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Influence of setting-dependent contacts and protective behaviours on asymptomatic SARS-CoV-2 infection amongst members of a UK university

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ABSTRACT

We survey 62 users of a university asymptomatic SARS-CoV-2 testing service on details of their activities, protective behaviours and contacts in the 7 days prior to receiving a positive or negative SARS-CoV-2 PCR test result in the period October 2020–March 2021. The resulting data set is novel in capturing very detailed social contact history linked to asymptomatic disease status during a period of significant restriction on social activities. We use this data to explore 3 questions: (i) Did participation in university activities enhance infection risk? (ii) How do contact definitions rank in their ability to explain test outcome during periods of social restrictions? (iii) Do patterns in the protective behaviours help explain discrepancies between the explanatory performance of different contact measures? We classify activities into settings and use Bayesian logistic regression to model test outcome, computing posterior model probabilities to compare the performance of models adopting different contact definitions. Associations between protective behaviours, participant characteristics and setting are explored at the level of individual activities using multiple correspondence analysis (MCA). We find that participation in air travel or non-university work activities was associated with a positive asymptomatic SARS-CoV-2 PCR test, in contrast to participation in research and teaching settings. Intriguingly, logistic regression models with binary measures of contact in a setting performed better than more traditional contact numbers or person contact hours (PCH). The MCA indicates that patterns of protective behaviours vary between setting, in a manner which may help explain the preference for any participation as a contact measure. We conclude that linked PCR testing and social contact data can in principle be used to test the utility of contact definitions, and the investigation of contact definitions in larger linked studies is warranted to ensure contact data can capture environmental and social factors influencing transmission risk.

1. Introduction

In the 2020/2021 academic year 37% of 18-year-olds in the UK were offered a higher education place (Bolton, 2021) and altogether approximately 2.5 million students are registered in higher education in the UK across over 160 providers (Higher Education Statistics Agency, 2021). Universities provide much of this education; many comprising of order tens of thousands students and staff (Higher Education Statistics Agency, 2021) with highly connected communities through teaching, research, leisure and residential networks. Prior to the emergence of SARS-CoV-2, there was limited data available on the contact networks of university members, nonetheless preliminary modelling studies flagged universities as settings of potential high risk for SARS-CoV-2 transmission (Hill et al., 2021; Brooks-Pollock et al., 2021). Despite mitigations to reduce transmission risk, many universities in the UK (UCU, 2020) experienced outbreaks of SARS-CoV-2 at the beginning of the 2020/2021 academic year (UCU, 2020), some of which may have amplified infection rates in their local community (Enright et al., 2021). Students in halls of residence were noted to be at higher risk of experiencing SARS-CoV-2 infection (Children's Task and Finish Group, 2021), however insight into the risk associated with other activities undertaken by university members is limited.

Contact diary studies have proved useful for measuring contact rates to parameterise epidemic models in structured populations (Mossong et al., 2008). However, the most relevant contact definition remains uncertain. For a pathogen with potential for aerosolised and fomite

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transmission, such as SARS-CoV-2 (Klompas et al., 2020), contacts need not be close or conversational contacts, as typically measured in many contact surveys (e.g. Mossong et al., 2008). Furthermore, contact networks may be modified by the adoption of protective behaviours such as mask wearing, social distancing and hand washing (Golding et al., 2023). It is thus of interest to examine the role of protective behaviours in concert with a broad definition of contact when surveying the potential transmission risk of a particular activity. For diseases with high rates of asymptomatic infection, including SARS-CoV-2 (Oran, 2021), it is difficult to examine the utility of contact measures for estimating transmission risk using commonly collected epidemiological data streams based on symptomatic status.

In this study we were motivated to understand the SARS-CoV-2 infection risk of university activities for staff and students in October 2020 to March 20201. To this end we link asymptomatic SARS-CoV-2 testing data with quantitative data on social interactions while on and off campus in the week preceding an asymptomatic SARS-CoV-2 PCR test result. Given the restrictions on social mixing in place during the study period, and the uncertainty around the role of these in mitigating transmission risk, our contact survey records information about the protective behaviours adopted in each activity. We consider the utility of different contact measures, and the potential role of protective behaviour, in explaining the setting-specific infection risk in our participants. Our analysis is structured as follows. In Section 3.1 we provide summary statistics for our data. We then explore the ability of different individual contact definitions, that variably account for the duration, number of contacts, and presence of extra-household members in each setting to explain asymptomatic SARS-CoV-2 test outcome amongst participating staff and students (Section 3.2.1). We present the inferred associations between setting-specific contact and infection risk in Section 3.2.2. To investigate why interactions in particular settings may present enhanced infection risk we pool activities across individuals and consider correlations between protective behaviours, setting type and participant characteristics (Section 3.3).

