

Open Research Online

The Open University's repository of research publications and other research outputs

Work-Related and Personal Predictors of COVID-19 Transmission: Evidence from the UK and US

Journal Item

How to cite:

Anand, Paul; Allen, Heidi; Ferrer, Bob; Gold, Natalie; Gonzales Martinez, Rolando; Kontopantelis, Evangelos; Krause, Melanie and Vergunst, Francis (2022). Work-Related and Personal Predictors of COVID-19 Transmission: Evidence from the UK and US. *Journal of Epidemiology & Community Health*, 76 pp. 152–157.

For guidance on citations see [FAQs](#).

© 2021 Author(s) (or their employer(s)).



<https://creativecommons.org/licenses/by-nc/4.0/>

Version: Accepted Manuscript

Link(s) to article on publisher's website:

<http://dx.doi.org/doi:10.1136/jech-2020-215208>

Copyright and Moral Rights for the articles on this site are retained by the individual authors and/or other copyright owners. For more information on Open Research Online's data [policy](#) on reuse of materials please consult the policies page.

oro.open.ac.uk

Work-Related and Personal Predictors of COVID-19 Transmission: Evidence from the UK and US

Paul Anand, Economics, Open University, Milton Keynes, MK7 6AA, CPNSS, London School of Economics, WC2A 2AE, Department of Social Policy and Intervention, Oxford University, OX1 2ER, UK
pa68@open.ac.uk

Heidi Allen, School of Social Work, Columbia University, New York City, NY 10027, USA
ha2332@columbia.edu

Bob Ferrer, Family Health Center, Robert B Green Campus, University of Texas, San Antonio, TX 78207, USA
ferrerr@uthscsa.edu

Natalie Gold, Faculty of Humanities, Oxford University, OX2 6GG, UK and Public Health England, London, UK SE1
natalie.gold@phe.gov.uk

Rolando Manuel Gonzales Martinez
Agder University, 4630 Kristiansand, Norway
rolando.gonzales@uia.no

Evangelos Kontopantelis
Division of Informatics, Imaging and Data Sciences, University of Manchester, M13 9NT, UK
e.kontopantelis@manchester.ac.uk

Melanie Krause
MRC Laboratory for Molecular Cell Biology, University College London WC1E 6BT, UK
melanie.krause.15@ucl.ac.uk

Francis Vergunst
Research Unit of Children's Psychosocial Maladjustment, University of Montreal, H3T 1C5, Canada
francis.vergunst@umontreal.ca

Abstract

Objective

To develop evidence of work-related and personal predictors of COVID-19 transmission.

Setting and Respondents

Data are drawn from a population survey of individuals in the US and UK conducted in June 2020.

Background Methods

Regression models are estimated for 1467 individuals in which reported evidence of infection depends on work-related factors as well as a variety of personal controls.

Results

The following themes emerge from the analysis. Firstly, a range of work related factors are significant sources of variation in COVID-19 infection as indicated by self-reports of medical diagnosis or symptoms. This includes evidence about workplace types, consultation about safety and union membership. The partial effect of transport related employment in regression models makes the chance of infection over three times more likely while in univariate analyses, transport related work increases the risk of infection by over 40 times in the US. Secondly, there is evidence that some home related factors are significant predictors of infection, most notably the sharing of accommodation or a kitchen. Thirdly, there is some evidence that behavioural factors and personal traits (including risk preference, extraversion and height) are important also.

Conclusions

The paper concludes that predictors of transmission relate to work, transport, home and personal factors. Transport related work settings are by far the greatest source of risk and so should be a focus of prevention policies. In addition, surveys of the sort developed in this paper are an important source of information on transmission pathways within the community.

Mandated BMJ Keywords

Environmental epidemiology, Health inequalities, Multi-level Modelling, Policy, Psychosocial Factors

The authors have no conflicts of interest to declare. They assign to BMJ an exclusive publication license.

Acknowledgements. The authors are particularly grateful to an anonymous referee, and Ron Smith (Birkbeck) for comments on an earlier version as well as Michel Belot (Cornell) for discussions about the database design. In addition, we thank particularly contacts at Pollfish, the press office at Manchester University and the Open University for funding data collection. Ethics Approval HREC3590 was given by the Open University.

Work-Related and Personal Predictors of COVID-19 Transmission: Evidence from the UK and US

1.Introduction

Preventing the transmission of COVID-19 related to work and amongst the poor potentially saves lives while contributing to other economic and social priorities. A large amount of scientific research has focussed on patterns of spread and underlying mechanisms of transmission but as economies and societies reopen, it is important to know more about the role of workplace, personal and household predictors of community transmission.[1-2] Heightened risks implied by spatial patterns [3] and attached to certain work-roles have emerged as important but there are many aspects of employment and consumption activities that are likely to contribute to transmission that have barely been researched. In addition, and closely connected, there is a growing body of knowledge about personal factors that contributes to mortality but, with the exception of ethnicity, only a smaller amount of literature of personal traits and circumstances relating to transmission risk within work and community settings. [4].

