Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Close encounters during a pandemic: Social habits and inter-generational links in the first two waves of COVID-19

Annalisa Cristini, Pedro Trivin

Department of Economics, University of Bergamo, 24127 Bergamo, Italy

ARTICLE INFO

JEL classification:
I1
I2
R10

Keywords:
COVID-19
Social contacts
Inter-generational households
Virus contagion
Excess mortality

ABSTRACT

Social habits are ingrained in a community and affect human behaviour. Have they played any role in the spread of the pandemic? We use high-frequency data for 220 regions in 15 European countries from March to December 2020 to compare the association between social contacts outside the household and within inter-generational families, on the one hand, and cases and excess mortality on the other. We find that a standard deviation increase in the percentage of people having daily face-to-face contacts outside the household is associated with 5 new daily cases and 2.6 additional weekly deaths, while the incidence of inter-generational households exhibits a less robust association with both COVID-19 transmission and mortality. We compare results across the first and the second wave of pandemic and show that differences are related to the average age of the most affected groups. Our findings are robust to the inclusion of a number of controls, fixed effects, the chosen sample of countries, and the estimation method. We argue that type and frequency of social interactions are interwoven with a region culture and habits and are informative on the potential transmission of contagion and on its lethality.

1. Introduction

When the pandemic reached Europe in early 2020, Italy was the first country to be dramatically hit: by March 1st, it had registered almost 1700 cases, more than half the total cases in Europe; by the end of March, the cases had risen to over 105,000 in Italy and almost 96,000 in Spain; on the whole, the two countries accounted for over 46% of the total cases in Europe.

Demographic and social characteristics typical of these Mediterranean countries gained a special attention as potential amplifiers of an epidemic that was disproportionately affecting the old. The indirect transmission of the virus to the elderly due to interactions between adult children and old parents and/or between grandchildren and grandparents was deemed relevant both in Europe (Dowd et al., 2020) and in the US (Harris, 2020, 2021) and family ties appeared then worth investigating. Inter-generational contacts coupled with a high incidence of aged people could also explain the observed high death rates in simulation models (Esteve et al., 2020).

Various studies used the share of multi-generational households in the country to proxy inter-generational links but the evidence on the expected statistical correlation with the spread of coronavirus disease 2019 (COVID-19) was not clear-cut (Arpino et al., 2020). Given the pronounced within-country heterogeneity observed both in COVID-19 outbreaks (Naqvi, 2021) and in the incidence of inter-generational families (Duranton et al., 2008; Kaasa et al., 2014), analyses performed at the country level could, at least partly, justify the weak evidence. In addition, the relatively few data points available at the beginning of the pandemic, together with the small number of countries considered (Bayer and Kuhn, 2020; Mogi and Spijker, 2021) were also constraining, with a few exceptions (Aparicio Fenoll and Grossbard, 2020), the degrees of freedom so that potential confounders were also a problem (Belloc et al., 2020).

The link between COVID-19 and social interactions outside the household was initially less investigated. However, as the epidemic spread to other regions and countries, and the effects of social

---

2 We thank the Editor and two anonymous referees for helpful comments on an earlier version of this paper. We also thank the participants at different seminars and conferences for their helpful comments and suggestions.

* Corresponding author.

E-mail addresses: annalisa.cristini@unibg.it (A. Cristini), pedro.trivin@unibg.it (P. Trivin).

1 Dowd et al. (2020) report that in Italy as of March 30, 2020, 96.9% of deaths were occurring in people aged 60 and over.

2 Indeed, for influenza the epidemiological literature agrees that children are a major driver of transmission (Mossong et al., 2008; Salathé et al., 2010). However, as data on COVID-19 epidemic accrued, epidemiological evidence was finding younger cohorts to play a less relevant role than in the transmission of influenza (Davies et al., 2020; Harris, 2021; Forbes et al., 2021).

3 For an exception, see Mogi and Spijker (2021); they use the percentage of people having frequent social meetings as one of the variables in a factor analysis. They find that it has a positive loading on the factor that positively relates to the spread of the virus.

https://doi.org/10.1016/j.ehb.2022.101180

Received 10 March 2022; Received in revised form 4 July 2022; Accepted 23 August 2022
Available online 2 September 2022
1570-677X/© 2022 Elsevier B.V. All rights reserved.
distancing measures were being assessed, the role of social interactions, lato sensu, gained further interest. Rodríguez-Pose and Burlina (2021) find that, after controlling for a bulk of economic, demographic, geographical and institutional factors, the share of the population meeting friends and family socially at least once a week is positively related to excess mortality across European regions in the first six months of the pandemic. Moreover, social capital, a notion which is ultimately rooted in dense social networks and sense of reciprocity (Putnam, 2000; van Oorschot et al., 2006) is found to be negatively associated with excess mortality (Rodríguez-Pose and Burlina, 2021) and positively related to citizens’ adherence to social distancing rules (Giuliano and Rasul, 2020; Borgonovi and Andrieu, 2020; Durante et al., 2021; Bartscher et al., 2021).

In this paper, we consider both a measure of face-to-face social interactions outside the household and a proxy of inter-generational links within the household. This allows us to capture two important aspects of a community social structure, both of which can relate to the virus transmission. We perform the analysis at the regional level and extend the time period to comprise the first and the second COVID-19 wave. These enriched spatial and temporal scopes provide the analysis with potentially informative additional variation in the data.

Specifically, we use NUTS 2 European data for a maximum of 220 regions in 15 European countries and exploit daily or weekly data on COVID-19 cases and mortality from the beginning of the pandemic to the end of 2020. This allows us to decrease the influence of unobserved heterogeneity by including NUTS 1 fixed effects and country-day (or country-week) specific dummies. We also account for the time lags between new cases and cases confirmed in the past 14 days and allow the correlation with past cases to differ within and between regions, according to Adda (2016).

We measure social interactions outside the household by the share of people that have daily contacts with friends or neighbours. Notice that with respect to epidemiological surveys, which trace the contacts that each person in the survey has with each other, our information render a depiction of the context in which the spread is occurring and in this sense it can be regarded as a macro or aggregated map, complementary to the typical epidemiological contact matrices and, as argued below, it can reflect culture-related attitudes.

To reduce the blur ingrained in the social contact data, in addition to a battery of controls explained below, we consider only those encounters that have been shown to facilitate the spread of diseases predominantly transmitted via droplets, i.e., face-to-face contacts⁴ that take place daily or almost daily (Read et al., 2008; Mossong et al., 2008; Salathé et al., 2010; Mastrandrea et al., 2015). The regional map of social contacts is derived from the latest European Quality of Life Survey (EQLS) conducted in 2016.⁵ As argued by the relational sociology literature (Dépelteau, 2018), the structure of social contacts, as part of network relations, is deeply interwoven with culture, which also contributes to the stability of social systems more generally (Fuhse, 2013). For this reason, the pattern of social relationships is expected to show some persistence across time and remain informative of features relevant for the virus transmission.

