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INCOME INSECURITY AND MENTAL HEALTH IN PANDEMIC TIMES *

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ABSTRACT: This paper provides novel evidence of the mental health effects of the Covid-19 outbreak. Between April 2020 and April 2022, we run four waves of a large representative survey in Spain, which we benchmark against a decade of pre-pandemic data. We document a large and sudden deterioration of mental health at the beginning of the pandemic, as the share of people reporting being depressed increased from 16% before the pandemic to 46% in April 2020. This effect is persistent over time, which translates into important and irreversible consequences, such as a surge in suicides. The effect is more pronounced for women, younger individuals and those with unstable incomes. Finally, using mediation analysis, event studies and machine learning techniques, we document the role of the labor market as an important driver of these effects, as women and the young are more exposed to unstable income sources.

JEL Codes: I1, I14, H2, H12, E24
Keywords: Mental health, Gender, Inequality, Labor markets, Pandemic, Covid-19

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1. Introduction

Economic insecurity and financial worries are an important contributing factor to individuals' mental health conditions. In general, recessions have been found to be detrimental for individual mental well-being (see Hiilamo et al., 2021; Bellés-Obrero and Vall Castelló, 2018, for recent surveys). However, while most of the prior literature has focused on recessions driven by economic motives, this paper provides novel evidence of the mental health impact of the crisis caused by the Covid-19 outbreak. Using four waves of longitudinal survey data from Spain, we document an important and persistent deterioration of mental health conditions relative to the pre-pandemic baseline.

The design of our survey allows us to match our data with four pre-pandemic surveys reaching back until 2009. We then use event-study models to precisely quantify the impact of the pandemic on mental health outcomes for different socio-demographic groups. While doing this analysis, we document the deviations caused by the pandemic from the long-term trends for equally composed groups along several characteristics such as gender, age, education, occupation and household income.

Although several studies have previously documented the effects of the Covid-19 outbreak on psychological conditions and mental health[1], we make two important contributions to this growing literature.

First, we are able to analyze the underlying mechanism behind the observed differences across socio-economic groups, which is relevant for the design of public sector interventions mitigating the exposure of vulnerable individuals. We show important differences in psychological well-being between men and women throughout the crisis. We then document that almost half of this gender gap can be explained by underlying differences in the distribution of the occupational status and labor market conditions between men and women.

Second, studies providing information on the persistence of these effects and their growth relative to pre-pandemic benchmarks are scarce. By collecting four waves of information during the pandemic (April '20, July '20, July '21 and April '22), we can precisely estimate the degree of persistence of the mental health effects over time and across different epidemiological moments and mobility restrictions.

The Spanish setting is particularly interesting to study the relationship between Covid-induced economic conditions and mental health, as Spain was among the first countries to be severely hit by the pandemic. In response, the government introduced strict confinement measures to contain the spread of the virus as early as spring 2020. At the same time, in order to counterbalance the negative effects on economic activity and the labor

[1]Evidence from a cross-country survey is provided by Gloster et al. (2020). There is further evidence for individual countries, such as the US (Adams-Prassl et al., 2022; Giuntella et al., 2021), Canada (Béland, Brodeur, and Wright, 2020), the UK (Proto and Quintana-Domeque, 2021; Etheridge and Spantig, 2022), Germany (Huebener et al., 2021), and Turkey (Altindag, Erten, and Keskin, 2022). Results for Spain are provided by Jacques-Aviñó et al. (2020) and Codagnone et al. (2020).

market, furlough measures were widely used during this period (*Expediente de Regulacion Temporal de Empleo*, *ERTE* for their acronym in Spanish). Figure 1 plots the evolution of the pandemic in Spain in terms of daily deaths (left axis) and social security affiliations (right axis, with and without furlough measures). The vertical lines in the figure indicate the timing of our survey waves. The large and persistent impact of the pandemic on the labor market is remarkable: not taking into account furlough measures, social security affiliations dropped by 17% from February to April '20. It was not until August '21 that pre-pandemic employment levels were restored.

Part of the recent literature on the labor market impact of the pandemic has focused on identifying heterogeneous effects across sub-groups of the population given that not all economic activities were equally affected (see Stantcheva (2022) for an overview; Immel, Neumeier, and Peichl (2022) for Germany; Adams-Prassl et al. (2020) and Montenovo et al. (2022) for the US). Even if most of these studies find that the gender dimension is particularly important (Adams-Prassl et al. (2020); Alon et al. (2020); Gupta et al. (2022)), none of them link their labor market results to mental health.[2] Therefore, we contribute to this literature by showing that those differential labor market impacts triggered important heterogeneous mental health effects.

To elicit the impact of the Covid-19 outbreak on physical and mental health, we include various questions, such as feeling depressed or facing insomnia. Furthermore, we collect detailed background information on respondents' personal characteristics and labor market situation. Although we do not detect any impact on physical health, we do report a substantial and very persistent decline in mental health. Before the pandemic more than half of respondents never felt unhappy or depressed (68%). This number reduced to 28% in April '20. The situation improved slightly in July '20 (34.5%) when restrictions where removed, contagion figures were low and the labor market situation improved, but remained well below pre-pandemic levels even two years after its outbreak (35% in July '21, 33% in April '22).

Using different but complementary methodologies, we provide evidence for an unequal impact of the pandemic on mental health across demographic groups. We first estimate a linear probability model showing that women, young individuals and those with an unstable labor market situation are much more likely to self-report worse mental health outcomes. Second, to overcome the correlation that exists between these three elements, we apply machine learning methods which corroborate, in a non-parametric

[2] Other important heterogeneous dimensions have been identified for the less educated (Adams-Prassl et al., 2020; Béland, Brodeur, and Wright, 2020; Low et al., 2020; Cortes, 2020; Gupta et al., 2022; Mongey, Pilossoph, and Weinberg, 2021; Gupta et al., 2022; Yasenov, 2020)), younger workers (Adams-Prassl et al., 2020; Béland, Brodeur, and Wright, 2020; Cortes, 2020; Gupta et al., 2022; Yasenov, 2020), immigrants (Béland, Brodeur, and Wright, 2020; Borjas and Cassidy, 2020; Gupta et al., 2022; Yasenov, 2020), the financially vulnerable (Alstadsæter et al., 2020; Low et al., 2020; Cortes and Forsythe, 2022; Mongey, Pilossoph, and Weinberg, 2021), parents (Alstadsæter et al., 2020), workers unable to work remotely (Béland, Brodeur, and Wright, 2020; Cortes and Forsythe, 2022; Mongey, Pilossoph, and Weinberg, 2021) or workers in non-essential industries (Gupta et al., 2022).

way, the high explanatory capacity of these characteristics. Finally, using mediation analysis, we show that an important share of the gender effect on mental health is mediated through the labor market.

