No 455
DECEMBER 2020

Center for European Studies
PAPER SERIES

Social contacts in the post-lockdown period

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DIPARTIMENTO DI ECONOMIA, METODI QUANTITATIVI E STRATEGIA DI IMPRESA

UNIVERSITÀ DEGLI STUDI DI MILANO BICOCCA

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Abstract

The COVID-19 pandemic has brought tighter restrictions on the daily lives of millions of people. In this paper, we investigate the effects of the pandemic on social contacts during the post-lockdown period in the UK. We find a negative correlation between social contacts and individual concerns for health risks and a new lockdown. We also find a substantial "inefficiency" in socialization in the post-lockdown period. These results support a scenario in which social contacts stay low for a long while, perhaps impacting negatively on well-being in the long run.

Version 1 December 2020

JEL classification: Z13, D91, H12, I18, C13
Keywords: social contacts, COVID-19, count model, inefficiency

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1. Introduction

Humans are extremely social creatures, spending much of their lives in the company of others. Indeed, social contacts are one of the greatest sources of human well-being (e.g. Diener and Seligman, 2002; Merz and Huxhold, 2010; Helliwell et al., 2017; Amati *et al.*, 2018). However, during the current COVID-19 pandemic, policymakers and health experts have been appealing to the social responsibility of their citizens to contain the spread of the virus, asking them to limit social contacts and follow strict distance recommendations.

In the UK, lockdown was introduced on 23 March 2020. From 1 June, restrictions and social distance measures were gradually relaxed.[2] Three different scenarios were possible. In the first scenario, social contacts suffered a downturn during the lockdown, but then bounced back up above the level it would have been in a pre-pandemic baseline. In this scenario, a good part of the social capital foregone during lockdowns was simply delayed, and was made up once social distance measured were relaxed. In the second scenarios, individuals permanently lost the social capital that would have occurred absent the lockdown, but social contacts very quickly returned to its pre-pandemic baseline. In the third scenario, the effects of the pandemic on social contacts last well beyond the relaxing of the restrictions and social distancing measures. Even after the health risks recede, many people may be reluctant to return to social life as it was before the pandemic. In facts, individuals could concern about another COVID-19 outbreak (and a new lockdown). According to this scenario, social contacts stay low and individuals permanently lose social resources for a long while. These resources may include: access to useful information, company (e.g., personal and intimate relationships, someone to talk to, have dinner with, go on holidays with), emotional support (e.g., support when experiencing distressing personal or family matters), and instrumental support (e.g., financial support, household administration, home-making). At the end, individual's well being could be negatively affected in the long run.

In this paper, we investigate factors affecting social contacts in the post-lockdown period in the UK. To the best of our knowledge, this is the first paper analyzing this issue. Our empirical results support the third scenario.

2. Data and empirical approach

We model the conditional distribution of social contacts in the UK during the post-lockdown period. We use BIDCUFU data[3], a survey launched on 19 June 2020. Conditional on participating in the survey, the sample (about 1,500 individuals) is representative of the UK population with regards age, sex and ethnicity (for details see Oreffice & Quintana-Domeque, 2020). Descriptive statistics are provided in table 1.

Our dependent variable is a numerical count (only taking on nonnegative integer values) indicating with how many people the individual socialized in June 2020.[4] The 64% of the sample has social contacts (see Figure1); however, this percentage seems indeed low if compared with the 85% percentage of adults going out socially or visiting friends in the pre-pandemic period.[5] On average individuals socialized with 1.7 people from other households (see Table 1).

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[2] Gatherings of people from more than one household were permitted from 1 June, even if with some restrictions (e.g. up to six people). "Support bubbles" (that is where a household can choose to join together with one other household to provide support and help avoid loneliness) were introduced in England on 13 June and Scotland on 19 June. On 19 June, there was the general re-opening of retail shops and public-facing businesses (apart from those that are on a list of specific exclusions).

[3] Data available at https://sites.google.com/site/climentquintanadomeque/covid-19-data

[4] We use questions: Q61 to have information whether the individual have or have not "socialised/gathered with people from other households" and question Q62 "Thinking about the last time you socialised with people from other households, with how many people did you socialise/gather?"