We consider the spread of COVID-19 in terms of new cases per day (or per week) and use excess mortality data instead of fatalities or case-fatality rate (CFR), which have been shown to suffer from measurement errors due to under reporting of cases and deaths and lack of comparability across countries due different ways to register COVID-19 deaths (Aron and Muellbauer, 2020; Rodríguez-Pose and Burlina, 2021).

According to some evidence (Monod et al., 2021), the channels of COVID-19 transmission changed between the two waves, also in response to the enforcement and lifting of non-pharmaceutical interventions. Using a subsample of countries for which data on cases and fatalities are available by age groups, we test whether the correlation between cases and social contacts differs by age groups across the two waves.

Throughout the analysis, we account for the possibility that social interactions could be correlated with other regional socioeconomic characteristics; for instance, skin-to-skin contacts are expected to be positively related to population density and employment rate, but negatively to the share of elderly people (see for example Brown and Ravallion, 2020). By including a rich set of controls, in our analysis we separate face-to-face contacts associated with the urban, economic and demographic structure of the region from those related to regional culture and habits.

Our analysis adds to the literature in several ways. First of all, we extend the inter-generational family-centred analysis to a broader concept of social networks, encompassing interactions both within and outside the household and compare their associations with the pandemic. In addition, we place this analysis at the regional level, whereas the role of multi-generational families on COVID-19 has typically been tested at the country level. Moreover, by considering a large number of regions and daily and weekly COVID-19 data on cases and excess mortality for the whole relevant period of 2020, we can address the weaknesses of this extant literature due to potential confounding factors and measurement errors in CFR. Finally, we contribute to the analyses that investigate the evolution of the pandemic, especially the changes intervened between the first and the second wave (Forbes et al., 2021). At this regard, by assessing how the correlation of interest has changed across time and by age groups, we add to the analyses on the age profile of the cases.

We find that face-to-face daily contacts help explaining the spread of the virus. In particular, when using weekly data, we observe that a standard deviation increase in the percentage of people having daily face-to-face contacts is associated, on average, with 5 new daily cases and with 2.6 more weekly excess deaths. On the contrary, the association between inter-generational families and COVID-19 cases and excess mortality is weak and not robust. When we allow for these relationships to vary over time, we find that regions with a larger share of daily contacts are associated with a larger share of COVID-19 cases in both waves, while the positive relationship with COVID-19 excess mortality is stronger in the first wave. We show that these results could be related to heterogeneity in the transmission of the virus across different groups of age in the different waves. Elderly people are more affected during the first wave, while the cases of cohorts under 60 years of age are those most strongly associated with daily contacts during the second wave. Again, no significant relations emerge along time between the share of inter-generational families on the one hand and COVID-19 spread or excess mortality on the other.

The paper is organized as follows. The next section introduces the data and presents some stylized facts. Section 3 describes the empirical specification and discusses the inclusion of control variables; regression results and robustness checks are presented in Section 4. Section 5 draws the main conclusions, pointing out the limits of the analysis and its usefulness to the understanding of the present pandemic.
2. Data and stylized facts

2.1. Data

The first variable of interest, to be correlated with COVID-19 spread and mortality, is a measure of social interactions. Specifically, we consider only those types of encounters that are sufficiently proximate in space and allow a direct transmission of the virus through droplets (Read et al., 2008; Mossong et al., 2008; Salathé et al., 2010; Mastrandrea et al., 2015).

We also exclude contacts with relatives outside the household, as the share of relatives can depend on migration trends and/or on work mobility patterns more generally, which could bias the comparison across regions.

The measure we use is based on the type and frequency of encounters as stated by representative individuals interviewed in social surveys. Among the various international surveys, EQLS distinguishes contacts according to whether they involve face-to-face proximity and also distinguish between contacts with relatives versus contacts with friends and neighbours outside the household; precisely, we define our variable of interest as:

\[
\text{FACE-TO-FACE CONTACTS: The percentage of people in the region that answered daily or almost daily to the question: How often do you have face-to-face contacts with friends or neighbours living outside the household?}
\]

As underlined by the sociological literature, social contacts result from individual relationships, which in turn adhere to the available cultural models (see, for example Dépelteau, 2018; Fuhse, 2018; Donati, 2018); in this sense, the habits of seeing friends and neighbours represent a cultural feature of a society, which is the element we intend to capture. In the light of this, we also expect our variable of interest to show some degree of persistence in time.

Inter-generational households are defined as those in which more than one generation live together; hence an inter-generational family is one in which the respondent co-habits with his/her children, and/or (grand)parents, and/or siblings of an age difference of at least 20 years. Our measure is similar to that used by Mogi and Spijker (2021). Others use more restrictive definitions, based on the share of cohabiting adult children aged 18–34, (Aparicio Fenoll and Grossbard, 2020) or as heads of households aged 30–49 that live with their parents (Bayer and Kuhn, 2020).

Regional data on COVID-19 cases are obtained from the COVID-19 European Regional Tracker developed by Asjad Naqvi (Naqvi, 2021). COVID-19 mortality is proxied using weekly excess mortality from Eurostat, the only exceptions being the poverty rate and the share of multi-generational families, obtained from the EQLS.7 Tables A.2 and A.3 in Appendix A show, respectively, the definitions and the descriptive statistics of the variables considered.

2.2. Face-to-face contacts, inter-generational households and COVID-19 spread

Fig. 1 shows the regional distribution of face-to-face contacts and of the inter-generational households, as defined above. The correlation coefficient between the two variables is positive and significant. On average, 39% of the families living in the regions considered are inter-generational and 42% of people state to have daily or almost daily face-to-face contacts outside the household. The variability across regions, both within and between countries, is high: regions with the largest values of daily contacts are located in the Centre and South of Italy, in the Western parts of Spain and in the North of Scotland. Regions with the lowest values are in the North and South-West of France and in most of Sweden. Regarding inter-generational families, in most Spanish and Polish regions the incidence is above the top quartile (48%). A particularly high share is also present in some regions of Italy, in a few regions of France, while such high percentages are very rare in Germany, Austria, Netherlands and absent in Denmark, Belgium, Finland, Sweden, Czech Republic, and Hungary.

Fig. 2 shows the evolution of the COVID-19 pandemic in our sample. In particular, the four panels display the number of cumulative COVID-19 cases per 10,000 people at four different moments of time. The well known initial epicentres that at the end of March 2020 are clearly recognizable in Lombardy and most parts of Spain (panel a), extend to some regions of the UK, Belgium and a few areas of Sweden by the end of June (panel b). In September the situation worsens in the South of France (panel c) and by December 21st, the last day with data available for the whole sample of 220 regions, the diffusion has increased in Eastern Europe, particularly in some regions of Czech Republic and Poland (panel d).

