The differential impact of physical distancing strategies on social contacts relevant for the spread of COVID-19

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Abstract

Physical distancing measures are intended to mitigate the spread of COVID-19. However, the impact these measures have on social contact and disease transmission patterns remains unclear. We ran the first comparative contact survey (N=53,708) across eight countries (Belgium, France, Germany, Italy, Netherlands, Spain, United Kingdom, United States) for the period March 13-April 13, 2020. Our results show that social contact numbers mainly decreased after governments issued physical distancing guidelines rather than after announcing national lockdown measures. Compared to pre-COVID levels, social contact numbers decreased by 48%-85% across countries. Except in Italy, these reductions were smaller than those observed in Wuhan (China). However, they sufficed to bring the R_0 below one in almost every context considered. Finally, in all countries studied, the numbers of contacts decreased more rapidly among older people than among younger people, indicating higher levels of protection for groups at greater risk.

Introduction

The coronavirus disease 2019 (COVID-19) epidemic has shown the importance of implementing non-pharmaceutical approaches, like physical distancing, to contain the spread of the virus and to avoid over-burdening health care systems.

The strain of the virus (SARS-CoV-2) that causes the disease spreads from person to person through small droplets from the nose or mouth. These droplets are typically expelled when someone coughs, sneezes, or speaks. Thus, a primary mode of disease transmission is via close social contacts, which generally occurs when a susceptible individual breathes in droplets from an infected individual, or touches his or her face after physical contact with those droplets (1).

The rapid spread of the virus across countries and continents, and the associated death toll, have led to the introduction of strong public health measures to contain the disease. These measures include travel restrictions, school closures, the cancellation of large gatherings, the promotion of physical distancing practices, and, in some countries, a full-scale nationwide lockdown. In the absence of a vaccine and effective viral treatments, the policies that have so far been implemented are largely non-pharmaceutical interventions aimed at changing the magnitude of social mixing patterns, which is a key factor in shaping the course of the epidemic. Thus, how people respond to these interventions is a critical factor to consider when assessing the effectiveness of public health measures designed to contain the disease and to prevent new waves of infection.

The epidemiological literature has shown that quantifying social contact patterns is a top priority, as doing so will improve our understanding of the determinants of the transmission of close-contact infectious diseases, and will enable researchers to design more realistic epidemic models and public health agencies to develop optimal control strategies (2). Such research is particularly important because social contact patterns are intimately related to key epidemiological parameters, like the basic reproduction number (R_0) of an epidemic (3). Despite the need to understand social mixing in the context of the COVID-19 epidemic, new information about contact patterns has so far become available for a very limited number of settings only, e.g., for China (4) and the UK (5). This is in part because during an epidemic, collecting data with standard surveys becomes more difficult or is subject to delays.

In this study, we leverage new opportunities for data collection enabled by the digitalization of our lives to assess the changes in social contact patterns on a daily basis and across countries, and to examine the implications of these changes for the spread of the coronavirus. More specifically, we launched a cross-national online survey, the "COVID-19 Health Behavior Survey" (CHBS), in which we recruited participants via targeted Facebook advertisements (6). This approach enabled us to rapidly reach a large number of survey participants across countries. The ability to collect data on a large number of people quickly is one of the main advantages of using online surveys. In addition, as this approach allowed us to control the demographic groups and geographic areas that were targeted for recruitment, we were able to draw balanced samples from the population of Facebook users. Then, using post-stratification weights, we produced model estimates that approximate those from nationally representative samples.

Early efforts to collect social contact data using diary-based surveys, which were initiated in the early 2000s by Wallinga and colleagues (3), led to the so called Polymod project (2), a multi-country study based on national representative samples in eight European countries. This project cleared the path for subsequent contributions that have significantly expanded our understanding of how social contact patterns differ across settings (7), how these patterns are associated with infection transmission (8–12), and what impact these patterns might have on public health measures like school closures (13,14). In our survey, we used metrics that are comparable to those proposed in the literature to evaluate the extent to which numbers of social contacts changed across countries and over time by examining the participants' standard contact numbers before and after the coronavirus outbreak. Our results are based on surveys carried out in Germany, Italy, the United Kingdom (UK), the United States (US), Spain, France, Belgium, and the Netherlands from March 13 to April 13 – a key period during which the global pandemic was well underway, but was also at different stages in different countries. We measured the participants' social contacts, as well as the behavioral determinants of their contact patterns, on a daily basis and across demographic groups, and quantified the relative impact of the reductions in social contact numbers on the speed of the spread of the disease.

Results

Sample description

A total of 53,708 participants completed the survey, and reported the number of social contacts they had in four different settings (home, school or college, work, and general community) on the day before they completed the survey. Thus, we were able to collect daily social contact data between March 12 and April 12. We used the information on the number of contacts per setting to estimate, for each participant, the overall number of contacts she or he had on the previous day, regardless of the setting.

Table S2 in the supplementary material shows the total number of respondents and proportions (unweighted) broken down by country, sex, age, and week. We note that the sample size for the 65+ age group (who are at higher risk of death from COVID-19 (1), and who usually have lower social media participation rates (15)), was fairly large in every country, ranging from 879 (11%) in Italy to 3,444 (28%) in the US.

Two features of the highly skewed distribution of the overall social contacts (Fig. S2 in the supplementary material) are worth noting. First, we found that the percentages of participants who reported having fewer than one contact per day were relatively high, at more than 30% in all countries except for Germany, the Netherlands, and the US. Second, the distribution was characterized by a long right tail, the length of which depended on the cut-off used to remove the outliers at the top of the distribution (Table S1 in the supplementary material). Under the 90% outlier cut-off scenario used in the main analysis (i.e., the most plausible scenario when assessing CHBS contacts by their setting in comparison with features of the distributions in the pre-COVID periods for countries where such data were available), we found that the maximum number of overall reported contacts per day was 16, while the maximum number under the 95% outlier cut-off scenario was 33.