[5] Source: Understanding Society The UK Household Longitudinal Study, 2017-18

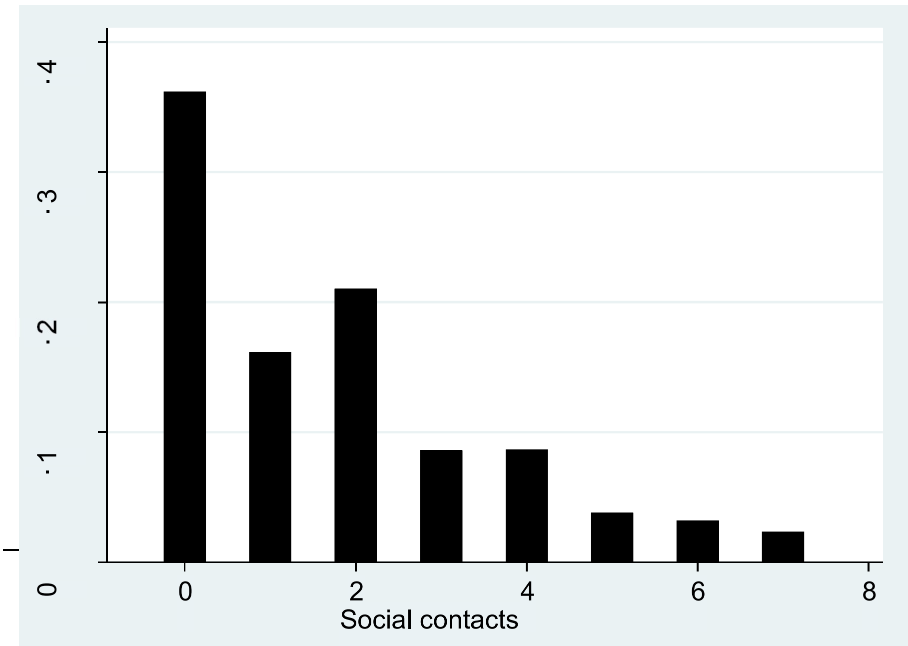
Table 1. Descriptive statistics

	Mean	Sd
Social contacts (with how many people did you socialize?)	1.734	1.847
Female	0.515	0.500
Age	46.26	15.59
Married	0.467	0.499
Children in the household	0.294	0.456
High education (=1 if Bachelor's degree or above)	0.542	0.498
Physical unhealthy (= 1 if health is bad or very bad)	0.046	0.210
Mental unhealthy (*)	0.000	1.000
Income before tax is less than £15,000	0.250	0.433
Face mask (**)	0.000	1.000
Lockdown	0.735	0.441
North East	0.040	0.196
North West	0.109	0.312
Yorkshire and the Humber	0.080	0.272
East Midlands	0.075	0.264
West Midlands	0.089	0.285
East of England	0.069	0.253
London	0.149	0.356
South East	0.154	0.361
South West	0.105	0.307
Wales	0.037	0.188
Scotland	0.077	0.267
Northern Ireland	0.016	0.126

(*) Variable constructed using factor analysis and information about "bothered by feeling down, depressed or hopeless", "anxiety attack", "feeling nervous, anxious or on edge", "not being able to stop or control worrying", "worrying too much about different things", "trouble relaxing", "being so restless that it is hard to sit still", "becoming easily annoyed or irritable", "feeling afraid as if something awful might happen". See Appendix1

(**) Variable constructed using factor analysis and information about "you wore a face covering when you entered a shop or a building", "wearing a face mask is effective to prevent you from getting Coronavirus", "wearing a face mask is effective to prevent you from spreading Coronavirus", "if everybody wears a face mask, everyone is protected from Coronavirus". See Appendix1

Figure 1. Socialization with people from other households



As empirical approach, we use a count data model. In particular, we use a mixed Poisson distribution with a log-half-normal mixing parameter (PHN) in the parlance of Fé and Hofler (2013). Although the motivation behind this model was the estimation of stochastic frontiers under discrete valued outcomes, the PHN can be also used for modeling underreported counts (Fé and Hofler, 2020). In our case, we wish to model social contacts deviations from its optimal level (that is the level achievable in the pre-pandemic period) through an inefficiency term. Thus, the mean pre-pandemic baseline level of social contacts can be written as

$$\log \tilde{\lambda} = x'\beta,$$

where $\tilde{\lambda} \in R^+$. Conditional on a level of inefficiency $\varepsilon \in R^+$, the mean level of social contacts in the post-lockdown period can be written as

$$\log \lambda = x'\beta - \varepsilon$$

Because we are modeling nonnegative count data, we transform the last equation to