We document that the pre-pandemic mental health gender and age gaps have grown larger during the pandemic. Relative to the benchmark year (2017), we find a larger deterioration of mental health conditions for women than men. We document an increase in the *unconditional* gap of 11 percentage points in April '20 (5.9 in July '20, 6.9 in July '21 and 7.6 in April '22) relative to the existing gap in 2017. A similar effect exists for the young (18-44 years old) and old (above 65) relative to the middle-aged (45-65). While the young are consistently less likely to report a positive mental health outcome, the percentage of the elderly reporting a positive outcome is higher than the middle-aged and higher than it was in 2017. Thus, we conclude that the effects are relatively persistent over time (except for the case of the elderly) and that the mental health gaps that appear during the high-incidence period of Covid-19 remain throughout the low-incidence periods for as long as two years since the initial outbreak.

We exploit the same dynamic setting to analyze the mechanism behind those differences. We first show that part of the heterogeneity across groups can be explained by underlying differences in occupations along the age and gender dimensions. More specifically, half of the mental health differences between men and women are explained by their exposure to different professional (and thus income) situations. The age gap decreases only slightly when controlling for the occupation of the younger group, but vanishes for the elderly as most of them are pensioners with stable incomes.[3]

The remainder of the paper is organized as follows. Section 2 explains the setting of the survey and data collection. Section 3 presents results on general and mental health while Section 4 focuses on the results related to the mental health gaps along the gender and age dimensions, and their deviation from long-term trends. Section 5 concludes.

2. Survey and data

2.1. Data collection and sample

We collect longitudinal data through a large-scale survey in four waves occurring April 2-3, 2020; July 20-23, 2020; July 22-30, 2021; and April 5-14, 2022. The internet-based survey was carried out by a professional survey company in Spain (Netquest), which hosts its own high-quality panel. Participation was only by invitation, and the long-term

[3]The mental health impacts documented in our paper are potentially correlated with the results of a growing literature studying the effects of the pandemic on socio-economic outcomes, such as economic anxiety (Fetzer et al., 2021), inequality across the income distribution (Martinez-Bravo and Sanz, 2021), the demand for religion (Bentzen, 2021), gender equality (Alon et al., 2020; Farré et al., 2022) or democracy (Amat et al., 2020), among others.

relationship with panelists secures reliable responses. All participants had to be above the age of 18 and reside in Spain.

During the first wave, all responses were collected within 24 hours[4], while subsequent waves required additional time to re-contact the maximum number of individuals from the first wave (and therefore minimize attrition levels). In April ’20, 1,097 individuals were surveyed. In July ’20, 2,000 individuals answered the survey, 795 of whom were from the first wave (72%). In July ’21, 2,014 individuals answered the survey, 74% (1,273 individuals) of whom were from the second wave from the second survey. In April ’22, 2,002 individuals answered the survey, 74% (1,498) of whom were from the third survey. Overall, 24% (475) answered the four waves. We find that attrition is mostly random, as only age shows a small impact on the probability of participating in subsequent waves.[5]

It is important to put the timing of the four survey waves into the appropriate context of each period. The day before we implemented the first wave of our survey, on April 1st, 2020, 913 people died due to Covid-19 and 8,008 new cases were diagnosed. While the first Covid-19 case in Spain was diagnosed on January 31st, the timing of our survey was exactly at the peak of the first Covid-19 wave with substantial lock-down policies. The exponential growth in the number of cases and deaths led the Spanish government to approve the implementation of the State of Alarm on March 14th which resulted in one of the strictest quarantine and confinement policies in Europe.[6] These measures controlled the spread of the virus, but they also had a strong impact on the labor market (see Figure 1). During the second wave of our survey (end of July ’20) most of the restrictions had been lifted and the incidence and mortality rates were among the lowest since the outbreak of the pandemic. The day before the second wave of our survey, 25 people died and 340 new cases were diagnosed. When we implemented the third wave (end of July ’21), Spain was hit by another surge in Covid-19 cases and some of the regions implemented a new set of restrictions. The the number of infections was very high, but mortality was relatively low because of the rapid adoption of the vaccination campaign. The day before the third wave was launched, 33 people died due to Covid-19 and 29,770 new cases were diagnosed. The employment level at that point was very close to its pre-pandemic level. As can be seen in Figure 1, during the fourth and last wave of our survey, in April

[4]The first wave of the survey includes an experimental design related to the information which individuals had on the Covid-19 fatality rate as well as on the accumulated incidence. Thus, for the first wave it was important to collect the answers for individuals who were exposed to the same official information on the Covid-19 situation in Spain.

[5]Table A1 shows the results of a linear probability model where the dependent variable measures the probability of answering more than one wave of the survey (first and second; second and third; third and fourth; first, second, third and fourth). We look at correlations with gender, age, income, education, occupation, having kids and region of residence, and age is the only characteristic that is statistically significant across all buckets.

[6]The State of Alarm imposed the closure of schools and all educational facilities, all tourist activities, bars, restaurants and all kinds of activities except industry and the construction sector. Freedom of movement was restricted and leaving home was only permitted for necessary tasks such as grocery shopping and medical visits.

’22, mortality was at stable and relatively low levels, all restrictions had been lifted and employment was higher than in pre-pandemic times.