Reductions in the numbers of contacts after the call for physical distancing

We show the evolution of overall social contact numbers over the study period, broken down by the setting of contact (work and general community) in Fig. 1 and Fig. 2. The trend in social contact numbers indicates that the predicted numbers of overall social contacts reported by respondents decreased during the study period in all of the surveyed countries, reaching a plateau around the lowest levels between calendar week 13 (March 23-29) and calendar week 14 (March 30-April 5). We found that the overall numbers of social contacts declined considerably after governments issued physical distancing guidelines (which mainly occurred during the first week of our study, week 11), rather than after governments announced lockdown measures, as might be expected. For instance, when we compared the trends before and after the announcement of physical distancing measures in the UK, we found that the average number of daily contacts (with 95% confidence intervals) decreased from 5.89 (5.07, 6.71) on March 12 to 3.07 (2.71, 3.43) on March 19, representing a reduction of 48%. When we looked at these trends in the US, we found that this number decreased from 5.45 (5.01, 5.89) to 3.77 (3.52, 4.01), representing a reduction of 31%. Our findings also showed that during week 14 – i.e., 14 days after the physical distancing guidelines had been announced, and after the implementation of the lockdown measures – the average number of social contacts had decreased even further, reaching a value of 2.04 (1.80, 2.28) in the UK and of 2.96 (2.77, 3.16) in the US, which corresponds to a total reduction of 34% and 21%, respectively, relative to March 19. In the other countries, where physical distancing guidelines had been introduced before the beginning of our study, we found that the average numbers of contacts had already declined to their lowest levels, ranging from 2.22 (1.96, 2.48) in Italy and 2.54 (2.16, 2.89) in Spain (where full lockdown measure were in place; i.e., people were required to stay at home, and were not permitted to go out except when necessary) to 3.64 (3.01, 4.27) in the Netherlands and 4.26 (3.94, 4.58) in Germany (where partial lockdown measures were in place; i.e., a stricter version of the physical distancing guidelines was imposed, but people had the freedom to go out). Finally, in a few countries, we noticed that the overall contact numbers rebounded slightly during week 15, which was Easter week: compared to their lowest levels, the numbers of contacts increased by 19% in the Netherlands and the US, by 20% in the UK, and by 25.

The trends in the numbers of contacts at work and in the general community were fairly similar to the trends in the overall numbers of contacts, as they decreased or plateaued following similar patterns. We found significant differences in the numbers of contacts in the two settings in only half of the surveyed countries: namely, in Germany, France, the Netherlands, and, to a lesser extent, the US. In these countries, we found that the numbers of contacts were generally higher at work than in the general community.

From our estimates, we found evidence of different declining patterns in the countries that eventually applied a full lockdown, such as Belgium, France, Italy, Spain, and the UK; and in the countries that opted for a partial lockdown, such as Germany and the Netherlands. For both Germany and the Netherlands, we estimated that each person had slightly more than four contacts per day in week 15 – a substantially higher value than those estimated for the other countries with full lockdown, which ranged from 2.55 in France to 3.24 in Italy. The largest reduction in contact numbers in response to the introduction of a lockdown was observed for the UK, where work contact numbers dropped by 80%, numbers of contacts in the general community declined by 70%, and overall contact numbers decreased by 60% from week 11 to week 14. Conversely, we found that after a partial lockdown was implemented in Germany, numbers of contacts in the general community contracted by 24%, while both work and overall contact numbers decreased by 17%.

For the US, it was not possible to evaluate the effectiveness of the lockdown measures, as these measures were enacted in different modalities and at different times in each state after the initial guidelines were issued on March 16. However, the states that introduced some type of state lockdown mostly did so between week 13 and 14 (see Data file S1 in the supplementary material). Hence, we found that, at the national level, numbers of both contacts at work and in the general community more than halved between week 11 and week 14, while the overall contact numbers decreased by 42%.

For a subset of countries for which social contact data from the pre-COVID period were available, either from the Polymod study (carried out between 2005 and 2006 in Belgium, Germany, Italy, Netherlands, and UK) (2) or from similar studies (i.e., a study conducted in France in 2012) (16), we were able to compare the contact numbers in the two periods (Table 1). Although the data collected for each country in the CHBS study were for different time points (e.g., the first week for Belgium was week 14, whereas the first week for Italy was week 11), this comparative analysis was nonetheless able to assess the extent to which contact patterns changed from the period before the epidemic started to the period during the epidemic. When we compared the contact numbers in the pre-COVID period with those in week 14, we found the largest reduction in Italy, at 85%, and substantial declines in the other countries, ranging from 48% in Germany to between 73% and 75% in Belgium, France, the Netherlands, and the UK. On the one hand, we found that in all of these countries, the largest reductions in contact numbers were in the general community, ranging from 88% in Belgium, the Netherlands, and the UK to 90% in France and 95% in Italy. On the other hand, we observed that the declines in work contact numbers were smaller in magnitude, ranging from around 65% in Belgium and the Netherlands to 80% in the UK and 90% and in Italy. Again, the exception was Germany, where the numbers of contacts in the general community had declined by 67%, and the numbers of work contacts had decreased by just 2% in week 13.

Our sensitivity analysis, in which we changed the contact distribution outlier cut-off from 10% to 5%, even though the numbers were slightly higher across all our results, confirmed the overall trends over time (for details on how to access the online supplementary material with the 5% plots, see section 1.3 in the supplementary material).

Evidence that social contact numbers declined more among the elderly

When we looked at the evolution of the overall contact numbers across age groups during the study period, we observed a general decrease, especially in the UK and the US (Fig. 3, panel A). There was little variation in social contact numbers among age groups, except for the 65+ age group, who were found to have the lowest numbers of overall contacts in all of the countries studied. The age gap in contact numbers was largest in the Netherlands and Belgium, where the 65+ age group reported having 35% fewer contacts than the reference group aged 45−64. Our results for Germany showed that the numbers of contacts reported by the 65+ age group were already much lower than the numbers reported by the other age groups (33% lower than the general population, and 44% lower than the 45−64 age group) prior to the beginning of the study, and remained lower than the numbers reported by the other age groups throughout the whole study period. This pattern contrasts with the evolution of contacts observed for Italy, the UK, and the US, where the numbers of social contacts reported by the 65+ age group converged to the numbers reported by the other age groups. The changes in the overall numbers of contacts over time can also be assessed by comparing our data with data collected in the pre-COVID period (2,16). We compared the pre-COVID overall numbers of social contacts by age groups with the numbers from the first week of data available for each country (Fig. 3, panel B). The results suggested that in all countries, the contact numbers declined. We found that in Italy, in particular, which was surveyed in the first week of our study (week 11), but also in France, Belgium, and the Netherlands, the overall contact numbers decreased substantially for all age groups. These findings were expected, given that physical distancing guidelines had already been issued, and lockdown measures were implemented in early March. However, the differences in the contact numbers between the two periods were found to be much smaller in Germany and the UK, especially for the 65+ age group.