Fig. A.1 completes the picture by showing the country-specific evolution of the number of COVID-19 cases and the excess mortality using weekly data. Regarding the number of cases, a general pattern is that the second COVID-19 wave, that hit European countries from week 30, is associated to a larger number of infections in all countries.8 Excess mortality data is instead more heterogeneous across countries; specifically, the sample is divided in two, with half of the countries showing larger mortality in one of the two waves.

3. Empirical strategy

To estimate the role of social habits in the pandemic, we model the spread of the virus following Adda (2016) and Qiu et al. (2020) and explicitly account for the dynamics of the virus transmission, by including lagged cases within and between regions, as well as for socio-economic indicators and fixed effects. Specifically, we estimate an equation such as:

\[
Y_{ij} = \sum_{s=1}^{14} a_{iws} Y_{i,t-s} + \sum_{s=1}^{14} a_{jwst} \sum_{ij} d_{ij}^{s-1} Y_{j,t-s} + \beta_{11} X_{ij} + \beta_{12} G_{ij} + \beta_{2} \mathbf{Z}_{ij} + \mu_{nats} + \Gamma' \Phi_{y} + \epsilon_{ij},
\]

where subcript \(i\) indicates the NUTS 2 region, \(Y\) refers to the number of new confirmed COVID-19 cases in region \(i\) on date \(t\), \(d_{ij}\) is the log of the distance between regions \(i\) and \(j\), and \(\sum_{s} d_{ij}^{s} Y_{j,t-s}\) is the inverse log distance weighted sum of new cases in other regions. \(X\) represents our variable of social contacts and \(G\) the percentage of multi-generational families. \(\mathbf{Z}\) is a row vector of control variables to be detailed below, \(\mu_{nats}\) are NUTS 1 fixed effects, \(\Gamma' \Phi_{y}\) are country-specific time dummies, \(\epsilon\) is a zero mean white-noise residual, and \(\beta_{11} \) and \(\beta_{12}\) are our main parameters of interest.

---

7 SHARE – Survey of Health, Ageing and Retirement in Europe – provides detailed measures of social contacts but it addresses people above 50 only and it does not differentiate between face-to-face and online interactions. Similarly, ESS – European Social Survey – does not explicitly distinguish between face-to-face and distant contacts and asks about the frequency of social meetings in general, involving either both relatives, friends and/or colleagues.

8 The countries included in our analysis are: Austria, Belgium, Czech Republic, Germany, Denmark, Spain, Finland, France, Hungary, Italy, Netherlands, Poland, Romania, Sweden and UK. Table A.1 in Appendix A shows the specific sample included in our preferred specification.

9 Although Eurostat also provides some regional poverty measures, the coverage is much limited, reducing our sample by almost 60%.

10 We have to be careful when interpreting this result as the first wave is likely characterized by a larger number of under-reported cases. Below we explain that this fact is not affecting our results.
The inclusion of $\alpha_{\text{within,}r}$ and $\alpha_{\text{between,}r}$ accounts, respectively, for within and between region COVID-19 dynamics and captures the spatial spread of the virus. The inclusion of up to 14 lagged days is based on the estimated duration of the infectious and the incubation period of the COVID-19. Using a different number of lags (between 7 and 13) does not change our results.\textsuperscript{11} The inclusion of NUTS 1 fixed effects mitigate problems related to regional unobserved heterogeneity, while country-specific time fixed effects aim to control for different COVID-19 related policy interventions and behavioural changes across countries.\textsuperscript{12}

The magnitude of the COVID-19 crisis has provoked an avalanche of studies on the determinants of the virus; in our analysis we draw from them and include a rich set of controls that can be classified into three groups: baseline, demographic and economic controls, and regional idiosyncrasies. As baseline controls we include six variables that have been widely acknowledged and are commonly used as the main determinants of the spread of the virus: GDP per-capita, which accounts for the economic activity and more general regional economic specificities; number of heating degree days, as corona-type viruses are normally seasonal and worsen with cold weather; population density, as the higher it is, the higher the probability of skin-to-skin contacts between an infected person and a susceptible one, as it may happen in busy public transports, markets and supermarkets, cafes and restaurants. Beyond the inclusion of lags of the dependent variable, we account for the stage of the epidemic curve by including the number of days since the first COVID-19 case was detected. If this information is not available, we include the number of cases per population in the first available date. Finally, following (Brown and Ravallion, 2020), we also include the logarithm of the population, which allows for a non-homogeneous relationship between the current number of infections and the population size.

The second block of controls includes variables related to the structure of the economy and demographics. In addition to the GDP per capita, the economic environment is captured by the income poverty rate, which is expected to be inversely related to the capability of adjusting to the required behavioural changes, as well as by labour market indicators and production sectors. Specifically, we consider the employment rate, the education level of the workforce and the share of employment in the service sector. All have a bearing on the way of living, which may in turn facilitate or hamper the transmission of the virus. For example, small craft businesses are likely to travel across local areas and regions, have contacts with different and numerous households and businesses to whom they provide their services; on the contrary, jobs in the advanced tertiary sector can in most cases be performed remotely, with minimum face-to-face contacts. Evidence for Italy, for example, corroborates the idea that areas specialized in manufacturing, which comprises activities largely involving skin-to-skin tasks are comparatively more likely to be subject to COVID-19.

\textsuperscript{11} Adda (2016) and Qiu et al. (2020) focus on the dynamics of the transmission and use lagged weather episodes to instrument the within and between lagged components. Since the spread dynamics of the virus is not the main focus of this paper, for the baseline analysis we use an OLS estimator, which allows us to consider a larger number of regions. In Section 4.4 we account for the dynamic endogeneity problem and show that our results are robust to using IV and to an alternative empirical specification.

\textsuperscript{12} In our empirical analysis we also show that our results are robust to the inclusion of NUTS 1-specific time dummies.
Fig. 2. Cumulative COVID-19 cases per 10K people.
infections (Ascani et al., 2020). Occupations that are unsuitable for remote work and require workers to work close to others (transportation, food-related, and personal care and service occupations) have also experienced an unprecedented rise in sickness-related absences during COVID-19 (Lyttleton and Zang, 2022).

Regarding the demographic variables, in the analysis we include the share of people aged 65 or more and the women to men ratio as the virus appears to affect more men than women and hit older people more often.

