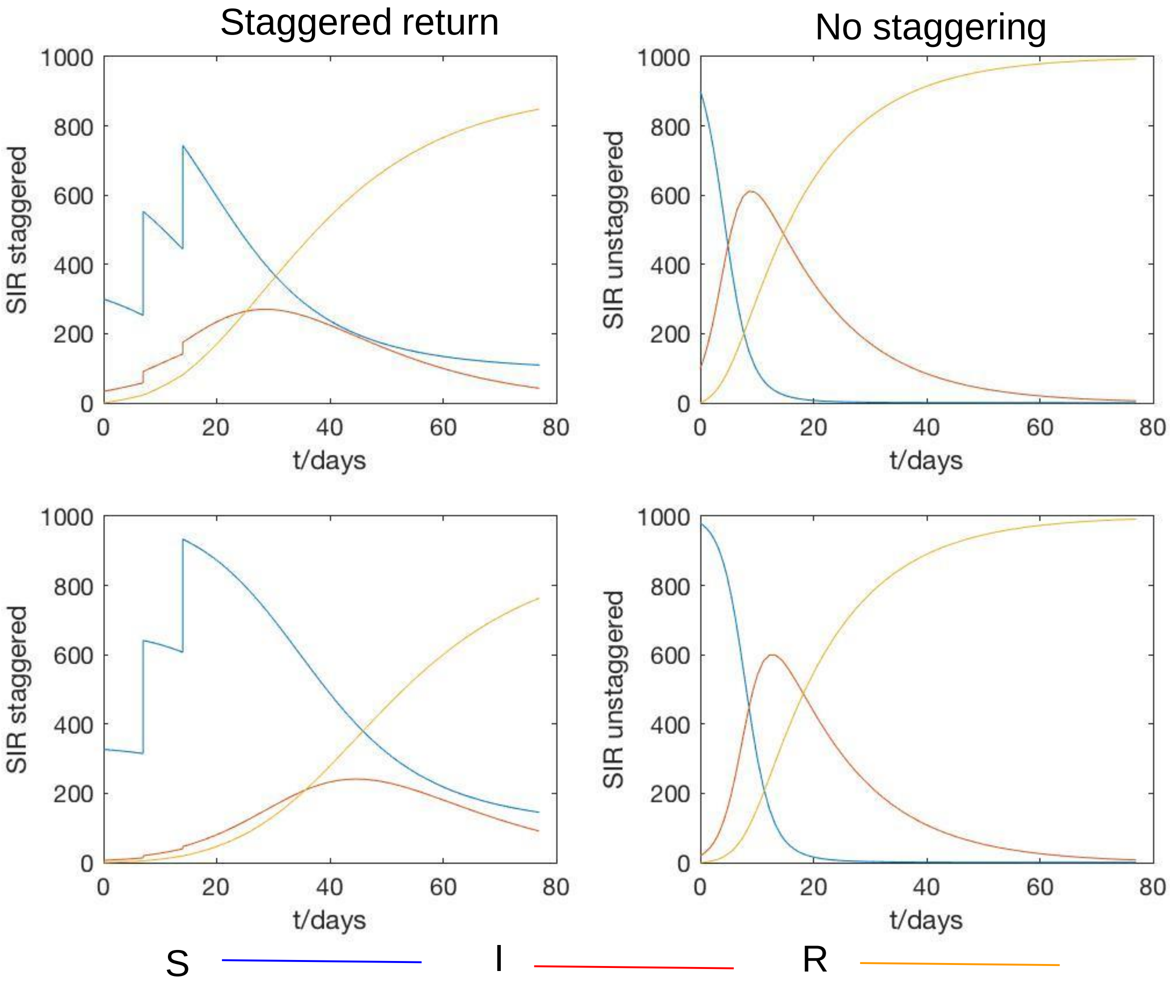
We first investigate the impact of staggering using a simple SIR model

- We assume N students return in three equal stages of N/3 students each week
  - i.e. we assume populations N/3, 2N/3, N for weeks 1,2,3-11

- Once at university the students interact without any restraint (density dependent mixing assumption).

- When each group of students return, we assumed a fraction *p* to be infected:
  - *p**N/3 returnees are infected
  - (1-*p*)*N/3 returnees are susceptible.

- Run model for an 11 week term



Baseline parameter set

$$N = 1000$$

$$\beta = 0.18$$

$$\gamma = 0.072$$

$$p = 0.1$$

Lower prevalence on return

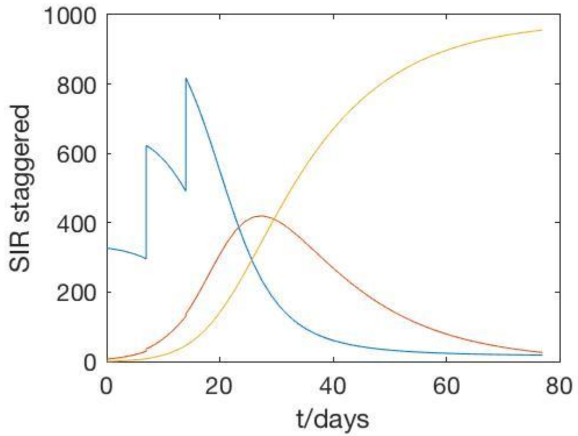
$$N = 1000$$

$$\beta = 0.18$$

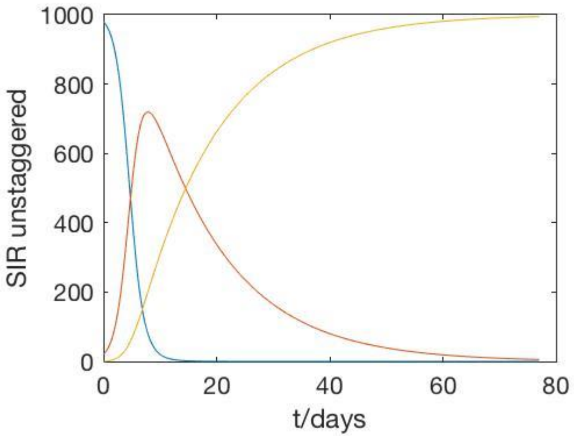
$$\gamma = 0.072$$

$$p = 0.02$$

Staggered return



No staggering



Increased transmissibility

$$N = 1000$$

$$\beta = 0.3$$

$$\gamma = 0.072$$

$$p = 0.02$$

- Staggering reduces and delays the size of the infection peak
- Long term impact is relatively small

1c. Impact of staggering over time: Network Model

- **Student population:** 25,000 (~7,000 on-campus, ~18,000 off-campus)

- **Four contact layers:** Household, study/coursemates, organised society & sports clubs, social.
  - If an individual is not isolating, but planned contacts do not occur due to corresponding individuals not having yet returned to university or being in isolation, no “compensatory” contacts are made.

- **Model calibration:** In absence of controls, early period 7-day averaged R returns a 50% prediction interval spanning 3-4.

- **Parameter uncertainty:** In each simulation run, several variables were sampled from a prior probability distribution.