To limit the spread of the virus, it is therefore important to study work-related and other factors (summarised in Figure 1) that contribute to or could limit its spread. This paper therefore reports on the development of data relating to a new set of diverse workplace and personal factors. More specifically, using a data on 1467 working age adults in the US and UK, the paper estimates regression models in which work, personal factors and a range of demographic controls are used to predict experience of Covid-19. Both countries are examples of high-income market economies are distinct from others in two ways. Unlike some Asian countries, they do not have recent similar epidemic experiences (es SARS) on which to draw and unlike many European countries, they do not have civil law traditions based on a ‘strong’ conception of the state. Yet the US and UK differ in the extent and manner in which they provide access to health care and welfare support. Furthermore, the US has experienced prevention measures that have varied significantly between states.

For these two countries, the paper draws on a new health and economics database (developed in June 2020) to estimate regression models of transmission experience. The dataset design used here contains several variables hypothesised to relate to community transmission and the analysis focuses on the possession of a medical diagnosis or positive test, as self-reported by the respondent. Results are reported in terms of descriptive results, univariate odds ratios and regression results and the following themes emerge from the analysis. Firstly, a range of work related factors are significant sources of variation in COVID-19 infection as indicated by self-reports of medical diagnosis or symptoms. This includes evidence that consultation about safety and union membership in the workforce are associated with infection. Secondly, there is evidence that some home related factors are significant predictors of infection, most notably the sharing of accommodation. Thirdly, there is some evidence that behavioural factors and personal traits are important also. In addition, there is some evidence that controls for risk aversion and extraversion also accounts for some variation in infection.

The paper concludes that predictors of transmission relate to work, transport, home and personal factors and that surveys of the sort used here can be a useful source of information on transmission pathways within the community. While there is support for the view that public health messaging should target a demographic sources of variation, our data highlights also the importance of work, transport and behavioural factors. The rest of the paper is structured as follows. Section 2 summarises the key variables and statistical techniques used. Section 3

carries the main results while section 4 discusses these results in community and policy contexts, some limitations and possibilities for follow-up work.

2. Methods and Materials

Data

The database described below (and in the online materials) from which the variables are drawn was developed during a period when general scientific pathways of transmission were becoming more widely accepted but there was little evidence on some of the possible predictors and mechanisms in US and UK communities. Variables were developed by drawing both on the literature relating to community transmission as well as on the capability approach which emphasises the importance of individual differences in translating economic and social resources into valued outcomes. The capability approach has been influential in health [5] and was used to inform the inclusion of variables in the original database. The approach helps in this context to emphasise the importance of individual differences as well as a diverse range of resources in shaping the ability to reduce the risk of infection. As a result, it provides a mix of standard as well as more novel data on a range of work, personal, and home factors. While all types of factors are plausibly related to infection, to facilitate interpretation in this paper, we treat work related predictors as focal variables and the rest as controls. The data used are described below and their summary statistics for the variables below are described in Table 1.

Table 1 Descriptive and Background Statistics for the UK and US

		Country		Total
		UK	US	
Diagnosis of COVID	Medical diagnosis or positive test			
	No	932	944	1876
	Yes	68	56	124
Work and Commuting Factors	Type of workplace			
	Intermediate	694	689	1,383
	Transport related	17	16	33
	Other work	28	23	51
	Other non-work	261	272	533
	Belong to a trade union			
	No	784	846	1630
	Yes	216	154	370
	Consultation on transmission			
	No	688	689	1377
Yes	312	311	623	
Can work from home mainly				
No	608	629	1237	
Yes	392	371	763	
Public transport to get to work				
No	767	844	1611	
Yes	233	156	389	
Personal factors	Age			
	18 - 24	185	120	305
	25 - 34	258	257	515
	35 - 44	257	257	514
	45 - 54	176	161	337
	> 54	124	205	329
	Gender			
	Male	500	500	1000
	Female	500	500	1000
	Income			
high_i	113	95	208	
lower_i	204	213	417	

lower_ii	179	284	463
middle_i	282	217	499
middle_ii	222	191	413
Shared accommodation/kitchen			
No	787	640	1427
Yes	213	360	573
Risk Preference			
No	379	365	744
Yes	621	635	1256
Extraversion			
No	505	454	959
Yes	495	546	1041
Taller than 6 ft			
No	832	829	1661
Yes	168	171	339

A key for income categories is given in the online supplementary materials Appendix 1.