Finally, we include a set of more heterogeneous factors that could still be relevant for the spread and mortality of COVID-19. Environmental factors such as pollution (Murgante et al., 2020) or humidity (Mäkinen et al., 2009) have usually been found to be important determinants of respiratory virus diseases similar to COVID-19. However, given the complex relationship between these factors and COVID-19 (e.g., different particles in the air could have different effects; pollution, humidity and temperature interact with each other) we opt for including an indicator that correlates with these factors in a general way: the crude death rate for diseases of the respiratory system for people aged 65 and more. Another potential factor in the transmission of COVID-19 is the inter-connectivity of the region with the rest of the world as regions with larger connectivity are more likely to be exposed to the virus. We proxy the connectivity of a region by the number of air passengers carried per population.

4. Regression results

In this section, we present our main results. Section 4.1 displays the baseline findings on the importance of social contacts and inter-generational families on the transmission and mortality of the virus; in Section 4.2 we use a more flexible approach and allow the estimated coefficient of the variables of interest to vary over time. In Section 4.3, we decompose the spread of the virus by groups of age. Finally, Section 4.4 shows that the results are robust to alternative sample selection, to weighting the data and to different estimation methods.

13 We are aware that interactions at the workplace might not be fully captured by our variables. Unfortunately, to the best of our knowledge, there are no better available proxy at this granularity level. This drawback could be problematic if our variable of interest, the share of people having daily face-to-face contacts with friends or neighbours, was systematically correlated with a particular employment component affecting the spread of the virus (e.g., workers that cannot avoid working neck-to-neck to other people indoors). We do not think this is the case for three reasons: (i) there is no correlation between the share of face-to-face contacts and the education level (−0.021) and the share of employment in the service sector (−0.0042), which are general measures of the employment structure and because of this should be more related, if anything, to the cultural components of the region; (ii) all our regressions include NUTS 1 fixed effects, implying that we are exploiting variation across regions that are relatively similar; and (iii) our results are robust to different empirical specifications and sample selection, which makes us confident that our results are not significantly affected by other factors.

14 As we have commented before, the number of skin-to-skin contacts in a region is likely to be correlated with other socioeconomic characteristics. By including a rich set of controls in the analysis we try to separate the cultural component of social contacts from face-to-face contacts that occur due to the urban, economic and demographic structure of the region. Although some of these variables may be related, they attempt to capture different concepts in order to reduce the unobserved heterogeneity as much as possible. Using a more parsimonious regression does not alter our findings. Table A.2 in Appendix A defines the variables used in our analysis. Besides the variables directly related to the pandemic (cases and mortality), our control variables are time-invariant. From Eurostat we use data from the last available year, usually 2018 or 2019.

4.1. Baseline results

4.1.1. Cases: daily data

Table 1 shows the importance of social contacts and inter-generational families on the transmission of the virus using daily data. Results are separated in two blocks depending on the fixed effects included in the specification. Columns [1-3] include NUTS 1 and country-specific time effects while columns [4-6] control for NUTS 1-specific time dummies. Our preferred specification corresponds to the first block, where a larger number of regions is included. The second block shows the robustness of our results to more restrictive specifications regarding unobserved heterogeneity.

Within each block, we present three different versions of Eq. (1): the first specification includes the baseline controls, the second adds demographic and economic controls, and the final one further considers air connectivity and deaths due to respiratory illnesses.

The first remarkable result is the positive and significant impact of face-to-face contacts on the number of COVID-19 cases, regardless of the fixed effects included. While in our preferred specification the positive impact of daily contacts is observed independently of the controls included and of the share of inter-generational households, when we control for NUTS 1-specific time effects the positive effect is significantly different from zero when all the control variables are considered (Column 6).13 According to the results of the first three columns, one percentage point increase in social contacts raises the number of daily cases by around 0.09. This coefficient decreases to around 0.07 if we include NUTS 1-specific time effects. In other words, if we assume an increase of 1 standard deviation of face-to-face contacts, the number of daily cases increases by 1.56 (0.096 ∗ 16.26), taking the coefficient of column 3. On the contrary, the share of inter-generational households is never significant across the specifications of Table 1.

Regarding the control variables, we find positive and robust relationships between the number of cases and population size, population density and cold temperatures, as it has been widely acknowledged by the epidemiology literature, as well as between cases and our air connectivity measure in our preferred specification. In contrast, we uncover a negative association with the share of people over 65 and the level of education of the workforce. The latter correlation in particular is consistent with the fact that the more educated white-collars could in most cases work from home, thus reducing the risk to be infected, while the less educated blue-collars were engaged in jobs where distancing was more difficult to maintain, let alone the possibility of smart working. The negative sign of the share of people over 65 is also in line with the importance of the workplace in the transmission of the virus. Using US counties data, Brown and Ravallion (2020) also find a negative impact of the share of elderly people on the transmission of COVID-19. They argue that “with higher retirement rates, the elderly will tend to face less economic pressure to be active outside home. Time-use surveys for the US indicate that elderly people have substantially lower contact rates in normal times (Cornwell, 2011)”. (Brown and Ravallion, 2020, p. 6). The number of days since the first case is also negatively associated with the number of cases, coherently with the idea that the epidemic curve first stabilizes and then decreases over time.

Using daily data we can exploit high-frequency within-region variation to estimate the impact of face-to-face contacts on new COVID-19 cases. However, there are two drawbacks associated to the use of daily data: (i) it is likely that the data are subject to a measurement error and (ii) we do not have reliable information on COVID-19 fatalities at that frequency. Next, we overcome these issues by using weekly data.

15 Note that this result is likely related to the fact that this specification exploits a lower source of variation to identify the relationship of interest.
words, a standard deviation increase in the share of daily contacts is associated with 0.312 new daily cases, on average. In other
stronger than before. Specifically, according to column [3] (our pre-
throughout all the specifications and the estimated relationship is
19 cases, Table 2 confirms the positive relationship between face-
transmission variables.

4.1.2. Cases: weekly data

In this section, we decrease potential measurement error issues
by computing the weekly average of the new daily COVID-19 cases.
We also study the relationship between our variables of interest and
COVID-19 fatalities using weekly excess mortality as a proxy. In this
case, Eq. (1) includes only 2 lags of the within and between region
transmission variables.

Table 2 and 3 display the results. Regarding the number of COVID-
19 cases, Table 2 confirms the positive relationship between face-
to-face contacts and coronavirus spread and the statically irrelevant
association with the incidence of inter-generational families. This time,
face-to-face contacts are positively associated with COVID-19 cases
throughout all the specifications and the estimated relationship is
stronger than before. Specifically, according to column [3] (our pre-
ferred specification), one percentage point increase in face-to-face contacts is associated with 0.312 new daily cases, on average. In other
words, a standard deviation increase in the share of daily contacts is associated with an increase of 5 new daily cases, on average. Reg-
arding the controls, the results of the previous section are confirmed.