2.2. Structure of the survey

Before starting the questionnaire, participants were briefly informed about the purpose of the study. To guarantee unbiased responses, the identity of the researchers and the institutions involved were not revealed and participants were only told that the study was being conducted by a leading public research institution in Spain.

After this brief introduction, several questions were included to collect basic information (demographics, residence, occupation and education). This block was also used to ensure the representativeness of participants by gender, age groups and regions.

The relevant structure of the survey can be summarized as follows[7]:

1. *Socio-economic background:*
   This block collects basic information such as gender, age, children, education, political ideology and income. Education and place of residence were directly obtained from the records of the survey company, as all registered members of the panel have to update this information regularly. Gender and age were asked in the survey but responses were double-checked with the information available in the company’s records.

2. *Employment circumstances:*
   We collect data on the employment status of each respondent at the time of the survey, but also ask participants about their status prior to the outbreak of the pandemic in February 2020.

3. *Health outcomes:*
   This block contains six questions to capture several health status dimensions. We first ask about their general health using the following question: "In general, how would you describe your health?" and the potential answers are "very good", "good", "normal", "bad", "very bad", "I don’t know" and "I prefer not to answer". Next, we ask whether they have any chronic illness as well as four questions that assess their mental health situation in the last two weeks, as follows:
   - "In the last two weeks, have you felt unhappy or depressed?"
   - "In the last two weeks, have you felt that you cannot overcome the difficulties you face?"
   - "In the last two weeks, have you constantly felt overwhelmed or tense?"

[7] The data used in this paper is part of a larger survey (Foremny, Sorribas-Navarro, and Castelló, 2020). Appendix B documents the full questionnaire. All questions that we use in this paper are collected before the experimental section.

- "In the last two weeks, do you feel that your worries have caused you to lose much sleep?"

  The possible answers are the same throughout all four questions: "not at all", "no more than usual", "a bit more than usual", "much more than usual", "I don't know" and "prefer not to answer". For our baseline results, we use the first question about feeling unhappy or depressed because it captures a slightly higher degree of mental distress. This question is also included in the four surveys implemented before the pandemic which allows us to capture any changes brought about by the outbreak of the pandemic. In any case, results using the other three questions are very similar and the main conclusions remain unchanged.

We also implement a quality check during the survey. We apply the method proposed by Meade and Craig (2012) and ask participants in the middle of the survey if they have been paying careful attention so far and if they believe that their responses should be included in the study. We also inform them that their answers to these questions will not have any consequences on their compensation for participating. The aim of this question is to raise respondents' awareness on the importance of their attention for the remainder of the survey. While its purpose is fulfilled regardless of whether their answer was honest, we observe that only 1.8% of respondents say they were not paying careful attention.[8]

The questionnaire for the second, third and fourth waves closely followed the structure of the first wave to maximize the comparability of the results over time.[9]

2.3. Pre-pandemic data

The design of the survey questions and answers related to health follows the exact wording of the National Health Survey of 2017 and 2011/12 to ensure the comparability of our results to pre-pandemic data. They are also comparable to the ones stated in the European Health Survey (for the Spanish sample) of 2014 and 2009.[10]

A potential concern of merging different surveys is that the data collected by our survey might not be balanced over certain characteristics relative to the sample available in the Spanish National Health Survey and the European Health Survey. This is of particular importance if those variables are likely to be correlated with health outcomes, such as gender, age, education, occupation or household income OECD (2019). Table A2 in the appendix shows the mean and the standard deviation of these characteristics for all data sources. As shown in panel a), while gender and some age categories are broadly balanced in the original samples, other variables show larger deviations. Respondents

[8]Dropping those observations from the data does not change our results.

[9]None of the questions about outcomes were changed. Modifications affected mostly questions used in Foremny, Sorribas-Navarro, and Castelló (2020).

[10]See Appendix D for the exact definition of the questions and answers in the previous surveys.

in our survey are more educated and have slightly higher incomes. There are also significant differences in terms of occupations. Given that the pre-pandemic surveys cover more observations (around 20,000 each) than our sample, we implement an exact matching based on strata defined by gender, age, education, occupation and household income groups. We then match each of the individuals in our sample to at least one observation from the Spanish National Health Survey and the European Health Survey with the same characteristics.

We implement the matching technique in a sequential way. First, we identify those individuals that answer more than one wave in our survey in order to consider them as one observation. Next, we match each individual in our survey with those of the National Health Survey of 2017. Then we match individuals in our survey with those in the European Health Survey of 2014. We proceed in the same way with the other two National Health Surveys of 2011/2012 and 2009. This procedure generates a final sample with individuals that have been matched aginst all the available pre-pandemic surveys. This final sample includes 6,928 observations from our survey (i.e. we do not find a match for 179 observations) and observation counts of 19,164, 17,797, 19,699 and 20,048 from the 2009, 2011/2012, 2014 and 2017 pre-pandemic surveys, respectively. Panel b) of Table A2 shows the summary statistics of the matched sample. As expected, there are no differences in terms of gender, age, education, occupation or household income among the samples compared. Thus, throughout the empirical analysis we use this sample and apply the corresponding matching weights in all estimations.

Finally, in order to guarantee representativeness of the final sample with the characteristics of the Spanish population, Table A3 compares each survey wave with population level data from the 2019 and 2020 Spanish census. Our sample matches closely the gender and occupation distribution of the Spanish population in most categories, but it is slightly younger, more educated and has lower household income than the average in the Spanish population. Hence, while our data is fully comparable with the matched pre-pandemic data, aggregate results are based on a sample that deviates slightly from the broader population in some characteristics.

