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SHARE ERIC SURVEY OF HEALTH, AGEING AND RETIREMENT IN EUROPE www.share-project.org

SHARE, the Survey of Health, Ageing and Retirement in Europe, is a research infrastructure for studying the effects of health, social, economic and environmental policies over the life-course of European citizens and beyond. From 2004 until today, 616,000 in-depth interviews with 160,000 people aged 50 or older from 28 European countries and Israel have been conducted. Thus, SHARE is the largest pan-European social science panel study providing internationally comparable longitudinal micro data, which allows insights in the fields of public health and socio-economic living conditions of European individuals, both for scientists and policy makers. SHARE has global impact since it not only covers all EU member countries in a strictly harmonized way but additionally is embedded in a network of sister studies all over the world, from the Americas to Eastern Asia. Considering its focus on people aged 50 and older, international orientation, and thematic coverage, SHARE is perfectly suited to provide data on respondents' health, economic, and living situation all across Europe and Israel before and during the ongoing COVID-19 crisis.

Therefore, the aim of this project is to analyse and evaluate the non-intended consequences of the epidemic control decisions to contain the COVID-19 pandemic in 27 European countries using data from SHARE, and to devise improved health, economic and social policies with a transdisciplinary and international team of SHARE researchers from different European research institutions. To reach these aims, several objectives will be pursued: identify healthcare inequalities before, during and after the pandemic; understand the lockdown effects on health and health behaviours; analyse labour market implications of the lockdown; assess the impacts of pandemic and lockdown on income and wealth inequality; mitigate the effects of epidemic control decisions on social relationships; optimise future epidemic control measures by taking the geographical patterns of the disease and their relationship with social patterns into account; better manage housing and living arrangements choices between independence, co-residence or institutionalisation.

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WP6

Changes in social relationships before – during – after COVID-19: Findings from 4 waves of the Survey of Health, Ageing and Retirement in Europe (SHARE)

In our current analysis, we used mixed-effects logistic and linear regression models to study changes in social relationships before (SHRAE wave 8), during (2 SHARE-COVID waves), and after (SHARE wave 9) the pandemic. We began by analyzing the mixed-effects logistic regression models to examine the likelihood of experiencing loneliness, participation in volunteering activities, providing instrumental care, personal care, receiving instrumental care, and personal care. Each of these served as dependent variables in separate models. The model formula includes several predictor variables: wave (time point), gender, age, stringency (how stringent a country is with COVID-19 regulations), covid (whether the subject was diagnosed with COVID-19 or not), household partner (whether a partner is living in the same household), and employment status (whether the person is retired or not). These predictors are considered fixed effects in the model.

Model Formula:

```
model_formula <- "dependent_variable ~ wave + gender + age + stringency + covid + hhpartner
+ work + (wave + 1 | subject)"
```

Model equation:

$$Dependent\ Variable_{ij} = \beta_0 + \beta_1 Wave_{ij} + \beta_2 Gender_{ij} + \beta_3 Age_{ij} + \beta_4 Stringency_{ij} + \beta_5 Covid_{ij} + \beta_6 Retired_{ij} + \beta_7 Hosehold_{ij} + \mu_{0j} + \mu_{1j} Wave_{ij} + \epsilon_{ij}$$

* Note, the dependent variable could have been providing instrumental help, providing personal care, receiving instrumental help, receiving personal care, loneliness, or volunteering.

Additionally, the model includes a random effect for the subject, allowing for random intercepts and random slopes for the wave variable, which accounts for the repeated measures within subjects over time.

This study aims to examine how demographic characteristics, COVID-19 diagnosis, household composition, employment status, and government stringency measures impact different social relationship measures. These measures include loneliness, volunteering, provision of instrumental help, personal care, receipt of instrumental care, and receipt of personal care. By including both fixed and random effects, the model can control for within-subject correlation and provide more accurate estimates of the effects of these predictors on the likelihood of the social relationship-dependent variables.

In addition to the mixed-effects logistic regression model, we also evaluated pairwise comparisons of the estimated marginal means (EMMs) across different time points (waves). This was accomplished using the `emmeans` package, which allows us to further interpret the fixed effects of the model by providing the average predicted probabilities of providing instrumental help at each time point.

Finally, the overall model's fit was assessed using McFadden's Pseudo R-squared, which is a measure used to evaluate the goodness-of-fit for models, particularly in the context of logistic regression and other generalized linear models. It serves as an analog to the traditional R-squared used in linear regression, indicating how well the model explains the observed outcomes.