4.2. Estimation Details

Moreover, we now observe a positive impact of the employment rate
on the number of COVID-19 cases, reinforcing the idea that contacts in the workplace or during the commuting time are relevant for the
transmission of the virus.

Table 3 shows the results on weekly excess mortality, where the
latter is the difference in the number of deaths in a given week in
2020 with respect to the average number of deaths in the same week
in the period 2015–2019. Again, we find a positive relation with face-
to-face contacts regardless of the controls and the fixed effects included in the regressions. One percentage point increase in the share of daily face-to-face contacts is associated with 0.16 additional weekly deaths, i.e., with 2.6 extra deaths per week for a standard deviation increase of face-to-face contacts. In contrast with what we found on daily and weekly cases, we also find a positive association with the share of inter-generational households. A 10% increase in the share of inter-

generational households, which is close to a standard deviation, is
associated to around one additional extra death per week. Hence the
within-household inter-generational contacts appear less than half as
lethal as outside-household social interactions.

Regarding the control variables, similar to the results observed for
the number of new COVID-19 cases, we find a positive relationship
between excess mortality and population size and employment rate.
Interestingly, we also find a positive association between the number of weeks since the first case and the excess mortality. This indicates a
larger persistence of COVID-19 mortality relative to the number of new

16 When we estimate the relevance of face-to-face contacts and inter-
generational households on excess mortality, we include the lags of the
dependent variable. In Section 4.2.2, we also include the number of COVID-19 cases as an explanatory variable.
2.1. Rolling window: Daily cases

Fig. 3 displays the estimated coefficient and the 90% confidence interval of face-to-face contacts on new daily COVID-19 cases from the beginning of the pandemic to the end of December 2020. For the sake of interpretation, the period is split into two intervals (February–July and August–December) corresponding to the two COVID-19 waves affecting countries in 2020.

As we expected, the estimated relation between new cases and face-to-face contacts is strong and rising at the beginning of the pandemic, when uncertainty about the virus is higher, behavioural recommendations are given but mobility restrictions are not yet enforced. Likewise, within families, once the pandemic became clear, distancing measures had at time being a relatively larger spread at the beginning of the pandemic, when uncertainty about the virus is higher, behavioural recommendations are given but mobility restrictions are not yet enforced. Likewise, within families, once the pandemic became clear, distancing measures had at time being adopted, especially where some members of the households used to get out for work, while older and/or trailer ones were staying at home. In the next section we use rolling window regressions to investigate how the estimated correlation changes in time.

4.2. Time-varying analysis

In this section, we allow for a time-varying impact of face-to-face contacts and inter-generational households on the number of new COVID-19 cases and excess mortality by estimating a rolling version of Eq. (1). In particular, we estimate Eq. (1) using a rolling time window of 30 (7) days (weeks) from the beginning of the pandemic until the end of December. To maximize the sample included in the regression, we include 10 (2) lags of the dependent variable and the inverse distance weighted sum of new cases in other regions.

cases, and it is in line with the nature of the virus, where a person may die after several weeks since the infection. Finally, we find evidence of a negative relationship with the share of workers employed in the service sector and with the poverty rate, which highlight the relevance of the job place and the economic idiosyncrasies of a region.

So far, we have estimated the average association between face-to-face contacts and inter-generational households, on the one hand, and COVID-19 spread and mortality across time and regions, on the other. However, given the nature of the pandemic and the timing of social distancing measures, we expect that the habit of daily face-to-face interactions with friends and neighbours bear a different relevance at different moments of the pandemic. For example, regions with a larger share of daily face-to-face contacts might show a relatively larger spread at the beginning of the pandemic, when uncertainty about the virus is higher, behavioural recommendations are given but mobility restrictions are not yet enforced. Likewise, within families, once the pandemic became clear, distancing measures had at time being adopted, especially where some members of the households used to get out for work, while older and/or trailer ones were staying at home. In the next section we use rolling window regressions to investigate how the estimated correlation changes in time.
In fact, face-to-face contacts can only be an incomplete proxy of social capital: while dense social networks are necessary for social capital to be formed, they are not sufficient. Social capital is often measured by the share of face-to-face contacts; the estimated coefficient reaches a maximum magnitude of 0.94 with the sample including observations from October 13th to November 13th and swiftly declines thereafter, in Figs. 5 and 6 we show the results using weekly data and compare the time-varying associations between our variables of interest and both COVID-19 cases and excess mortality. In Fig. 5 the blue line displays the time-varying coefficient of face-to-face contacts on the average new daily cases in the week; the positive relationship is confirmed in both waves. In particular, in the second wave, the coefficient estimated on average daily cases per week is not only larger than the coefficient estimated on the corresponding daily data, but it is also more persistent in time. The green line, which displays the time-varying association between daily contacts and excess mortality, suggests that the estimated relationship is positive and statistically significant up to week 20 while in the second wave it drops close to zero, though it remains statistically significant between weeks 43 and 47 with a coefficient around 0.2.

4.2.2. Rolling window: weekly data

For the sake of comparability, we restrict the sample to be the same for the two dependent variables in a given time window.
A. Cristini and P. Trivin

Fig. 3. Daily cases and face-to-face contacts: 30 days rolling window (full sample). Notes: Figures show the marginal effect of face-to-face contacts on daily COVID-19 cases. Dashed lines indicate 90% confidence intervals. Coefficients are obtained from a regression such as column [3] in Table 1 using a 30 days rolling window. The regression includes up to 10 lags of the dependent variable and the inverse distance weighted sum of new cases in other regions. Only regions with at least 5 observations are included.

Fig. 4. Daily cases and inter-generational families: 30 days rolling window (full sample). Notes: Figures show the marginal effect of inter-generational families on daily COVID-19 cases. Dashed lines indicate 90% confidence intervals. Coefficients are obtained from a regression such as column [3] in Table 1 using a 30 days rolling window. The regression includes up to 10 lags of the dependent variable and the inverse distance weighted sum of new cases in other regions. Only regions with at least 5 observations are included.

Fig. 5. Weekly data: Cases and excess mortality (full sample). Notes: Figures show the marginal effect of face-to-face contacts on Covid-19 cases and excess mortality using weekly data. Coefficients associated with COVID-19 cases are obtained from a regression such as column [3] in Table 2. Regarding excess mortality, results come from a regression like column [3] in Table 3. We use a rolling window estimation with 7 weeks of sample size. Blue (green) dashed lines indicate 90% confidence intervals for cases (excess mortality).
With regard to face-to-face contacts, the sharp contrasts between the two waves could be related to the different age-structure of the cases. For the US, Monod et al. (2021) find that as of October 29, only adults aged 20–49 had a reproduction number greater than 1 and disproportionately contributed to the virus transmission with 75 out of every 100 new infections. Also in Europe, as the pandemic evolved and restrictions were lifted, the rebounding in mobility involved mainly young adults and this could help explaining the different strength of the estimated associations between face-to-face contacts and the virus spread and mortality in the two waves. 19

To check if this is a plausible explanation, we carry on by disaggregating the spread of the virus by groups of age.