- **Time horizon:** 11 weeks (1 week before term + 10 week term).

- **Four staggering scenarios:** 1,000 simulations per scenario (20 runs per network realisation, 50 distinct network realisations)

- **Testing on return:**
  - Default strategy: Two LFTs, spaced three days apart. Positive result underwent confirmatory PCR.
  - Test sensitivity dependent on time since infection;
  - Equivalent for asymptomatics & symptomatics.

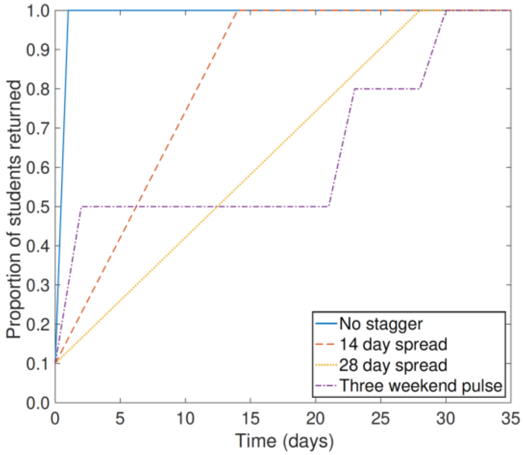
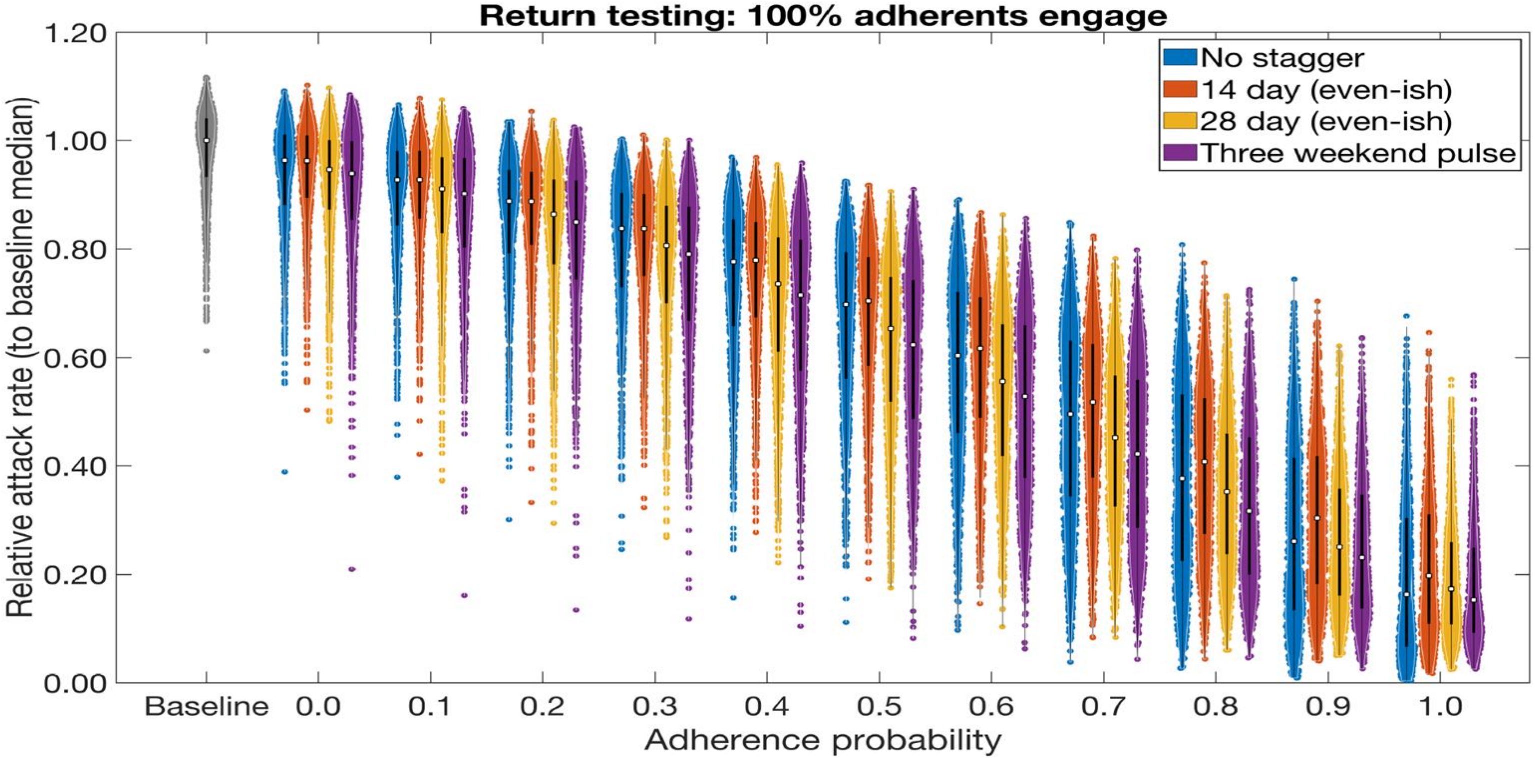
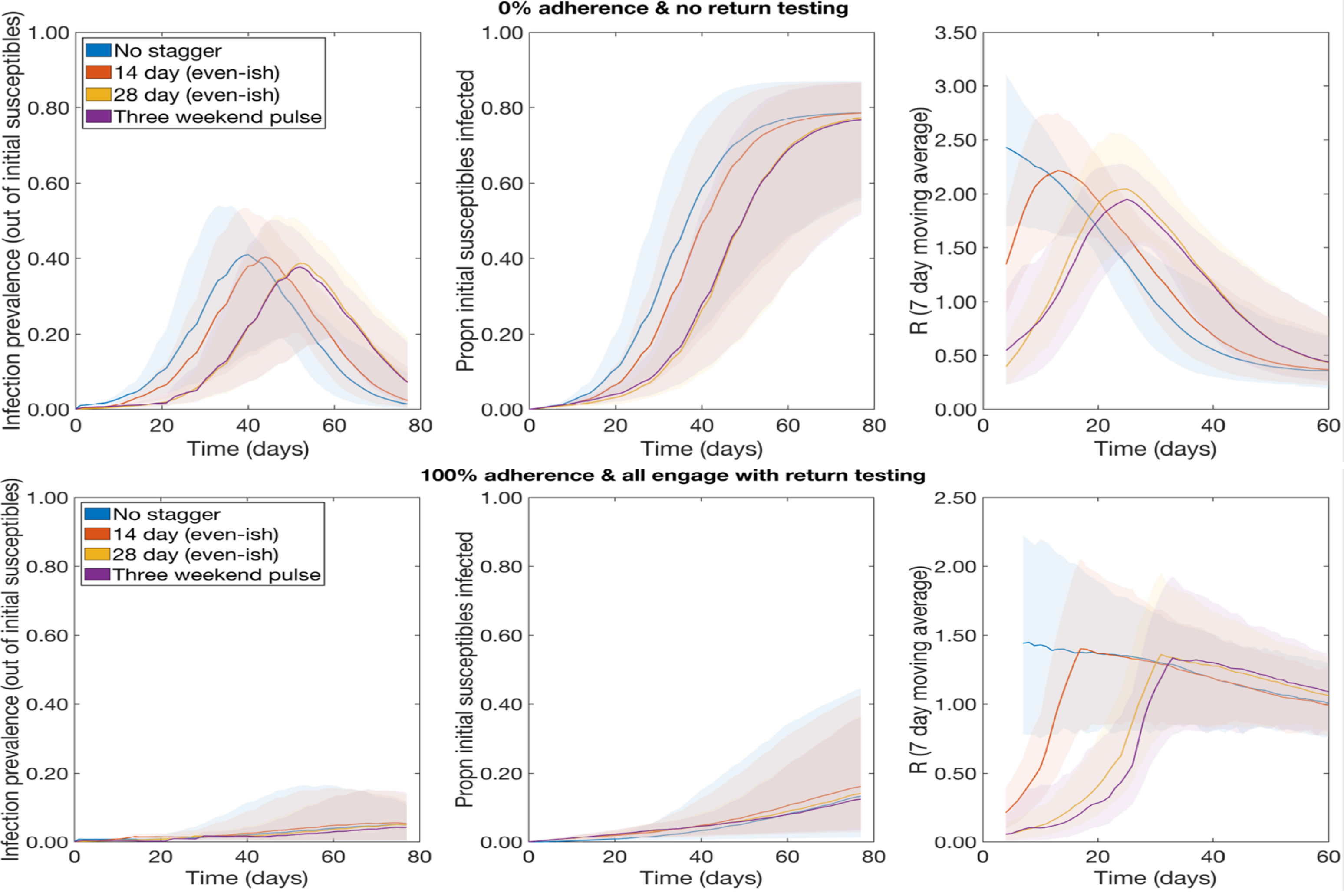