Work Related Factors

A focal set of predictors relate to work and commuting. The main workplace setting was recorded in a variable with fifteen response categories which on the basis of evidence and reasons of tractability is used in three groupings. Some of the underlying workplace settings are already known to contribute to transmission,[6] particularly those related to transport. In addition, there are two variables that record whether a person is forced to use public transport to commute to work and whether they are able to work mainly from home. Both are potential risk factors although the sign on the ability to work from home is difficult to assess *a priori*. At the time of variable development, unions in the UK were being reported in the media for their advocacy of health and safety issues at work and yet no investigations to date appear to have studied the contribution of trade unions.

Personal Controls

This paper draws on some standard and novel personal variables including variables related to risk-aversion, extraversion, sex, age, household income and height. To assess risk aversion, the survey contains a single question that has been used previously and validated against other measures in economics.[7] Risk preference plays a central role in the economic theorising of behaviour and it is hypothesised that it also plays an important role in transmission related behaviours. Extraversion in addition, is one the Big-five personality traits used extensively in psychology [8] and may also drive social behaviours that account for infection. Height has been associated both with health and income.[9-12] and is included as a further control. In our analyses sex and age are also included following research on mortality. and may also be connected to transmission. Data is also available on the use of cash payments given concerns about sequential touching of surfaces in public settings. [13]

While involvement in lorry driving has also been implicated in the spread of Covid-19, [14] car ownership might also be a significant protective factor if the use of private transport enables individuals and family members to social distance for more of the time. To the extent, that safety is a good, household income could also be an indicator of a range of omitted factors that impact risk such as having access to a private garden. We include, in addition, a binary variable that records whether a person responds yes or no to question about whether they live in shared accommodation or make use of a shared kitchen. Finally, the database includes data on whether a respondent was other 6ft in height. If downward falling particles were a predominant community transmission mechanism the partial effect of shortness would be positive for infection risk. Accordingly, we employ a height control.

The dataset on which these variables draw was developed by a survey that took place over the first week of June 2020. Samples of 1000 adults in the US and UK were obtained from a professional survey company using quota sampling to obtain a national sample broadly representative for those of working age with some oversampling to reflect contrasts of interest. There are no missing data as respondents needed to complete all questions. That said, our analysis focuses on a subset of 1467 employees so as to exclude respondents in non-work categories (mainly retirees and homemakers). All survey recruitment and completion was done by electronic means (via phones or personal computers but not face-to-face meetings). Towards the end of the sampling period some of the quotas were relaxed and the final distribution of some socio-economic characteristics in the data used here appear in Table 1. The company provides, *ex post*, a set of weights that can be used to construct nationally representative results and these weights are used in the pooled regression results. Respondents were paid a small amount for completing the survey which took about 5 minutes on average to complete. It is important to reiterate that survey responses are self-reports and that said, overall reported infection rates are comparable to those reported elsewhere for the UK [15] and US [16] bearing in mind the predominance of early transmission experience. Those who became ill at points closer in time to the survey were, plausibly, less likely to respond probably because they were still ill.

Methods

The outcome of primary interest was a confirmed diagnosis of COVID-19 (“Have you had a medical diagnosis or positive test for COVID”). Pooled regression models for the USA and UK samples are reported, with area of residence modelled as fixed-effects for responders within fourteen states in the US and four constituent countries (England, Scotland, Wales, Northern Ireland or unknown) in the UK. Country specific models are given in the supplementary materials (Appendix 2). Stata 14 is used for the analysis.

4. Empirical Results

In Table 2, univariate odds ratios and 95% confidence intervals are presented for several predictors of transmission. As there is an exploratory aspect to the research these results should be interpreted in light also of the main regression models that follow and which they help to motivate.

Table 2 Univariate odds ratios for work and personal predictors of COVID-19 infection risk in the UK and US.

		UK		US		Pool	
		OR	CI	OR	CI	OR	CI
Work and Commuting Factors	Type of workplace						
	Transport related	11.165	[2.90, 43.02]	40.758	[8.62, 192.63]	19.612	[7.29, 52.74]
	Other work	7.889	[2.32, 26.84]	18.877	[3.94, 90.52]	11.207	[4.32, 29.09]
	Others						
	Belong to a trade union	2.102	[1.25, 3.54]	7.037	[4.03, 12.28]	3.671	[2.52, 5.35]
	Consultation on transmission	2.353	[1.43, 3.86]	2.941	[1.7, 5.07]	2.602	[1.8, 3.75]
	Can work from home mainly	1.603	[0.98, 2.63]	2.380	[1.38, 4.11]	1.925	[1.34, 2.77]
	Public transport to get to work	1.517	[0.89, 2.6]	5.882	[3.37, 10.26]	2.843	[1.94, 4.16]
Personal Factors	Age						
	18 - 24	0.683	[0.4, 1.17]	0.683	[0.4, 1.17]	0.683	[0.4, 1.17]
	25 - 34	1.311	[0.66, 2.6]	1.868	[0.74, 4.71]	1.465	[0.85, 2.52]