2. Methods

2.1. Data collection and curation

Participant enrolment was based on a convenience sample of university staff and students returning SARS-CoV-2 positive saliva samples via the Nottingham Asymptomatic Testing (NATS) service. For each participant testing positive, we randomly invited a consenting NATS user with the same university role (staff or student) who had returned a negative test result. Ethical approval was obtained via the University of Nottingham Faculty of Medicine and Health Sciences ethics board (FMHS 96-0920). Participants provided informed consent. A copy of the survey is available upon request.

We divide participants into three groups; those who tested positive (positive), tested negative and had never had a positive test (negative) and those who tested negative but when surveyed had previously tested positive (previous). Unless stated otherwise the analysis is performed on the individuals in the groups positive and negative, minimising any bias due to the impact of SARS-CoV-2 immunity or assumed immunity on susceptibility and behaviour.

Participants were asked to recall information about social interactions and protective behaviours in each activity outside their home undertaken 7 days preceding the receipt of an asymptomatic PCR SARS-CoV-2 test result using a structured interview, offered in person or online. This interview was developed by two psychologists (KV & HK) and piloted prior to use. If prompting was needed, participants are encouraged to check their calendars or social media feed. Protective behaviours include whether the participant wore a mask, socially distanced (over 2 m away from possible contacts) and cleaned (washed or hand sanitised) their hands before and/or after each activity. Activities are assigned one of twelve settings. These are; abroad/aeroplane, campus other, exercise, hospitality, non-university work, non-private travel, other, research, retail, social, teaching and testing (see A1, Supplementary Information). Survey questions were motivated to capture adherence to pre-July 2021 guidelines for COVID-secure workplaces (Department for Business, Energy & Industrial Strategy and Department for Digital, Culture, Media & Sport, 2020).

Participants are prompted to recall each transition to a new activity and estimate the number of people present (0, 2–5, 5–10, 10–20, 20–50, 50–100, 100+) and duration of the activity. Note that we use the term contact in the broad sense of others present in the same setting, unlike many social contact surveys that assume contacts involve touch or conversation (e.g. Mossong et al., 2008). To capture social contact behaviour that could plausibly result in transmission via combinations of droplets, aerosol and/or fomites, we consider seven contact definitions when constructing setting-specific contact measures over the 7 day survey period: participation in the setting, the number of distinct activities, total contacts (the sum of the mid-points of estimated contacts during each activity), total duration of activities, and person-contact-hours (PCH) calculated as the summed product of the midpoint of the estimated contacts and the duration (in hours) of each activity, the total contacts not including the participant's household members and PCH not including the participant's household members. We conservatively set a maximum contact number of 100 for the 100+ option when computing contact measures. We assume that the number of possible household contacts is equivalent to the participant's household size. Therefore, if the number of household contacts is not given for an activity we calculate the non-household contacts and PCH as the difference between the maximum possible household contacts and reported contacts, providing a lower limit on the non-household contacts.

2.2. Setting-specific contact measures associated with asymptomatic SARS-CoV-2 PCR test result

We use a logistic regression model to regress asymptomatic SARS-CoV-2 test result on contact measures. Due to separation issues in the data (all participants who visited the aeroplane/abroad or non-university work setting tested positive) a Bayesian logistic regression is performed in Stan (2019) with a logit link function. As recommended by Gelman et al. (2008) priors for the logistic regression coefficients are assumed to follow independent Cauchy distributions centred at 0 and with scale parameter 10 for the constant term and 2.5 for all other coefficients (Gelman et al., 2008). Prior to fitting the data the binary input (whether a setting was visited) was transformed to have mean 0 and the numeric inputs (all others) are scaled to have mean 0 and standard deviation 0.5 (Gelman et al., 2008).

We assess the significance of regression covariates using Bayes factors. Since the model posteriors are sensitive to the prior a support interval (SI) is computed for the coefficient for each setting-specific contact measure (Wagenmakers et al., 2020). SIs provide information regarding the change in the credibility of values from the prior to the posterior indicating which values of a parameter gain support. Here we present values receiving 'moderate support', with a Bayes factor larger than 3, using the *bayestestR* package (Makowski et al., 2019). A leave-one-out error analysis is performed on the bounds of the SIs.

We estimate the marginal likelihoods and posterior model probabilities (PMPs) for the logistical model for each set of setting-specific contact measures generated by a contact definition using the *bridgesampling* package (Gronau et al., 2020). The PMPs are rescaled to sum to 1 across models considered. To examine the support for each contact definition we compute PMPs, averaging over 10 repetitions of the bridge sampling procedure to obtain an empirical estimate of the estimation uncertainty. For the model associated the largest PMP we present posterior predictive checks for the positive and negative groups, and generate an out of sample prediction for test outcome in the previous group.

