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The impact of COVID-19 lockdown stringency on loneliness in five European countries

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ABSTRACT

Rationale: The coronavirus pandemic has forced governments to implement a variety of different dynamic lockdown-stringency strategies in the last two years. Extensive lockdown periods could have potential unintended consequences on mental health, at least for at-risk groups.
Objective: We present novel evidence on the heterogeneous direct and indirect effects of lockdown-stringency measures on individuals' perception of social isolation (i.e. loneliness) using panel data from five European countries (Germany, France, Spain, Italy and Sweden), which tracks changes in both in-person and remote social interactions between May 2020 and March 2021.
Method: We combine data from the COME-HERE panel survey (University of Luxembourg) and the Oxford COVID-19 Government Response Tracker (OxCGRT). We implement a dynamic mixture model in order to estimate the loneliness sub-population classes based on the severity of loneliness, as well as the evolution of social interactions.
Results: While loneliness is remarkably persistent over time, we find substantial heterogeneity across individuals, identifying four latent groups by loneliness severity. Group membership probability varies with age, gender, education and cohabitation status. Moreover, we note significant differences in the impact of social interactions on loneliness by degree of severity. Older people are less likely to feel lonely, but were more affected by lockdown measures, partly due to a reduction in face-to-face interactions. On the contrary, the younger, especially those living alone, report high levels of loneliness that are largely unaffected by changes in the pandemic after lockdown measures were initially implemented.
Conclusions: Understanding the heterogeneity in loneliness is key for the identification of at-risk populations that can be severely affected by extended lockdown measures. As part of public-health crisis-response systems, it is critical to develop support measures for older individuals living alone, as well as promoting continuous remote communication for individuals more likely to experience high levels of loneliness.

1. Introduction

The spread of the COVID-19 pandemic forced governments worldwide to balance multiple competing health, social and economic goals, and a wide range of virus-containment strategies were implemented across countries. While these measures have been critical in terms of controlling the spread of the virus, one particular health concern is that the extended restrictions on social interactions can produce greater perceived social isolation (i.e., loneliness) in the population. Loneliness has been linked to an increased risk of morbidity and mortality, especially when experienced over extended periods of time (Hawkley and Cacioppo, 2010; Lara et al., 2020). Individuals with greater loneliness are at a higher risk of mental illness, cardiovascular disease, and cognitive decline (Valtorta et al., 2016; Beutel et al., 2017; Donovan et al., 2017).

Recent longitudinal work has established positive but weak associations between COVID-19 lockdowns and loneliness during the first few months of the pandemic (Brodeur et al., 2021; Bu et al., 2020a; Killgore et al., 2020; Hu and Gutman, 2021; Losada-Baltar et al., 2021; Prati and Mancini, 2021). One potential explanation for the lack of association

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between changes in lockdown stringency and loneliness is the short-term nature of most of these contributions, with many considering only the initial stages of the pandemic. A recent meta-analysis suggests that the short-term psychological impact of COVID-19 lockdowns is only small in magnitude, and unlikely to have detrimental effects for most of the population (Prati and Mancini, 2021). In general, there is little variation over time in the results that use validated scales of loneliness; however, there was a distinct decrease during the second half of 2020, with a subsequent increase as COVID-19 related restrictions were tightened up during winter in the Northern Hemisphere (Hu and Gutman, 2021).

Overall, young age and lower educational background have been shown to predict higher levels of loneliness. Equally, women are more likely to report greater loneliness than men, as do students, conditional on age (Bu, Steptoe and Fancourt, 2020b). In terms of social interactions, there is evidence that fewer interactions led to increased loneliness during the pandemic (Cohn-Schwartz, Vitman-Schorr and Khalaila, 2021).

As noted above, most longitudinal work to date that reports associations between lockdown stringency and loneliness have not accounted for objective changes in social interactions or other potential mechanisms. In this study we present novel estimates on the heterogeneous direct and indirect effects of lockdown-stringency policies on social interactions and loneliness in five European countries (France, Germany, Italy, Spain and Sweden) during the first year of the COVID-19 pandemic. We use a balanced sample from the novel COVID-19, MEntal HEalth, REsilience and Self-REgulation (COME-HERE) panel survey, developed by the University of Luxembourg, to explore changes in living conditions during the pandemic, and the Stringency Index from the Blavatnik School of Government (University of Oxford) to track changes in lockdown measures. The empirical approach is based on the evolutionary framework, posing that individuals perceive loneliness as the pain signal which indicates the need to increase or maintain social connections given changes in environmental factors (Cacioppo and Cacioppo, 2018).

Our work contributes to the growing literature documenting the impact of COVID-19 on mental health and wellbeing (see Prati and Mancini, 2021, Richter, Riedel-Heller and Zürcher, 2021 for a review of the most-recent evidence). We extend the current literature in four critical aspects. The COME-HERE survey leverages data from a representative sample in five countries that correspond to over one-third of the population in Europe. Second, the rich nature of the panel survey allows us to directly observe changes in face-to-face and remote social interactions, considering variation across different dimensions by type of relationship. Third, we use a direct measure of the intensity of lockdown stringency to identify changes in social interaction and loneliness, instead of relying on solely on individual comparisons over time. Finally, we estimate the impact of lockdown stringency allowing for unobserved heterogeneity at the population level, using latent classes based on the unconditional distribution of loneliness while accounting for individual risk factors, consistent with a finite mixture model with fixed effects.

Our work has three specific aims. The first is to model the individual dynamics of changes in social interactions, both in-person and remotely. Second, to identify the direct effect of lockdown stringency on loneliness, as well as the indirect effects via changes in social interactions. Third, to disentangle the heterogeneous effects of policy stringency on loneliness across latent sub-populations determined by loneliness intensity and personal characteristics, while accounting for fixed effects at the individual level. We hypothesise that more-stringent lockdown measures can affect loneliness directly via subjective perception of limitations to social interactions, as well as indirectly by objectively changing the frequency of interpersonal interactions, leading to an increase in loneliness. From the results in Bu, Steptoe and Fancourt (2020a), we also expect distinct patterns in both the level of and changes in loneliness by the population sub-groups defined by age, gender, and family composition (as well as other unobserved factors).

