Enhancing modelling impact through collaboration: The case study of SARS-CoV-2 infection in UK university students

Emily Nixon (University of Bristol/University of Oxford) & Ed Hill (University of Warwick)





Isaac Newton Institute Higher Education working group

Participants in alphabetical order: Kirsty Bolton¹, Ellen Brooks-Pollock², Chris Budd³, Louise Dyson⁴, Jess Enright⁵, Emma Fairbanks¹, Julia Gog⁶, Jason Hilton⁷, Ed Hill⁴, Rebecca Hoyle⁷, Matt Keeling⁴, Emily Nixon², Lars Schewe⁸, Helena Stage⁹, Maria Tang⁶, Michael Tildesley⁴

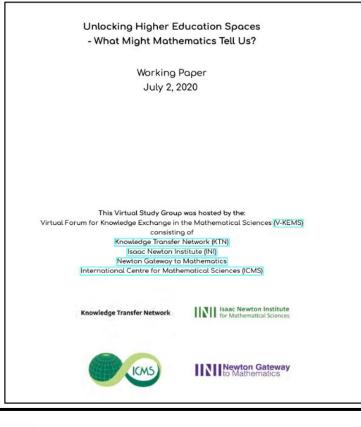
¹University of Nottingham; ²University of Bristol; ³University of Bath; ⁴University of Warwick; ⁵University of Glasgow; ⁶University of Cambridge; ⁷University of Southampton; ⁸University of Edinburgh; ⁹University of Manchester

Background to the INI Higher Education group

- Ahead of the 2020/2021 academic year, there was significant uncertainty around whether students would be able to return to face-to-face teaching and what policies would be put in place in order to mitigate risk.
- From 15th to 17th June 2020, a Virtual Study Group on 'Unlocking Higher Education Spaces' was hosted by the Virtual Forum for Knowledge Exchange in the Mathematical Sciences (V-KEMS).

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Background to the INI Higher Education group

COVID-19 transmission in a university setting: a rapid review of modelling studies

Hannah Christensen^{1+,} Katy Turner²⁺, Adam Trickey¹, Ross D. Booton², Gibran Hemani, Emily Nixon³, Caroline Relton¹, Leon Danon^{4,5}, Matthew Hickman¹, Ellen Brooks-Pollock². Part of the University of Bristol UNCOVER group.

https://doi.org/10.1101/2020.09.07.20189688

High COVID-19 transmission potential associated with re-opening universities can be mitigated with layered interventions. Ellen Brooks-Pollock^{1,2}, Hannah Christensen², Adam Trickey³, Gibran Hemani³, Emily Nixon⁴, Amy Thomas¹, Katy Turner^{1,2}, Adam Finn⁵, Matt Hickman², Caroline Relton³, Leon Danon⁶

https://doi.org/10.1101/2020.09.10.20189696

Modelling SARS-CoV-2 transmission in a UK university setting $% \mathcal{A} = \mathcal{A} = \mathcal{A} = \mathcal{A}$

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Edward M. Hill^{*}, Benjamin D. Atkins, Matt J. Keeling, Michael J. Tildesley, Louise Dyson.

https://doi.org/10.1101/2020.10.15.20208454

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- Two virtual events (part of the Isaac Newton Institute Infectious Dynamics of Pandemics Research Programme) in July & August 2020.
- Investigated the application of mathematical tools and models to various issues linked to the challenges of reopening higher education.
- After these events, a working group continued to meet virtually on a weekly basis.

Background to the INI Higher Education group

SARS-COV-2 INFECTION IN UK UNIVERSITY STUDENTS: LESSONS FROM SEPTEMBER-DECEMBER 2020 AND MODELLING INSIGHTS FOR FUTURE STUDENT RETURN

Royal Society Open Science, **8**(8): 210310. (2021)

https://doi.org/10.1098/rsos.210310

JESSICA ENRIGHT^{*}, EDWARD M. HILL^{*}, HELENA B. STAGE, KIRSTY J. BOLTON, EMILY J. NIXON, EMMA L. FAIRBANKS, MARIA L. TANG, ELLEN BROOKS-POLLOCK, LOUISE DYSON, CHRIS J. BUDD, REBECCA B. HOYLE, LARS SCHEWE, JULIA R. GOG^{*}, AND MICHAEL J. TILDESLEY^{*}

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- 1. Observational analyses based on data from autumn term of the 2020/2021 academic year.
- 2. Prospective modelling of control measures that were under consideration for the full return of UK higher education students in January 2021

Our contribution to collaborative study

• Exploratory modelling of the impact of staggering the return of Higher Education students in the UK in January 2021.