3. Results

3.1. Baseline results

We begin with a simple descriptive comparison of the general and mental health outcomes. Figure 2(a) illustrates the distribution of responses to the **general health** question[11] between April '20 and April '22 and the average of all pre-pandemic years. We observe a reduction in the percentage of individuals that consider their general health to

[11]The exact wording of the question is "*In general how would you describe your health?*"

be "very good" relative to pre-pandemic data.[12] At the same time, there is a higher share of the population that states that their health is "good" in 2020, 2021 and 2022 relative to the pre-pandemic average.[13] Part of the drop in the "very good" category is attributable to a shift into the "normal" category. Finally, we observe higher values for the "bad" and "very bad" categories before the pandemic than in the 2020, 2021 and 2022 surveys. However, the share of people reporting these categories is always very small (at most 4%). Overall, our results document that general health has not significantly decreased after the onset of the pandemic and. If anything, it has slightly improved. This result is consistent with the large literature studying health effects of business cycle fluctuations which finds very small effects (and sometimes even improvements) in *general* health during economic downturns within the context of developed countries.[14]

Next, we turn to **mental health**. Figure 3(a) similarly shows the distribution of responses to the question about feeling unhappy or depressed[15]. We document that previous to the pandemic more than half of the sample (68%) responds "not at all" to this question. In April ’20, this percentage is reduced to 28% and only recovers slightly to 34% in July ’20. It remains at 35% and 33% in July ’21 and April ’22, respectively. Thus, two years after the outbreak of the pandemic there is almost no recovery in terms of the mental health of the Spanish population. The same can be observed in the negative answers. By grouping together the "a bit more than usual" and "much more than usual" answers, we document that previous to the pandemic only 16% of respondents are feeling more depressed than usual in the last two weeks. However, this percentage increases to 46% in April ’20, 30% in July ’20, 28% in July ’21, and 30% in April ’22. Thus, the share of respondents in these two categories has more than doubled since before the pandemic, providing clear evidence of the deterioration in the mental health conditions of the population. The percentage of respondents answering "no more than usual" does not change much relative to pre-pandemic data in April ’20 (24.5%), but increases to about 33% in July ’20 and remains there through July ’21 and April ’22. Overall, after the outbreak of the pandemic we document a strong increase in the share of the population that reported feeling more depressed or unhappy than usual in the last two weeks. Although the numbers are larger in April ’20 and there seems to be a mild recovery from July ’20 onward, it is important to highlight that the share of individuals feeling depressed in April ’22 (de-

[12]The share of responses changes from 23% previous to the pandemic to 17%, 15%, 11% and 9% in April ’20, July ’20, July ’21, and April ’22, respectively.

[13]In April ’20, July ’20, July ’21 and April ’22 more than 60% of respondents (66.5%, 62.4%, 63.1%, and 62.6%, respectively) consider their health to be "good" whereas before the pandemic this answer is given by just 55% of respondents.

[14]The arguments and mechanisms behind this relationship are usually related to reductions in the probability of eating out (which is typically associated with higher caloric intake) as a result of lost income and an increased probability of exercising due to the increase in free time resulting from joblessness. Furthermore, lower stress levels are also reported as work-related demands disappear. This leads to increases in the number of hours slept and a reduction in the incidence of cardiovascular problems (see Bellés-Obrero and Vall Castelló, 2018, for a survey of the literature).

[15]The exact wording of the question is "*In the last two weeks, have you felt unhappy or depressed?*".

spite it being two years after the onset of the pandemic and there being no restrictions in place) is still significantly higher than before the pandemic.[16] Taken together, our results indicate that the mental health deterioration is not followed by a similar drop in general health.

3.2. Heterogeneous effects

3.2.1. Group-level differences

We continue by documenting the unequal effects of the pandemic on the health conditions of different socio-economic groups.[17] Figures 2(b) and 3(b) show results for general and mental health, respectively. Dots show the results for April '20, diamonds for July '20, squares for July '21 and triangles for April '22. We report 95% confidence intervals around the group means, and the dashed vertical lines represent mean values of the dependent variable for each survey wave.

Figure 2(b) shows that differences in general health are small across groups. Results indicate some deterioration in the health status of the labor market category "others", which includes individuals that are unable to work (representing 4% of our sample), in later periods (July '21 and April '22).

Figure 3(b) shows the results for mental health. Here, in contrast, important heterogeneity emerges. First, women report not being unhappy or depressed at lower rates than men in all four waves of our survey and are more likely to suffer from depression. The likelihood that women report having good mental health is 15 percentage points lower than men in April '20 and around 11 percentage points lower in July '20, July '21 and April '22.

In addition, we observe significant mental health differences across the occupational categories of respondents. Our results indicate that individuals with a stable employment situation (civil servants, those with a permanent contract or pensioners) are more likely to report positive mental health outcomes than the unemployed or students. Furthermore, individuals that have lost their job during the pandemic have a lower likelihood

[16] Figures A2, A3, and A4 replicate results for the other three questions that capture additional dimensions of mental health: insomnia, feeling overwhelmed and tense, and finding it difficult to overcome the difficulties in life. The general pattern is comparable to the question on feeling depressed or unhappy, although changes during the pandemic seem a bit milder in these other three outcomes.

[17] As a first step, we document heterogeneity by estimating a linear probability model where we group positive outcomes and code them as a binary variable (see Table D1 in the appendix for the exact grouping of all variables used.):

$$H_{i,g} = \sum_{g=1}^{g=n} \beta_g \times D_{i,g} + \epsilon_{i,g} \tag{1}$$

where $H_{i,g}$ is the binary health variable indicating a positive outcome when it is equal to 1, $D(i,g)$ is a dummy equal to 1 if individual i belongs to group g, and β_g measures the probability that members of a given group report a positive mental health outcome. We run a separate regression for the group characteristics that have been identified in the literature as having substantial within-group differences.

of reporting a good mental health status.[18]

When we look at differential effects by age, we observe that the young (18-44) are less likely to report positive mental health outcomes while the older group (66 and older) is substantially more likely to do so in all four waves of the survey. In April ’20, only 46% of young individuals report positive outcomes (63% in July ’20, 65% in July ’21 and 63% in April ’22). This share is 74% for the older group (82% in July ’20, July ’21 and April ’22). Thus, it is striking that those individuals with the highest risk of being hospitalized as well as the strongest mortality risk are in better mental health than the younger group. One possible explanation is that potentially higher social needs of younger people drive this effect.