2. Methods

2.1. Data

The COME-HERE panel survey developed by the University of Luxembourg, follows individuals from five European countries (Germany, France, Italy, Spain and Sweden), to explore changes in living conditions during the COVID-19 pandemic (see Vögele, Lutz, Yin, and D'Ambrosio, 2020, for additional details). The survey is conducted by Qualtrics, who invite potential adult respondents using multiple market research double-opt-in panels, using stratified sampling in order to achieve nationally-representative samples by age groups (18–24, 25–34, 35–44, 45–54, 55–64, 65+), gender and region of residence within each country. The COME-HERE survey received ethics approval from the Ethics Review Panel of the University of Luxembourg. Five waves were collected between April 2020 and March 2021 (see Fig. 4), with data collection ending in May 2020, June 2020, August 2020, December 2020, and March 2021. Questionnaires are available in a secure website, and it takes respondents approximately 20 min to complete the survey. In Wave 1, 8063 individuals were interviewed. All Wave-1 respondents were invited to participate in each of the subsequent waves, and 3172 individuals appear in all five waves. The Wave-1 distribution of respondents by country appears in Table 1 and the distribution of respondents according to the number of waves in which they appear is shown in Online Supplement Table A2. COME-HERE contains extensive socio-demographic information, and multiple scales to assess mental health, changes in social behavior, health status, and other life events.

2.2. Measures

Our key outcome variable here is loneliness, which is measured by the short form of the UCLA Loneliness Scale (ULS-8), developed by Hays and DiMatteo (1987), ranging from 8 to 32 points. Individuals answer eight questions each on a four-point scale: Never (1), Rarely (2), Sometimes (3) and Always (4). Analysis on a sample of university students shows that the ULS-8 is consistent with a single common factor (Hays and DiMatteo, 1987). Online Supplement Table A1 contains the ULS-8 questionnaire.

Information on the intensity of lockdown stringency comes from the Oxford COVID-19 Government Response Tracker (OxCGRT), which provides an index of the stringency of policy responses (on a 1–100 scale) based on 8 domains, including restrictions on social interactions, school closures, curfews, and other similar measures. The OxCGRT stringency index has been shown to be strongly correlated with social-

Table 1
COME-HERE descriptive statistics in wave 1.

Covariate	Mean	SD
Age	47.5	16.9
Gender (Female = 1)	0.51	0.49
Education vocational or higher [1]	0.55	0.49
Lives with partner [1]	0.58	0.49
Any isolation status [1]	0.03	0.17
Any mental health condition [1]	0.20	0.40
Any medical condition [1]	0.52	0.50
No negative experience [1]	0.71	0.45
Log household income	7.08	2.35
Any physical activity [1]	0.71	0.45
Log COVID-19 cases	7.50	0.51
Log COVID-19 deaths	5.64	0.58
Respondents by country		
France	1706	21%
Germany	1720	21%
Italy	1710	21%
Spain	1711	21%
Sweden	1216	15%

Notes: COVID-19 cases and deaths are measured as 2-week moving averages. Wave 1 data was collected in April and May 2020.

distancing scores based on Google Mobility data (Hussain, 2020). Using publicly-available data, we also constructed 2-week moving averages of daily COVID-19 cases and deaths for each country considered in the analysis; these will appear in logarithmic form in the analyses.

Social interactions in the COME-HERE survey are presented as questions on the change in face-to-face and remote activities as compared to the previous survey wave, using the last week as the reference (in Wave 1 individuals reported the change relative to the beginning of lockdown). These interactions cover a variety of relationships: family at home, direct family out of home, close friends, co-workers, acquaintances and other relatives. For each relationship type, individuals report the change in the number of days per week with such interactions (decrease, increase or no change) relative to the previous wave.

Our analysis is restricted to the balanced sample in order to avoid bias due to individual unobserved factors related to loneliness, social interactions and attrition. We include as covariates those that have been considered to be important for loneliness in the previous literature: age, gender, education (vocational or higher), cohabitation status (at baseline), COVID-related isolation, any mental-health diagnoses (binary), any medical (physical) conditions (binary), the absence of any COVID-19 related negative experiences in the last week (major personal loss, such as the death of someone close, a major household income loss, food and housing insecurity, illness etc.), the log of household income, and a binary indicator for any physical activity. Table 1 presents the summary statistics for the covariates included in our analysis at baseline.

2.3. Empirical strategy

Following Cacioppo and Hawkley, 2003 and Cacioppo and Cacioppo (2018), we investigate changes in loneliness using an evolutionary-based framework, built on the idea that individuals perceive loneliness as the inherent pain signal associated to insufficient social connections given changes in environmental factors. As such, there are two key elements incorporated in our analysis: 1) environmental factors can impact loneliness by restricting social interactions, and 2) loneliness varies substantially at the individual level given genetic, contextual and social factors.

Our empirical strategy consists of the estimation of a mixture model (latent class) with unobserved factors to summarise the changes in social interactions with correlated fixed effects in linear loneliness regressions within each class. This approach allows for the identification of the model parameters in a structural equation modelling (SEM) framework (Bollen and Davis, 2009). There are broadly speaking two SEM components: a *measurement level*, where the latent variables (including the class distributions) are measured from the observed covariates, and a *structural level*, where the relationships between the observed and unobserved variables are defined.

Formally, for a vector of j ordinal variables u_{it} representing the change in social interactions (in-person or remote) across all j relationships for an individual i in a given time period t, we can consider the measurement system for the distribution of unobserved continuous variables u^*_{itk} for each latent class k as:

$$u^*_{itk} = \Delta_{tk} f_{itk} + \varepsilon_{itk} \tag{1}$$

$$u_{ijtk} = \begin{cases} 0 \; if \;\; u^*_{itk} < \tau_{a,jtk} \\ 1 \; if \;\; \tau_{a,jtk} \leq u^*_{itk} \leq \tau_{b,jtk} \\ 2 \; if \;\; \tau_{b,jtk} < u^*_{itk} \end{cases} \tag{2}$$

where μ represents the three possible outcomes: decrease (0), no change (1), and increase (2). u^*_{itk} is a continuous measure of the change in social interactions for each j relationship. The set of latent variables f_{itk} indicates the common continuous intensity of the change in social interactions across all relationships, normalised to zero. As such, f_{itk} contains the latent measures of social interactions, in-person and remote, for all periods. Δ_{tk} are the loading factors, representing the relative importance of each observed variable on the latent factor, and ε_{itk} is a vector of normally-distributed residuals. The $\tau_{a,jtk}, \tau_{b,jtk}$ are the thresholds defining the link between the ordinal and continuous latent responses for each period and variable (within class). Finally, we can describe the conditional latent class distribution of the variable $c = 1, 2 \ldots$, K as:

$$ln\left[\frac{P(c_{ik} = 1|z_i)}{P(c_{iK} = 1|z_i)}\right] = \lambda_{c_k} + \Gamma_{c_k} z_i \tag{3}$$

The parameters λ_{c_k} and Γ_{c_k} describe the effects of the observed time-invariant covariates that characterise the probability of belonging to each latent class (i.e. each loneliness sub-group in the population).