Caveats

- Analyses were parameterised using data from specific Higher Education institutes.
- We focused on the high-level, qualitative insights rather than the specific findings or quantitative figures from individual modelling contributions.

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- 1. Impact of staggering: Stochastic compartmental model
- 2. Impact of staggering: Network model
- 3. Achievements and lessons

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2. Impact of staggering: Network model

3. Achievements and lessons

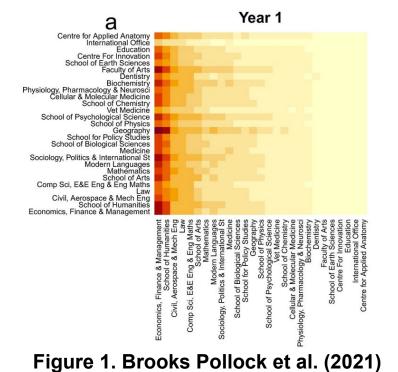




- 160 school/year groups
- Uses contact data to estimate the contact rate between each of these groups by context – home, university, leisure/other, travel

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https://doi.org/10.1038/s41467-021-25169-3

Susceptible (S)

Latently infected (E)

Pre-symptomatic and infectious (P)

Asymptomatic and infectious (A)

Self-isolating (Q)

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Recovered and immune (R)

Infected with symptoms (I)

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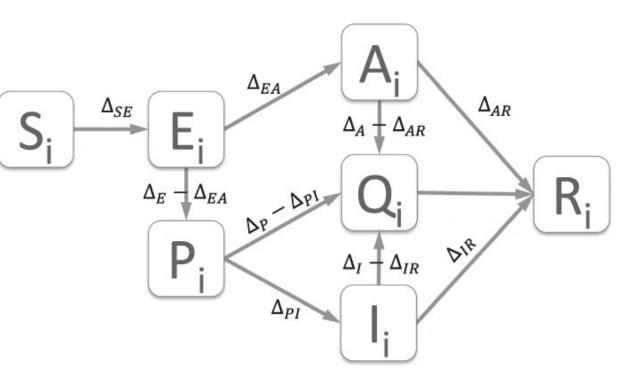


Figure 2. Brooks Pollock et al. (2021) https://doi.org/10.1038/s41467-021-25169-3

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- Student population: 28,000
- **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

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- 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.

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Caveats

- 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 were not changed based on events that happened in the autumn term of the 2020/2021 academic year
- The results are to be interpreted qualitatively.

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Staggered return scenarios

No stagger- all students return on day 1

14 day spread & 28- day spread- return day for each student sampled from a uniform distribution

Three-weekend pulse (by course):

- Day 1: medical, dental and vets (31% present)
- Day 22: all other practical (51% present in total)
- Day 29: all remaining students

Testing

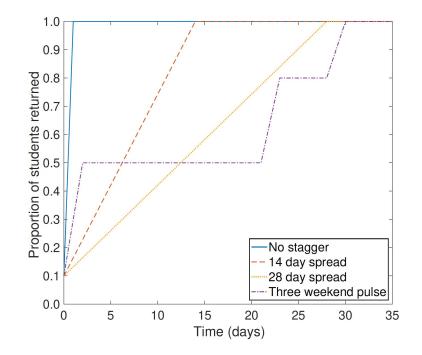
- No testing,

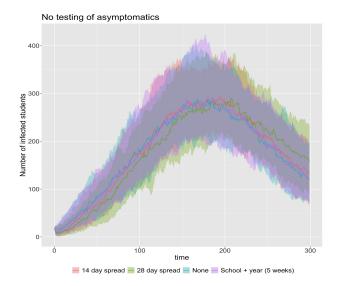
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- Symptomatic testing (two LFTs, 3-4 days apart)

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- 50% sensitivity and 100% specificity

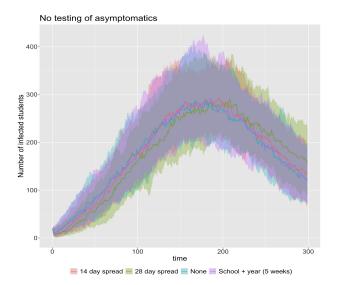




• Similar overall case burden across all considered staggering strategies.