When we looked at the trends in work contact numbers, we found that the 65+ age group reported having much smaller numbers of contacts than the other age groups. When we focused on the countries with the longest observation time periods, we noticed that among the youngest age groups in the US and the UK, there was an overall decrease in work contact numbers throughout the study period (Fig. S4, panel A, in the supplementary material) that appears to reflect the implementation of physical distancing measures over time. On the other hand, when we examined countries such as Spain and Italy, we found that the younger age groups already had few to no contacts, which is likely because in these countries, the full lockdown measures were already preventing a large portion of the population from going to work. The trends for contact numbers in the general community did not differ significantly by age group, or by week (Fig. S5, panel A, in the supplementary material). Moreover, these contact numbers had already reached their lowest levels by the beginning of the study period in each country. This evidence might suggest that the big drop in the overall contacts shown in Fig. 3 is mostly attributable to a reduction in work contact numbers, and not to a reduction in contact numbers in the general community.
In the sensitivity analysis, in which we changed the outlier cut-off in the distribution of contacts from 10% to 5%, the results were only slightly different. More broadly, the overall trends were very similar to the trends presented here (for details on how to access the online supplementary material with the 5% plots, see section 1.3 in the supplementary material).

The impact of physical distancing interventions on the basic reproduction number

We evaluated how the basic reproduction number (R_0, i.e., the expected number of new infections produced by an infectious individual in a totally susceptible population) changed from its baseline range of values in the absence of any mitigation strategy in response to the reduction in the number of contacts following the introduction of physical distancing interventions. We assumed that (i) the baseline R_0^b expected at the initial stage of the epidemic was compatible with the social contact patterns by age measured in the pre-COVID period; and that (ii) although the mixing patterns under the physical distancing interventions changed in terms of intensity, they did not change in terms of their overall structure.
The weekly R_0^w decreased in all of the surveyed countries for which data on pre-COVID social mixing patterns between age groups were available (Fig. 4, panel A). However, we found a high level of heterogeneity in this decreasing trend. For countries like Italy, the UK, Belgium, and the Netherlands, we found evidence that the reduction in the numbers of contacts alone was enough to bring the R_0^w to a value lower than one, which is the necessary condition for the infection to decay exponentially (Fig. 4, panel A). In particular, we found that in Italy, the reduction in overall social contact numbers led to a decrease of at least 80% in the baseline R_0^b as early as in calendar week 11. For the UK, we found that evidence of the R_0^w falling below one did not appear until week 13, after the lockdown had begun, when changes in the social contact numbers led to a reduction in the baseline R_0^b of 70%. The same pattern could be observed for Belgium and the Netherlands, where there were reductions of around 70% in both contact numbers and R_0^b (Figure 4, panel B).
Conversely, in Germany and in France, we observed that the decline in the numbers of overall social contacts alone was not enough to cause the R_0^w to fall below one, as the R_0 dropped to about half of the baseline value as a result of the changes in social contact numbers during the study period. Indeed, we found that the minimum R_0^w in France was equal to 1.20, with 95% CI 0.71–1.70, in week 13; while the minimum R_0^w in Germany was equal to 1.47, with 95% CI 0.86–2.08, in week 12. These reductions can be attributed to physical distancing only, while other synergistic interventions that were being implemented contributed to the further decline in the R_0.

Discussion

Quantifying social contact patterns is a top priority, as doing so will improve our understanding of the transmission of close-contact infectious diseases, and enable researchers to design realistic epidemic models and public health agencies to implement control strategies (2). In this paper, we provided and discussed the first estimates of the number of social contacts, overall and by setting of contact, that people reported during the COVID-19 pandemic in Belgium, France, Germany, Italy, the Netherlands, Spain, the UK, and the US, disaggregated by weeks.

In this paper, we provided and discussed the first estimates of the numbers of social contacts – both overall numbers and numbers by setting – that people reported during the COVID-19 pandemic in Belgium, France, Germany, Italy, the Netherlands, Spain, the UK, and the US; disaggregated by weeks. Analyzing the evolution of social contacts between March 12 and April 12, we found a significant reduction in the overall numbers of social contacts across all surveyed countries between this period and the pre-COVID period (2,16). Except in Italy, the reductions in contact numbers we observed were smaller than the reduction of 86% reported in Wuhan (4), ranging from 48% in Germany to 75% in the UK and to 85% in Italy. To the best of our knowledge, our estimates of social contact numbers are consistent with those from other independent studies that were carried out in the same countries between March and April 2020, and that used the same social contact definition; e.g., studies performed in the US (2.7 overall social contacts (17)) and in the UK (2.9 overall social contacts (5)). However, we found that this reduction was not uniform across all countries, as Italy and Spain reported the lowest average numbers of social contacts, of around three, while Germany and the Netherlands reported the highest average numbers of social contacts, of more than four.

Our findings suggest that the countries with the highest numbers of social contacts were those that implemented partial lockdowns (or stricter versions of the physical distancing guidelines), whereas the countries that implemented full lockdown measures had significantly lower numbers of social contacts. However, we also found that the overall social contact numbers declined much more sharply after governments issued physical distancing guidelines than they did after governments announced lockdown measures. This distinction was particularly clear in the UK, Germany, and the US (even though there was no uniform lockdown date across the different states), for which we were able to assess the contact patterns before and after the different non-pharmaceutical interventions were implemented. This general result seems to hold regardless of the type and severity of the lockdown.

For those countries for which we have social contact data in the pre-COVID period, we also estimated the net effect of reductions in social contacts on the basic reproduction number R_0. We found that a 70% reduction in contacts was associated with an equivalent reduction in the baseline R_0, which was enough to bring the R_0 significantly below one in Italy, Belgium, the UK and the Netherlands, but not in Germany or, to a lesser extent, in France. The findings for Germany and France can be explained by the relatively low social contact numbers in these two countries in the pre-COVID era (on average, 7.5 in Germany and 9.3 in France) and by the smaller reductions (between 30% and 50%) in social contact numbers during the study period. Nonetheless, these results should not be interpreted as evidence that the infection spread was exceptionally high in Germany and France despite their physical distancing interventions. Independent estimates of R_0 at the beginning of April in the Ile de France (0.68 with 95% CI 0.62–0.73) (18)) and in Germany (1.1 with 95% CI 0.9–1.4 (19)) were slightly lower than the estimates we present in this paper. This is because changes in the R_0 are brought about not only by changes in social contact patterns, but by changes in infection transmissibility, which might be affected by several additional factors, such as travel restrictions, increased hand washing or sanitizing, use of face masks and avoidance of face touching, and increased distance while having conversations in public spaces (e.g., supermarkets). In this paper, we have simply quantified the pure effect of reducing social contact numbers on the R_0.