In the structural part, the direct and indirect effects are estimated within each class as follows:

$$l_{itk} = a_{ik} + f_{itk}\varphi_k + \beta_k s_{it} + \Gamma_{lk} X_{it} + \varepsilon_{itk} \tag{4}$$

$$f_{itk} = \gamma_{tk} s_{it} + \Gamma_{fk} X_{it} + \zeta_{itk} \tag{5}$$

where l_{itk} is the measure of loneliness, s_{it} is the stringency index z-score, and X_{it} is a vector of time-varying covariates. ε_{itk} and ζ_{itk} are residuals with zero autocorrelation, and are independent of the latent factors. $a_{ik} = a_k + \alpha_{ik}$ are individual effects that are allowed to be correlated with the error terms and to vary across classes. The set $\{\varphi_k, \beta_k, \Gamma_{lk}, \gamma_{tk}, \Gamma_{fk}, a_k\}$ contains the parameters to be estimated, alongside the implicit joint variance-covariance distribution of the observed and unobserved variables. Consistently with fixed-effects models, the parameters in the structural system are fixed over time.

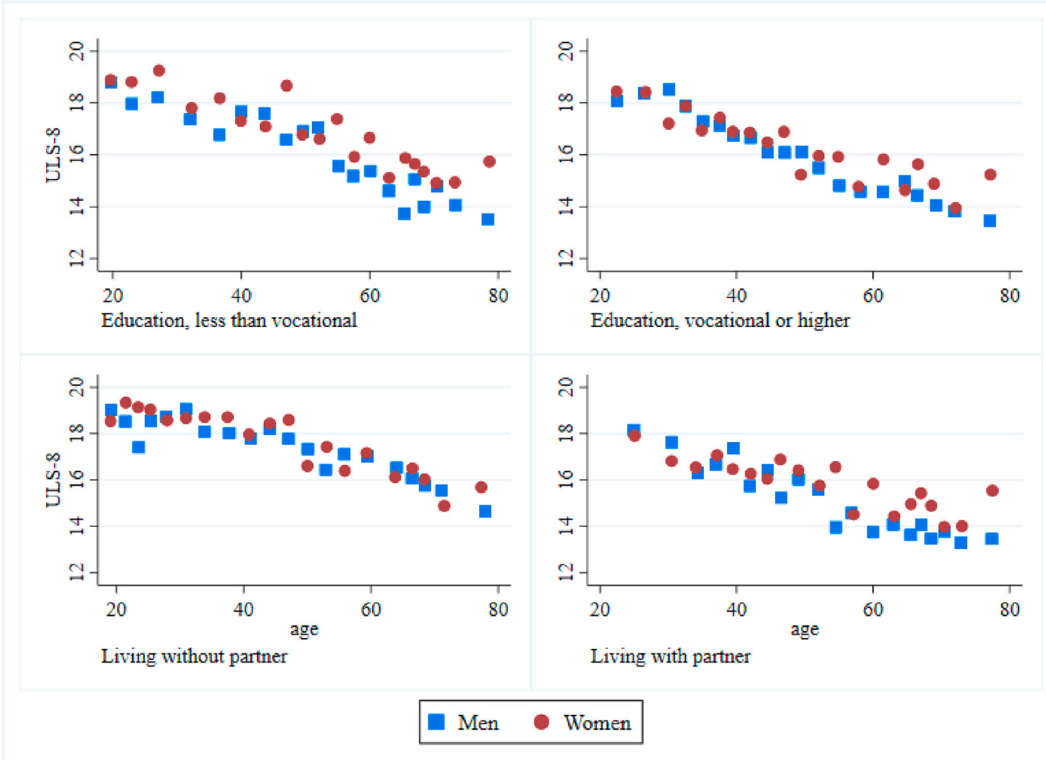
In order to identify and reduce the complexity of the model, we place some additional restrictions on the final configuration to be estimated. First, as noted in Hamaker and Muthén (2020), we estimate the within-person effect in the structural level by centering the variables on their latent means over time within each class. We moreover restrict the coefficients to be fixed over time in each class, to help reduce the number of parameters to be estimated. For the measurement part, the factor loadings remain fixed across classes and time, so that the underlying process is the same for all individuals in the population, while changes over time come from both within and between changes in the population (Liu et al., 2017). This allows us to interpret changes in social interactions only as changes in the intensity for each individual, while keeping the same scale over time. Our estimates are, therefore, comparable to a fixed effects model within a finite mixture approach (Deb and Trivedi, 2013), while being able to incorporate the latent component directly in the joint distribution of the observed variables.

Given the significant degree of entry and exit in the panel, we address attrition bias and in-sample representativeness using the inverse probability weighting approach, as described in Wooldridge (2007). Weights have been constructed based on the exogenous covariates that predict response in each wave. Online Supplement Table A2 shows the pattern of attrition over time. The model is estimated by maximum likelihood using the expectation-maximisation algorithm, reporting robust standard errors. Due to the categorical and censored nature of the data, we use Gauss-Hermite integration to recover the underlying non-normal distribution of the dependent variables. Convergence is tested using multiple random starting values to ensure that the solution is a global maximum.

3. Results

3.1. Descriptive statistics

Fig. 1 shows the distribution of the ULS-8 score by age, gender, education and cohabitation status at baseline (i.e. as reported in survey Wave 1). As has been found in previous work, loneliness falls with age,



Notes: ULS-8 indicates the UCLA Loneliness Scale (short version). Optimal-sized bins estimated to minimize mean-squared error. Estimates based on the balanced sample.