Findings

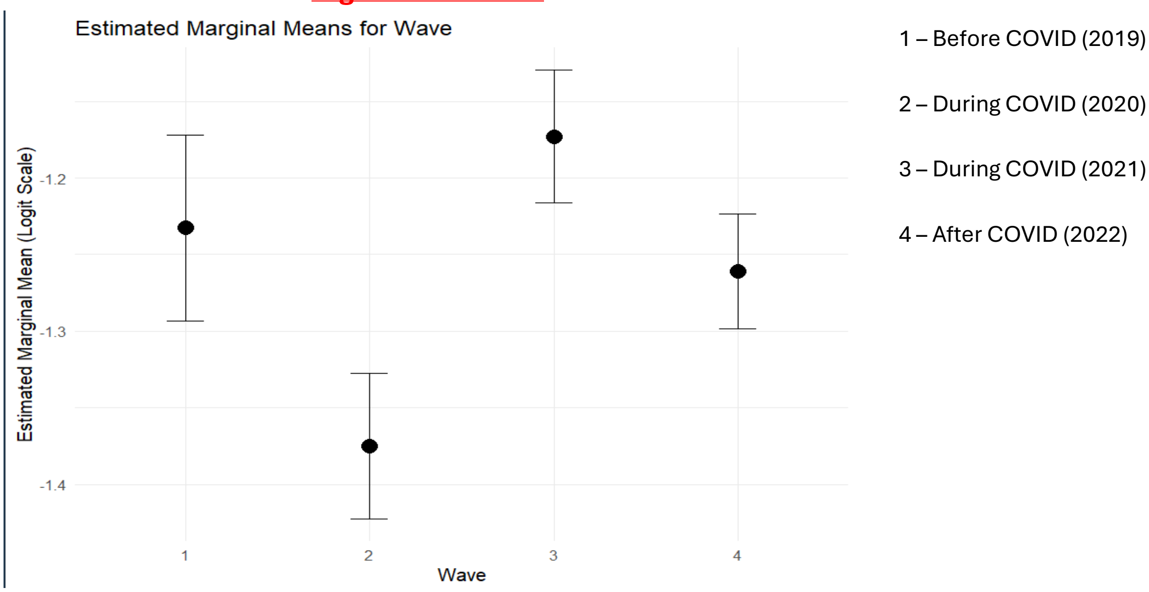
1. **Loneliness**

We conducted a study to measure loneliness before, during, and after the pandemic. Using data from SHARE Wave 8 before the pandemic, the two SHARE COVID waves during the pandemic (June 2020 and July 2021), and SHARE Wave 9 after the pandemic, we found that there was a decrease in reported loneliness from before the pandemic to the initial phase of the pandemic. However, this decrease was not significant. There was a significant increase in loneliness between the first COVID wave and the second wave conducted a year later in 2021. After the pandemic, there was again a significant decrease in reported loneliness. These results are depicted in Graph 1.

Given the harmful consequences that loneliness has, special emphasis should be placed during the period when the epidemic is ongoing and there are cumulative effects of the social distancing imposed during the epidemic. During the first period of the epidemic, most people stayed at home, and most of them worked from home, so it is possible that the time created was directed to social connections, thereby easing the feeling of loneliness. However, when the epidemic continued and a significant part returned to a certain routine life, the feeling of loneliness increased among those left behind. Especially the old people who were defined as a risk group to suffer from complications of the coronavirus disease and therefore imposed on themselves and a significant social distance was also imposed on them.

Graph 1: Experiencing loneliness - pre-during-post pandemic: A mixed-effects logistic regression model

1.




```
contrast       estimate     SE   df z.ratio p.value
 wave1 - wave2   0.1426 0.0758 Inf   1.882  0.2360
 wave1 - wave3  -0.0597 0.0723 Inf  -0.826  0.8420
 wave1 - wave4   0.0284 0.0499 Inf   0.568  0.9415
 wave2 - wave3  -0.2023 0.0254 Inf  -7.974  <.0001
 wave2 - wave4  -0.1142 0.0383 Inf  -2.981  0.0152
 wave3 - wave4   0.0881 0.0352 Inf   2.503  0.0595
```

Results were corrected using Tukey correction

```
Log likelihood = -52069.4
Null log likelihood = -54905.8
Pseudo R Square 1 - 0.9483406 = 0.0516594
```