We also provide evidence that mental health varies by household income: members of low-income households (below 1,250 Euros per month) are less likely to report positive mental health than those with higher income. Interestingly, having children at home shows a small but positive effect on participants’ psychological well-being in the first two waves of our survey. Finally, we do not observe that education level has a significant impact on mental health. All these heterogeneous effects are similar for the other three mental health questions in the survey.[19]

It has to be noted that in Spain there are important correlations between the labor market situation, income, gender and age. The unemployment rate is higher for women and unemployment is a substantial problem in the Spanish labor market.[20] Due to these correlations the analysis implemented so far is unable to isolate the effect on mental health that can be attributed to each of these three characteristics. This limitation is addressed in the analysis implemented in the following sub-section.

3.2.2. Machine learning

To deliver a more causal interpretation of heterogeneity and to overcome the potential problem of correlation between various socio-economic dimensions, we apply machine learning methods to disentangle the most important dimensions of heterogeneity in a non-parametric way. We apply a random forest algorithm to rank the characteristics previously identified in the heterogeneity analysis.

Figure 4 shows the results for the relative importance ranking. The variables on the vertical axis rank characteristics by their importance relative to the most important one (on the top of the axis) for the different waves of our survey. In April ’20, the algorithm

[18] We ask individuals for their current situation in the labor market and also for the situation in February 2020. Combining these two questions allows us to identify individuals that became unemployed during the pandemic. We also consider as unemployed those that are placed on furlough schemes implemented throughout the pandemic.

[19] The results are reported in panel b) of Figures A2, A3 and A4.

[20] For instance, in the first quarter of 2020 in Spain, the overall unemployment rate was 14.41%; the unemployment rate for women was 16.24%, while it was 12.79% for men. At that same point in time, the unemployment rate for individuals younger than 25 was 32.99% (source: INE).

identifies gender as the most important determinant for reporting a good or bad mental health status, followed by living in a low-income household with a predictive capacity of 92% relative to the gender effect. This is followed by being young, the labor market situation, education and having kids. Results are very similar for the July '20 wave, where the algorithm identifies gender as the most important determinant, followed by being highly educated, loosing employment, being young and having kids (with an explanatory capacity of between 95% and 88% of that of gender). These characteristics are also identified as the main determinants of the mental health status in July '21, but with changes in their relative importance. In this wave, the algorithm identifies being unemployed, gender, being highly educated and being young (88%) as the most important determinants of the mental health status. In the same line, in April '22 being highly educated, being self-employed, being young, being a civil servant, and gender (92%) are the most important determinants of mental health.

Overall, gender, age and labor market conditions (measured by occupational categories) turn out to be the main determinants of individuals' mental health conditions. While at the very beginning of the pandemic (April '20) gender has a significantly higher explanatory capacity, it becomes similar to the explanatory capacity of age and the labor market situation in later periods. Household income, having kids and being highly educated are the following most important characteristics. These groups are very similar to those identified in our previous analysis.[21] Fortunately, for all these variables information exists in the pre-pandemic surveys, which allows us to analyze if those differences emerged as a consequence of the pandemic or are permanent gaps that already existed between these groups prior to the pandemic. Section 4 discusses this point.

3.3. Mediation analysis

As a further step, we implement a mediation analysis to analyze the mechanisms behind the main heterogeneous effects documented so far. To highlight the importance of this issue, one could think about the gender effect as either genuine differences in the mental health conditions of men and women or by gender differences in reporting behavior. However, part of this effect likely depends on other conditions which affect all individuals' psychological conditions in crisis situations, while some groups might be more exposed to them than others. As shown before, besides personal characteristics, labor market conditions play an important role. In this analysis, we document the relative importance of direct effects of unchangeable characteristics (i.e. gender and age) and potential underlying mediators (such as occupation, education, and income). This is

[21] Again, we find very similar results for the three other questions related to mental health status. Figures A2, A3 and A4 show the results in panel c). Panel a) of Figure A1 shows results for general health. In line with previous results, the relative explanatory power of variables is decreasing much faster than for mental health variables, indicating less heterogeneity in this case.

particularly important when thinking about policy responses to crisis situations, as many mediator variables could be alleviated through proper policy responses.

We follow the estimation procedure of Yu and Li (2017), which implements mediation analysis in the presence of categorical variables. Note that the total effect $\hat{\beta}$ corresponds to the results from Equation 1 documented before. Including all potential mediators as controls allows us to estimate the direct effect. The difference between the total and direct effect is the indirect effect. The impact of different mediators on the total indirect effect is then estimated by a system of simultaneous equations.[22]

Table A4 shows the estimated direct effects. After controlling for occupational status, age, household income, education and having kids, the gender gap in mental health persists, but the magnitude decreases relative to the unconditional difference documented before. In April '20, the probability that a woman reports good mental health is 7.9 percentage points lower than that of a man (vs. 15 without controls, which represents the measure of the total effect of gender on mental health). The direct effect of gender accounts for 5.4, 6.6 and 8.3 percentage points of the gap between men and women in July '20, July '21 and April '22, respectively (vs. 11 in July '20 and July '21, and 12.5 in April '22 without controls). This shows that throughout all four waves of the survey the direct effect of gender on mental health is estimated to be around 50% of the total effect of gender on mental health.

As a next step, we decompose the total indirect effect into the components of different mediator variables. Figure 5 summarizes the results for all survey waves. Each of the panels first reports the contribution of the direct effect to the total effect in the first (blue) bar and the remaining bars indicate the contribution of the different mediators. Results show that, in the first three waves of the survey, an important share of the effect of gender on mental health is due to mediation effects through the labor market. More specifically, in April '20, 30% of the effect of gender on mental health is explained by the labor market shock which had a stronger impact on women. This share goes down to 17.4% in July '20 and up again to 30.7% in July '21. In April '22, the labor market no longer acts as