Fig. 1. Loneliness by age and sub-group (binned averages). *Notes*: ULS-8 indicates the UCLA Loneliness Scale (short version). Optimal-sized bins estimated to minimize mean-squared error. Estimates based on the balanced sample.

education, and cohabitation. It can also be seen that men often report being less lonely than women, particularly at older ages. Overall, the distribution of loneliness is stable over time (see Online Supplement Figure A1), although there is a slight decrease in loneliness during the Summer of 2020. As noted in Table 1, individuals in the sample are (roughly) evenly distributed across countries and gender.

Figs. 2 and 3 show the number of participants by category of change in social interactions in each wave (balanced sample). For remote social interactions in Fig. 2, we can see an overall fall after the introduction of lockdown measures, although there is a fraction of participants who report an increase in remote communication. After the Summer of 2020, we do not find a significant change in remote interactions, despite the increase in lockdown stringency towards the end of the year. By way of contrast, the dynamics of face-to-face interactions in Fig. 3 closely follow the timing of changes in lockdown stringency, except for those with colleagues and direct family living at home.

Fig. 4 depicts the evolution of the stringency index by country from the beginning of the pandemic up to March 2021, as well as the end dates of data collection for each wave of the COME-HERE survey. Despite small country differences in the intensity of lockdown measures, there is a clear general U-shape: restrictions eased during the Summer of 2020, but were then tightened towards the end of the same year.

3.2. Exploratory latent analysis

To test the configuration of the latent factors and determine the number of latent classes, we use an auxiliary model for the measurement part alone. Panel (a) of Table 2 lists the fit indices for different model specifications for the joint distribution of the latent variables describing the flow of social interactions, using all categorical measurements. Due to the substantial correlations between the observed variables, we only consider models where all observed variables load onto one factor in each period, distinguishing remote from face-to-face interactions. Moreover, simple inspection of the data shows that the remote and face-to-face variables load onto distinct latent factors. The fit indices suggest that the unrestricted model provides a better representation of the data (higher CFI, TLI and lower RMSEA), performing slightly better than the model assuming longitudinal invariance. While there is a small loss of overall model fit from imposing longitudinal measurement invariance, we use this model structure as the baseline to facilitate the interpretation of the changes over time. In practice, there is no theoretical basis to presume that the scale and meaning of the underlying variables changed in the sample over the time period.

In order to determine the number of latent classes for the mixture distribution of the loneliness scale, we compare the fit indices for models that fit the unconditional distribution of our main outcome variable (i.e. describing the changes solely on loneliness), allowing class membership to be a function of time-fixed covariates (information criteria and entropy). Panel (b) in Table 2 suggests that the final model should be estimated with four or five latent classes, without any meaningful loss of information. Conditional on the small loss in overall model fit, we favour the gain in group classification (entropy) and thus use four classes. Online Supplement Tables A4 and A5 show the loneliness distribution under the 4-class and 5-class solutions. In the 5-class model, the precision in class classification decreases substantially, especially among individuals with low levels of loneliness.

3.3. Loneliness distribution

Prior to the estimation of the full conditional model for the ULS-8 distribution, we produce unconditional estimates using four latent classes that describe the mean and variance of loneliness, as noted in

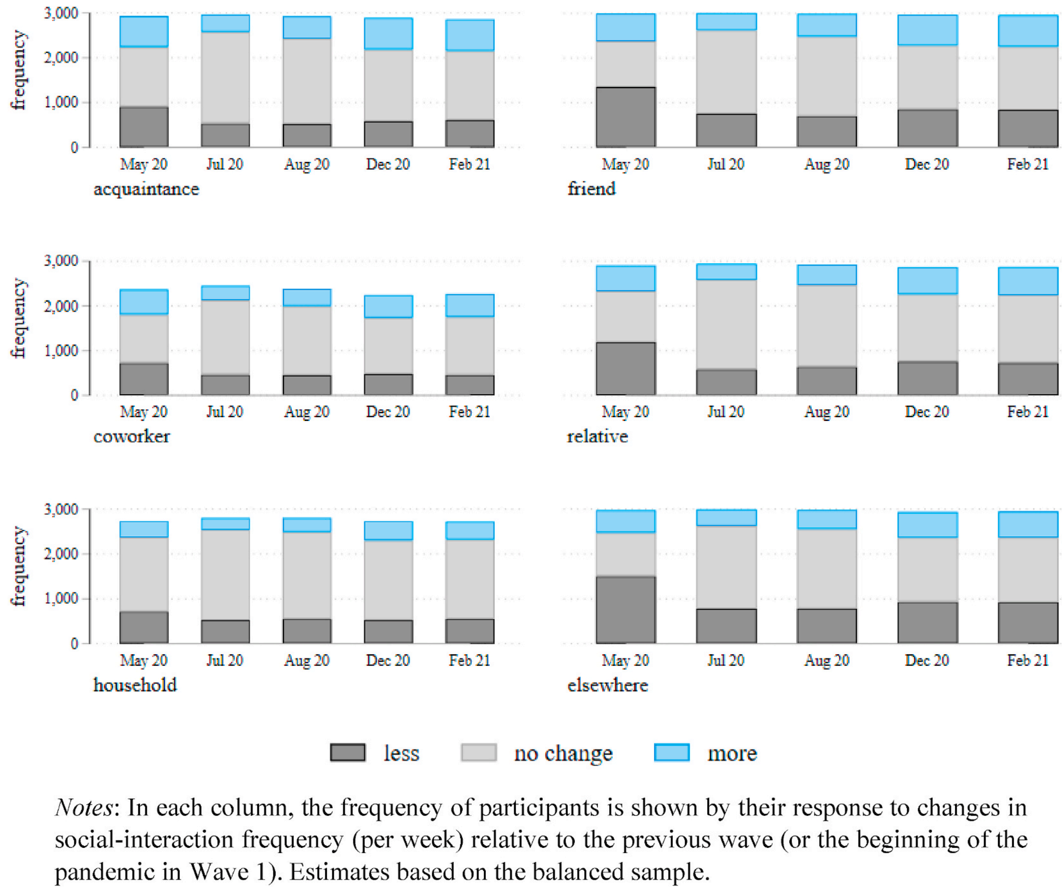


Fig. 2. The change in remote interactions by wave. *Notes*: In each column, the frequency of participants is shown by their response to changes in social-interaction frequency (per week) relative to the previous wave (or the beginning of the pandemic in Wave 1). Estimates based on the balanced sample.