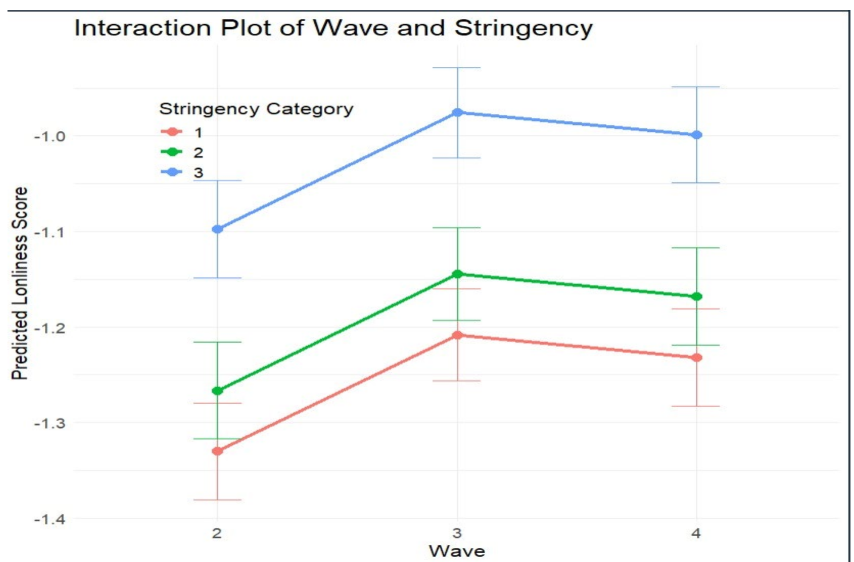
Graph 2 illustrates the impact of the stringency index on loneliness. It demonstrates that countries that implemented stricter measures, such as lockdowns, to combat the spread of COVID-19 experienced higher rates of loneliness. Moreover, even after the epidemic ended in these countries, the rates of loneliness remained elevated. This indicates that the effects of the epidemic and the stringent measures taken to control it continued to manifest in higher loneliness rates. Considering the detrimental effects of loneliness on health and well-being, it is important to carefully balance measures aimed at controlling the epidemic.

Graph 2: Experiencing loneliness - pre-during-post pandemic: A mixed-effects logistic regression model with interaction of the stringency effect

2 – During COVID (2020)

3 – During COVID (2021)

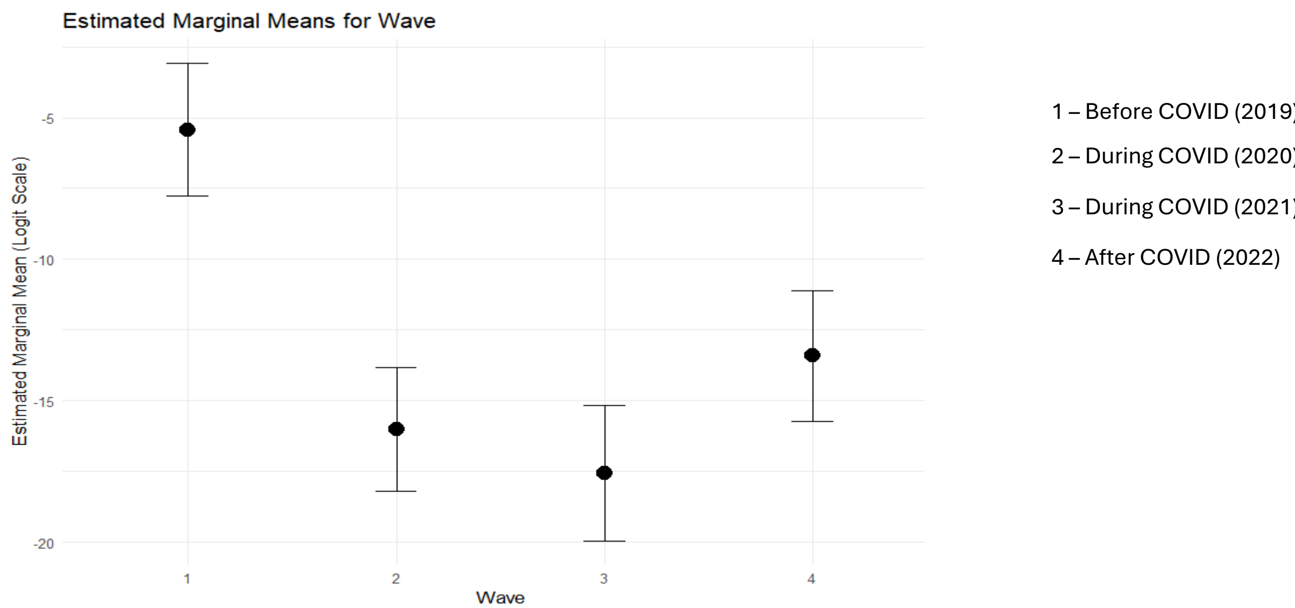
4 – After COVID (2022)