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14 day 28 dav 0.6 by course 0.4 Relative risk reduction 0.2 0.0 -0.2 -0.4 0 50 100 150 200 250 300 Time

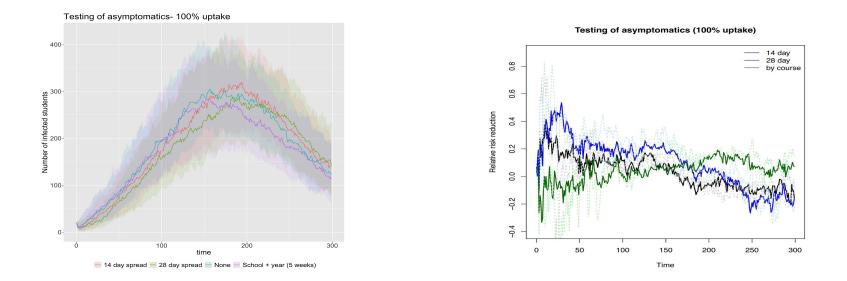
No testing of asymptomatics

• Similar overall case burden across all considered staggering strategies.

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 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.

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2. Impact of staggering: Network model

3. Achievements and lessons







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

• Four contact layers:

- (i) Household
- (ii) Study/coursemates
- (iii) Organised society & sports clubs
- (iv) Social

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- **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.

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- **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).

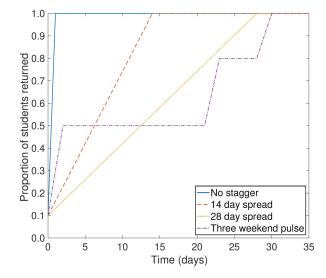
• Testing on return:

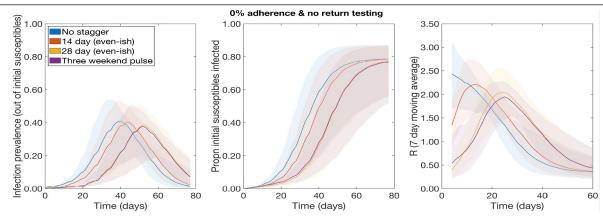
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• Two LFTs, spaced three days apart.

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- Positive result underwent confirmatory PCR.
- Test sensitivity dependent on time since infection.

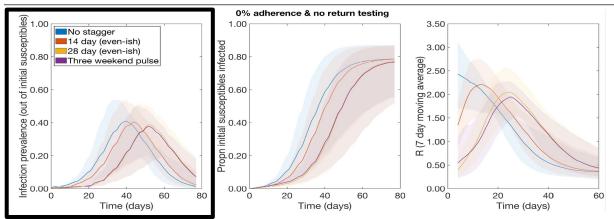




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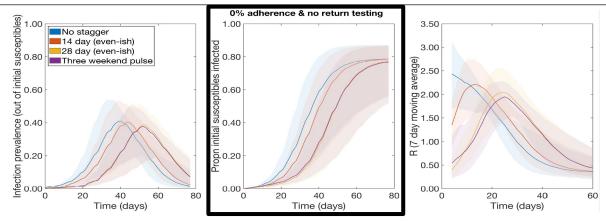




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- Staggering slightly reduces and delays the size of the peak.
- Long term impact is minimal.

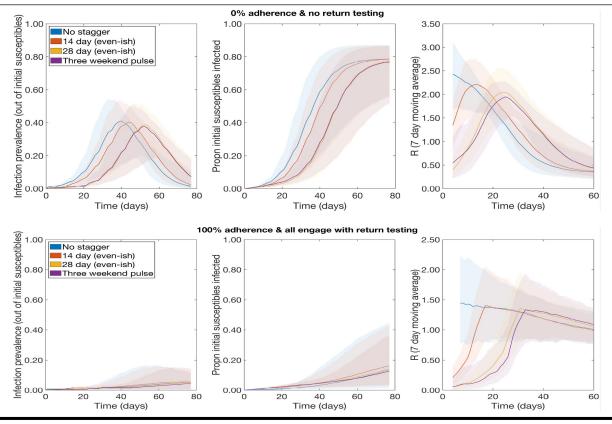


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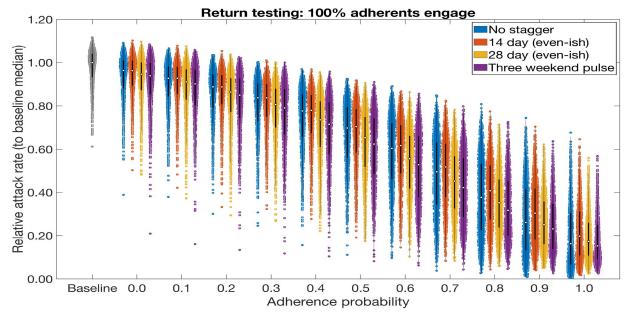
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- Staggering slightly reduces and delays the size of the peak.
- Long term impact is minimal.