Online Supplement Table A4. We name these groups according to their mean loneliness levels: Low (accounting for 28% of the sample), Medium (36%), High (28%) and Severe (8%). Within each group, and in the overall sample, the mean levels of perceived social isolation remain stable across waves, as can be seen in Online Supplement Figure A2. A small drop occurs for all groups during the Summer of 2020, and then a rise towards the end of the year, in line with the implementation of stricter lockdown measures. Table 3 shows the odds ratios for class membership across the estimated latent groups. Relative to the Low loneliness group, age significantly reduces the likelihood of belonging to a group with higher levels of perceived social isolation. The educated and those living with a partner at baseline also have a lower risk of being in a group with higher loneliness scores, although education is less important here and does not differ significantly between the Low and Medium loneliness groups. Finally, women are more likely to be in higher social-isolation groups, at least compared to the Low loneliness group.

3.4. Social interactions

Our estimates for the latent factors of social interactions account for the ordinal nature of the data, and the variables are thus normalised to zero, indicating no change in social interactions relative to the previous period. Positive (negative) values then represent a rise (fall) in daily social interactions. The factor loadings for each latent variable appear in Online Supplement Table A3. For the change in remote interactions, the overall variation mostly comes from changes in social interactions with close friends, other relatives and direct family away from home; the common signal accounts for over 80% of the variance (full results available upon request). Interactions with direct family at home is the least correlated with overall changes, both between and within individuals (this is also the type of interaction with the smallest variance over time). For face-to-face interactions, the variables with higher loadings are interactions with close friends, acquaintances and other relatives. As was the case for remote social interactions, face-to-face interactions with direct family at home is the measure that contributes the least to the overall change in social interactions.

Online Supplement Figure A3 summarises the evolution of the latent measures of remote (panel a) and face-to-face (panel b) social interactions by latent class. There is a slight increase for remote interactions, in line with the easing of restrictions during Summer 2020 for the Low and Medium loneliness groups, but a marked decrease for the group with High ULS-8 levels. Face-to-face interactions increased during the Summer for the Low and High loneliness groups, consistent with the easing of lockdown restrictions. There are almost no changes in average remote or face-to-face interactions over time for the High loneliness group. As we impose longitudinal loading invariance, the metric represents the same scale across waves; however, mean differences can reflect both movements in each subpopulation as well as changes in the thresholds for the measured ordinal variables. However, our estimates reveal no meaningful differences in the estimated factor thresholds and variances over time. The changes in the latent means therefore mainly reflect overall mean changes in social interactions between subpopulations over time.

3.5. Lockdown stringency and loneliness

Online Supplement Table A6 shows the effects of lockdown stringency on both social interactions and loneliness in the overall sample. Greater stringency has a small but significant negative effect on both

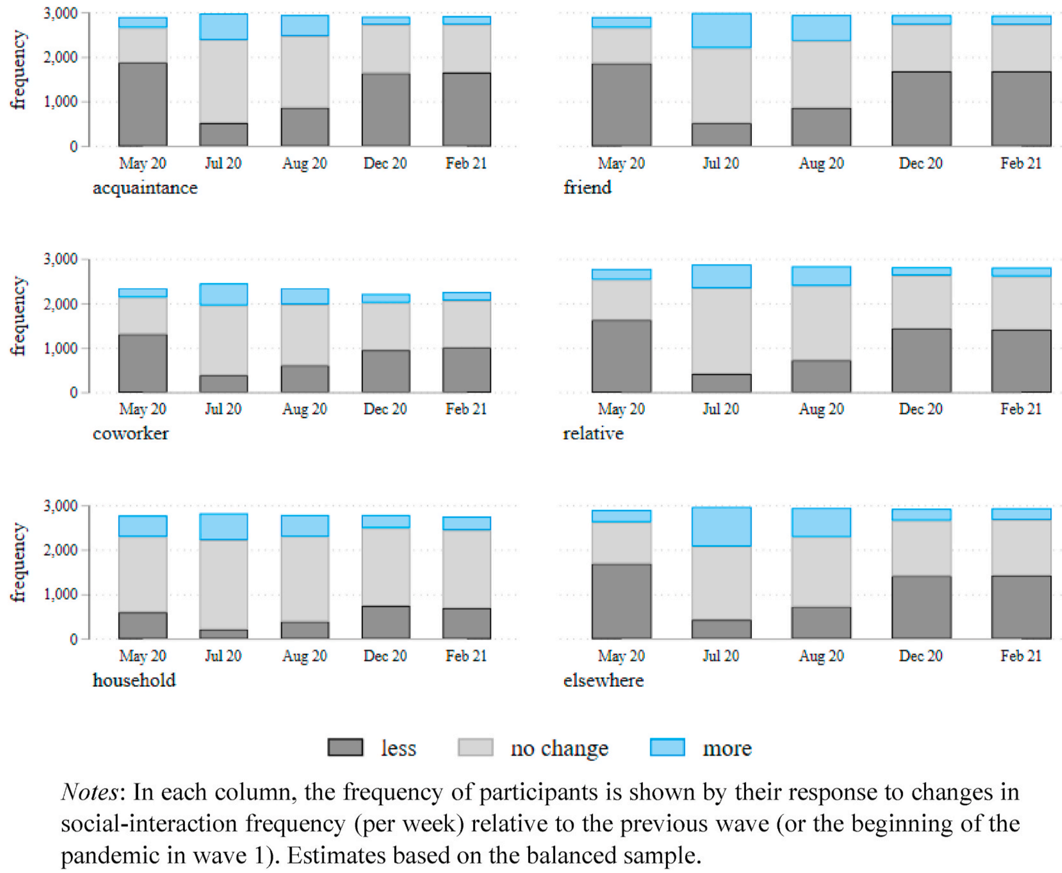


Fig. 3. The change in face-to-face interactions by wave. *Notes*: In each column, the frequency of participants is shown by their response to changes in social-interaction frequency (per week) relative to the previous wave (or the beginning of the pandemic in wave 1). Estimates based on the balanced sample.

face-to-face and remote interactions. A one SD rise in the OxCRCT z-score produces a 0.03 SD drop in our standardised index of face-to-face interactions. When accounting for unobserved heterogeneity, individuals who have faced no negative experiences (a major personal loss in the last week) are also more likely to report higher levels of face-to-face social interactions. Our estimates indicate that, once the dynamics of COVID-19 related deaths are accounted for, lockdown stringency does not have a direct effect on loneliness at the mean of the overall sample. While COVID-19 related deaths are associated with higher loneliness, the estimated effect is minuscule. Mandated (or voluntary) isolation is linked to increased loneliness, as well as the diagnosis of mental or physical health conditions. While face-to-face interactions lead to a small reduction in loneliness, there is no significant association with remote interactions.