2. Volunteering

According to Graph 3, there was a significant decrease in volunteering from before COVID-19 to the initial phase of COVID in the summer of 2020. As the epidemic continued, volunteering rates decreased further. There was a recovery in volunteering rates after the epidemic (wave 9), but they did not return to the levels reported before the epidemic. There was a clear difference in participation rates before and after the pandemic, with volunteering rates remaining lower even after the pandemic ended. In other words, the effects of the pandemic persisted, leading to fewer people taking part in voluntary activities. Efforts should be made to increase older adults' participation in volunteering to maximize health and well-being benefits.

Graph 3: Volunteering - pre-during-post pandemic: A mixed-effects logistic regression model

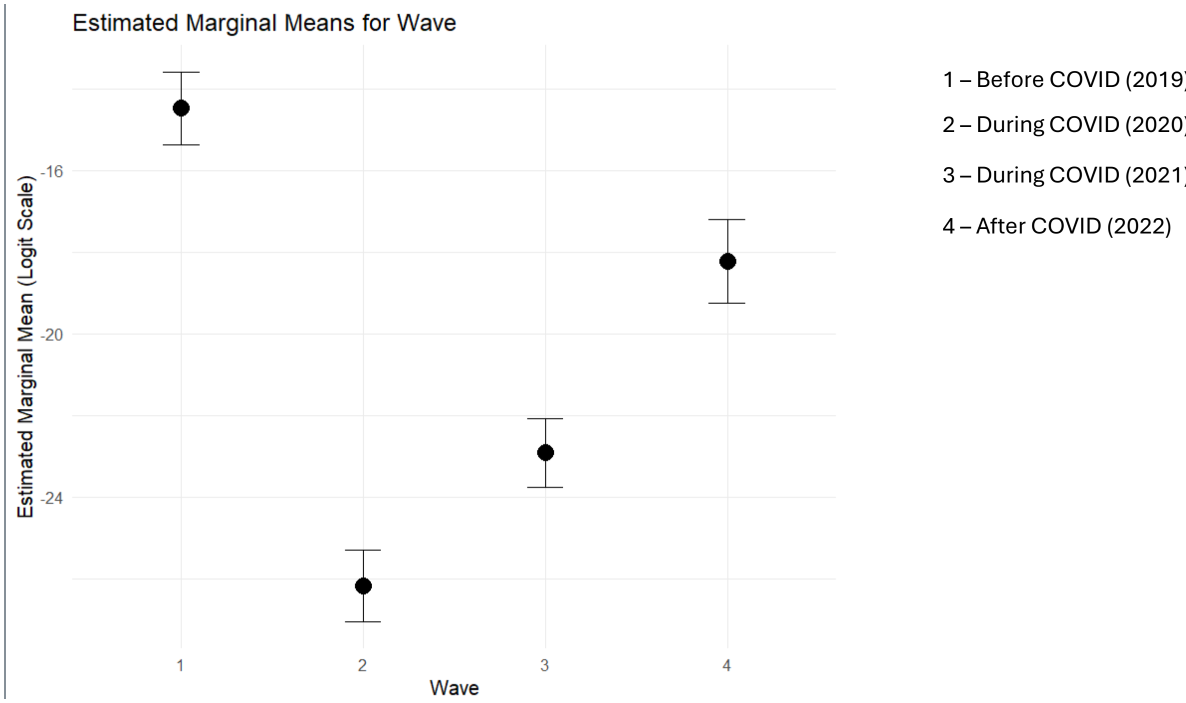



```
contrast       estimate   SE   df z.ratio p.value
wave1 - wave2 1.84 10.60     Inf0001.>   5.769
wave1 - wave3 2.29 12.14     Inf0001.>   5.305
wave1 - wave4 1.50 7.99      Inf0001.>   5.346
wave2 - wave3 1.44 1.55      Inf0.7055   1.074
wave2 - wave4 1.35 2.60-     Inf0.2166   1.927-
wave3 - wave4 1.90 4.15-     Inf0.1273   2.185-
```

3. Providing personal care

The analysis of personal care provision before, during, and after the epidemic (Graph 4) shows a notable decrease in the support provided at the onset of the epidemic. There was some improvement during the second wave of the pandemic. As the epidemic persisted, the number of individuals reporting providing personal care increased. This trend continued even after the epidemic ended in 2022. However, the rate of providing help after the epidemic did not return to pre-epidemic levels, indicating that the impact of the epidemic lingers even after its conclusion. This may suggest a limited capacity to provide this type of care.