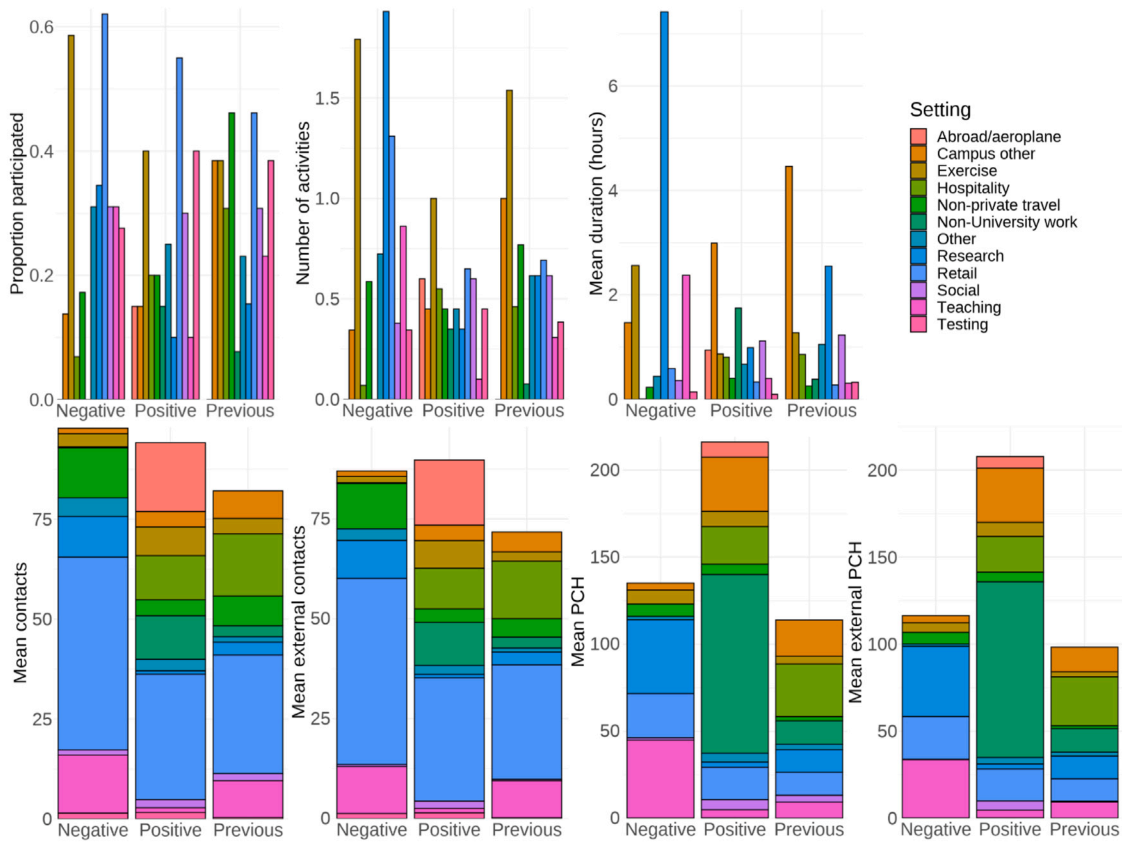

Fig. 1. The proportion of participants who took part in an activity, as well as the mean number of activities, duration spent, contacts, non-household contacts, PCH and non-household PCH in each setting, by test result.

2.3. Protective behaviours

To examine whether protective behaviours performed during an activity are influenced by the setting or environment we consider the relationship between these behaviours and the university role, gender, age and SARS-CoV-2 test result. As protective behaviours vary between activities even for individuals in the same setting, we pool individual data for this analysis. Each activity is described by nine properties; (i) age of the participant, (ii) gender of the participant, (iii) role (UG, PG, or employed), (iv) test result, (v) setting, (vi) environment (outdoors, ventilated indoors or unventilated indoors), (vii) did the participant wear a mask, (viii) did the participant socially distance at all times and (ix) did the participant use hand sanitiser or wash their hands before and/or after? To assess room ventilation participants were given the example of a room with doors and/or windows open being ventilated.