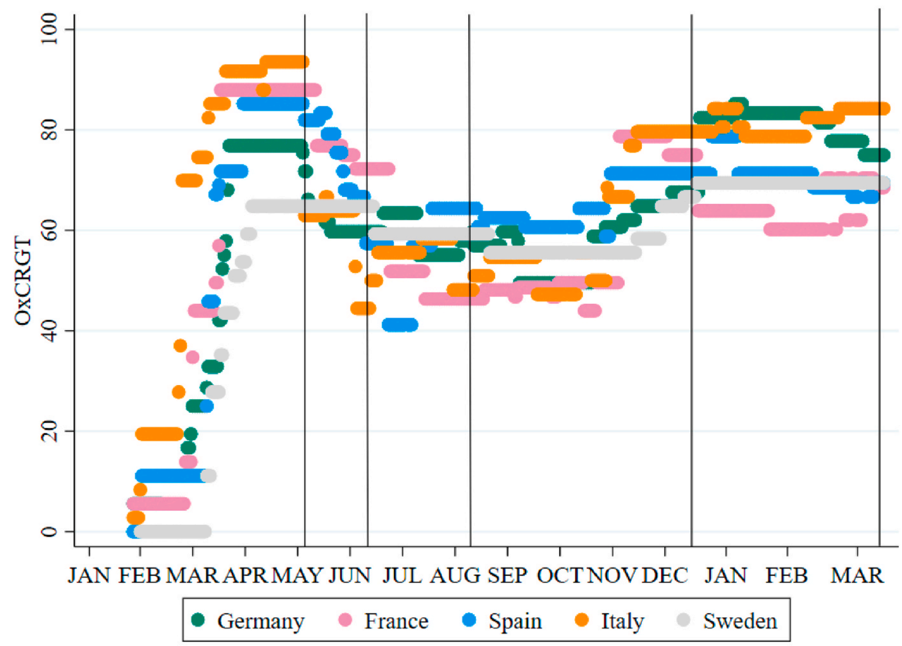
Table 4 presents the main effects of lockdown stringency for each latent class. As expected, there is substantial heterogeneity in our estimates by class, which in many cases are not in direct relation to the severity of loneliness. In addition, the proportion of individuals per class changes significantly, particularly due to a large rise in the High loneliness group. In relative terms, individuals in the Low group are substantially older and more likely to cohabitate, while those in the Severe group are much younger and often live without a partner. Those in the Medium and Severe groups are more likely to be less educated or female, while the reverse is true for the Low and High sub-populations.

Regarding social interactions, lockdown stringency leads to a significant reduction in remote and face-to-face communication; however, the size of these effects does not depend on the severity of loneliness. The effects due to imposed isolation status or adverse experiences also vary by latent class. For example, for some individuals with average levels of perceived social isolation (Medium group), imposed isolation leads to more face-to-face communication. On the contrary, for those with High or Severe loneliness, the absence of negative experiences leads to more in-person communication, with the opposite result being found for those in the Medium group.

The individuals who are least lonely are the most sensitive to changes in lockdown stringency and the overall evolution of the pandemic. For those with low loneliness, a rise in the number of COVID-19 cases slightly decreases loneliness, while the announcement of more-strict lockdown measures leads to a direct increase in the ULS-8 scale, after accounting for the indirect changes via reduced social interactions. There is no direct effect of lockdown stringency for those in the High group, while the indirect impact, via fewer face-to-face social interactions, is much larger. For the Severe loneliness group, lockdown stringency exhibits neither direct nor indirect effects on loneliness.

Overall, face-to-face interactions reduce loneliness for all groups except for the Medium, while remote communication only benefits those in the Medium and Severe loneliness groups. While mandated isolation increases loneliness in general, it actually reduces it among those in the group with highest loneliness (Severe). Moreover, negative experiences due to COVID-19 lead to increased ULS-8 levels, except in the High group.

As an additional sensitivity analysis, we estimated the model using the unbalanced sample, replicating the results of the model under the missing completely at random (MCAR) assumption. Online Supplement Table A7 lists the results for the unbalanced sample (excluding singletons). As expected, the results are quite similar, but the standard errors are much larger, especially for the association with the latent variables. We infer that this reflects correlation between attrition and social interactions, thus invalidating the MCAR assumption.



Notes: Vertical lines represent the timing where the collection period ended for each of the five waves of the COME-HERE survey. The Oxford COVID-19 Government Response Tracker (OxCRGT) figure is bounded between 0 and 100. Daily values are plotted for each country between February 2020 and March 2021.

Fig. 4. The OxCRGT COVID-19 stringency index and the COME-HERE timeline. *Notes*: Vertical lines represent the timing where the collection period ended for each of the five waves of the COME-HERE survey. The Oxford COVID-19 Government Response Tracker (OxCRGT) figure is bounded between 0 and 100. Daily values are plotted for each country between February 2020 and March 2021.

Table 2
Fit indices for latent classes and the latent-factor structure.