Graph 4: providing personal care - pre-during-post pandemic: A mixed-effects logistic regression model

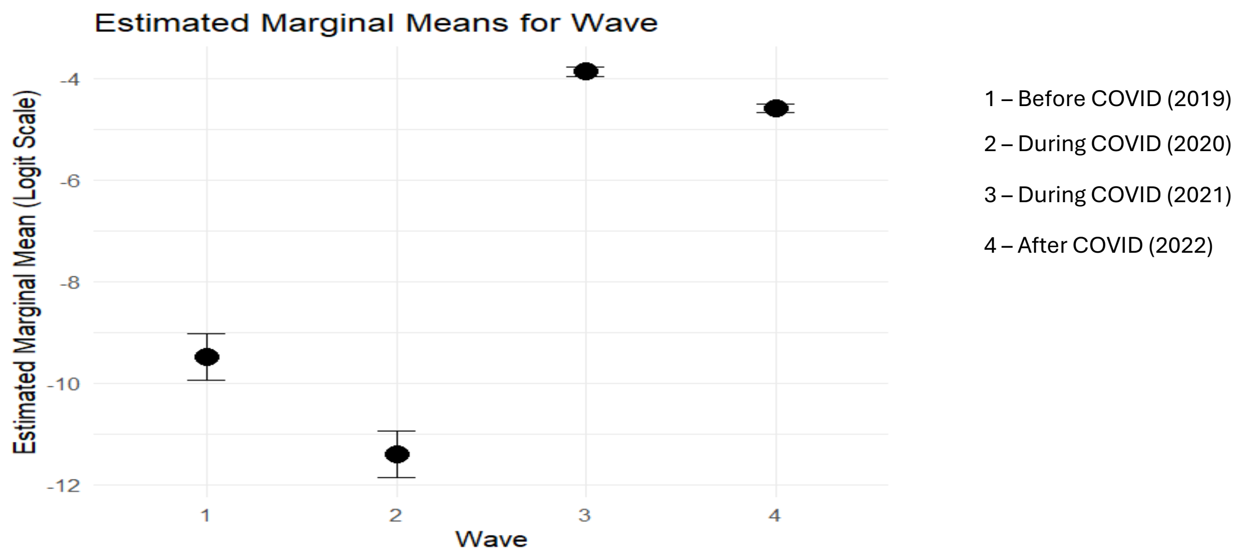



```
contrast      estimate    SE  df z.ratio p.value
 wave1 - wave2    11.70 0.686 Inf  17.061  <.0001
 wave1 - wave3     8.43 0.834 Inf  10.117  <.0001
 wave1 - wave4     3.75 0.891 Inf   4.207  0.0002
 wave2 - wave3    -3.26 0.611 Inf  -5.337  <.0001
 wave2 - wave4    -7.95 0.904 Inf  -8.791  <.0001
 wave3 - wave4    -4.69 1.015 Inf  -4.618  <.0001
```

4. Receiving personal care

Graph 5 illustrates the trend in receiving personal care during the pandemic. There was a noticeable decrease in receiving personal help at the onset of the epidemic, possibly due to the fear of providing assistance that involves close physical contact during a health crisis. However, as the epidemic progressed, there was a significant increase in receiving personal help, with a further rise in the post-epidemic period. These findings suggest a growing demand for this type of assistance and reduced fear of both receiving and giving personal care.

Graph 5: Receiving personal care - pre-during-post pandemic: A mixed-effects logistic regression model