We perform a multiple correspondence analysis (MCA) in RStudio Team (2020) using the *FactoMineR* package (Husson et al., 2008) to examine the relationship between these properties. Since responses were not given for all activity properties, the *missMDA* package was used to estimate the number of dimensions for the MCA by leave-one-out cross-validation and impute missing values by cross-validation. Age is denoted a quantitative supplementary variable and gender, role, test result and setting as qualitative supplementary variables. The MCA is performed on the remaining 'active' variables (environment, mask wearing, social distancing and hand washing). Coordinates for the supplementary variables are predicted using the information from this MCA. The *dimdesc* function is used to determine which categorical variables best describe each dimension and whether age (the continuous variable) is correlated to each dimension. For the quantitative variable, age, correlation coefficients are calculated. For the categorical variables, a univariate ANOVA model is performed for each variable and dimension. An F-test examines whether each variable influences the dimension.

Fisher's exact test is performed on each pair of variables to determine whether they are significantly linked, with p-values corrected for multiple comparisons using the Benjamini–Hochberg method (Benjamini and Hochberg, 1995). Results are compared to the Bayesian logistic regression and used to verify consistency of the MCA analysis.

3. Results

3.1. Descriptive statistics

Participants are predominantly students between 18 and 30, however staff up to 60 years old are represented. The majority of participants completed the survey online (50, 23 positive and 27 negative), the remaining 12 (9 positive, 3 negative) completed the interviews in person. In all we have data on 447 distinct activities from the 62 participants. There were 20 participants in the positive group, 29 participants in the negative group and 13 in the previous group. The test result dates of the positive group are skewed towards the early period of NATS operation, reflecting the epidemic of self-reported PCR-confirmed SARS-CoV-2 infection within the University (UCU, 2020) (see Figure A1(a), Supplementary Information).

The mean and standard deviation of each setting-specific contact measure is provided in Table A1 (Supplementary Information). Retail settings were visited by the largest proportion of participants and had the highest mean non-household contacts, with exercise the most frequently reported activity. Research settings had the highest mean activity duration and mean non-household PCH, with teaching the highest mean PCH. Fig. 1 shows the proportion of individuals who participated, mean number of activities, mean total contacts, mean total

Table 1
The percentage of activities in each setting where a protective behaviour was performed. Data given are percentage who wore a mask, socially distanced (SD) at all times and when they washed their hands and the percentage of activities which these questions were answered (Ans.). Here individuals who washed their hands both are included in the percentage of people who washed their hands before and after.

Setting	Respiratory protection			Hand cleaning				
	Mask	SD	Ans.	No	Before	After	Both	Ans.
Abroad/Aeroplane (12)	0	0	75	92	8	8	8	100
Campus other (19)	74	74	100	6	94	94	94	95
Exercise (72)	41	79	99	9	57	91	57	97
Hospitality (13)	15	23	100	15	77	54	46	100
Non-private travel (26)	96	31	100	54	46	46	46	100
Non-university work (7)	100	14	100	100	100	100	100	100
Other (30)	53	70	100	17	60	80	57	100
Research (63)	89	62	97	2	89	98	80	98
Retail (51)	95	39	86	2	63	94	59	100
Social (23)	5	45	87	26	57	74	57	100
Teaching (27)	–	54	96	0	100	96	96	96
Testing (19)	82	82	89	5	89	95	89	100

duration, mean total PCH, mean non-household contacts and mean-non-household PCH for each setting by test result. Of interest, the mean number of contacts across all activities was highest in the negative group, but mean PCH and non-household PCH was higher in the positive group. A Kruskal–Wallis test showed no significant differences between the positive, negative and previous groups for total distinct types of activity (χ^2 = 0.17, df = 2, p = 0.92), number of activities (χ^2= 4.93, df = 2, p = 0.08), number of contacts (χ^2= 0.76, df = 2, p = 0.69), duration of activities (χ^2 = 1.91, df = 2, p = 0.38) or PCH (χ^2 = 0.44, df = 2, p = 0.80). There was however a significant difference between the non-household contacts (χ^2 = 9.71, df = 2, p = 0.008) and non-household PCH (χ^2 = 6.78, df = 2, p = 0.03). The mean household size of participants who tested positive was 2.9 (sd = 2.6), whereas the mean household size of participants who tested negative was 3.1 (sd = 2.0).

Protective behaviours reportedly practised in activities by setting are summarised in Table 1. The percentage of participants who provided answers for whether they wore a mask or socially distanced was the same for all activities except teaching. In teaching settings the participant was only asked about socially distancing. However, for 78% of teaching activities students stated that they wore a mask in the "additional comments" free text field. At the time of this study mask wearing was compulsory (unless exempt) during teaching activities at the university.

3.2. Contact measures associated with asymptomatic SARS-CoV-2 PCR test result

3.2.1. Comparison of models with different contact definitions

Table A2 (Supplementary Information) shows the median, minimum and maximum marginal likelihood estimates PMP for each contact definition. The narrow range of the marginal likelihood estimates indicates that the estimation uncertainty is small. The model adopting participation as a contact definition had the most support (PMP = 0.38), followed number of activities (PMP = 0.23) and the non-household PCH (PMP = 0.15). The duration of activities and PCH received less support (0.09 and 0.08, respectively). The models with the least support were the number of contacts and non-household contacts in each setting (PMP = 0.03).