[22] See Keele, Tingley, and Yamamoto (2015) and Gelbach (2016) for a detailed description of mediation analysis. In brief, mediation analysis estimates a simultaneous equations model. Equation 2 estimates the direct effect of the various mechanisms on mental health, including all potential mediators and covariates (i.e. Equation 1 with the addition of mediators as controls):

$$H_{i,g} = \theta \times D_{i,g} + \sum_{g=1}^{g=n} \beta_g \times M_{i,g} + \gamma \times X_{i,g} + \epsilon_{i,g} \tag{2}$$

where, if D is *Female*, $\hat{\theta}$ captures the direct effect of gender on mental health, M denotes a potential mediator of the effect of gender on mental health and X is a vector of control variables (that include all other potential mediators). A set of equations 3 estimate the effect of gender on the potential mediators ($\hat{\delta}$):

$$M_{i,g} = \mu \times D_{i,g} + \delta \times X_{i,g} + \epsilon_{i,g} \tag{3}$$

The effect of gender mediated by a given mediator (indirect effect) is equal to $\hat{\mu} \times \hat{\beta}$, where $\hat{\mu}$ is the estimated coefficient of the mediator M in equation 3 a mediator for the gender effect on mental health. This is consistent with what we report in Figure 1 as by then the negative effect of the pandemic on employment has fully recovered.

These results are robust to the specific mental health question used, as shown in panel d) of Figures A2, A3 and A4. In general, the effect is larger in the first wave of our survey, potentially due to higher uncertainty in the labor market. The mediator effect disappears after two years, in 2022.

We repeat the analysis to document the mediator effects on the heterogeneous effect of age. Results (see Figure A5) indicate that none of the potential mediators gains significance, and the impact of age is entirely driven by its direct effect.

4. Long-run trends and the impact of occupation

We complement the previous analysis by documenting the differences in mental health across groups over a longer time horizon. We explore the evolution of the mental health gap along five dimensions (age, gender, income, education, and having children) which we can consistently observe over time.

We proceed in three steps. First, we show the long-run trend across groups by plotting mean outcomes over time. We then estimate the difference between groups relative to a baseline group and to 2017 (as the last pre-pandemic data point) using the following equation:

$$MH_{i,g,t} = G_g \times \left[\sum_{y=-3}^{y=-1} \beta_y * \mathbf{1}(t-0) + \sum_{y=1}^{y=3} \delta_y * \mathbf{1}(t-0) \right] + \gamma + \epsilon_{i,g,t} \tag{4}$$

where MH is coded binary as before, $\mathbf{1}(y = t-0)$ are indicators for each event year relative to $t = 0$ (2017), β_y correspond to the gap in mental health for group g relative to the reference group before the pandemic and δ_y measure the evolution of the mental health gap during the pandemic. We include a full set of cell-level fixed effects γ to our estimations.[23] These cell fixed effects capture any time invariant element for a given combination of a specific group. We cluster standard errors at the cell level. In an alternative specification, we also perform this regression controlling for occupation-group effects over time in order to separate the impact of our variable of interest from any occupation specific element, i.e.

[23]We include fixed effects for age, gender, education, occupation and household income. In total, there are 490 fixed effects.

$$
\begin{aligned}
MH_{i,g,t} = & G_g \times \Big[\sum_{y=-3}^{y=-1} \beta_y * \mathbf{1}(t-0) + \sum_{y=1}^{y=3} \delta_y * \mathbf{1}(t-0) \Big] \\
& + O_g \times \Big[\sum_{y=-3}^{y=-1} \mu y * \mathbf{1}(t-0) + \sum_{y=1}^{y=3} \nu y * \mathbf{1}(t-0) \Big] + \gamma + \epsilon_{i,g,t}
\end{aligned}
\tag{5}
$$

The main difference between Equations (4) and (5) is that the latter controls for differences over time on the occupational status. In other words, the first equation assumes that the mental health effect of having a full-time or part-time contract, being unemployed, or any other occupational group is the same across periods, while the latter model allows for a differential impact of these occupational categories over time.

Panels on the left of Figure 6 show the evolution of each group over time, while panels on the right plot the estimates for each period according to Equations (4) and (5).[24]

Panels a) and b) of Figure 6 illustrate the gender effect. Panel a) shows that previous to the pandemic, on average, men's mental health is better than that of women and that this difference is approximately 6 percentage points and was quite stable over time.[25] During the pandemic, the figure shows a clear decline in mental health for both men and women, but this drop is more pronounced for women and in April '20 the mental health gap by gender has increased to 15 percentage points. Panel b) shows the estimates of Equations (4) and (5). Before the pandemic, there was no difference in the gender gap on mental health relative to 2017. Panel b) shows an *unconditional* gap between men and women, relative to that of 2017 of 11 percentage points in April '20, which decreases to 5.9 in July '20, followed by an increase to 6.9 in July '21 and to 7.6 in April '22. However, the gap shrinks once we control for the dynamic effects of occupation. The dashed-dotted line shows a *conditional* gap in April '20 of 5.6 percentage points, 2 and 3 percentage points in July '20 and July '21, respectively and the results are only marginally significant. Only in the last wave of our survey, in April '22, does the gap in mental health widen again (5.2 percentage points) and become significant. These results indicate that around half of the gender difference in mental health can be explained by differences in occupations across groups.[26] These results document that women's mental health is more affected by the pandemic, but that an important part of the effect is related to underlying labor market

[24] Table A8 in the appendix shows the point estimates for various specifications and combinations of fixed effects. The graphs correspond to columns b) and c) in the table, which also shows OLS results (column a), a model controlling for all group trends in a dynamic way (column d), and estimations including cell-region fixed effects for those models in columns e) to f).

[25] For instance, in 2009, at the beginning of the previous economic crisis, there is a difference between men's and women's mental health status of 5.8 percentage points (the share of respondents with a positive mental health status is 78.6% for women and 84.5% for men). In 2017 this difference is 5.4 percentage points (85.5% for women and 91% for men).

[26] In line with our mediation analysis, controlling for all group effects as indicated in column d) of Table A8 reduces the gap even further. In one of the more demanding specifications, where we control for occupation effects that vary over time, cell fixed effects per region and cell effects that vary over time (column f), we estimate a significant mental health gap of 6.5 percentage points in April '20 and persistent to 5.3 in April '22, relative to that in 2017.

conditions, in line with results from the mediation analysis.