With respect to differences by age, we found that the overall contact numbers uniformly decreased across individuals between 18 and 64 years of age. Moreover, we found little evidence that any particular age group had higher contact numbers than the other age groups, and was thus at higher risk of spreading the disease.

Conversely, we observed that individuals in the 65+ age group reported significantly lower numbers of contacts than the other age groups, which is consistent with the higher risk of infection associated with this age group. We also found that the work contact numbers were much higher among respondents under age 64 than among those aged 65+. However, the numbers of contacts in the general community were found to be of similar intensity across all age groups.

In addition to the substantial contributions this paper makes to improving our understanding of the changes in and the dynamics of social contact numbers during the COVID-19 pandemic, it has, to the best of our knowledge, provided the first international comparable set of statistics on social contacts patterns during the COVID-19 pandemic, disaggregated by week. As these estimates offer a more grounded alternative to the assumptions that have so far been applied (18,20,21), the community of epidemiologists and policy-makers can use this important information in developing epidemic models of COVID-19.

The study has a number of limitations that should be discussed in light of the findings. First, the survey respondents were recruited through the Facebook Ads Manager, which might have led to some issues of self-selection. Indeed, the participants might differ to some extent from the general population in terms of their sociability patterns (due to their Facebook use) and their concerns about health-related issues (as they opted in to participate in the health survey). We tackled this issue in two main ways: (i) we designed a survey stratified by age, gender, and region, all of which are factors that we believe are linked to both survey participation and the outcomes of interest of the survey (22); and (ii) we ensured that only respondents who were shown the Facebook advertisement and clicked on the link could participate in the study (thereby avoiding spillover biases in the sample that we cannot adjust for). As a future step, we will consider including Facebook campaign metadata in our analysis in order to further refine the weights and the statistical models for self-selection (e.g., by adjusting for the image that prompted respondents to click on the survey advertisement and the Facebook reach of every sample stratum defined on Facebook).

Second, due to technical problems on the Facebook platform for some countries, very few respondents accessed the survey for certain countries on certain days between March 20 and March 25. Even though we excluded in the data for each country for the days on which there were fewer than 10 respondents, this issue might have increased the uncertainty in the model predictions (especially in the daily ones). However, we believe that the analysis by week is more robust, and is less affected by this issue.

Third, as our survey began at different time points for different countries, it was difficult to compare the estimates across all countries. For example, the survey in Italy and Spain started after the implementation of physical distancing and lockdown measures; whereas for the UK and the US, no preventive measures had been implemented by the beginning of the survey. The implications of these discrepancies are considerable, as we were able to assess the reduction in social contact numbers due to physical distancing guidelines and lockdown measures only for the few countries for which we had data before any non-pharmaceutical interventions were introduced. Nonetheless, as pre-COVID social contact data were available – even though they were collected over a decade ago – we were able to assess the impact of these interventions on contact patterns, and the likely epidemiological consequences.

Our survey design allowed us to create post-stratification weights to correct for biases in the non-representativeness of the sample as a whole. Because of data sparsity, we did not generate weights separately for each week. Although we expect this issue to have a very small impact on our estimates, it is possible that our weekly values might suffer from slightly increased biases. To tackle this issue in the future, we aim to expand our weighting scheme by applying the multilevel regression and poststratification (MRP) approach (23,24). MRP has proven to be useful for dealing with both data sparsity and self-selection issues, including when applied to epidemiological surveys (25). The use of MRP will likely enable us to achieve greater consistency among differently sized strata and greater precision in the estimates for population subsets, such as the weekly estimates presented here.

Finally, the next step of our study is to carry out a follow-up survey on the participants who agreed to provide their email address (around 40% of the total sample). This panel perspective offers us a unique opportunity to examine how the COVID-19 pandemic is affecting the population in general over the long run, and, more specifically, to assess the impact of the loosening of the lockdown measures on social contact patterns and on health behaviors from an international perspective.

Materials and Methods

Experimental design

We designed the CHBS as an online survey in multiple countries (and multiple languages) to collect key information about people's health and behavior in a time of growing uncertainty due to the COVID-19 pandemic (6). Participation was voluntary and anonymous, and open to people who were at least 18 years old. Recruitment occurred through the Facebook Ads Manager (FAM), which is a tool that can be used to quickly reach large numbers of survey participants across several countries. The online survey was stratified by age groups, gender, and country regions using the FAM to ensure that a minimum number of respondents was reached for all strata.

The questionnaire was divided into multiple sections covering different areas of interest: i.e., socio-demographic indicators (age, gender, country of birth, region of residence, level of education, and household size), health indicators (symptoms experienced in the previous seven days, among others), opinion and behaviors (preventive measures taken and disruption to daily routine, among others), and social contact data. For the purposes of validation and comparability, we adapted our questionnaire to include standard questions taken from relevant sources, such as the European Social Survey (26) for socio-demographic questions, and an Ipsos poll for questions related to public opinion on the COVID-19 outbreak (27).

We defined social contacts, which are the focus of this paper, as any interaction involving either physical contact (such as a handshake or a hug) or a conversation of three or more words in the physical presence of one another. This definition is consistent with the definition employed in the most authoritative social contact surveys conducted in the past, and that we used as the baseline for comparison in this work (2,16). In particular, we asked respondents to report the number of individuals with whom they interacted on the day before the survey in different settings: i.e., at home, at school or college, at work, and in the general community (such as during commuting or leisure activities); while making it clear that the respondent should not report multiple interactions with the same person in different settings. However, unlike in the previous contact surveys, we did not ask about the characteristics of the contacted individuals (e.g., age and sex) to avoid overburdening respondents, given the nature of the online survey. The text describing the social contact question can be found in S1 in the supplementary material. For the full questionnaire and an exhaustive description of the study design, see (6).

This study was conducted in compliance with German regulations on privacy and data collection, treatment, and protection. Informed consent was obtained from all participants, who had to be 18 years old or older, to enable the collection, storage, and treatment of data. Individual-level data were stored on a server in a secure and protected environment at the Max Planck Institute for Demographic Research. Approval for the study was obtained from the Ethics Council of the Max Planck Society.