3.2.2. Associations between setting-specific contact measures and test outcome

Fig. 2 gives the coefficient ranges within the SI for each covariate and contact measure, indicating values that received moderate support. We observe that the model with the most support, using whether participants entered each setting as the contact measure, has SIs which are all positive for the covariates aeroplane/abroad and non-university work and all negative for the covariates research and teaching. Reassuringly, more generally, the trends in distributions of the SIs appear similar for the five models with the most support (Section 3.2.1), however the distribution for the two models for the least support (contact definitions contacts and non-household contacts) are sometimes at odds with the SI for the other models. We discuss the consistency of SIs across contact definition models further below.

The SIs for household size, campus other, hospitality, retail and testing straddled zero, or were non-existent, for all contact definition models. For settings that had a strictly positive or negative SIs for at least one contact definition model, none of the models contradicted each other (i.e. with strictly positive SIs for one model and strictly negative SIs in another). When considering settings that are inferred as significant in the best-performing model, aeroplane/abroad and teaching had median and SIs with consistent sign across models, but moderate support was not found for any values for aeroplane/abroad in some models. In contrast the other significant settings, non-university work and research, had SIs that straddled zero in some of the poorer performing models. However, we note that these SIs barely traversed zero (the moderate support for non-university work had a lower bound of −0.03 and research had an upper bound of 0.02).

For the five best-performing models coefficients in the SI for exercise is skewed towards negative values, and these are strictly negative for the models adopting the number of activities and the duration as the contact measure. Similarly, for all models non-private travel SI distributions appear to mostly contain negative values, but SIs are strictly negative for models with non-household PCH and PCH as the contact measure. The covariate "Other" has an all negative SI for contacts, however this model had poor support. The models adopting the duration or PCH as the contact measure yield an all positive SI for social activities. For the best five performing models coefficients in the SI for social are skewed towards positive values.

It is clearly of interest to understand the extent to which SIs are driven by the activities of individual participants, and we explore this in a leave-one-out analysis (A4.2, Supplementary Information). In brief, the model with the largest PMP (based on the participation contact definition) displayed stable SIs across the leave-one-out deletions, but models with low PMPs have large standard deviations in the bounds for the SIs, and signs of the SI bounds are not always consistent with those obtained in the main analysis. Further model checks based on the Fisher's analysis and the posterior predictive checks for the group previously testing positive are provided in §A4 (Supplementary Information).