Panels c) and d) of Figure 6 plot the percentage of individuals who never feel unhappy or depressed for three different age groups: the young (18-44), the middle-aged (45-65) and the elderly (66 and older). Panel c) shows that those in good mental health represent between 80% and 90% of the respondents in each of the three age groups and that the three groups exhibit similar trends over time before the pandemic. We observe a strong drop in the percentage of respondents who never feel unhappy or depressed in first wave of our survey. This is particularly pronounced for the young (to less than 50%) and the middle-aged (around 55%). It slightly improves in July '20 and remains at those levels in July '21 and April '22. In panel d) we observe that, relative to the middle-aged, there was no statistical difference in the mental health gap over time for the young or elderly before the pandemic. After the outbreak of the pandemic, the elderly group is reporting much better mental health outcomes while the younger group experiences substantially worse mental health outcomes.[27] Results indicate that differences do not disappear when we control for occupational status (although they do become slightly smaller) and they are persistent two years after the onset of the pandemic (April '22). Although the elderly group shows an improvement in their mental health status, this effect vanishes once we control for occupation. This suggests that the improvement for the elderly is driven by the fact that most of them have stable incomes, in particular old-age pensions.

The role of income is documented in panels e) and f) of Figure 6. The share of respondents in good mental health is higher for people with high household income. Positive mental health outcomes decrease during the pandemic across all income groups and there is no clear change in the gap between income groups after the pandemic.[28] The evolution of mental health by income groups follows similar trends in both periods, before and after the pandemic. Similar results emerge for low- and high-educated individuals in panels g) and h). The share of respondents in good mental health is higher for highly educated people but positive mental health outcomes decrease during the pandemic in all groups to a similar extent.

Finally, we compare households with and without children (panels i) and j). Results show a very similar evolution before the pandemic and an improvement for households with children in 2020. This positive impact disappears once we control for the occupational situation of the respondent, indicating that the labor market status and work organization arrangements may partly explain the protective (mental health) impact of children.

We repeat this exercise for the other dimension of mental health included in our sur-

[27]Point estimates in Table A8 confirm that the share of young individuals who report not feeling unhappy or depressed is around 10 percentage points smaller than the share reported by the middle-aged group.

[28]To provide a cleaner graph, we merged the two middle-income categories (household income between 1251 and 2500 Euros per month, and 2501 and 4500 Euros per month).

vey. Results are shown in Figure A6 and Tables A9, A10 and A11 in the appendix. The most important results are that low-income individuals have a higher probability of facing insomnia and being overwhelmed/tense. The elderly report a lower probability of insomnia, consistent with the result on feeling depressed. The question of individuals' ability to face problems and overcome difficulties shows very similar patterns to the depression question across all groups.

These results highlight some important elements. First, we document a strong deterioration of the mental health status of the Spanish population during the pandemic. Second, this effect is so large that there are no previous events with a similar mental health shock when looking at data from the previous decade. Third, the strongest differences that appear across groups during the pandemic are along gender and age dimensions. Fourth, for the groups where we document a mental health gap, we show that the effect can be at least partially explained by occupational differences. Thus, the individuals' labor market situation explains a substantial part of the effect of the pandemic on mental health.

5. Conclusion

This is the first paper providing longitudinal evidence of the impact of Covid-19 on the mental health gaps across gender and age dimensions for the Spanish population. It uses a large survey implemented at four different points in time: at the peak of viral incidence (April '20), in a low-incidence scenario but with mobility restrictions (July '20), in a mid-incidence scenario with almost no mobility restrictions (July '21) and, finally, in a no-restrictions but mid-incidence scenario (April '22). We benchmark the questions included in our survey against those used in previous surveys to precisely quantify the deviations from long-term trends in the existing mental health gaps driven by the outbreak of the virus.

When compared to the pre-pandemic situation, our results show a strong deterioration in all the mental health outcomes included. This effect is unequally distributed across sub-groups of the population: women and younger individuals are more affected by the negative mental health effects. On the other hand, citizens with a more stable labor market status are less exposed to the negative mental health consequences. Importantly, we document that those gaps in mental health are relatively persistent over time, even in the low-incidence contagion scenario.

Our results are policy relevant for several reasons. First, the absolute drop in mental well-being is worrisome and must be addressed by the healthcare system. The magnitude of our results also indicate that more resources are likely to be needed, a point which must be carefully considered by policy makers. Second, our results have highlighted groups of the population which are particularly vulnerable. Community workers should be particularly attentive to those groups and precautionary measures should be introduced to foster the mental health recovery of people in vulnerable conditions. However, it is important to note that we document a negative effect that affects all people, and general access to universal assistance is crucial.

The use of survey data is subject to some criticism. Self-reported health evaluations can be biased. However, as administrative data takes more time to be released at the individual level, survey data can be used to fill this gap. At the aggregate level, we already have some early evidence using administrative sources on the consequences of this mental health distress. Figure 7 plot the number of suicides in Spain from the mortality registers for men and women by age group. The increase in suicides for women aged 45-65 in 2020 (with respect to the previous years) becomes apparent. Therefore, our survey results can be seen as a warning signal to implement preventive measures before the more severe consequences are reflected in administrative data.

We believe our findings are important to inform policy makers on the potential healthcare needs of the population once the emergency situation progressively fades away. It is crucial to start thinking about the following phases and to plan the response according to the medical needs of the community. In that sense, our results suggest a need to design mental health action plans to address the size of the reported mental health effects. Plans will also have to account for the expected persistence of these effects in the medium- to long-term which could lead to more severe consequences.

Lastly, the heterogeneous role of occupations should be considered when designing safety nets, such as unemployment programs and labor market regulations. We show that much of the effect can be explained by individuals who are exposed to more vulnerable situations. To avoid some of the psychological costs of future crisis and recessions, the benefits of more stable assistance programs must be considered. While not all parts of society can be sheltered against unemployment during a crisis, properly defined welfare programs can mitigate the economic consequences of losing ones' job. In parallel, labor market reforms might prove helpful in minimizing the pre-crisis level of exposure for people with vulnerable conditions by restricting the (over)use of short-term contracts, for example, which in the Spanish context are concentrated within the most vulnerable groups.