Statistical Analysis

Since online surveys are not random samples of the population, we attempted to correct for that bias by adjusting our survey using a post-stratification weighting approach. In particular, given that our aim was to achieve a nationally representative sample, we stratified the survey by age group, gender, and subnational region, which are all important variables that are related to differences in people's responses to the pandemic. In order to create post-stratification weights, we divided the true population proportion in each stratum (i.e., a combination of age group, gender, and country subnational region) from nationally representative data available through Eurostat (2019) (28) and the US census (2018) (29), by the sample proportion from the same stratum in our survey.

For the data on social contacts, we defined a variable for the overall number of contacts reported by each participant as the sum of contacts in the four different settings. Participants who selected the option 'Prefer not to answer" were excluded from the analysis. Following a visual inspection of the distribution of social contacts in each setting, we noticed an implausible number of social contacts on the right tail of the distribution (e.g., people who reported having over 200 contacts). As our aim was to summarize the contact distribution using adjusted sample means and model predictions (which are affected by outliers), we decided to remove the outliers, and considered different upper quantiles as cut-off points. The analysis presented in this manuscript excludes the top 10% of the distribution of both overall contact numbers and setting-specific contact numbers. We believe that this approach provides the most plausible picture of the underlying distribution, given the comparison between the CHBS contact numbers by setting and the respective data from the pre-COVID period (from countries where such data were available). As a robustness check, we also carried out a sensitivity analysis in which we excluded the top 5% of the contact distribution, and reported the results in the supplementary material.

Our aim was to assess the relationship between social contact patterns and the implementation of non-pharmaceutical interventions during the study period. For this purpose, we used negative binomial regression to model the number of contacts reported by participants. The negative binomial distribution was preferred over the Poisson for dealing with possible overdispersion in the number of contacts reported by participants (30,31).

We focused on overall, work, and general community contact numbers only because the numbers in these settings displayed the greatest variability during the study period. As expected, home and school contact numbers showed little to no variability, with the former remaining constant during the study period, and the latter being reduced to zero due to school closures in every surveyed country (we provide Fig. S3 in the supplementary material, which shows the little variability in these two settings).

For each contact type, two different models were designed. The first model was designed to predict the number of contacts by calendar week, and included the following categorical variables as explanatory factors: gender, age group, country region (in interaction with age), education level, household size categories (with 5+ being the biggest household size), day of the week of the reported contacts (from Monday to Sunday), being foreign-born, and week of the reported contacts (in interaction with age).

The second model was designed to predict the number of contacts by day using a flexible parametric model. For this purpose, we applied fractional polynomials (32) to the day variable, and let the statistical software automatically determine the polynomials associated with the best-fitting model. We also adjusted for the following variables: gender, age group, country region, education level, household size categories (with 5+ being the biggest household size), and being foreign-born.

All data analyses were performed with the R software version 3.6.1 and Stata 16.

Epidemiological modeling: deriving the basic reproduction number following the reduction in social contacts

We performed an epidemiological assessment of the consequences of the reduction in social contact numbers on the basic reproduction number, R_0, comparing the effect of social mixing patterns in the pre-COVID period and in the study period. This analysis was performed on a subset of countries for which data on social mixing patterns in the pre-COVID period were available.

The R_0 can be estimated as the spectral radius (or dominant eigenvalue), denoted by the function ρ, of the next generation matrix $\boldsymbol{N}$, i.e., $R_0 = \rho(\boldsymbol{N})$ (33). A common way to derive $\boldsymbol{N}$ using social contacts is based on the *social contact hypothesis* (3,8), which states that $\boldsymbol{N}$ is proportional to $\boldsymbol{C}$, which is the age-specific social contact matrix that reports the contact rate per day between individuals in different age groups, rescaled by the parameters D, the length of the infectiousness period (i.e., the number of days that an infected person can transmit the virus), and q, a constant scaling factor regulating the infection transmissibility (i.e., the proportion of contacts that result in infection transmission). Given the lack of information on the transmissibility parameter q, which can be estimated using seroprevalence data (8, 12), we can exploit the following relationship between the social contact matrix $\boldsymbol{C}$, the next generation matrix $\boldsymbol{N}$, and the R_0 (5,34):

$$\boldsymbol{N} = \frac{Dq\rho(\boldsymbol{C})}{\rho(\boldsymbol{C})}\boldsymbol{C} = \frac{R_0}{\rho(\boldsymbol{C})}\boldsymbol{C}. \qquad (1)$$

Based on Eq. 1, we find that the R_0 is proportional to the dominant eigenvalue of the contact matrix, $\rho(\boldsymbol{C})$. Hence, the change in the R_0 under different social mixing patterns could be assessed by comparing the dominant eigenvalues of the different contact matrices.

To account for social contact patterns in the pre-COVID period, we used data collected in the Polymod study, a multi-country social contact survey conducted in eight European countries, including Belgium, Germany, Italy, the Netherlands, and the UK (2). This study was conducted between May 2005 and September 2006, and gathered data on the number of contacts each participant had on a given day. The participants also provided details on the contacted person's age and sex, the setting of the contact (such as home or work), the type of contact (physical or non-physical), and the duration and the frequency of the contact. For France, we used data from the Comes-F study, which was carried out in 2012 and used a survey design consistent with the Polymod study (16). Drawing on these two data sources, we derived age-specific social contact matrices $\boldsymbol{C}$ reporting the average number of overall social contacts c_{ij} between respondents in age group i with contactees in age group j, following the methodology described in (31).

In order to account for changes in social contact patterns during the study period, we assumed that the mixing patterns after the physical distancing interventions were introduced changed in terms of intensity, but did not change in terms of structure (e.g., age assortativeness of contacts, intergenerational contacts between parents and children, and homogeneous mixing among working-age adults (2)). Hence, we rescaled the pre-COVID contact matrices $\boldsymbol{C}$ by normalizing them with respect to the predicted number of overall contacts at the population level (i.e., dividing each matrix cell for the pre-COVID predictions shown in the second column of Table 1), and then multiplying the normalized matrices by the weekly predictions of number of contacts shown in the same table (column three to seven).

Given the pre-COVID social matrices, $\boldsymbol{C}^{pre}$, the rescaled matrices for each study week w, $\boldsymbol{C}_w^{res}$, a baseline range of values for R_0^b (which we assumed to be consistent with the pre-COVID social contact patterns, regardless of their structure and intensity of contact), we computed the distribution of the weekly values of the R_0^w during the study period as $R_0^w = R_0^b f_R^w$, where the weekly reduction factor f_R^w was given by the ratio between the dominant eigenvalue of the weekly rescaled matrix and that of the pre-COVID matrix, i.e., $f_R^w = \frac{\rho(\boldsymbol{C}_w^{res})}{\rho(\boldsymbol{C}^{pre})}$.