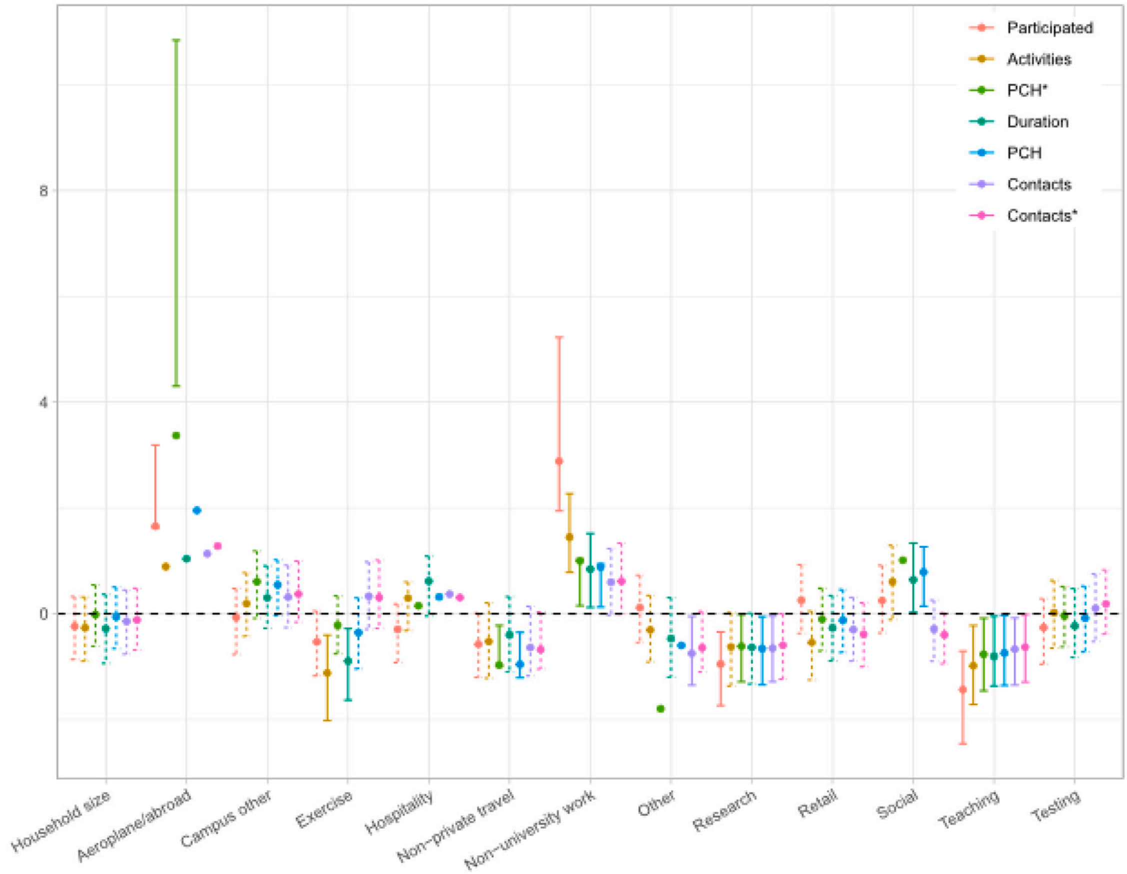

Fig. 2. Median (circles) of the covariate coefficients for each contact definition. Support intervals (SIs) give ranges of parameters with a Bayes factor larger than or equal to 3, interpreted as moderate support (bars). * = contact definitions include only external non-household contacts. Solid bars represent SIs where all supported values have the same sign. Note that as the Bayes factor depends on the prior, the marginal posterior median does not always lie in the SI.

3.3. Protective behaviours

Altogether, four dimensions are required to explain 70.9% of the variance in the MCA analysis (Figure A4, Supplementary Information). Fig. 3 shows how the active and qualitative variables relate to the first two dimensions of the MCA, and provides evidence that patterns of protective behaviour differ between settings. Significant components for the first four dimensions are provided in Table A5 (Supplementary Information) and results from the Fisher's exact tests in Table A6 (Supplementary Information).

Fisher's tests showed positive test results were positively correlated with no hand washing and females, and were negatively correlated with mask wearing, washing hands after and maintaining social distancing at all times. Explanations for the association of test positivity with gender in our sample are considered in §A5 (Supplementary Information).

Of the activities on campus, teaching and retail are associated with wearing a mask and washing hands both before and after. PGs activities are positively correlated with indoor unventilated environments, social distancing and hand washing. Being classified as staff is negatively correlated with hand washing.

Outside of campus-based activities we find that retail was associated with mask wearing and washing hands before and after an activity. Masks are unlikely to be worn in social settings and outdoors. The MCA analysis shows an association between the abroad/aeroplane setting and not cleaning hands before or after travel. The Fisher's analysis indicates a negative correlation of air travel with wearing a mask and social distancing. Participants in the study that were staff were more likely to participate in travel activities.

4. Discussion

We have presented linked asymptomatic SARS-CoV-2 testing and social contact data for a UK university collected from October 2020 to March 2021, after the initial surge in infections at the beginning of the 2020/2021 academic year (UCU, 2020). During the study period, restrictions on mixing outside of your household/bubble and educational activities were in place, with particularly stringent rules about social contact with those outside of your household in place during tier 3 restrictions (30 October 2020–5 November 2020), and the second (5 November 2020–2 December 2020) and third (6 January 2021–8 March 2021) national lockdowns (UK Government, 2020, 2021). Strict social distancing measures were also in place on campus throughout the study period. Teaching was undertaken in a hybrid (online/in-person) manner to accommodate social distancing. During the third national lockdown only students on a limited selection of courses (Medicine & Dentistry, Health & Social Care including Nursing & Midwifery, Physiotherapy and Veterinary Science, Education, and Social Work) were permitted to travel to campus without exemption. Research staff were asked to work from home whenever possible (University of Nottingham, 2021).