35 - 44	0.811	[0.39, 1.71]	1.261	[0.48, 3.31]	0.946	[0.53, 1.69]
45 - 54	0.894	[0.4, 1.99]	1.258	[0.44, 3.56]	0.995	[0.53, 1.86]
> 54	0.099	[0.01, 0.77]	0.093	[0.01, 0.78]	0.087	[0.02, 0.38]
Gender						
Male	1.788	[1.07, 2.98]	0.859	[0.5, 1.48]	1.273	[0.88, 1.84]
Female	0.559	[0.93, 0.34]	1.164	[2, 0.68]	0.785	[1.13, 0.54]
Income						
high_i	0.563	[0.26, 1.21]	0.563	[0.26, 1.21]	0.563	[0.26, 1.21]
lower_i	1.518	[0.58, 3.99]	2.323	[0.66, 8.22]	1.776	[0.83, 3.8]
lower_ii	0.618	[0.19, 1.97]	2.449	[0.71, 8.4]	1.369	[0.63, 2.97]
middle_i	1.735	[0.69, 4.35]	1.638	[0.45, 6.01]	1.719	[0.81, 3.64]
middle_ii	1.292	[0.49, 3.43]	0.995	[0.24, 4.07]	1.185	[0.53, 2.63]
Others						
Shared accommodation/kitchen	1.855	[1.09, 3.16]	4.078	[2.29, 7.26]	2.491	[1.73, 3.59]
Risk preference	2.073	[1.17, 3.69]	1.611	[0.88, 2.95]	1.839	[1.21, 2.79]
Extraversion	1.827	[1.1, 3.04]	1.977	[1.1, 3.55]	1.867	[1.27, 2.74]
Taller than 6 ft	2.575	[1.5, 4.41]	2.676	[1.5, 4.78]	2.616	[1.76, 3.88]

Several of the work-related variables, with the exception of being able to work from home, have a statistically significant impact on the risk of infection. Being employed in transport related work stands out as the biggest single risk factor causing respondents to be 19 times more likely to report infection in the pooled data. In the US, the risk is double this. Being employed is also a risk factor and the impact is greater for those on reduced earnings. Consultation and union membership are also significant predictors of elevated risk in both countries while other work-related factors are significant or close in at least one country. For the pooled data, being forced to take public transport to get to work increases the risk of infection by 284%.

Turning to other variables here being as controls, the use of shared accommodation or kitchen stands out as a significant risk factor in both countries. In the UK risk increases by 85% and in the US by over four times. By contrast being over 54 is a protective factor in this data and seems to be clear evidence of adaptive behaviour by this age group. And it is worth noting that risk preference and extraversion are positive behavioural predictors of risk also as is height (something we consider in the discussion section below). While these univariate results are useful for prediction and exploratory purposes, to isolate more specifically the impact of work features on transmission, controlling for other factors, we estimate multiple regression models focussing in Table 3 to isolate the partial effects.

Table 3 Pooled Regression Models of Community Transmission in UK and US with Fixed Spatial Effects

	Work related controls		Work related and additional controls	
	Unweighted	Weighted	Unweighted	Weighted
Type of workplace				
Transport related	3.634*** (1.5772)	3.531*** (1.3188)	3.049** (1.3707)	2.819** (1.1417)
Other work	2.309** (0.956)	2.32 (1.1922)	1.934 (0.8179)	1.864 (0.9762)
Work and Commuting Factors				
Belong to a trade union	2.403*** (0.5233)	2.614*** (0.6409)	2.198*** (0.4932)	2.282*** (0.5732)
Consultation on transmission	1.787*** (0.3802)	1.759** (0.4083)	1.563** (0.347)	1.507* (0.34)
Can work from home mainly	1.311	1.366	1.26	1.277

		(0.2775)	(0.3127)	(0.2721)	(0.299)
	Public transport to get to work	2.012***	2.09***	1.803**	1.838**
		(0.4508)	(0.5107)	(0.4117)	(0.4562)
	Age (54 years or more)			0.196**	0.223**
				(0.1429)	(0.1638)
	Gender (male)			0.818	0.767
				(0.2039)	(0.2171)
	Income (lower_ii)			1.03	0.961
				(0.2609)	(0.2474)
Personal factors	Shared accommodation/kitchen			1.742**	1.855***
				(0.3767)	(0.4364)
	Risk preference			1.838**	1.834**
				(0.4628)	(0.4959)
	Extraversion			1.115	1.09
				(0.2558)	(0.2638)
	Taller than 6ft (men)			1.604	1.737*
				(0.4653)	(0.5644)
Model performance					
	Number of observations (n)	1,467	1,467	1,467	1,467
	Pseudo-R2	0.1126	0.1184	0.1473	0.162
	Log-likelihood	-355.564	-298.201	-283.4598	-341.6548
	Akaike information criterion (AIC)	759.127	644.403	628.9196	745.3096
	Bayesian information criterion (BIC)	886.111	771.386	792.9398	909.3298