The R_0^w estimates account for three main sources of uncertainty: (i) the uncertainty in the baseline R_0^b, which we assumed to be normally distributed with mean 2.6 and standard deviation 0.54 (5); (ii) the uncertainty in the weekly predictions of the overall number of contacts, which we assumed to be normally distributed with mean equal to the prediction and standard deviation equal to the standard error (Table 1); and (iii) the uncertainty in the pre-COVID contact matrices, which were derived by applying nonparametric bootstrap to the original data (i.e., by resampling the participants with replacement and assigning them to their contactees from the original data). For each source of uncertainty, 10,000 replicates were taken.

Supplementary Materials

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Figures and Tables

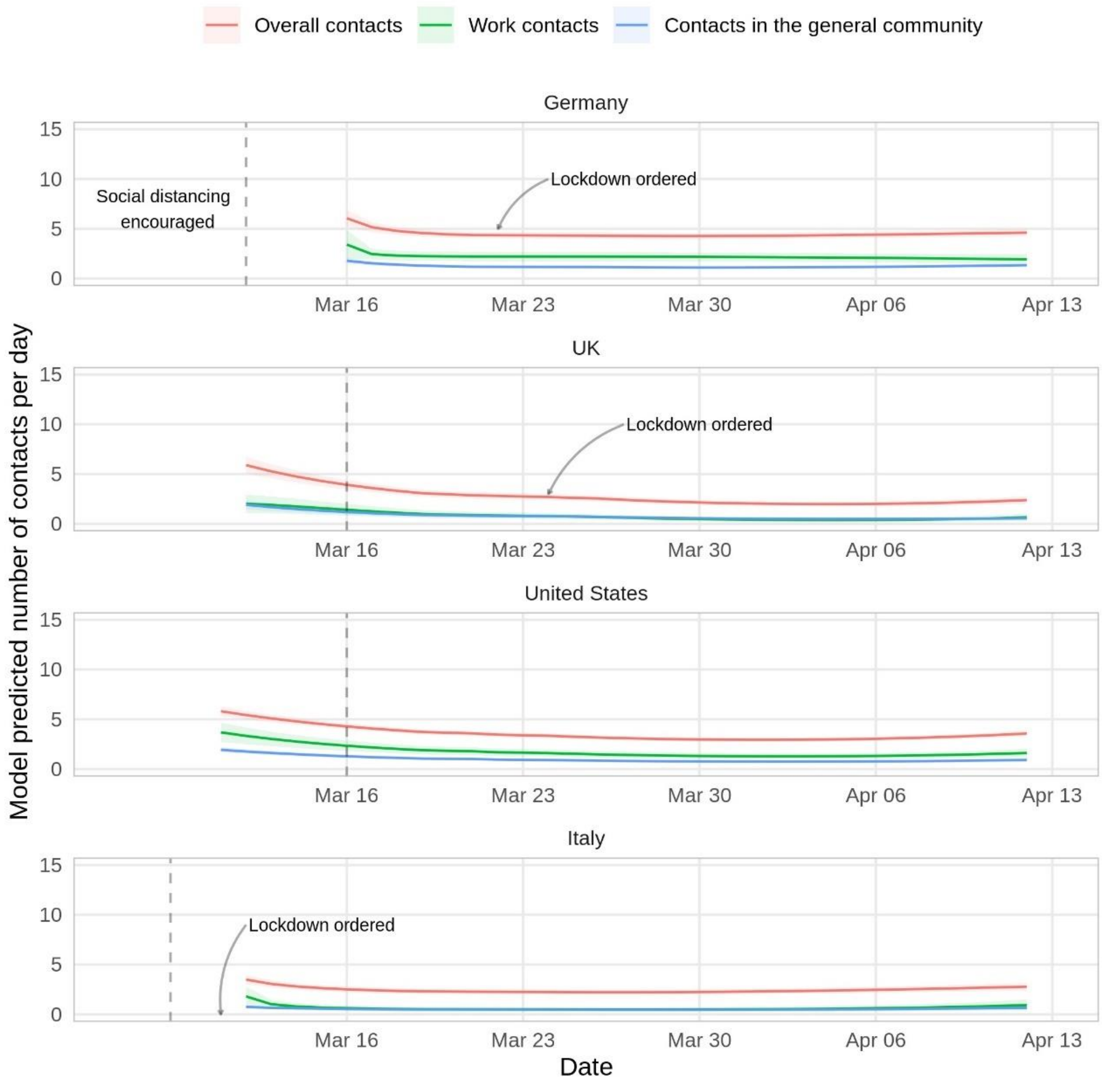

Fig. 1. Daily number of social contacts by setting (90% outlier scenario): trends in overall social contact numbers and contact numbers in the general community by day for Germany, the UK, the US, and Italy. Model predictions adjusted for age, gender, region of residence, education, being foreign-born, day of the week, and household size. All social contact numbers exclude the top 10% of the distribution.