4.3. Covid cases by age

Daily COVID-19 regional data by age is difficult to obtain. In this Section, we include 4 countries that provide this information from official sources: Belgium, France, Germany, and Spain. Homogenizing the different datasets, we construct the number of daily COVID-19 new cases for four different age groups: 0–40, 40–60, 60–80, and 80+. Figs. 7–10 show the results of running Eq. (1) using the number of new cases for each group of age as the dependent variable. 20

In the first wave, a positive relationship between face-to-face contacts and the spread of the virus is observed for people under 60 and people above 80. The relation is stronger for the elderly, where one percentage point increase in face-to-face contacts is associated with 0.4 new daily cases in April. For people under 60, the relationship is smaller (around 0.2) but observed also in March. When we consider the second wave, the new cases associated with face-to-face contacts are mostly of people under 60. The strongest association is with the group aged 40–60, which presents a coefficient of 0.5 statistically different from 0 between October and December. We also observe a similar result for the group of people under 40, but the effect wears off in December. On the contrary, during the second wave, face-to-face contacts are not found to be associated with the infections of the 80+ people, and the estimated coefficient is also small for the group of age 60–80. These results confirm the role of young adults in the transmission of the virus, as found by Monod et al. (2021) for the US. In addition, they confirm that older cohorts were hit relatively more in the first wave.

This is compatible with changes in the behaviour of different cohorts due to the knowledge of the virus over the course of the pandemic. For example, in the first months of the epidemic, when the virus was still largely unknown and the way the pandemic was spreading was not fully understood, it was more difficult for people to avoid the contagion. However, this could have changed in the second wave, where more information about COVID-19 spread and mortality was available. In this new context, it is logical to think that frailer groups (i.e., older cohorts) may be more cautious regarding their exposure to the virus (i.e., inter-personal contacts). All in all, further research on the transmission channels across and within different age cohorts, and on the role of changes in the behaviour of people of different ages is necessary to confirm these initial results (see for example Harris, 2021), but it is beyond the scope of this paper.

4.4. Robustness checks

Along the paper, we have shown that our findings are robust to different specifications including different fixed effects and controls. In this section, we further check the robustness of the results to the sample of countries selected, to the number of persons included in the EQLS survey in a given region, and to the potential bias arising from the dynamic nature of our analysis.
Fig. 7. Daily Covid cases (0–40): 30 days rolling window. Notes: Figures show the marginal effect of face-to-face contacts on daily COVID-19 cases under 40. Dashed lines indicate 90% confidence intervals. Coefficients are obtained from a regression such as column [3] in Table 1 using a 30 days rolling window. The regression includes up to 10 lags of the total number of COVID-19 cases and the inverse distance weighted sum of new cases in other regions. Only regions with at least 5 observations are included.

Fig. 8. Daily Covid cases (40–60): 30 days rolling window. Notes: Figures show the marginal effect of face-to-face contacts on daily COVID-19 cases 40–60. Dashed lines indicate 90% confidence intervals. Coefficients are obtained from a regression such as column [3] in Table 1 using a 30 days rolling window. The regression includes up to 10 lags of the total number of COVID-19 cases and the inverse distance weighted sum of new cases in other regions. Only regions with at least 5 observations are included.

Fig. 9. Daily Covid cases (60–80): 30 days rolling window. Notes: Figures show the marginal effect of face-to-face contacts on daily COVID-19 cases 60–80. Dashed lines indicate 90% confidence intervals. Coefficients are obtained from a regression such as column [3] in Table 1 using a 30 days rolling window. The regression includes up to 10 lags of the total number of COVID-19 cases and the inverse distance weighted sum of new cases in other regions. Only regions with at least 5 observations are included.
4.4.1. Sample selection and number of interviews

Regarding the sample used in the analysis, our criteria was to include any country with available data in the variables of interest. This implies that our baseline sample consists of an heterogeneous group of countries, though all Europeans, including small countries that could be driving our results. To rule out this possibility, in Appendix B we run again Eq. (1) including only the biggest countries in our sample: Germany, France, Italy, Spain, and the UK. Results are qualitatively robust.

Another source of concern comes from the fact that in the EQLS, the number of interviewees is based on the regional population. The measures of face-to-face contacts and inter-generational households could then be calculated with insufficient precision in small regions.

To account for this issue, we estimate a weighted version of Eq. (1) using the number of survey respondents as the weights. The results, reported in Appendix C, reinforce our previous findings in that we observe a larger impact of face-to-face contacts on the spread and mortality of the virus. In addition, the share of inter-generational households is also significant and positively associated with daily and weekly cases.

4.4.2. Dynamic bias

A major threat to our identification may come from the dynamic structure of Eq. (1). That is, the inclusion of lags of the dependent variable in the right hand side of Eq. (1) may lead to a bias in all regression coefficients estimated by OLS (Nickell, 1981). In Appendix D we present two robustness exercises to see to what extent this dynamic bias could be affecting our results.

In the first exercise, we follow (Adda, 2016) and Qiu et al. (2020) and instrument the lags of the dependent variable with previous weather events. Specifically, using daily weather data at the NUTS 2 level from (Felice and Kavvadias, 2022), we follow (Qiu et al., 2020) and use as instrumental variables weekly averages of daily heating degree days, runoff, wind speed at 10 m, and the interaction between runoff and wind speed, during the preceding third and fourth weeks.

Tables D.1 and D.2 show, respectively, the results for cases and excess mortality using weekly data. Regardless of the sample under consideration and the decision to use weights or not, our results show a positive relationship between face-to-face contacts and the number of new cases. The coefficients range from 0.214 to 0.491, very similar to those observed in the OLS regressions, which reinforces our confidence in the previous results. When we focus on excess mortality, we can also see a positive relationship with face-to-face contacts, although in this case the range of values is wider than in the OLS regressions and is only significant when we use weighted regressions.

It is worth noting that our IV strategy is designed for the number of new infections while it may be less suitable for excess mortality. In Table D.3 we show the F-test of joint significance of the instruments and its associated p-values from the first-stage. For the number of cases, the values are not far from the ones obtained by Adda (2016), with the p-values below the 5 percent level when we include NUTS 1-week fixed effects. However, when we consider excess mortality, as expected, the results indicate that the instruments could be weak. For this reason, below we show an alternative exercise to ensure the validity of our results.

Figure D.1 completes the IV analysis by displaying the rolling window results for new cases and excess mortality. The picture is very similar to the one observed in the OLS results. That is, regions with a larger share of face-to-face contacts are associated with a larger number of new cases and excess mortality at the beginning of the pandemic. In the second wave, however, this positive association is only observed for the number of new cases. Results are robust and consistent for the different samples under consideration and the use of weights.