***p-value < 0.01, **p-value < 0.05, *p-value < 0.10. Standard errors in brackets below each estimated coefficient.

Diagnosis: logit estimated for the question "Have you had a medical diagnosis or positive test for COVID?" (Yes = 1).

Estimated coefficients are presented as odds ratios. People performing non-working activities were excluded from the estimations. Regional dummy coefficients suppressed.

Table 3 estimates the impact of different work factors allowing for controls in multiple regression models without and with weights that provide an indication of results would be in a more nationally representative sample. In order of materiality, transport related employment, having to use public transport to get to work, union membership and consultation about COVID safety are significant predictors of infection. While coefficients are reduced somewhat, the overall picture is robust to the introduction of a diverse set of person related controls. Thus the partial effect of transport related employment still increases the risk of infection by a factor between 2.8 and 3.0. In this analysis shared accommodation and risk-preference have a similar impact as being required to go work on public transport (which roughly doubles the probability of infection). Being taller than 6ft for men is also significant in the weighted version of the regression. These models have focussed on the results that seem to apply in both the UK and US but there is also evidence of some country differences as indicated by the country regressions (Appendix 2 Tables S1 and S2). It is noticeable that car ownership seems to more protective in the US than in the UK for example.

4. Discussion

The models of transmission experience add to what is known about transmission in the community [17-18]. Several points about work-related transmission of COVID-19 can be made. Firstly, there is evidence that working in transport related roles is a risk factor for infection. Given the nature of social contact that bus-drivers and taxi-drivers experience, for example, this is unsurprising but does help to raise an issue for health and safety regulation. While employers such as bus companies can be expected to research experiment and develop protective measures for their workers and customers, it is less likely that self-employed taxi drivers will be able to do the same. Public health policy design needs therefore to be aware of the employment context in considering how it develops and regulates work-place protection. Secondly, there is evidence that consultation and union membership are both positively related

to infection. The fact that consultation is positively related indicates that in the early part of the pandemic consultation was rather reactive. Half the respondents claimed not to have been consulted furthermore and as a result, there may be a need for public health policy-makers to mandate a more proactive and preventative approach to consultation as informed workers are likely to be a good source of data on potential risks. Thirdly, these analyses show the importance of commuting practices in transmission. Having to use public transport to get to work is a significant risk factor also. This supports the view that doing what is possible to make public transport as safe as possible should be an important priority.

The personal controls contribute to robustness by reducing problems of omitted variable bias and in some cases may be of interest in their own right. With the addition of controls for age, gender, income shared accommodation, risk-preference, extraversion and height, there large differences between the impact of different types of work, consultation, public transport commuting and union membership. In this analysis and others not reported, living in shared accommodation or sharing a kitchen has a particular large and significant impact. Country based analysis in the online supplementary materials confirm this is true both in the US and UK. The issue has received less attention that living in multi-generational households and merits more emphasis from public health policy makers. It is also interesting to note that risk-aversion and extraversion are risk factors as economic theory and psychological concepts would suggest and that the in Table 3 the impact of risk-aversion is similar to that of accommodation sharing. Behavioural scientists who are increasingly arguing for the use of their insights in the design and evaluation of non-medical interventions have good reason as a result to include risk aversion in their analyses. Finally, we note that the control for height for men in this analysis is on the verge of being significant but stress there is nothing in the data to indicate why this might be the case. It could be a statistical artefact of the datasets used or reflect some more substantive social, physical or biological difference related to height. For example, we do now know that air-borne transmission is not just related to physical proximity but not whether physical or behavioural characteristics are material. [19] Whether some of these controls speak to more substantive issues is therefore a matter that must be left to future research.