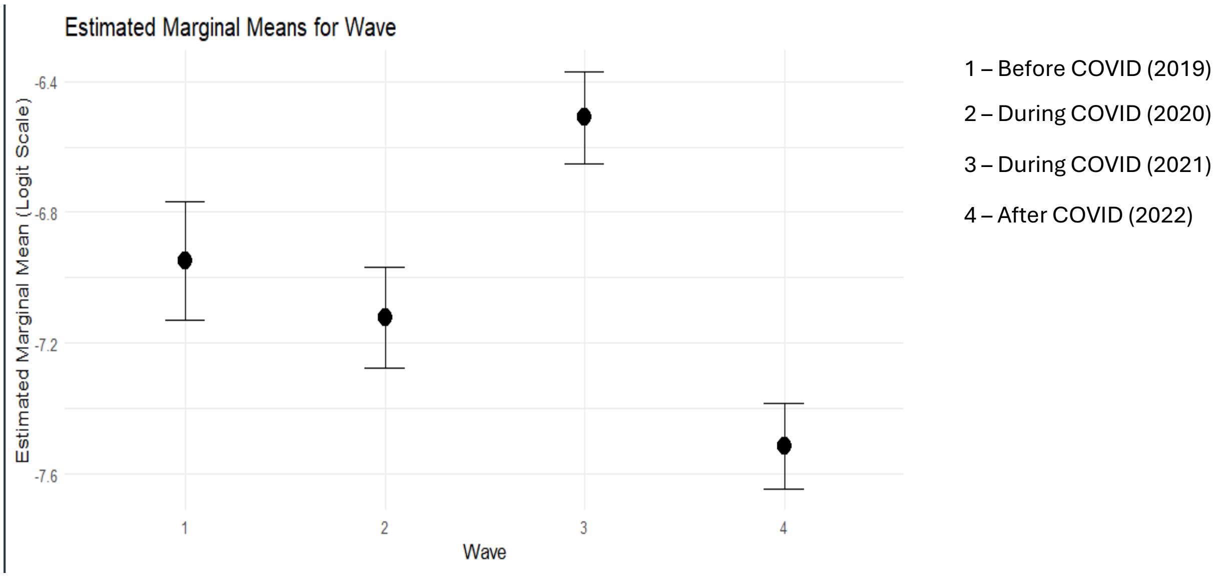

```
contrast      estimate     SE  df z.ratio p.value
 wave1 - wave2    1.918 0.6387 Inf   3.003  0.0142
 wave1 - wave3   -5.617 0.4637 Inf -12.114  <.0001
 wave1 - wave4   -4.899 0.4476 Inf -10.945  <.0001
 wave2 - wave3   -7.535 0.4466 Inf -16.870  <.0001
 wave2 - wave4   -6.817 0.4580 Inf -14.884  <.0001
 wave3 - wave4    0.718 0.0853 Inf   8.412  <.0001
```

```
> loglike_mixed_rec_inst
'log Lik.' -44239.45 (df=20)
> loglike_null_rec_inst
'log Lik.' -53571.69 (df=11)
> Pseudo_r_square_vol = 1 - loglike_mixed_rec_inst[1] / loglike_null_rec_inst[1]
> Pseudo_r_square_vol
[1] 0.174201
```

5. Providing and Receiving instrumental care

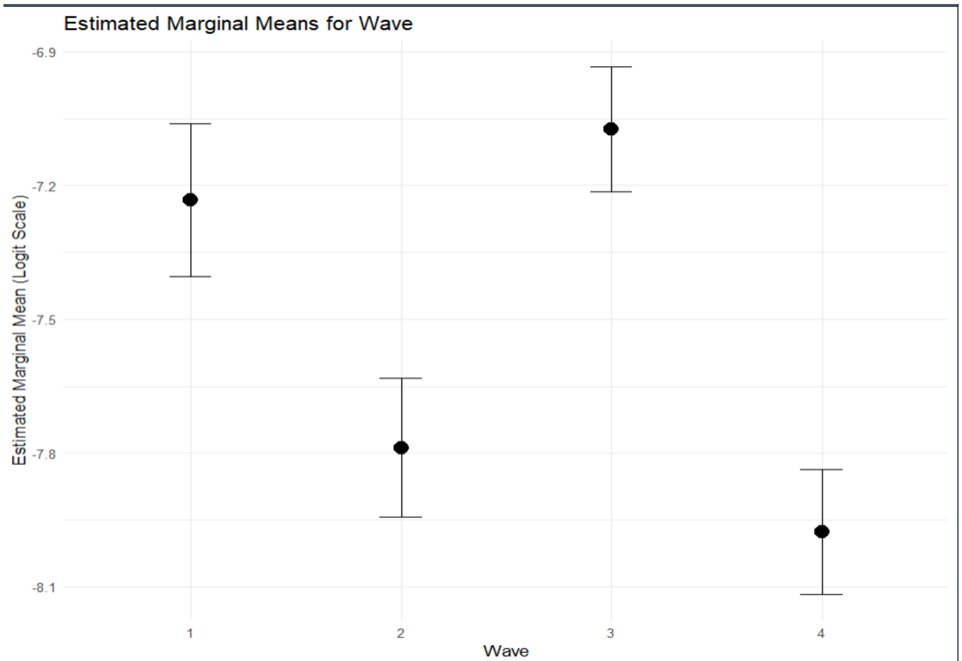
According to graphs 6 and 7, there was a decrease in the giving and receiving of instrumental care to and from network members from the period before the epidemic to the first period of the epidemic (2020). The decrease was significant for receiving instrumental help but not significant for providing this type of care. Subsequently, between the two waves of the epidemic, there was a clear increase in both giving and receiving instrumental aid. Following the end of the epidemic in 2022, a sharp and significant decrease was observed in the giving and receiving of instrumental care. It is possible that the need for providing and receiving this kind of help decreased after the epidemic as external limitations decreased and had less impact on the social and physical environment.