Figure: proportion of students returning under four staggering scenarios; three weekend pulse by course

Figure: Attack rate distributions under differing assumptions for adherence to isolation, test and trace measures, in combination with strategies for staggered return of all students. White squares represent the medians. Solid black lines depict the interquartile range.



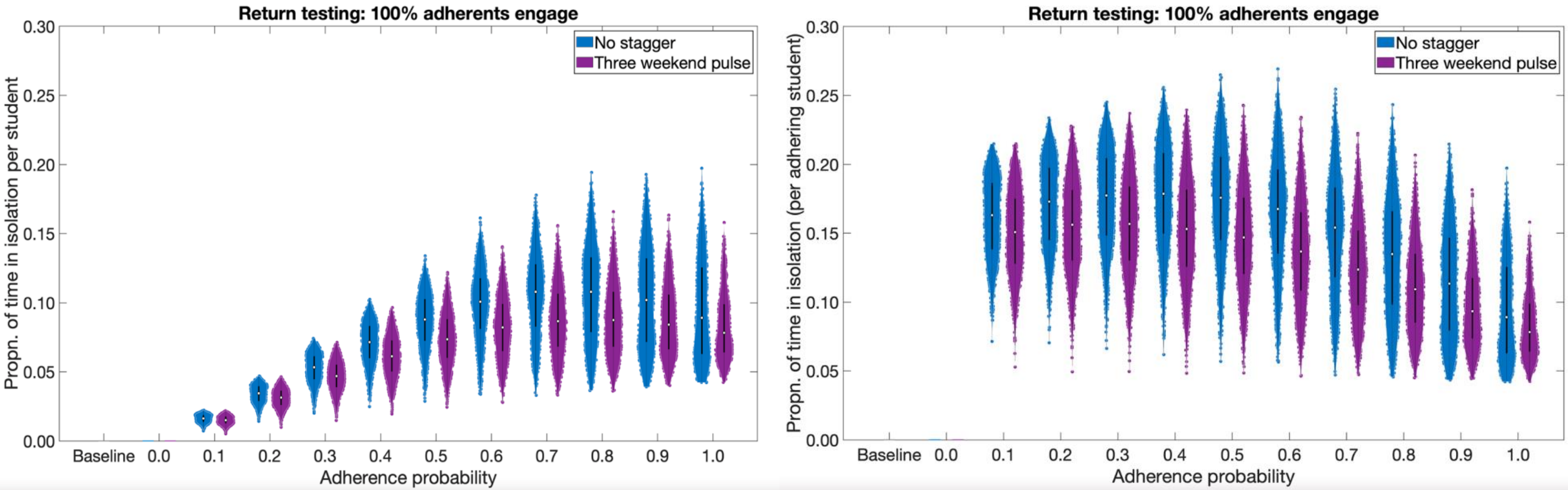
- Adherence to isolation guidance and following test and trace procedures is crucial in reducing the overall case burden within the student population.
- Our considered collection of staggering strategies, in which all students ultimately return, have minimal impact on the attack rate.



As for the simple model, staggering slightly reduces and delays the size of the peak but the long term impact is minimal.

Risk of outbreaks of campus is significantly reduced with high levels of adherence to testing and isolation.

Figure: Distributions of estimated proportion of time students spend in isolation under differing assumptions for adherence to isolation, test and trace measures, in combination with strategies for staggered return of all students. White squares represent the medians and solid black lines the interquartile range. We consider two measures: **(Left)** Per each student; **(Right)** Per adherent student.



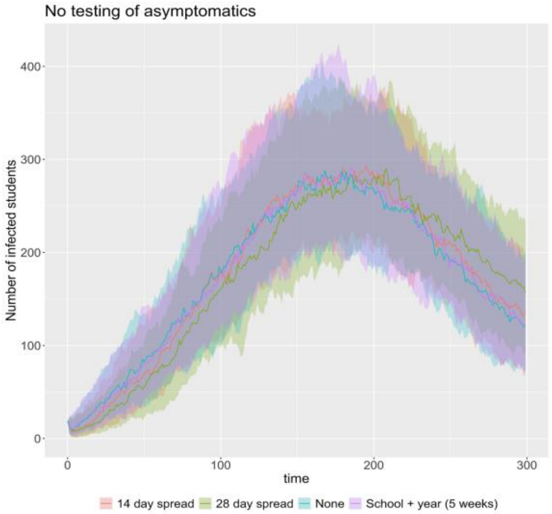
- A collective response (high adherence) reduces the time each adherent is estimated to spend in isolation.

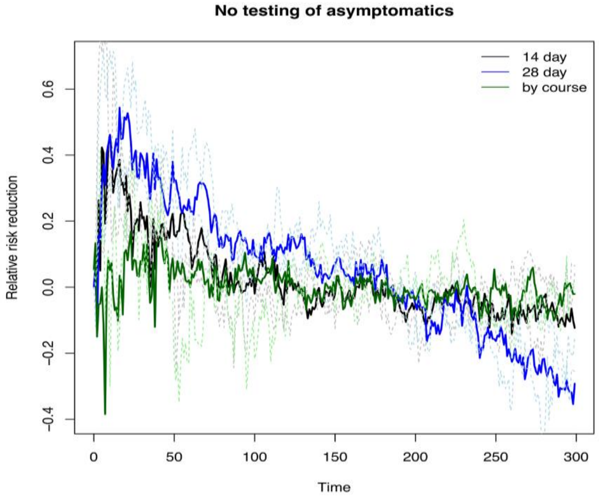
- The staggered strategy generally lowers the expected time spent in isolation
    - Caveat: For those students waiting to return to university, we only account for isolation due to onset of symptoms (possible isolation due to household member infection or via contact tracing away from university not included).