We conclude that surveys of potential risk factors, and sources of ability to avoid them, provide essential supplements to standard prevalence surveys or computer projections of infection numbers based on r-number modelling. Some important limitations of this analysis include the fact that the database from which it was drawn contained only two thousand observations. The regression models estimated could be substantially refined, we believe, with country samples of between four and ten thousand where funds permit. A second limitation concerns the lack of sub-population analyses particularly with respect to ethnic minorities. Although the database provided for some oversampling of ethnic minorities, it did not envisage or allow for a pattern of spread that focussed on whites very early on and then some ethnic minorities subsequently. It seems from an examination of our underlying data, that Whites were disproportionately impacted only in February and that Blacks, Asians and other groups were disproportionately affected in the US as internal transmission became predominant. Future work on ethnic minorities will need take into account the fact that risks to different groups may change dramatically over time in response to public health messaging and social media coverage. In addition, it would be helpful to have repeated observations so that more could be said about changes over time as well as causality: indeed, it would be useful to have patient or lay input into the development of a fuller set of predictors based on possible causal mechanisms. Furthermore, it was not possible to audit responses. It would also be useful to gather data on

the measures that workplaces are now taking to protect workers and customers so that public health policy makers could refine their understanding of what is working.

These limits aside, the study implicates transport related employment and travel in various ways with transmission risk, identifies novel employment related predictors of infection risk, and provides evidence of ways in which personal traits, circumstances and behaviours impact on transmission experience. This is, as far as we are aware, the first study to investigate a range of work and personal predictors of Covid-19 transmission risk in the US and UK. If similar work and related activity data were collected routinely along with other medical data, it should be possible to identify types of settings where transmission is most likely to take place. If repeated, as the US and UK face the prospect of new waves, new surveys could help public health officials and researchers refine the workplaces that should be targeted for additional protective measures.

Summary Box

What is already known on this subject?

A lot is now known about the underlying mechanisms of transmission of COVID-19 as well as their spatial patterns within populations particularly from virological and environmental sources as well as clinical records. The paper uses survey data to provide evidence about work-related and other predictors of community transmission.

What does this study add?

The study shows that in multiple regression models a variety of work-related and personal attributes predict transmission experience. It is also the first to identify in regression models using data for COVID-19 transmission models in the US and UK, impacts that include those due to workplace types and public transport commuting. The study shows, inter alia, that work-related employment can increase the probability of infection by over 40 times in the US and therefore provides strong evidence for paying more attention to transport related employment as a major factor in community transmission. It also identifies novel behavioural and personal predictors (risk preference, extraversion and height) which merit further research.

References

[1] Khalatbari-Soltani, S., Cumming, R.G., Delpierre, C. and Kelly-Irving, M., 2020. Importance of collecting data on socioeconomic determinants from the early stage of the COVID-19 outbreak onwards. *J Epidemiol Community Health*.

[2] Bogg, T. and Milad, E., 2020. Slowing the Spread of COVID-19: Demographic, personality, and social cognition predictors of guideline adherence in a representative US sample.

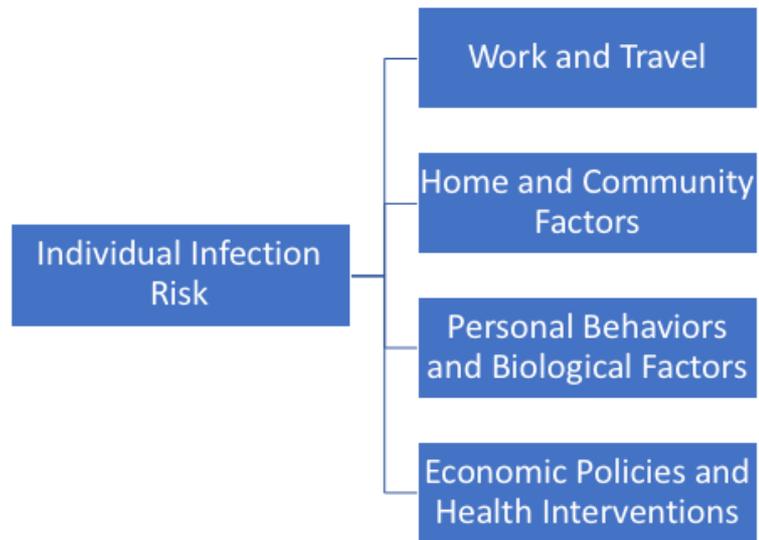
[3] Desmet, K. and Wacziarg, R., 2020. Understanding Spatial Variation in COVID-19 across the United States (No. w27329). National Bureau of Economic Research.

[4] Semple S, Cherrie JW. Covid-19: Protecting Worker Health. *Ann Work Expo Health*. 2020;64(5):461-464. doi:10.1093/annweh/wxaa033

[5] Mitchell, P.M., Roberts, T.E., Barton, P.M. and Coast, J., 2017. Applications of the capability approach in the health field: a literature review. *Social Indicators Research*, 133(1), pp.345-371.