Within this context and for the cohort studied, participating in air travel (and holiday activities) and non-university work increases the probability of a positive asymptomatic SARS-CoV-2 PCR test result. This is consistent with evidence that workers with public facing roles are at higher risk of infection (see P.H.E. Transmission Group, 2020 and references therein, Thomas et al., 2021). Students or staff in part-time work in other settings could mediate spillover between the University and community. Encouraging vaccination of these groups could be

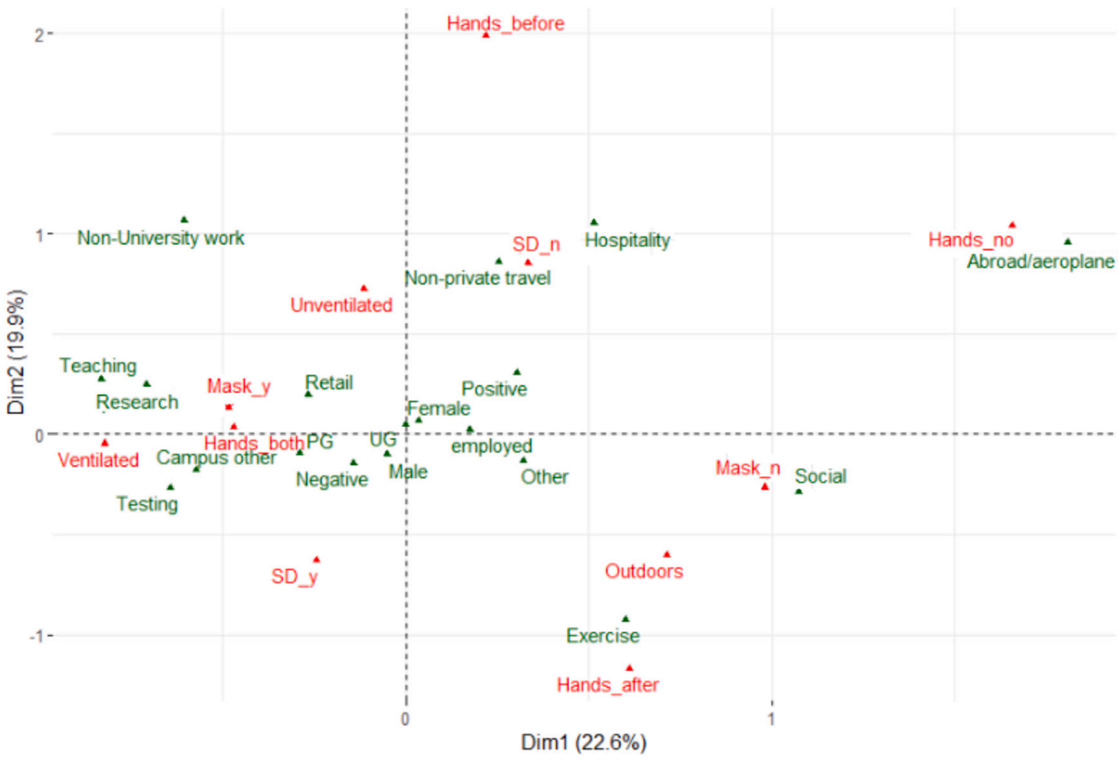

Fig. 3. Graph visualising the coordinates of each variable categories in dimensions 1 and 2. The distance between any points gives a measure of their similarity. Supplementary variables are shown in green and active variables are shown in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

particularly important for mitigating the risk of university outbreaks in periods of restrictions.

Participating in research and teaching activities at the university was associated with a lower risk of a positive asymptomatic SARS-CoV-2 PCR test result, however no association was found with participation in other activities on campus. Although our data does not permit estimate of the risk attributable to any activity or setting, our results are consistent with teaching and research activities having lower infection risk than other activities noted by participants.

Participation in a setting was the best-performing contact measure, followed by counts of the number of activities in each setting and the non-household PCH (each for 7 days preceding test result). Out of sample model predictions for the group previously testing positive yielded an expected test positivity between that for the negative and positive groups across all contact definitions.

Indications that non-household PCH and duration of activities provide a better model of SARS-CoV-2 PCR test status than contacts or PCH provides tentative evidence for the role of contact duration in infection risk, also reported by Thompson et al. (2021). There are several potential reasons for the difference in model performance between contact definitions, and in particular the superior performance of participation in a setting rather than the definitions capturing contact numbers. Infected people can remain PCR positive for up to 3 weeks following exposure (Sethuraman et al., 2020) depending on the sensitivity of the saliva assay (Teo et al., 2021) and therefore we cannot guarantee we have surveyed participant behaviour during the period of exposure. Additionally, contacts in each activity were assumed to extend for the duration of an activity. We have not collected data on repeated contacts, and it is possible that the participation contact definition is preferred because of this. Contact definitions that capture the proximity and duration of every contact in each activity may perform better. While collecting more detailed contact data was considered prohibitive from a recall perspective in our retrospective survey, similar contact diary studies have been piloted (Bolton et al., 2012), and it would be of interest to link these to repeated asymptomatic test outcome data for SARS-CoV-2 or other respiratory viruses in larger studies with greater statistical power.