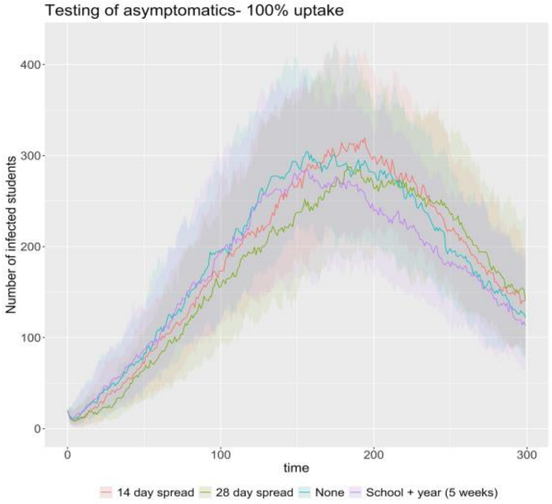
1d. Impact of staggering over time: Stochastic compartmental Model

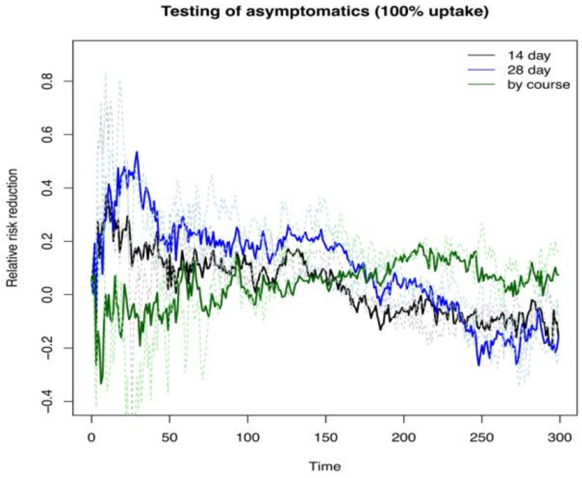
- **Student population:** 28,000
- **Contact matrices:** Household, study and random contacts based on survey data, 160 groups based on school and year.
- **Model calibration:** In absence of controls, assumed that asymptomatic cases are 50% less infectious than symptomatic cases, gave R~3, calibrated to estimations at the start of the academic year.
- **Main parameters**
  - Mean probability of a case being asymptomatic: 75%
  - Relative infectiousness of an asymptomatic: varied between 0 and 1
  - Self-isolation rates: 0.5 for symptomatics, testing scenario dependent for asymptomatics.
  - Probability student remained in university accommodation during vacation: 20%
- **Time horizon:** Run from the start of the academic year for 300 days.

These scenarios assess what impact staggering and testing upon return may have had at the start of the 2020/2021 academic year, if this had taken place. The model parameters do not change based on events that have happened since the beginning of the academic year and consequently the results are to be interpreted qualitatively.









Four scenarios are considered:

- No staggering
- 14 day spread
- 28 day spread
- Staggering by school/year groups over five weeks, prioritising “practical” courses

- Similar overall case burden across all considered staggering strategies.

- Relative to no stagger return, lower prevalence in early phase paired with higher prevalence in late phase (14 day and 28 day stagger strategies)

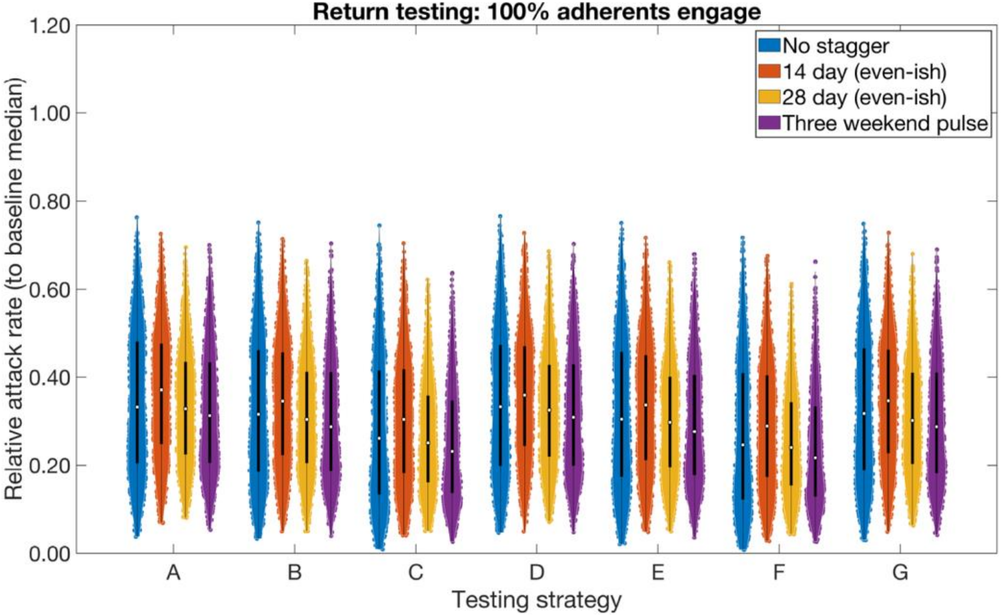
- With the inclusion of testing upon return of all students, we observe similar temporal trends.

2. Asymptomatic testing

We consider insights from two network models. These are parameterised to (different) individual HE institutions

2a. Impact of return testing strategies with staggering

Figure: Relative attack rate distributions under different test before return to study procedures, in combination with strategies for staggered



	LFT 1	LFT 2	Confirmatory PCR?	Isol. b/w LFT tests?
A	✓	✗	✓	N/A
B	✓	✓	✓	✗
C	✓	✓	✓	✓
D	✓	✗	✗	N/A
E	✓	✓	✗	✗
F	✓	✓	✗	✓
G	Single PCR test only			

Assumed 90% adhere to isolation, test and trace guidance. For test strategies using two LFTs, the two tests were spaced three days apart. Specificity of both PCR and LFT was assumed to be 100% (we acknowledge that is high for LFT, where 99.7%(ish) would be more appropriate). White squares represent the medians. Solid black lines the interquartile range.