Panel (a) Fit indices for latent factor structure					
	Baseline	Loading restricted	Factors restricted	Threshold restricted	Fully restricted
RMSEA	0.031	0.034	0.062	0.090	0.091
CFI	0.981	0.976	0.610	0.818	0.812
TLI	0.980	0.975	0.597	0.817	0.811
Parameters	225	185	177	137	129
Panel (b) Fit indices for number of latent classes					
	2 classes	3 classes	4 classes	5 classes	6 classes
AIC	87,424	85,225	84,293	83,931	83,810
BIC	87,545	85,406	84,536	84,234	84,174
Adjusted BIC	87,482	85,311	84,409	84,075	83,983
Entropy	0.894	0.848	0.844	0.802	0.771
LRT	7981.2	2219.5	939.5	337.3	139
p-value	0.000	0.000	0.000	0.009	0.125

Notes: Panel (a) indicates the model fit for the latent structure of social interactions under different model restrictions. The root mean square error of approximation (RMSEA), comparative fit index (CFI) and Tucker–Lewis index (TLI) are calculated for each model configuration, considering that all measurements load into one factor in each period. Panel (b) indicates the model fit based on the number of latent classes by severity of loneliness. The Akaike information criterion (AIC), Bayesian information criterion (BIC) and entropy are calculated for the conditional distribution of the ULS-8 in all periods, without any structural restrictions. The Likelihood Ratio Test (LRT) is calculated for the null hypothesis that using "c-1" classes provides equivalent information to the model with "c" classes. The p-value for the LRT is based on the Chi-squared distribution.

Table 3
Odds ratios for latent classes.

	Estimate	S.E.	Lower 2.5%	Upper 2.5%
C2 to C1 (Medium to Low)				
Age	0.981	0.004	0.973	0.989
Gender (Female [1])	0.996	0.113	0.798	1.244
Educn. vocational or higher [1]	0.975	0.110	0.782	1.216
Lives with partner [1]	0.517	0.063	0.407	0.657
C3 to C1 (High to Low)				
Age	0.966	0.005	0.957	0.976
Gender (Female [1])	1.389	0.200	1.048	1.841
Educn. vocational or higher [1]	0.661	0.094	0.499	0.874
Lives with partner [1]	0.763	0.121	0.559	1.043
C4 to C1 (Severe to Low)				
Age	0.946	0.004	0.938	0.954
Gender (Female [1])	1.156	0.136	0.918	1.456
Educn. vocational or higher [1]	0.775	0.091	0.615	0.977
Lives with partner [1]	0.330	0.041	0.260	0.420

Notes: Estimates based on the structural model, with latent classes as a function of age, gender, educational level and cohabitation status. Robust standard errors and 95% confidence intervals based on the delta method.

4. Discussion

This study presents novel estimates on the effects of COVID-19 lockdown stringency on loneliness, combining the COME-HERE panel survey with the Oxford COVID-19 policy stringency index. We focus on both the direct and indirect effects of lockdown stringency, by measuring reported changes in both remote and face-to-face social interactions, while allowing heterogeneity across population sub-groups with different levels of loneliness.

Table 4
Main estimates by latent classes.

	a) Loneliness							
	Low		Medium		High		Severe	
OxCRCT z-score	**0.201**	*0.108*	**0.223**	*0.110*	−0.018	*0.235*	0.002	*0.150*
Any isolation status [1]	**3.431**	*0.337*	**1.986**	*0.322*	**1.254**	*0.668*	**−0.726**	*0.304*
Remote interactions (z-score)	0.056	*0.131*	**−0.299**	*0.152*	0.342	*0.279*	**−0.344**	*0.117*
Face-Face interactions (z-score)	**−0.418**	*0.137*	0.046	*0.150*	**−1.129**	*0.307*	**−1.107**	*0.153*
Any mental health condition [1]	**1.427**	*0.175*	**1.717**	*0.160*	**2.633**	*0.244*	**0.886**	*0.207*
Any medical condition [1]	−0.062	*0.085*	**0.428**	*0.110*	**0.966**	*0.201*	**0.256**	*0.111*
No negative experience [1]	**−0.516**	*0.104*	**−1.132**	*0.120*	**0.821**	*0.215*	**−0.517**	*0.113*
Log Income	−0.045	*0.038*	0.029	*0.026*	0.003	*0.031*	**−0.068**	*0.021*
Any physical activity [1]	**−0.160**	*0.085*	0.134	*0.114*	**−0.666**	*0.147*	**−0.651**	*0.101*
Log COVID-19 cases	**−0.171**	*0.089*	0.067	0.105	−0.051	*0.118*	−0.041	*0.116*
Log COVID-19 deaths	0.067	*0.052*	0.052	0.060	**0.224**	*0.126*	−0.060	*0.074*
	b) Face to face interactions (z-score)							
	Low		Medium		High		Severe	
OxCRCT z-score	**−0.045**	*0.014*	**−0.026**	*0.013*	**−0.057**	*0.012*	−0.005	*0.011*
Any isolation status [1]	−0.082	*0.084*	**0.211**	*0.056*	−0.029	*0.052*	*−0.014*	*0.033*
No negative experience [1]	0.001	*0.015*	**−0.043**	*0.016*	**0.208**	*0.016*	**0.042**	*0.012*
	c) Remote interactions (z-score)							
	Low		Medium		High		Severe	
OxCRCT z-score	**−0.054**	*0.014*	**−0.045**	*0.014*	0.021	*0.020*	−0.006	*0.011*
Any isolation status [1]	−0.098	*0.075*	−0.053	*0.051*	**0.170**	*0.078*	**0.149**	*0.033*
No negative experience [1]	**0.040**	*0.017*	**0.146**	*0.018*	**−0.144**	*0.021*	0.007	*0.013*
Proportion by class	28.6%		31.3%		13.7%		26.4%	

Notes: Panel a) indicates the direct effect of each variable on the loneliness scale (in units), while panels b) and c) show the impact of stringency and other COVID-19 related events on social interactions. Estimates based on the structural model, with latent classes as a function of age, gender, educational level and cohabitation status. Oxford COVID-19 Government Response Tracker (OxCRGT) standardised to the values in Wave 1. COVID-19 cases and deaths are 2-week moving averages of the daily values. By construction, remote and face-to-face interactions are standardised to the values in Wave 1. Robust standard errors in italics, significant values at the 10% level in bold.

4.1. Loneliness distribution and changes in social interactions

We identify four latent groups by the level of loneliness, all of them with fairly stable mean levels during the first year of the pandemic. As noted in previous work, we found that age, gender, education and cohabitation status play key roles in determining the severity of loneliness (Pinquart and Sörensen, 2003). In the unconditional distribution describing only the heterogeneity on loneliness trajectories, we find that around 8% of the population has a Severe level of loneliness, lower than the 14% found in previous work on the United Kingdom during the first few months of the pandemic (Bu et al., 2020a). Overall, young people and those living alone are at more risk of Severe loneliness, consistent with previous studies (Lara et al., 2020; Losada-Baltar et al., 2021).