 With high levels of adherence, outbreak risk is substantially reduced.

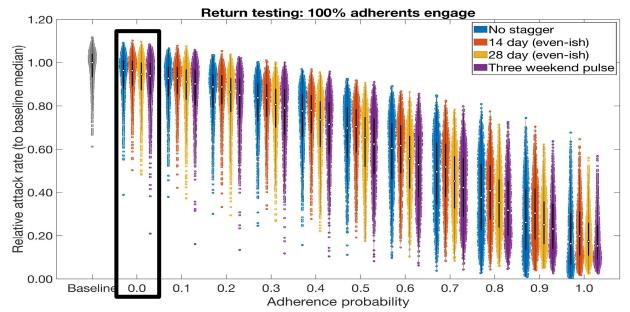
Figure: Attack rate distributions under differing assumptions for adherence to isolation, test and trace measures, in combination with strategies for staggered return of all students. White squares represent the medians. Solid black lines depict the interquartile range.



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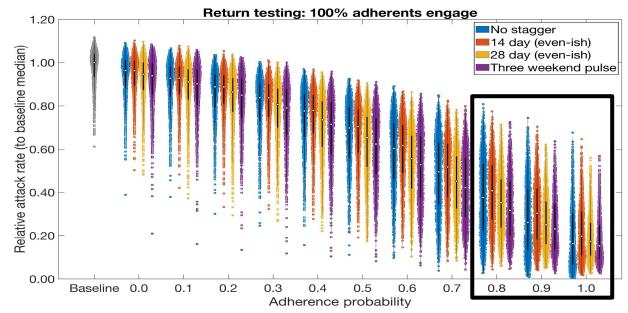
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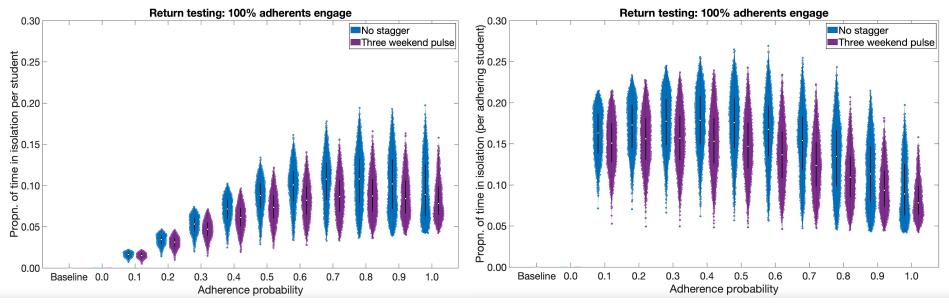


 Adherence to isolation guidance and following test and trace procedures is crucial in reducing the overall case burden within the student population.

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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 reduces the time each adherent is estimated to spend in isolation.

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- Impact of staggering: Stochastic compartmental model
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Achievements

- Provided new understanding on SARS-CoV-2 outbreaks at universities in England and how these could be mitigated.
- Other uses of the models



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Epidemics Volume 36, September 2021, 100476



Modelling SARS-CoV-2 transmission in a UK university setting

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Impacts of vaccination and asymptomatic testing on SARS-CoV-2 transmission dynamics in a university setting

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Emily Nixon, Amy Thomas, Daniel Stocks, Antoine M.G. Barreaux,
Go Gibran Hemani,
Adam Trickey, Rachel Kwiatkowska, Josephine Walker, David Ellis,
Leon Danon, Caroline Relton, Hannah Christensen, Ellen Brooks-Pollock

doi: https://doi.org/10.1101/2021.11.22.21266565

• Independent modelling approaches permitted a robust discussion comparing and challenging the different models' results.

Lessons

- When viewing the results in a **broader context** there are several other important aspects that warrant consideration, including (but not limited to):
 - educational needs
 - long COVID

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- mental wellbeing
- To facilitate collaborative studies across institutions and swift analyses:
 - ensuring barriers to data access are purposeful and necessary,
 - encourage establishment of a centralised nationwide student testing data resource.

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Acknowledgements

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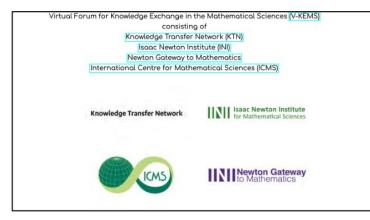
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