$$\lambda = \exp\{x'\beta - \varepsilon\}$$

where the social contacts, y, have a Poisson distribution conditional on a set of covariates, x, and an inefficiency term, ε, with λ as the conditional mean of the distribution. Since the inefficiency term, ε, follows a half-normal distribution, we can write $\varepsilon = |u|$ where u has a normal distribution. Therefore, the conditional distribution of y given x follows by averaging $P(y|x, u)$ over the range of u

$$P(y|x; \sigma, \beta) = E\ [\text{Poisson}\ \{\exp(x'\beta - \sigma|u|)\}]$$

where expectations are taken with respect to the standard normal distribution. The model can be estimated by maximum simulated likelihood estimation (Fé and Hofler, 2013 and 2020).

3. Results and Discussion

Table 2 presents the estimated coefficients of our PHN model. We also report estimates of a standard Poisson model as benchmark. The set of covariates includes commonly cited factors impacting on the individual social contacts (as gender, age, household composition, education, income, physical health and mental health) and our variables of interests. The latter are: (i) a measure of the individual attitude related to COVID-19 preventive health habits (face mask) and (ii) a variable indicating the individual expectations about a new lockdown before the end of 2020 (lockdown).

Table 2. Estimates

	Poisson model Dependent variable is y=social contacts			Poisson log-half-normal model Dependent variable is y=social contacts		
	Coef		Std.Err	Coef		Std.Err
Female	0.067		0.040	0.056		1.180
Age	-0.069	***	0.008	-0.064	***	0.012
Age*age	0.001	***	0.000	0.001	***	0.000
Married	0.215	***	0.046	0.196	***	0.063
Children	0.095	**	0.047	0.118	*	0.066
High education	0.046		0.041	0.048		0.056
Physical healthy	-0.389	***	0.122	-0.338	**	0.153
Mental unhealthy	-0.061	***	0.023	-0.060	**	0.030
Low income	-0.196	***	0.050	-0.161	**	0.067
face_mask	-0.100	***	0.020	-0.088	***	0.028
Lockdown	-0.166	***	0.044	-0.148	**	0.062
Region dummies	yes		yes	yes		Yes
Constant	2.276	***	0.179	3.081	***	0.259
log σ				0.547	***	0.049
Log likelihood			-2801.8395			-2610.533
No. Obs			1498			1498

∗ $p < 0.05$, ∗∗ $p < 0.01$, ∗∗∗ $p < 0.001$

Social contacts are negatively correlated with income, physical health and mental health. Young and married individuals have more social contacts. Of more interest, we find the following results.

Firstly, social contacts results negative correlated with both our variables of interest. Individuals socialize less it they believe that preventive health habits are necessary. People also socialize less if they expect a new lockdown before the end of 2020. Since concerns for health risks and new COVID-19 outbreaks could persist over time, we expect social contacts stay low and individuals permanently lose social resources for a long while.

Secondly, the PHN model returns a statistically significant log σ, which suggests that there is substantial "inefficiency" in the sample in the form of lower social contacts given the optimal levels achievable in the pre-pandemic period (as predicted by our model). However, part of the inefficiency may depend on other factors rather than the pandemic. Some inefficiency could perhaps exit before the pandemic. For example, unobservable individual attributes (e.g. personality traits – see Poggi and Anand, 2018) could determine some inefficiency in the data.

We observe a substantial variation in inefficiency across individuals depending on the attitude related to preventive health habits and the expectations about a new lockdown. Individuals that appears less concerned register on average more inefficiency (the estimated inefficiency score is higher, 0.390 vs 0.355). These individuals seems to "underperforming" in socialization, perhaps because social interactions are limited in the society (e.g. friends prefer do not meet them). Consistently with this hypothesis, we find that who normally socialize more (e.g. young individuals and healthy people) underperforming in socialization.

Both the above results suggest the effects of the pandemic on social contacts last well beyond the lockdown period. Social contacts will recover slowly, perhaps returning to its pre-pandemic baseline only after a successful vaccination campaign.