All in all, this exercise seems to indicate that our results are not importantly affected by the dynamic bias. This could be due to the relatively large time dimension of our panel as the dynamic bias decreases with T. In order to confirm the robustness of our results, in a second

---

21 The main assumption here is that, given the incubation period of COVID-19, weather conditions in the preceding 2 weeks do not affect directly the probability that a person contracts the virus in period t, but they affect the number of other persons who have become infectious within the 2-week window.

22 The difference in observations between the IV and OLS estimations is due to data limitations regarding the weather variables. In this exercise we focus on weekly data for two reasons: (i) it is more parsimonious (there are only 2 lags instead of 14) and (ii) we are able to compare new cases and excess mortality. Results with daily data are available upon request.

23 Figure D.2 shows that our results do not change if we also considered endogenous the lagged inverse log distance weighted sum of new cases in other regions. In this case, beyond the previous instruments (daily heating degree days, runoff, wind speed at 10 m, and the interaction between runoff and wind speed), we further include the inverse log distance weighted sum of each of these variables in other regions, during the preceding third and fourth weeks, as instrumental variables in the IV regressions.
In the first wave. Exploiting age-specific information from a subset of COVID-19 cases in a given week in region \(i\) and \(\sum_{i\neq j} d_{ij} \ln T_{ij} Y_t\) is the inverse log distance weighted sum of the cumulative number of COVID-19 cases in the rest of regions.\(^{26}\) The rest of control variables are explained in Section 3.

Figure 3.3 shows the results using weekly data. The time variation in the figures is obtained by estimating Eq. (2) in different weeks.\(^{27}\) The results are consistent with our previous findings, regions with a larger share of face-to-face contacts have a larger number of new cases during the first wave which dramatically increases during the second wave.\(^{28}\) Regarding excess mortality, we observe an increase during the first wave that remains constant over the whole period.

All in all, we do not find evidence of the dynamic bias playing a relevant role in our results. Our findings are robust to different samples, the inclusion of weights, and different estimation strategies.

5. Conclusions

This paper moves from the socioeconomic research that relates COVID-19 spread to the inter-generational interactions occurring within the household, and extends it in several ways. We place the analysis at the regional NUTS 2 level, consider a total of 220 regions of 15 European countries and high frequency data on COVID-19 cases and excess mortality spanning from March to December 2020, thus covering the first and the second wave of pandemic. We show that both new infections and excess mortality are positively associated with the percentage of people having daily face-to-face contacts with friends or neighbours. On the contrary, the relevance of the share of inter-generational households in the transmission of the epidemic is not robust, except when using weighted LS, but even in this case the magnitude and significance of the coefficient is comparably lower than that of social interactions outside the household. Similarly, with regard to excess mortality, the approximated within-household inter-generational contacts appear less than half as lethal as outside-household social interactions.

Our results indicate that a standard deviation increase in the percentage of people having daily face-to-face contacts is associated with an increase of 5 daily COVID-19 cases, on a weekly average, and 2.6 fatalities on top of the ‘normal’ number of deaths. When we allow our coefficients to vary over time, we observe that this positive relationship is evident in both COVID-19 waves as far as the number of new cases is concerned, whereas for excess mortality the relationship is stronger in the first wave. Exploiting age-specific information from a subset of countries, we find evidence that the age groups have played different roles in the transmission of the epidemic: the cohort of adults aged 40–60 is particularly important in the second wave, as face-to-face contacts are strongly associated with the infections of this age group; on the contrary, in the early months of the epidemic, face-to-face contacts show a relatively stronger association with the contagion of younger adults and 80+ elderly.

Results are robust to the sample of countries used and to the estimation strategy. The statistical significance of face-to-face contacts is also robust to the inclusion of economic, demographic and epidemiological controls, to within and between region lagged cases as well as to fixed effects that should absorb unobserved heterogeneity. Nonetheless, as some residual unobserved regional heterogeneity cannot be excluded, we do not claim causality.

On the whole, our findings are consistent with the view that the frequency and type of social contacts incorporate cultural features, as posits by relational sociology, and that the patterns of such contacts show some degree of persistence. This implies that the macro map of daily face-to-face interactions that characterizes a region is informative on the potential transmission of contagion and on its lethality.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ehb.2022.101180.

References

Addo, J., 2016. Economic activity and the spread of viral diseases: Evidence from high frequency data. Q. J. Econ. 131 (2), 891–941.
Aparicio Fenoll, A., Grossbard, S., 2020. Intergenerational residence patterns and COVID-19 fatalities in the EU and the US. Econ. Hum. Biol. 39 (C).
Arno, J., Muellbauer, J., 2020. Measuring Excess Mortality: England Is the European Outlier in the COVID-19 Pandemic. Technical Report, VOX CEPR Policy Portal.
Arpino, B., Bordone, V., Pasqualini, M., 2020. No clear association emerges between inter-generational relationships and COVID-19 fatality rates from macro-level analyses. Proc. Natl. Acad. Sci. 117 (32), 19116–19121.
Ascani, A., Faggian, A., Montresor, S., 2020. The geography of COVID-19 and the structure of local economies: The case of Italy. J. Reg. Sci. 61.
Bartcher, A.K., Seitz, S., Siegloch, S., Slotwinski, M., Wehrhofer, N., 2021. Social capital and the spread of COVID-19: Insights from European countries. J. Health Econ. 80, 102531.
Bayer, C., Kuhn, M., 2020. Intergenerational Ties and Case Fatality Rates: A Cross-Country Analysis. IZA Discussion Papers 13114, IZA Institute of Labor Economics.
Belloc, M., Buonanno, P., Drago, F., Galbiati, R., Pinotti, P., 2020. Cross-Country Correlation Analysis for Research on COVID-19. Technical Report, VOX CEPR Policy Portal.
Borgonovi, F., Andrieu, E., 2020. Bowling together by bowling alone: Social capital and COVID-19. Soc. Sci. Med. 265, 113501.
Brown, C.S., Ravallion, M., 2020. Inequality and the Coronavirus: Socioeconomic Covariates of Behavioral Responses and Viral Outcomes Across US Counties. NBER Working Papers 27549, National Bureau of Economic Research, Inc.
Cornwell, B., 2011. Age trends in daily social contact patterns. Res. Aging 33 (5), 598–631.
Davies, N.G., Klepac, P., Liu, Y., Prem, K., Jit, M., Pearson, C.A.B., Quilty, B.J., Kucharski, A.J., Gibbs, H., Clifford, S., Gima, A., van Zandvoort, K., Munday, J.D., Edmunds, W.J., Houben, R.M.G.J., Hellewell, J., Russell, T.W., Abbott, S., Funk, S., Bosse, N.I., Sun, Y.F., Flasche, S., Rosello, A., Jarvis, C.I., Eggo, R.M., CMMID COVID-19 working group, 2020. Age-dependent effects in the transmission and control of COVID-19 epidemics. Nat. Med. 26 (8), 1205–1211.
Dépeleau, F., 2018. The Palgrave Handbook of Relational Sociology. Springer.
Donati, P., 2018. An original relational sociology grounded in critical realism. In: The Palgrave Handbook of Relational Sociology. Springer, pp. 431–456.
Dowd, J.B., Andriano, L., Brazel, D.M., Rotondi, V., Block, P., Ding, X., Liu, Y., Mills, M.C., 2020. Demographic science aids in understanding the spread and fatality rates of COVID-19. Proc. Natl. Acad. Sci. 117 (18), 9696–9698.
Durante, R., Guiso, L., Guiso, G., 2021. Associable capital: Civic culture and social distancing during COVID-19. J. Public Econ. 194 (C).
Duranton, G., Rodriguez-Pose, A., Sandall, R., 2008. Family types and the persistence of regional disparities in europe. Econ. Geogr. - Econ. Geogr. 85, 23–47.
Esteve, A., Permanyer, I., Boerriam, D., Vaspel, J.W., 2020. National age and co-residence patterns shape COVID-19 vulnerability. Proc. Natl. Acad. Sci. 117 (28), 16118–16120.