- [6] Papageorge, N.W., Zahn, M.V., Belot, M., van den Broek-Altenburg, E., Choi, S., Jamison, J.C. and Tripodi, E., 2020. Socio-Demographic Factors Associated with Self-Protecting Behavior during the COVID-19 Pandemic (No. 13333). Institute of Labor Economics (IZA).
- [7] Lönnqvist, J.E., Verkasalo, M., Walkowitz, G. and Wichardt, P.C., 2015. Measuring individual risk attitudes in the lab: Task or ask? An empirical comparison. *Journal of Economic Behavior & Organization*, 119, pp.254-266.
- [8] Gosling, S.D., Rentfrow, P.J. and Swann Jr, W.B., 2003. A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37(6), pp.504-528.
- [9] Özaltın, E., 2012. Commentary: the long and short of why taller people are healthier and live longer. *International Journal of Epidemiology*, 41(5), pp.1434-1435.
- [10] Morawska, L and Milton, DK It is Time to Address Airborne Transmission of COVID-19, *Clinical Infectious Diseases*, , ciaa939, <https://doi.org/10.1093/cid/ciaa939>
- [11] Nikitin, N., Petrova, E., Trifonova, E., & Karpova, O. (2014). Influenza virus aerosols in the air and their infectiousness. *Advances in virology*, 2014.
- [12] Lu, J., Gu, J., Li, K., Xu, C., Su, W., Lai, Z., ... & Yang, Z. (2020). COVID-19 outbreak associated with air conditioning in restaurant, Guangzhou, China, 2020. *Emerging infectious diseases*, 26(7), 1628.
- [13] Auer, R., Cornelli, G. and Frost, J., 2020. Covid-19, cash, and the future of payments (No. 3). Bank for International Settlements.
- [14] Bajunirwe, F., Izudi, J., & Asiimwe, S. (2020). Long distance truck drivers and the increasing risk of COVID-19 spread in Uganda. *International Journal of Infectious Diseases*.
- [15] Office of National Statistics.
<https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/conditionsanddiseases/bulletins/coronaviruscovid19infectionsurveypilot/28may2020#number-of-people-in-england-who-had-covid-19>
- [16] Centers for Disease Control and Prevention.
<https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/commercial-lab-surveys.html>
- [17] Lee, V. J., Chiew, C. J., & Khong, W. X. (2020). Interrupting transmission of COVID-19: lessons from containment efforts in Singapore. *Journal of Travel Medicine*, 27(3), taaa039.
- [18] Qui, Y, Chen X, Shi W (2020) Impacts of Social and Economic Factors on the Transmission of Coronavirus Disease 2019 (Covid-19) in China, IZA Discussion Paper 13165
- [19] Bezant, M Z and Bush J W M (2021) A guideline to limit indoor airborne transmission of COVID-19, PNAS, 118, 17 12pp

Figure 1 Community Transmission Risk-Factors for Covid-19



Supplementary File

Appendix 1

Link to Data and questionnaire from which variables drawn

https://osf.io/v9t8a/?view_only=8531e8dd672f41e6bf532e280a2f31e6

Key to per annum household income categories

US

Lower i Under \$25000

Lower ii Between \$25000 and \$49000

Middle i Between \$50000 and \$74999

Middle ii Between \$75000 and \$99999

UK

Lower i Under £12500

Lower ii Between £12500 and £18499

Middle i Between £18500 and £49999

Middle ii Between £50000 and £62499

Source: <https://resources.pollfish.com/pollfish-school/household-income-mapping/>

Variable	Definition	Notes on variable construction	US	UK
Type of workplace	Transport related: boat/ship, taxi, bus/tram. Intermediate: airplane, care-home, factory, food, hospital, office, retail shop or school. Other: Garden centre or farm, lorry, train. Other non-work: Prison, other	Classifications based on question "Which of these best describes your main current workplace?"	Q10	Q9
Belong to a trade union	Binary variable equal to one if a person belongs to a trade union	Equal to one if "Yes" in question(s):	Q8.6	Q7.6
Consultation on transmission	Binary variable equal to one if the workplace of persons has asked them about their views on ways to limit transmission of Covid	Equal to one if "Yes" in question(s):	Q8.7	Q7.7
Can work from home mainly	Binary variable equal to one if a person can in principle work mainly from home	Equal to one if "Yes" in question(s):	Q8.9	Q7.9
Public transport to get to work	Binary variable equal to one if a person must you use bus, train or plane to get to work	Equal to one if "Yes" in question(s):	Q9.1	Q8.1

Shared accommodation/kitchen	Binary variable equal to one if a person shares a kitchen with other households / live in a shared house	Equal to one if "Yes" in question(s):	Q9.6	Q8.6
Risk preference	Binary variable equal to one if respondent self-rates greater than 5 on a 10 point scale and 0 otherwise	Equal to one if higher than five in question:	Q14	Q13
Extraversion	Binary variable equal to one if persons see themselves as extrovert and not reserved	Equal to one if "Yes/Agree" in question(s): and equal to one if "No/disagree" in question(s):	Q8.1 Q8.2	Q7.1 Q7.2