Graph 6: Providing instrumental care - pre-during-post pandemic: A mixed-effects logistic regression model



contrast	estimate	SE	df	z.ratio	p.value
wave1 - wave2	0.172	0.2047	Inf	0.840	0.8354
wave1 - wave3	-0.439	0.1901	Inf	-2.310	0.0957
wave1 - wave4	0.565	0.1355	Inf	4.172	0.0002
wave2 - wave3	-0.611	0.0602	Inf	-10.158	<.0001
wave2 - wave4	0.393	0.1033	Inf	3.810	0.0008
wave3 - wave4	1.005	0.0901	Inf	11.146	<.0001

Graph 7: Receiving instrumental care - pre-during-post pandemic: A mixed-effects logistic regression model



contrast	estimate	SE	df	z.ratio	p.value
wave1 - wave2	0.555	0.1788	Inf	3.105	0.0103
wave1 - wave3	-0.159	0.1680	Inf	-0.947	0.7795
wave1 - wave4	0.743	0.1213	Inf	6.127	<.0001
wave2 - wave3	-0.714	0.0576	Inf	-12.389	<.0001
wave2 - wave4	0.188	0.0929	Inf	2.029	0.1772
wave3 - wave4	0.902	0.0836	Inf	10.801	<.0001

1 – Before COVID (2019)
2 – During COVID (2020)
3 – During COVID (2021)
4 – After COVID (2022)

7. Interactions with social networks: before – during and after the pandemic

In addition to the logistic model, we utilized a linear mixed-effects regression model to examine the predictors of network frequency using the `lmer` function from the `lme4` package in R. The dependent variable was the frequency of contact with the social network, and the model included several fixed effects: wave (time point), gender, age, stringency of COVID-19 regulations, COVID-19 diagnosis status, household partner presence, and retirement status. The model formula also incorporated random intercepts and random slopes for the wave variable nested within subjects to account for the repeated measures and within-subject correlation over time. Continuous variables such as age and stringency were standardized. The model was fitted using the REML method with adjusted control parameters to address convergence issues. After fitting the model, we used the `emmeans` package to obtain and interpret the estimated marginal means (EMMs) for different waves, and conducted pairwise comparisons to assess the differences across time points.

Model equation:

$$
\begin{aligned}
&Network\ Contact_{ij} = \beta_0 + \beta_1 Wave_{ij} \\
&+ \beta_2 Gender_{ij} + \beta_3 Age_{ij} + \beta_4 Stringency_{ij} + \beta_5 Covid_{ij} + \beta_6 Retired_{ij} + \beta_7 Hosehold_{ij} \\
&+ \mu_{0j} + \mu_{1j} Wave_{ij} + \epsilon_{ij}
\end{aligned}
$$

The analysis of social interactions across time indicates a decrease in face-to-face and electronic contact during the early days of the pandemic in 2020. There was a slight increase between the first (2020) and second waves (2021) of the pandemic and a sharper increase after the pandemic ended (2022). The removal of social gathering restrictions led to an increase in interaction with network members, although not to the same level as before the pandemic. This suggests that the impact of the pandemic on social interaction persisted even after it ended.