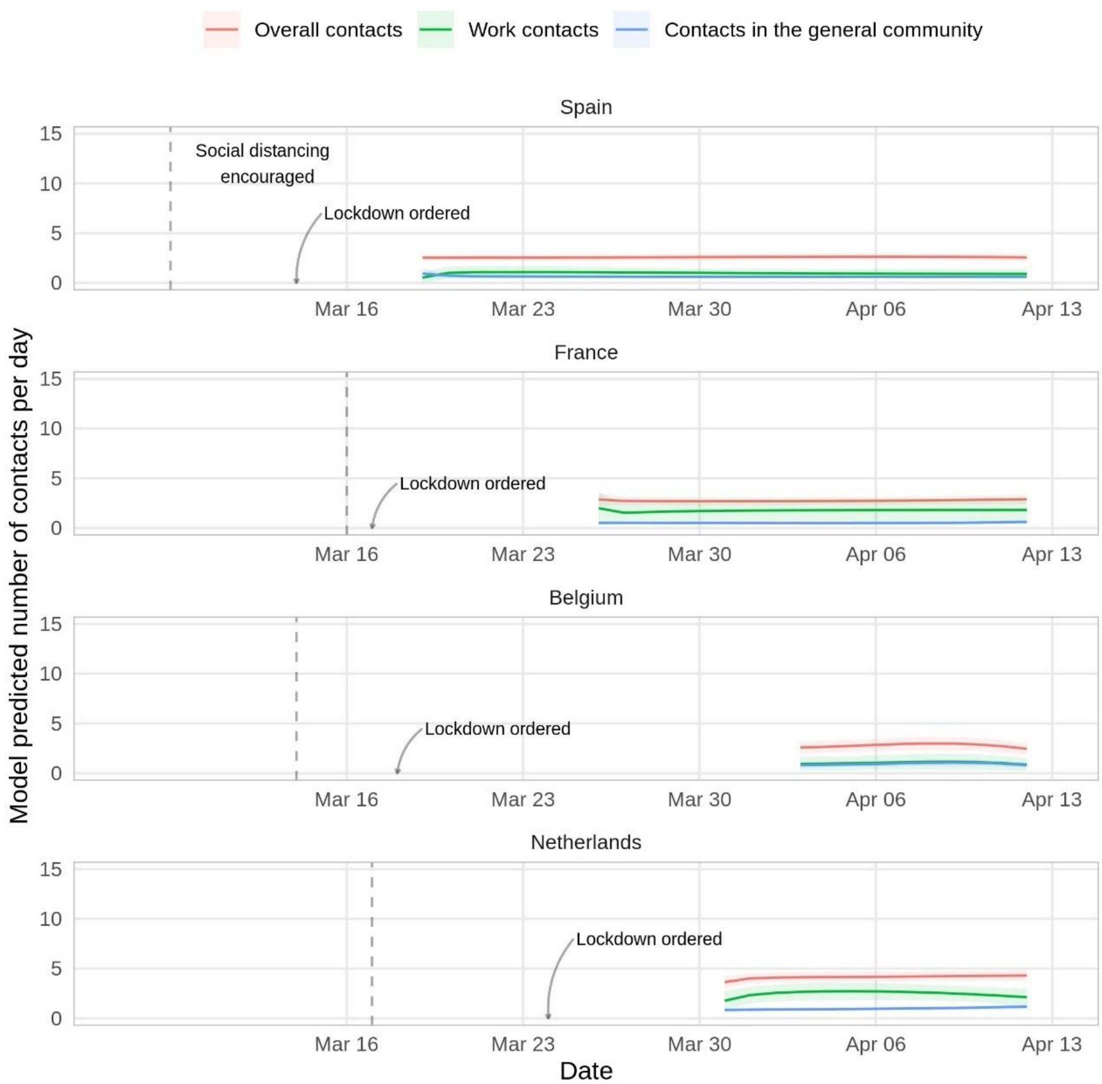

Fig. 2. Daily number of social contacts by setting (90% outlier scenario): trends in overall social contact numbers and contact numbers in the general community by day for Spain, France, Belgium, and the Netherlands. Model predictions adjusted for age, gender, region of residence, education, being foreign-born, day of the week, and household size. All social contact numbers exclude the top 10% of the distribution.

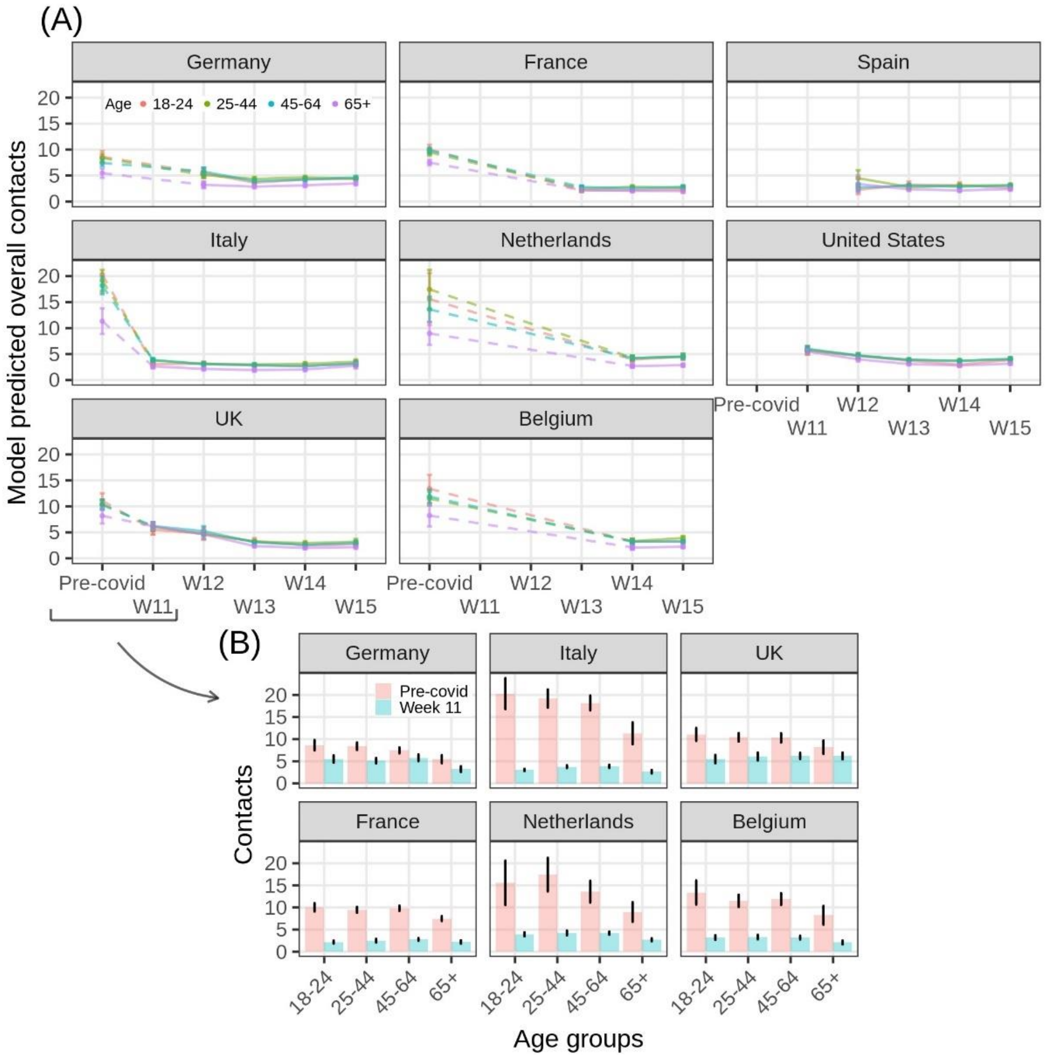

Fig. 3. Weekly overall social contacts by age (90% outlier scenario): trends for the model that predicts overall social contact numbers by age group and by week (**A**), and comparison of the model that predicts overall social contact numbers between the pre-COVID period and the first week of available data for each country (**B**). Pre-COVID model predictions adjusted for age, sex, education, and household size. CHBS model predictions adjusted for age, gender, region of residence, education, day of the week, being foreign-born, and household size. All social contact numbers exclude the top 10% of the distribution.