Appendix 2

Table S1 Models of Transmission for the US

		Work related controls		Work related and additional controls	
		Unweighted	Weighted	Unweighted	Weighted
Type of workplace					
	Transport related	4.624** (2.942)	4.919** (2.5745) *	3.844** (2.5969)	4.079** (2.4298)
	Other work	1.224 (0.8052)	1.424 (1.3599)	0.867 (0.5863)	0.937 (0.96)
Work and Commuting Factors	Belong to a trade union	4.352*** (1.495)	4.865** (1.7068) *	4.293*** (1.5815)	5.015** (1.8768) *
	Consultation on transmission	1.692 (0.5712)	1.591 (0.5678)	2.116** (0.7607)	1.898 (0.77)
	Can work from home mainly	1.289 (0.4362)	1.418 (0.4733)	1.108 (0.3914)	1.147 (0.3938)
	Public transport to get to work	3.245*** (1.1145)	3.279** (1.1829) *	2.424** (0.8658)	2.409** (0.9956)
	Personal factors	Age (54 years or more)			0.131* (0.1382)
	Income (lower_ii)			1.962* (0.6846)	1.902 (0.7516)

Shared accommodation/kitchen			3.047***	3.152** *
			(1.0591)	(1.1252)
Risk preference			0.444**	0.552
			(0.168)	(0.244)
Extraversion			0.72	0.7
			(0.267)	(0.2643)
Taller than 6ft (men)			0.656	0.717
			(0.2864)	(0.3247)
Model performance				
Number of observations (n)	728	728	728	728
Pseudo-R2	0.1991	0.2177	0.264	0.2845
Log-likelihood	-152.081	-124.095	-113.5099	-
Akaike information criterion (AIC)	342.161	286.190	277.0198	139.748
Bayesian information criterion (BIC)	429.377	373.406	391.7773	2
				329.496
				3
				444.253
				9

***p-value < 0.01, **p-value < 0.05, *p-value < 0.10. Standard errors in brackets below each estimated coefficient. Diagnosis: logit estimated for the question “Have you had a medical diagnosis or positive test for COVID?” (Yes = 1). Estimated coefficients are presented as odds ratios. People performing non-working activities were excluded from the estimations. Fixed-effects were included to account for area-level regional (sub-national) factors.

Table S2 Models of Transmission Experience for UK

		Work related controls		Work related and additional controls	
		Unweighted	Weighted	Unweighted	Weighted
Work and Commuting Factors	Type of workplace				
	Transport related	3.945** (2.48)	3.491** (2.0894)	3.441* (2.3048)	2.849 (1.8238)
	Other work	3.892** (2.1087)	3.489** (2.0163)	2.473 (1.3962)	1.966 (1.2017)
	Belong to a trade union	1.605 (0.5086)	1.756 (0.6738)	1.397 (0.4698)	1.466 (0.6236)
	Consultation on transmission	1.848** (0.5619)	1.877* (0.6467)	1.503 (0.4866)	1.443 (0.4816)
	Can work from home mainly	1.252 (0.3786)	1.305 (0.4504)	1.279 (0.4017)	1.321 (0.4658)
	Public transport to get to work	1.224 (0.408)	1.429 (0.5203)	1.027 (0.359)	1.194 (0.4528)
	Gender (male)			1.626 (0.6043)	1.195 (0.4691)
	Income (lower_ii)			0.478 (0.2396)	0.414* (0.2104)
	Shared accommodation/kitchen			1.637 (0.5393)	1.736 (0.6817)
Risk preference			1.951* (0.7282)	2.257* (0.9816)	
Extraversion			1.326 (0.4371)	1.236 (0.4381)	
Taller than 6ft (men)			1.99* (0.7795)	2.375* (1.0554)	
Model performance					
	Number of observations (n)	686	686	613	613
	Pseudo-R2	0.0718	0.0685	0.1224	0.1148
	Log-likelihood	-170.907	-144.447	-128.46617	156.2387
	Akaike information criterion (AIC)	363.813	310.895	290.93224	346.4774

Bayesian information criterion (BIC)	413.653	360.735	366.0444	421.5896
--------------------------------------	---------	---------	----------	----------

***p-value < 0.01, **p-value < 0.05, *p-value < 0.10. Standard errors in brackets below each estimated coefficient. Only data of March and April symptoms was included in the sample. Diagnosis: logit estimated for the question “Have you had a medical diagnosis or positive test for COVID?” (Yes = 1). Estimated coefficients are presented as odds ratios. People performing non-working activities were excluded from the estimations. Fixed-effects were included to account for area-level regional (sub-national) factors.