\(^{24}\) A popular way to deal with the dynamic bias is to use the Difference or System GMM estimators. However, in our context these estimators are not appropriate for two reasons: (i) we have a relatively small cross-section dimension with respect to the time dimension and (ii) our main variable of interest and most of our controls are time-invariant.

\(^{25}\) The number of cumulative cases refers to the sum of the weekly averages of new daily COVID-19 cases.

\(^{26}\) When we estimate the relevance of face-to-face contacts on excess mortality, the dependent variable is the cumulative number of excess deaths and we do not include the inverse log distance weighted sum of new cases in other regions.

\(^{27}\) To be on the safe side, as this time we do not exploit within-region variation, we limit the analysis to weeks where there is no change in the number of regions in the sample.

\(^{28}\) Note that the different shape in the figure is related to the dependent variable, which now is the cumulative number of cases.\(^{26}\)
Felice, M.D., Kavvadias, K., 2022. ERA-NUTS: Meteorological time-series based on C3S ERA5 for European regions (1980–2021). http://dx.doi.org/10.5281/zenodo.633977, Zenodo.

Forbes, H., Morton, C.E., Bacon, S., McDonald, H.I., Minassian, C., Brown, J.P., Rentsch, C.T., Mathur, R., Schultz, A., DeVito, N.J., et al., 2021. Association between living with children and outcomes from COVID-19: Opsensafely cohort study of 12 million adults in England. BMJ 372.

Fuhse, J.A., 2013. Social relationships between communication, network structure, and culture. In: Applying Relational Sociology. Springer, pp. 181–206.

Fuhse, J.A., 2018. Deconstructing and reconstructing social networks. In: The Palgrave Handbook of Relational Sociology. Springer, pp. 457–479.

Giuliano, P., Rasul, I., 2020. Compliance with social distancing during the COVID-19 crisis. Technical Report, VOX CEPR Policy Portal.

Harris, J.E., 2020. Data from the COVID-19 epidemic in florida suggest that younger cohorts have been transmitting their infections to less socially mobile older adults. Rev. Econ. Household 18 (4), 1019–1037.

Harris, J.E., 2021. Los angeles county SARS-CoV-2 epidemic: Critical role of multi-generational intra-household transmission. J. Bioecon. 23 (1), 55–83.

Kaasa, A., Vadi, M., Varblane, U., 2014. Regional cultural differences within European countries: Evidence from multi-country surveys. Manag. Int. Rev. 54 (6), 825–852.

Lyttelton, T., Zang, E., 2022. Sickness-related absences during the COVID-19 pandemic: The role of occupations. J. Health Soc. Behav..

Mäkinen, T.M., Juvonen, R., Jokelainen, J., Harju, T.H., Peitso, A., Bloigu, A., Silvennoinen-Kassinen, S., Leinonen, M., Hassi, J., 2009. Cold temperature and low humidity are associated with increased occurrence of respiratory tract infections. Resp. Med. 103 (3), 456–462.

Mastrandrea, R., Fournet, J., Barrat, A., 2015. Contact patterns in a High School: A comparison between data collected using wearable sensors, contact diaries and friendship surveys. PLoS One 10 (9).

Mogi, R., Spijker, J., 2021. The influence of social and economic ties to the spread of COVID-19 in Europe. J. Popul. Res..

Monod, M., Blenkimop, A., Xi, X., Hebert, D., Bershaw, S., Tietze, S., Baguelin, M., Bradley, V.C., Chen, Y., Goupaland, H., et al., 2021. Age groups that sustain resurging COVID-19 epidemics in the United States. Science 371 (6536).

Moxson, J., Hens, N., Jit, M., Beutels, P., Auranen, K., Nikolajczyk, R., 2008. Social contacts and mixing patterns relevant to the spread of infectious diseases. PLoS One 5 (4).

Murgante, B., Borruso, G., Balietto, G., Castiglia, P., Dettori, M., 2020. Why Italy first? Health, geographical and planning aspects of the COVID-19 outbreak. http://dx.doi.org/10.20944/preprints202005.0075.v1, Preprints.

Naqvi, A., 2021. COVID-19 European regional tracker. MedRxiv, Cold Spring Harbor Laboratory Press.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49 (6), 1417–1426.

Putnam, R.D., 2000. Bowling Alone: The Collapse and Revival of American Community. Simon & Schuster, New York.

Qiu, Y., Chen, X., Shi, W., 2020. Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. J. Popul. Econ. 33 (4), 1127–1172.

Read, J.M., Eames, K.T.D., Edmunds, W.J., 2008. Dynamic social networks and the implications for the spread of infectious disease. J. R. Soc. Interface 5, 1001–1007.

Rodríguez-Pose, A., Burlina, C., 2021. Institutions and the uneven geography of the first wave of the COVID-19 pandemic. J. Reg. Sci..

Salathé, M., Kazandjieva, M., Lee, J.W., Levin, P., Feldman, M.W., Jones, J.H., 2010. A high-resolution human contact network for infectious disease transmission. Proc. Natl. Acad. Sci. 107 (51), 22020–22025.

van Oorschot, W., Arts, W., Gelissen, J., 2006. Social capital in Europe. Measurement and regional distribution of a multi-faceted phenomenon. Acta Sociol. 49 (2), 149–167.