Given high adherence to interventions and engagement with rapid testing:

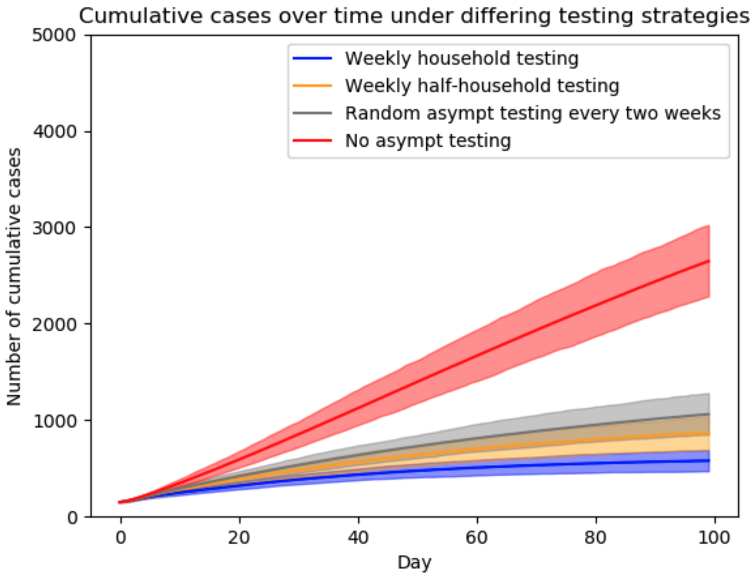
- Inclusion of second LFT and isolation between the LFTs gives minor reductions in attack rate.
- Distributions comparable across considered staggering strategies.

2b. Impact of Asymptomatic Testing in Higher Education

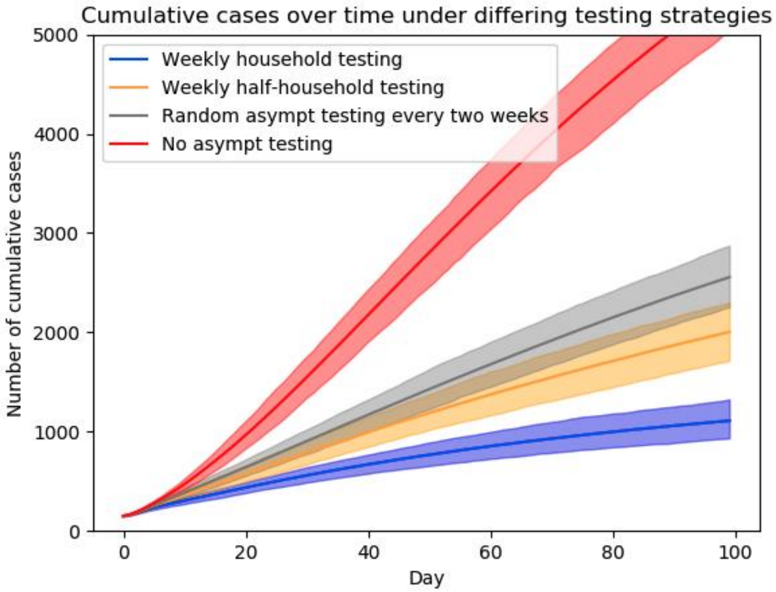
- SEAIR network model simulating contact within households and in other settings (e.g. social, teaching, sport), including pre-symptomatic and asymptomatic individuals.
- 15,000 students in population - household sizes approximating household size distributions in a university setting (25% of size 10, 50% of size 7, 25% of size 5).
- Consider impact of no asymptomatic testing and **three competing asymptomatic testing strategies**:
  (i) No asymptomatic testing
  (ii) Weekly household-pooled PCR testing
  (iii) Weekly half-household pooled PCR testing
  (iv) Random asymptomatic testing (covering 50% population weekly)
- We assume 50% probability of each non-household contact of a test-positive being traced and isolated.
- Household immediately isolates upon a positive test or symptoms, but household members do not isolate from one another.
- Household contacts infect with probability 0.2/day for “old variant”, 0.3/day for “new variant” (an increase of x1.5). Additional group contacts transmit at rate 1/10th of household contacts.

Impact of Asymptomatic Testing in Higher Education

Old-variant



New-variant (transmission probs increased x1.5)



Each line represents 500 model runs, with envelopes corresponding to 95% prediction intervals.

- **Observe increased cases with more transmissible variant, decreased ability of (particularly) partial-population weekly screening to control case numbers.**
- **Very large outbreaks are almost certain without any regular asymptomatic testing when considering variants with increased transmissibility**

3. Infection risk in residential student halls

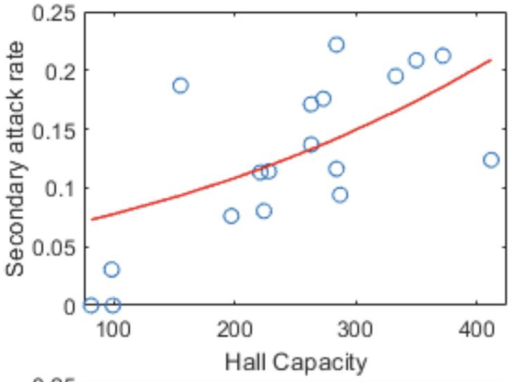
Infection risk in residential student halls

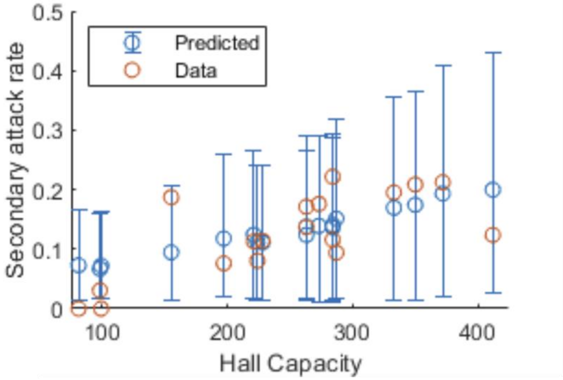
Self-reported data from one English HE Institution indicate that during the Autumn 2020 term students residing in halls were more likely to have a confirmed SARS-CoV-2 infection compared to students living in other accommodation types. Here we examine the distribution of self-reported positive pillar 2 test results within halls and their associated households.

Hall secondary attack rate

Table 1: Results of univariate and multivariate logistic regression analysis for predictors of the hall SAR.

Univariate regression			
	Coefficient	p-value	Standard Error
Constant	*-3.0842*	<0.0001	0.2050
Hall size	*0.0033*	<0.0001	0.0007
Constant	-1.3218	<0.0001	0.1590
Median household size	-0.0539	0.0029	0.0181
Multivariate analysis			
	Coefficient	p-value	Standard Error
Constant	-2.5776	<0.0001	0.2682
Hall size	0.0035	<0.0001	0.0006
Median household size	-0.0247	0.2073	0.0196