Factor analysis is used to identify the underlying structure of changes in daily social interactions over time, both remote and face-to-face. This strategy allows us to (1) understand the relative importance of each type of relationship for the overall variation in reported interactions during the pandemic, and (2) reconstruct the overall dynamics of changes in social interactions over time. The variations in communication with colleagues and direct family at home are the least related to overall changes in social interactions (both at the within- and between-person level), indicating that the work and home environments remained mostly stable despite the changes in lockdown stringency. In contrast, remote and face-to-face communication with close friends, direct family away from home and other individuals away from home vary in line with the course of the pandemic. Face-to-face changes in social interactions vary consistently with the stringency of lockdown measures. For remote interactions, there is an overall reduction at the beginning of the pandemic, while the distribution remains largely unchanged afterwards. Among those individuals with High (but not Severe) loneliness, there is a clear trade-off between in-person and remote interactions in response to changes in the stringency of lockdown measures. While, to our knowledge, this is the first study to model changes in social interactions across sub-populations in response to lockdown policies, our findings are consistent with evidence on the relative distribution of in-person and remote communication in a small sample of UK residents during the first few months of the pandemic (Sun et al., 2020).

4.2. Changes in lockdown stringency and perceived social isolation

In the overall sample, lockdown stringency measures have a minor but significant impact on social interactions (particularly face-to-face), which in turn affect loneliness (the indirect effect). In addition, once we control for the evolution of deaths during the pandemic, stickier lockdown policies impact negatively those with lower levels of loneliness, independent of the objective changes in social interactions. In other words, the direct effect occurs via changes in the subjective perception of limitations to social interactions. In addition, within-individual changes in isolation status (due to COVID-19 infection, for example) and mental or physical ill-health lead to higher levels of loneliness. Adverse experiences, mainly loss of household income or the death of someone close, are also likely to affect both face-to-face interactions and overall loneliness (although income generally plays an insignificant role). However, while the mean effects of lockdown stringency and social interactions are significant, they are too small to have a meaningful impact on the average level of loneliness. As such, results in the overall sample are consistent with the remarks in Prati and Mancini (2021) that lockdowns are unlikely to have significant detrimental effects on mental health. Still, as noted in the previous section, ignoring heterogeneity in the population may well hide critical at-risk groups.

Our latent-class estimates underscore considerable heterogeneity by the latent class of loneliness. Those with Low and Medium levels of loneliness are likely to be affected by lockdown stringency, both directly and indirectly, via reduced social interactions (remote and face-to-face), especially if they have to quarantine. Individuals with Severe loneliness are unlikely to be influenced by lockdown stringency, and benefit more from remote communication and physical activity. These individuals exhibit lower loneliness when physically isolated, most likely due to an increase in remote communication. While not directly comparable, our results are in line with the findings on multiple latent trajectories in a sample of UK adults (Bu et al., 2020a).

Taken together, we find that loneliness is a complex and fairly persistent phenomenon, with markedly different dynamics across subpopulations with different risk levels of loneliness, which in turn are partly determined by socio-demographic characteristics. Older individuals are more sensitive to physical isolation and the subjective perception of limitations due to lockdown stringency, while younger individuals (those at higher risk of loneliness), do not seem affected by lockdown stringency but rather by changes in social interactions alone. Moreover, while mandated isolation has a significant negative effect in older people, it can actually lead to lower loneliness levels among the young.

4.3. Limitations

There are a number of strengths and limitations to our analysis here. First, the external validity of our results is most likely limited to countries with similar socioeconomic and cultural characteristics to those in the COME-HERE panel. While the ULS-8 is likely to be useful for comparisons across different cultures, recent evidence suggests that relationships between social interactions and loneliness can be different across countries with distinct cultural patterns (e.g. individualistic *vs.* collectivistic countries) and levels of socioeconomic development (Hudiyana et al., 2021). Considering only the five countries analysed here, we found no difference in the latent class structure by place of residence.

Second, while we account for time-invariant heterogeneity and many contextual variables, there can be other unobserved factors that are correlated with changes in both social interactions and loneliness, thus affecting the estimates of the mediation paths between lockdown stringency and perceived social isolation. Nevertheless, since lockdown stringency does not appear to directly impact perceived social isolation (once we control for the evolution of the pandemic), our estimates remain robust. Moreover, we account for selective attrition by weighting the sample to maintain representativeness.

Third, while this study is unique in its use of repeated measures of social interactions across a wide range of social relationships, our metric is based on the relative change rather than levels, thus we cannot distinguish low versus high degrees of social interactions. Nonetheless, our analyses focus on the impact of stringency on the intensity and direction of change. Relying on the level of social interactions could be extremely helpful to answer questions regarding potential risk levels, although that is beyond of the scope of our analyses.

Finally, our latent class model does not allow for group membership to change over time, which could be the case for some individuals. However, given the time period considered and the limited variation in loneliness over time, our estimates are an appropriate approximation of the latent profiles and mean effects, on average. Moreover, the class predictors we used here are not only quite significant but also mostly time-invariant (at least over the study period).

5. Conclusions

Our findings stress the importance of a deeper understanding of the population heterogeneity in the links between loneliness and changes in social interactions over time. Older individuals living alone and those working from home are particularly vulnerable to the negative effects of lockdown stringency, reducing their capacity to maintain social interactions (both remote and face-to-face). Moreover, while the extent of face-to-face social communication has been shown to be sensitive to the evolution of the pandemic, at-risk groups are more sensitive to changes in remote communication and physical activity. Remote interactions play a key role on loneliness among women and younger adults, which in turn is largely affected by physical isolation (i.e., mandate or self-quarantine) and COVID-19 related negative experiences. Looking ahead on future public health challenges, we recognise the importance of creating support systems for those individuals while living alone, as well as the need for continuous remote communication for groups with high baseline levels of loneliness.

Credit author statement

Juan C. Caro: Conceptualization, Methodology, Writing – original draft, Formal analysis, Software, Data Curation, Reviewing and Editing.; **Andrew E. Clark**: Supervision, Reviewing and Editing.; **Conchita D'Ambrosio**: Funding acquisition, Project Administration, Investigation, Reviewing and Editing.; **Claus Vögele**: Reviewing and Editing, Supervision, Investigation.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115492.

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