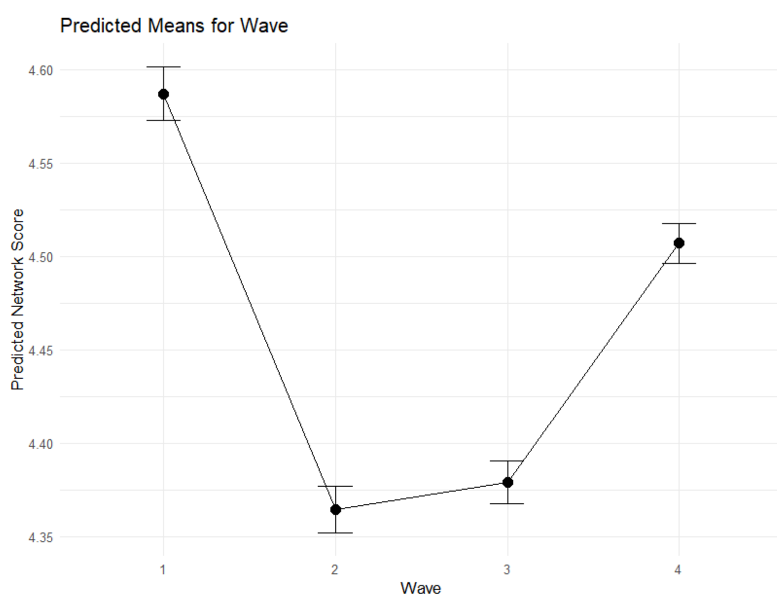
Graph 8: Frequency of interactions with the network - pre-during-post pandemic: A mixed-effects linear regression model

1 – Before COVID (2019)

2 – During COVID (2020)

3 – During COVID (2021)

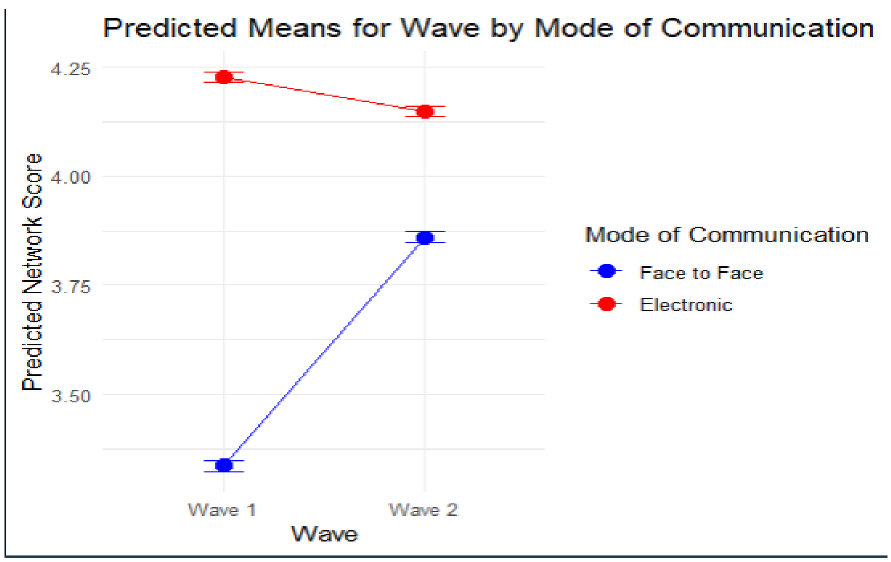
4 – After COVID (2022)



```
contrast       estimate      SE    df t.ratio p.value
Wave1 - Wave2    0.2228 0.01637 58799  13.607  <.0001
Wave1 - Wave3    0.2082 0.01567 58799  13.287  <.0001
Wave1 - Wave4    0.0802 0.00995 58799   8.056  <.0001
Wave2 - Wave3   -0.0146 0.00600 58799  -2.438  0.0702
Wave2 - Wave4   -0.1426 0.00850 58799 -16.783  <.0001
Wave3 - Wave4   -0.1280 0.00789 58799 -16.220  <.0001
```

```
> loglike_mixed_network = logLik(mixed_model_network)
> loglike_mixed_network
'log Lik.' -70474.13 (df=21)
> loglike_null_network = logLik(null_mixed_model_network)
> loglike_null_network
'log Lik.' -71029.92 (df=12)
> pseudo_r_square_netwrok = 1 - loglike_mixed_network[1]/loglike_null_network[1]
> pseudo_r_square_netwrok
[1] 0.007824785
```

Graph 9: Two-Way Interaction with Mode of Communication



1 – Before COVID (2019)

2 – During COVID (2020)

During the pandemic, there was a significant increase in electronic communication compared to face-to-face interaction in the initial stages. However, as time passed, electronic communication slightly decreased while face-to-face communication saw a sharp rise. Overall, electronic communication remained higher throughout both phases of the pandemic.

Considering the potential negative effects of electronic communication and the numerous benefits of face-to-face interaction, it's important to find a balance between the two and promote in-person interaction even during an epidemic.