We adjusted for participant household size in our regression, but did not find a significant effect. Other studies examining the risk associated with household size have been mixed, with an analysis of setting-dependent transmission risk not identifying household size as significant (Thompson et al., 2021), but recent SARS-CoV-2 prevalence higher in larger households (ONS, 2021). Analysis of contact patterns in another UK university suggested that extra-household contacts were higher amongst those living in smaller households (Nixon et al., 2021), and it is plausible that such an effect could offset the enhanced risk of importation into larger student households. Outbreaks in halls of residence may have been more strongly influenced by hall than household size (Enright et al., 2021) and it is possible that there are other risks associated with residential contacts in this setting that we have not captured.

Positive asymptomatic SARS-CoV-2 PCR test results were negatively associated with mask wearing, social distancing and hand washing, as reported in another case-control study of asymptomatically infected contacts of SARS-CoV-2 cases (Doung-Ngern et al., 2020). Our MCA highlighted differential adoption of protective measures between settings and suggests that protective behaviours can be different in university and non-university activities. Teaching and research setting may be lower risk (despite similar or larger mean contact measures across contact definitions) as they were associated with mask wearing and hand washing. Although mask wearing and hand washing was practised uniformly in non-University work settings, this was less likely to be in a ventilated space with complete adherence to social distancing than other settings. Other studies suggest that adoption of protective behaviours is also determined by psychological factors (Zickfeld et al., 2020; Faasse and Newby, 2020; Wise et al., 2020), which could explain some of the variability between participant behaviour. Measuring the prevalence of micro-distancing behaviour as well as macro-distancing behaviour now widely captured by mobility patterns has shown utility in estimating the effective reproduction number in low-prevalence settings (see, e.g., Golding et al., 2023) and may also aid in parameterising agent-based simulation of transmission (Kerr et al., 2021).

Our results come with a number of important caveats. Our sample size is relatively small, was chosen based on consenting positive cases, and may not be representative of all users of the NATS or the wider University population. A greater proportion of positive cases in our study were from periods with lower levels of restriction which could generate time-varying confounding in our analysis. A larger sample would likely allow for adjustment for this and other potential confounders, and potentially provide statistical power to include setting-specific protective behaviours in the regression model. As discussed elsewhere (Royal Society SET-C, 2020), the opportunities for contact and transmission depend on community prevalence and the social restrictions in place. Data for this study was collected over a period during which there were strong (albeit changing) restrictions on permitted social and travel activities, which may partly explain the absence of a significant effect of social interactions on risk of obtaining a positive test result as reported in other studies (Hobbs et al., 2020). Similarly, occupancy on campus was low during the study with much teaching online, and we expect the relative risk of activities in different settings will change depending on how university and national policies, and the behavioural response to these, evolve. Furthermore, participants were surveyed at a time when the circulating SARS-CoV-2 strain was either phenotypically akin to the original Wuhan strain, or the alpha variant of concern, and it is plausible that different patterns of risk would be observed for delta or other variants with different infectiousness profiles.

Although the structured interview adopted aims to optimise recall of social contact behaviour, the limitations of recalling such details accurately are well documented (e.g. Garry et al., 2021). Participants who received positive test results could be experiencing stress/anxiety that may influence their ability to recall events (Garry et al., 2021). Others have suggested that recall bias could act in the opposite direction, with SARS-CoV-2 positive participants more likely to recall possible contact events (Delgado-Rodríguez and Llorca, 2004). The significant delays between test result and survey (Fig. A2, Supplementary Information) may also influence recall ability (Hipp et al., 2020). Our findings relate to a highly educated population, a characteristic that has been associated with adopting protective behaviours (Vally, 2020). Despite likely ready access to PPE and other resources enabling protective behaviour, protective behaviours were not uniformly reported amongst participants. For all of these reasons – but in particular our small sample and potential for recall bias – we prefer our work to be considered a proof of concept study; demonstrating the types of questions about contact measure, settings and infection risk that can be addressed with linked testing and detailed contact data. Future work in this area may require the development of real-time data streams efficiently capturing details of contact *and* protective behaviours, that can be embedded within community and/or strategically targeted surveillance of respiratory pathogens.

CRediT authorship contribution statement

Emma L. Fairbanks: Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing. **Kirsty J. Bolton:** Conceptualization, Funding acquisition, Investigation, Methodology, Software, Visualisation, Supervision, Writing – original draft, Writing – review & editing. **Ru Jia:** Conceptualization, Investigation, Methodology, Project administration, Writing – review & editing. **Grazziela P. Figueredo:** Conceptualization, Funding acquisition, Data analysis, Writing – review & editing. **Holly Knight:** Conceptualization, Methodology, Project administration, Writing – review & editing. **Kavita Vedhara:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Software, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.epidem.2023.100688.

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