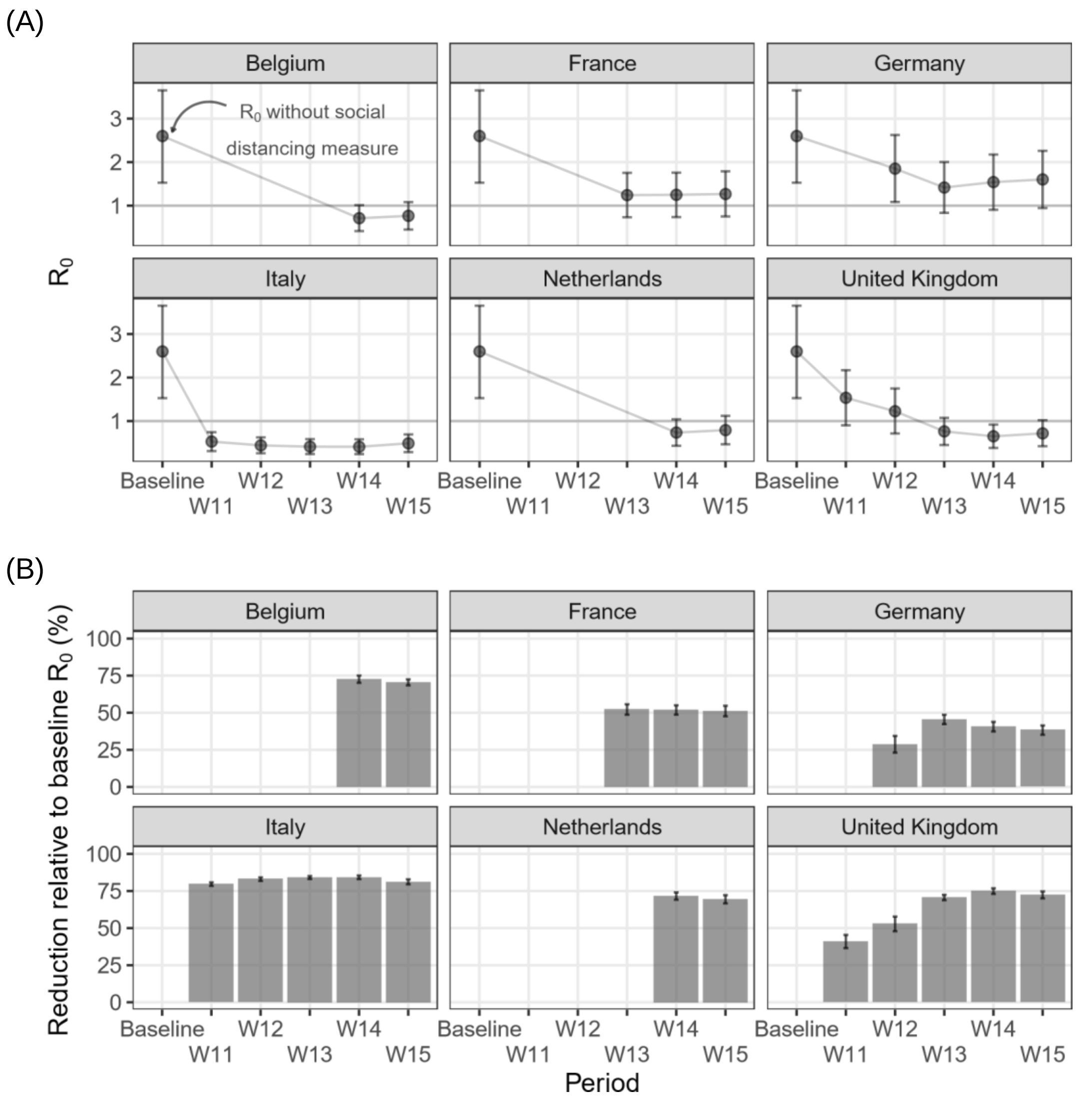

Fig. 4. Weekly changes in the basic reproduction number (90% outlier scenario): Expected change in R_0^b of COVID-19 by calendar week following the reduction in the number of overall social contacts due to the physical distancing measures. Panel (**A**) shows the reduction in the R_0^b and panel (**B**) shows the reduction as a percentage. The 95% CIs are based on 10,000 replicates. The CHBS social contacts exclude the top 10% of the distribution.

Table 1. Number of overall contacts by week (90% outlier scenario). Model-predicted number of overall contact numbers per person per day (with S.E.) by calendar week in Italy, the United Kingdom, Germany, France, the Netherlands, Belgium, the United States, and Spain. Comparison with the pre-COVID model predictions (and S.E.). All social contact numbers exclude the top 10% of the distribution.

Country	Pre-COVID*	Week 11† 3/9–15	Week 12 3/16–22	Week 13 3/23–29	Week 14 3/30–4/5	Week 15 4/6–12
Italy	17.31 (0.52)	3.39 (0.09)	3.01 (0.12)	2.68 (0.07)	2.68 (0.10)	3.24 (0.14)
United Kingdom	10.11 (0.28)	6.34 (0.23)	4.65 (0.28)	3.04 (0.08)	2.56 (0.11)	2.85 (0.12)
Germany	7.51 (0.22)		4.72 (0.18)	3.90 (0.11)	4.05 (0.09)	4.21 (0.08)
France	9.28 (0.16)			2.40 (0.09)	2.54 (0.08)	2.55 (0.09)
Netherlands	14.58 (0.97)				3.84 (0.11)	4.22 (0.13)
Belgium	11.31 (0.41)				3.08 (0.13)	3.20 (0.09)
United States		5.89 (0.16)	4.60 (0.12)	3.69 (0.08)	3.39 (0.08)	3.85 (0.09)
Spain			3.26 (0.33)	2.92 (0.11)	2.82 (0.09)	2.91 (0.08)

* Model predictions for pre-COVID data are adjusted for age group, gender, education, day of the week, and household size.

† Model predictions for weekly CHBS data are adjusted for age group (in interaction with week), gender, region of residence (in interaction with week), education, day of the week, being foreign-born, and household size.