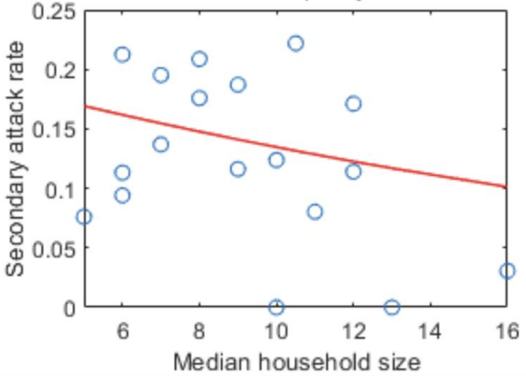
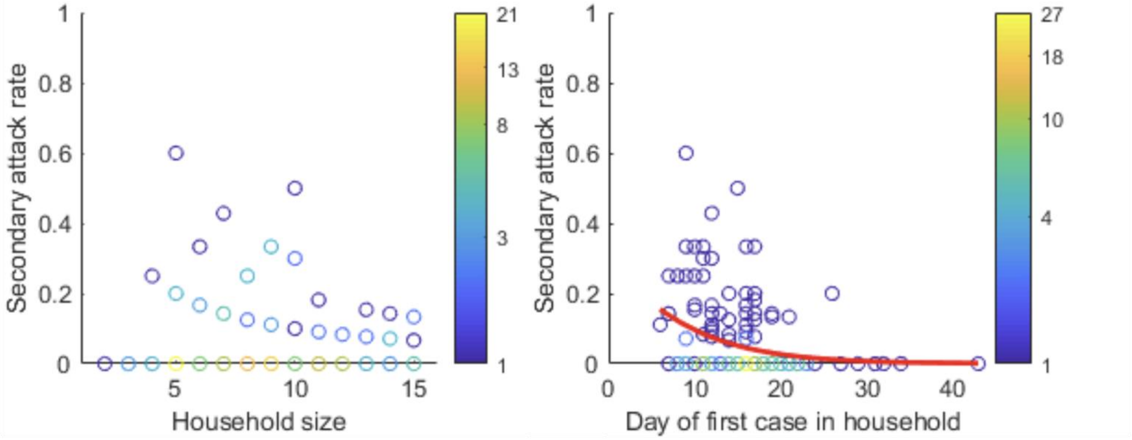


Figure 1: Univariate analysis: reported confirmed hall SAR by hall capacity (top left) and median household size (left). Multivariate analysis: reported confirmed hall SAR by hall capacity and median household size (above). Error bars represent 95% CI.

Household secondary attack rate

A significant caveat is that we have incomplete data on student households (missing for approximately 50% of reported confirmed tests) and although some serological data is available, collection was not designed to address details of transmission within halls.

Figure 2 (right): We test for predictors of the symptomatic reported confirmed household SAR within households. (Left) Household size not significant ($p = 0.14$) by logit regression. (Right) Date of first infection in household significant ($p < 0.0001$) by logit regression. This may be due to a number of effects including shifts in background prevalence, or changes in mixing and/or reporting behaviour.



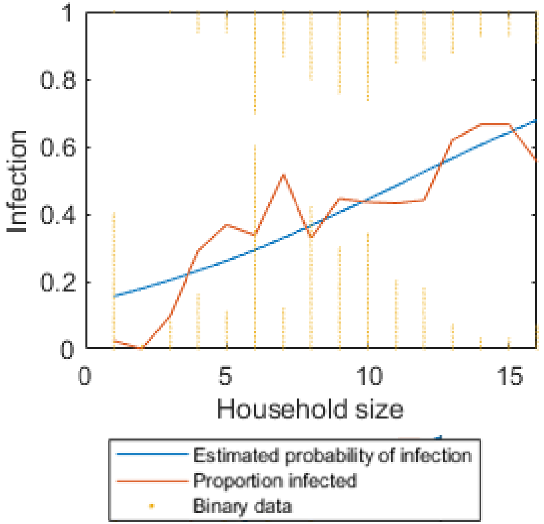


Figure 3 (left): Probability of at least one reported confirmed case by household size. Binomial probability of student in infected household reporting was:

- 0.0758541 (95% CI:[0.0638065, 0.0893653]) between all reported cases.
- 0.0568345 (95% CI:[0.0452513, 0.0703324]) between symptomatic cases.

These estimates do not correct for underascertainment of household infections (asymptomatic cases, underreporting, etc.), and thus likely represent a lower limit.

Summary: Analysis of one HE institution found that students living in larger halls were at higher risk of SARS-CoV-2 infection in the autumn term. We ***did not find evidence*** of a dependence on household SAR with household size, potentially suggesting household structures are less important than hall capacity.

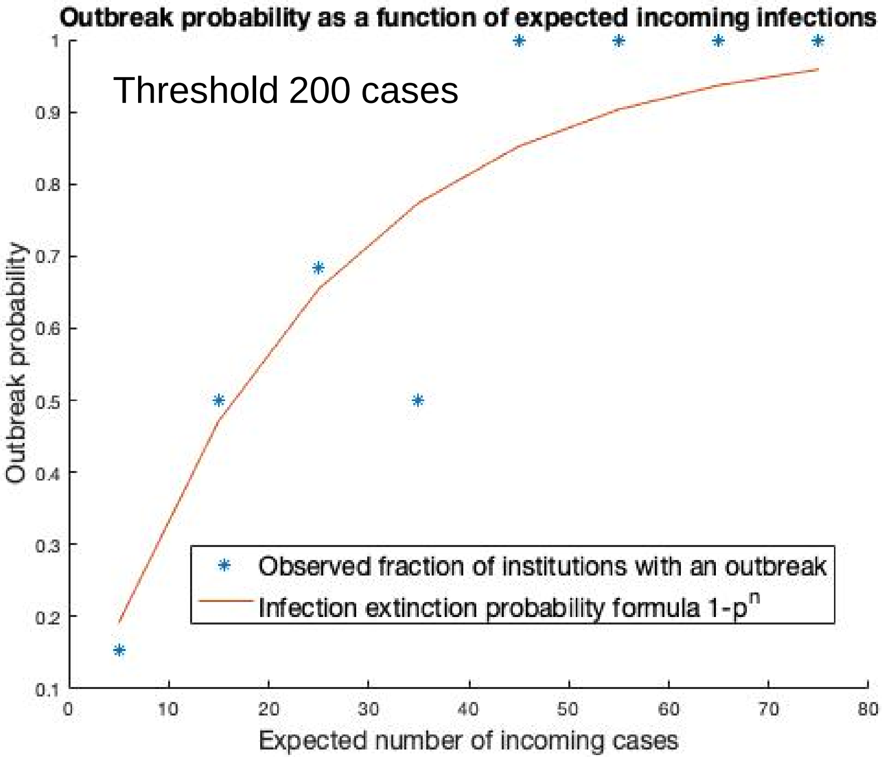
4. Transmission to/from the community

We consider insights from:

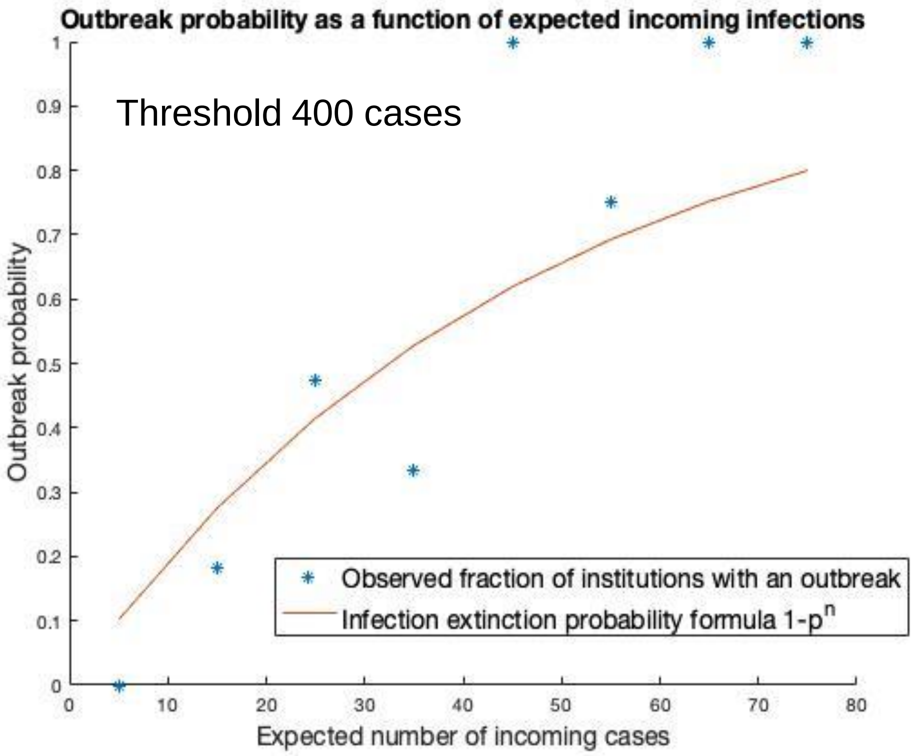
A. Analysis of expected and observed incoming infections
B. Case study of test positive rates for one campus relative to the LA
C. Analysis of positive cases at MSOA and LTLA level

4a. Impact of initial incoming infections on university outbreaks

- We calculate expected incoming infection numbers at a sample of 72 UK universities based on 2018 HESA data on their student intake by UK region ar prevalence by region at the end of Sept 2020.
- We use data from the UCU dashboard in Nov 202(on the cumulative number of student infections at these universities to define an outbreak.
- We plot the observed fraction of universities with a outbreak and a theoretical outbreak probability based on the extinction probability p for a single incoming infection. Here we use a flat threshold of 200 cases.
- Using MLE we fit the extinction probability as 0.95ε 95% confidence interval [0.945 0.972]. The fit is reasonable suggesting that incoming infections are fairly good predictor of outbreaks.



- Higher thresholds for outbreak definition increase p: a threshold of 400 gives p=0.979 (95% confidence interval [0.971 0.987]).
- Higher incoming case numbers are likely to increase the probability of an outbreak at a university.
- We would expect a lower extinction probability for a more transmissible SARS-CoV-2 variant. As a consequence, the outbreak probability would be higher.

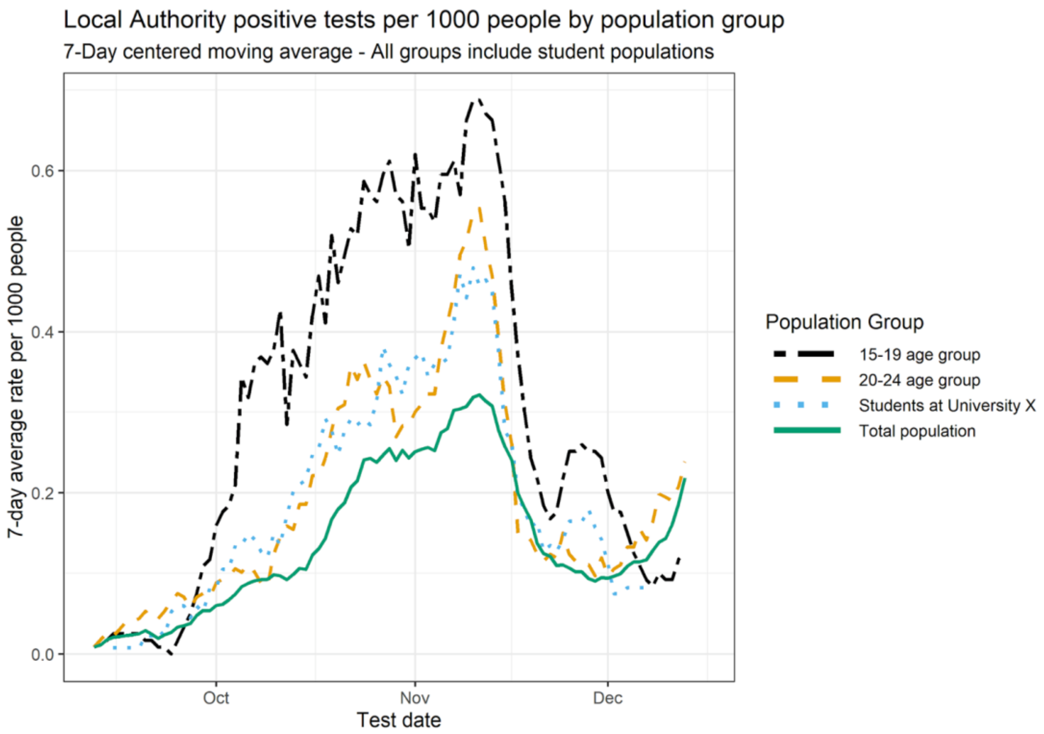


4b. A case study - comparison of test positive rates on one English campus and the Local Authority

Rates of new COVID-19 infections among a population of university students at one HE institution appear very similar to those for the general community aged 20 to 24 in that local authority, and slightly lower than those in the 15-19 age group.

Caveats / confounding factors:

- Students are included in LA figures
- Asymptomatic screening in student population
- About 15% of students are aged 25+
- Not all students physically located in the LA



4c. Investigating the evidence of spillover from higher education to the community

- We investigate the potential for spillover from higher education to the community, analysing data at LTLA level.

- We consider age-stratified positive cases at LTLA level scaled by population size, using ages 18-24 as a proxy for students (we note that not all cases in this age group are students).
  - Cases in the community include all other ages.
    - Is there a spike or excess in expected community cases following a university outbreak?
    - Do community cases grow faster following a university outbreak?

  - We also consider age-stratified positive cases relative to the respective NHS region, scaled by population size.
    - Is there proportionally higher growth in local community cases than across the region?

  - Finally we consider cases at MSOA level, scaled by population size.
  - Do we see more cases in locations close to areas with a high concentration of students than compared to locations further away from student-dominated areas?

Variable testing rates and students not being registered at their term-time address are key confounders in the data. **These are all indicators of correlation, and not causation.** It is possible that the higher transmission among students (often due to larger household sizes and mixing) merely amplified underlying national dynamics, which needed 2-3 more weeks before being visible in the community cases.

Redactions have been made to remove figures containing statistically disclosive / identifiable data.

- We observe a peak in student-aged cases in Manchester in early October (top panels). Student and community populations appear equally affected by late October.

- Students cases known to the University of Manchester (UoM) are reported alongside a more detailed breakdown of cases by age (bottom panels). The UoM outbreak was preceded by an earlier outbreak at Manchester Metropolitan University.