Table 3. Inefficiency estimates

Inefficiency	mean	Sd
all sample	0.377	0.194
face_mask<=-1 & new_lockdown==0	0.390	0.201
face_mask>=1 & new_lockdown==1	0.355	0.192
Good health	0.378	0.194
Bad health	0.353	0.184
age<30	0.386	0.198
age>=30 & age<45	0.386	0.196
age>=45 & age<55	0.354	0.187
age>=65	0.370	0.185
Ho: Inefficiency not present in the sample		
chi2(1) = 382.61		
Prob > chi2 = 0.00		

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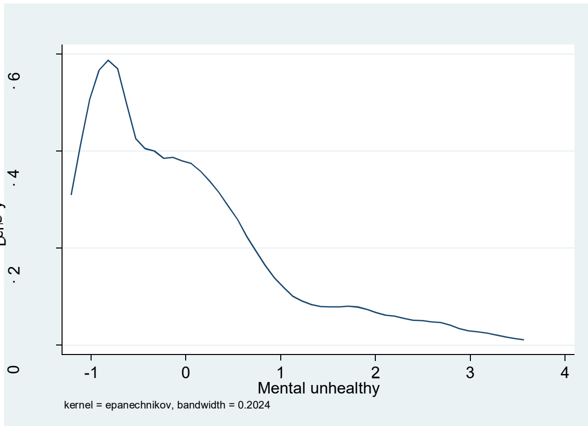
Appendix 1. Factor analysis

We use exploratory factor analysis as a dimension reducing strategy to help produce the following indicators: “face mask” and “mental unhealthy”. Factor analysis is a statistical data reduction technique used widely in psychology to explain variability among observed random variables in terms of fewer unobserved random variables called factors. In general, factor analysis models the observed variables as linear combinations of the factors, plus normally distributed error terms. The algorithm produces a factor structure matrix representing the correlations between the variables and the factors and is called the factor loading matrix. The interpretation of each factor is marked by high loadings on a certain sub-sample of attributes that give information on a specific kind of unobservable.

We retain only factors which account for sufficient variance: meaning that unless a factor extracts at least as much as the equivalent of one original variable, we do not consider it (Kaiser criterion). Since factor analysis is based on a correlation matrix, it assumes that the observed variables are measured continuously, are distributed normally, and that the association among indicators is linear. Many of our observed variables are discrete, so we assume that they are indicators of underlying continuous unobserved variables and use the appropriate correlations in the factor analysis.

Tables A1 and A2 report the factor analysis used to construct our variables. Each variable has mean zero and a variance of one by construction. In both analysis, the Kaiser–Meyer–Olkin measure of sampling adequacy (KMO) confirming that the factor analysis to be valid.

Figure A1. Kernel densities



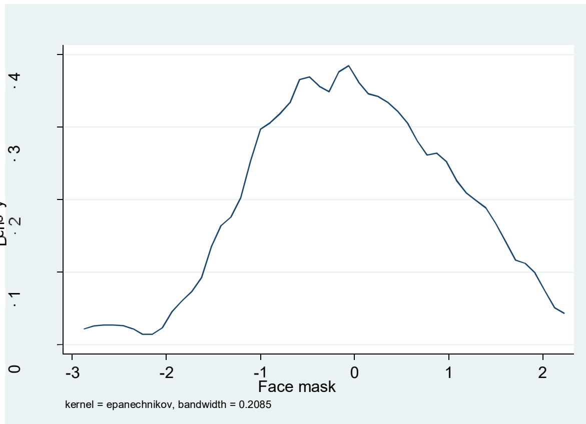


Table A2. Factor loadings

Variable	mental unhealthy
Bothered by feeling down, depressed or hopeless in the last two week (0-3)	0.8072
anxiety attack in the last two week (0-1)	0.6236
Feeling nervous, anxious or on edge (0-3)	0.8758
Not being able to stop or control worrying (0-3)	0.8888
Worrying too much about different things (0-3)	0.8711
Trouble relaxing (0-3)	0.837
Being so restless that it is hard to sit still (0-3)	0.7158
Becoming easily annoyed or irritable (0-3)	0.7121
Feeling afraid as if something awful might happen (0-3)	0.8101
Proportion of total variance explained	0.6369
Kaiser-Meyer-Olkin measure of sampling adequacy	0.9393

Table A3. Factor loadings

Variables	Face mask
Last time you went out, You wore a face covering when you entered a shop or a building	0.6445
Wearing a face mask is effective to prevent you from getting Coronavirus	0.7169
Wearing a face mask is effective to prevent you from spreading Coronavirus	0.7389
If everybody wears a face mask, everyone is protected from Coronavirus	0.7576
Proportion of total variance explained:	0.5123
Kaiser-Meyer-Olkin measure of sampling adequacy:	0.7284