- Ages consistent with first and second year undergraduates are disproportionately affected relative to older age groups.

Manchester

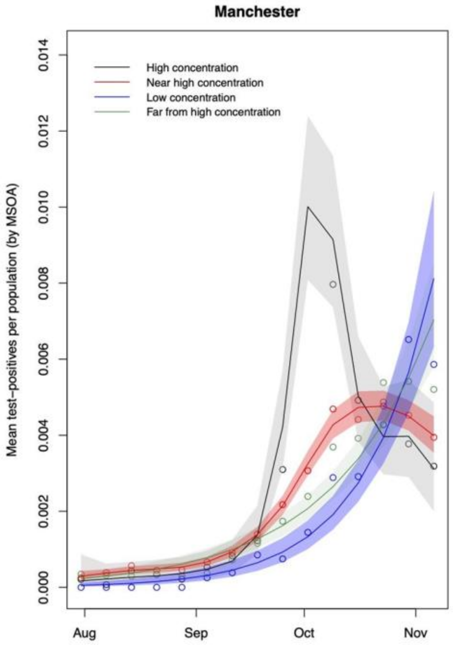
[redacted]

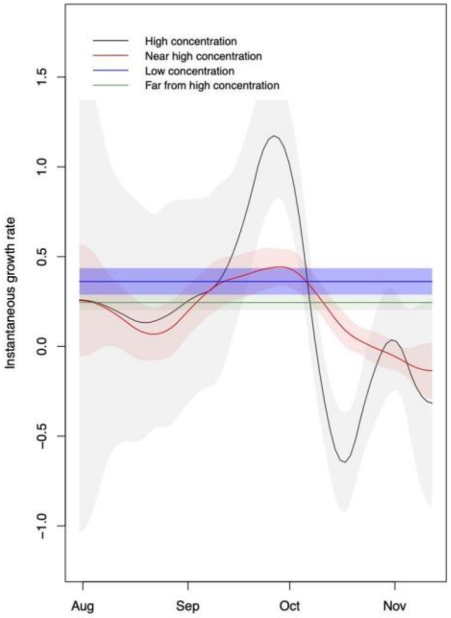
[redacted]

[redacted]

[redacted]

Note: The figures on the left show (in order given by legend): cases per capita for a given age group, followed by tests per capita for that age group - repeated for subsequent age groups. Tests are reported jointly for 18 and 19 year olds. In some cases, these have been scaled (the % value listed) to plot over the same range and aid comparison. This also applies to similar plots on slides 30-32.





Manchester

[redacted]

- At the MSOA level, the mean scaled positive tests in areas with a known high concentration of students mirror the age-stratified timeline. Cases near high concentrations of students are lagged by approximately a week, and do not grow as much. This suggests a spread of infection from areas with a high student concentration to nearby surrounding areas. Other areas do not appear to be directly affected.
- The scaled community cases are above the scaled cases across the North West, but do not experience a sustained growth following the peak in student cases.

Redactions have been made to remove figures containing statistically disclosive / identifiable data.

Redactions have been made to remove figures containing statistically disclosive / identifiable data.

- The situation in Manchester is in contrast to that in Hull - there is some excess in cases in early October following the return of students, but this is a weak signal due to the noisiness of the data. Student and community populations appear equally affected by late October.

- Ages consistent with first and second year undergraduates are disproportionately affected relative to older age groups in the 18-24 category.

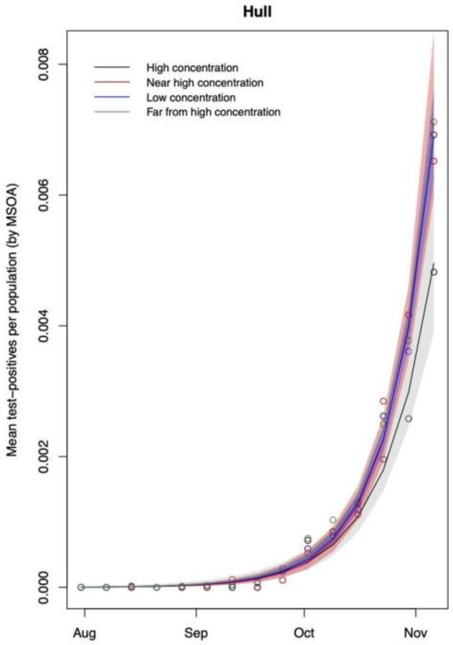
Hull

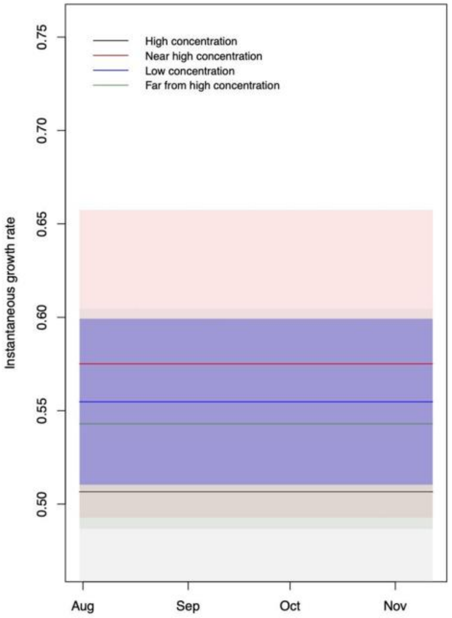
[redacted]

[redacted]

[redacted]

[redacted]





Hull

[redacted]

- At the MSOA level, the mean scaled positive tests in areas with a known high concentration of students mirror the age-stratified timeline. There is a small spike in the first week of October in some areas, but the overall trend is pure exponential growth (with overlapping rates). This does not suggest a pattern of infection driven by areas of high student concentration.
- Following the peak in student cases, the scaled community cases rise sharply relative to community cases in the North East & Yorkshire (double the regional level in one week).

Redactions have been made to remove figures containing statistically disclosive / identifiable data.

Community Spillover Summary

Caveats and limitations

- It is impossible to completely attribute a rise in community cases to an earlier or concurrent outbreak in the student population.
- Where indications of spillover do exist, they may also be the result of non-students aged 18-24 who seed infections in the wider community.
- Outbreaks at universities may simply be a result of the increased mixing of this age bracket, and the typically larger household sizes in halls of residence and other shared accommodation.

Summary of findings

- Indications of student-community spillover have been found across several (but not all!) studied LTLAs. The strength and type of the signal varies.
    - Some excess community cases can often be found 2-3 weeks following a sharp rise in student cases.
    - Some LTLAs with relatively low community prevalence and a significant student outbreak saw a marked increase in later community growth rate (or cases relative to those reported at the regional level).
    - A clear wave of infections spreading from areas of high student concentrations is rarely observed.
- There is some correlation between the size of the university outbreak, and the strength/robustness of the spillover signal for the different metrics.
- Assuming similar contact patterns, and allowing for the possibility of a higher community prevalence than in 2020, it is advisable to prepare for the possibility of future outbreaks as university students return.

Full report with extended analysis available upon request.