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Figures and Tables

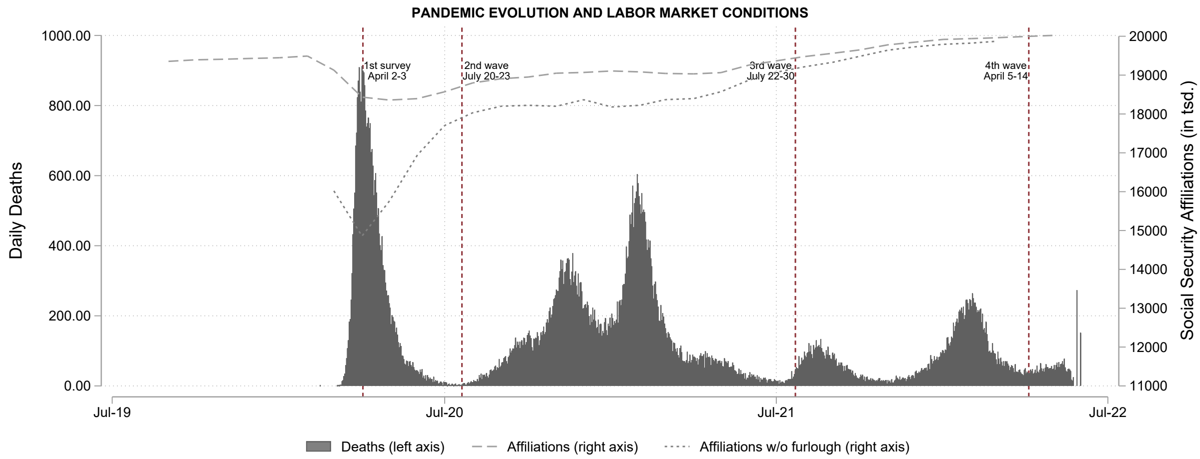
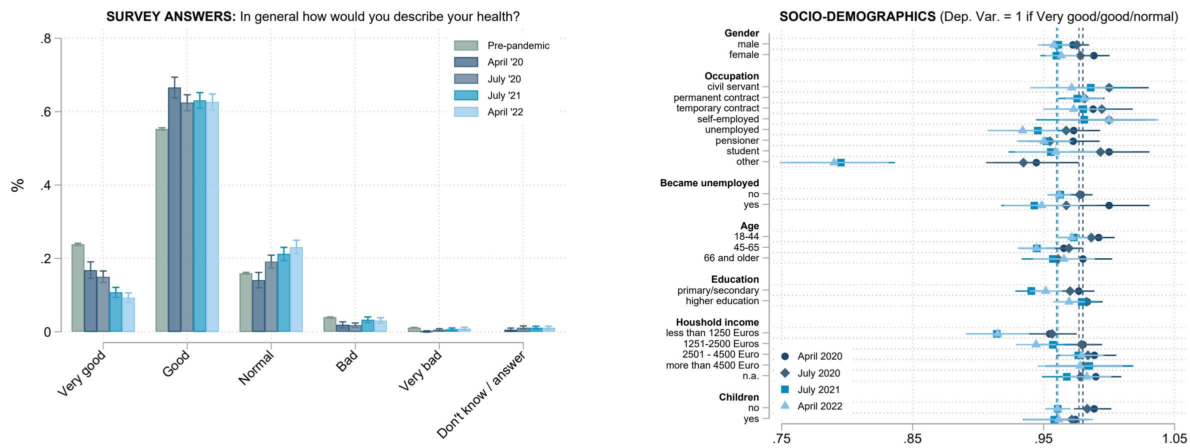


Figure 1: *Survey timing and pandemic evolution*

Notes: The figure shows the daily observation of cases (left axis). Source: World Health Organization. Vertical lines indicate the timing of our survey. The right axis measures social security affiliations including and excluding furlough policies. Data source: INE (*Instituto Nacional de Estadística*, National Statistics Institute - Spanish Statistical Office.

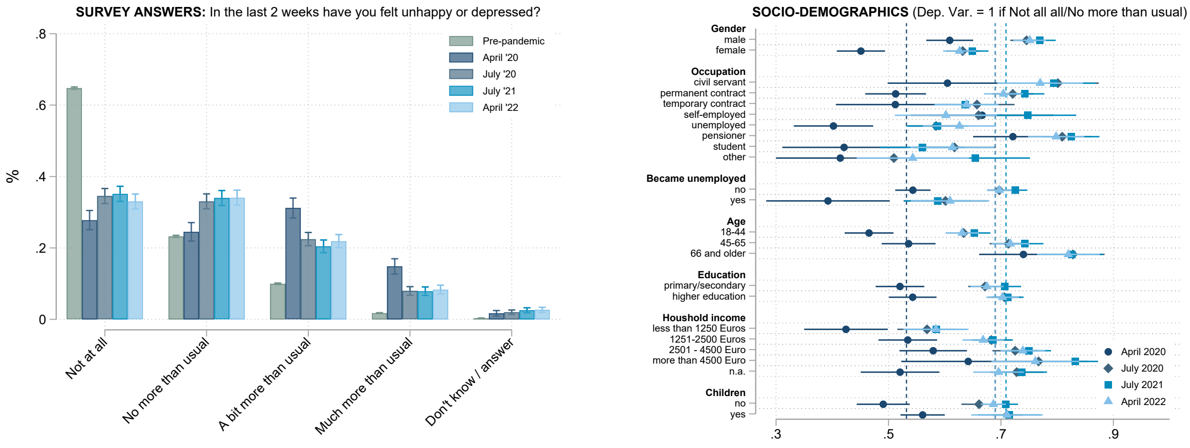


(a) Evolution over time

(b) Heterogeneity

Figure 2: *General health*

Notes: Panel a) combines the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), n=73,866) with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey. Panel b) shows heterogeneous effects for wave one (n=1,065; dots), wave two (n=1,949; diamonds), wave three (n=1,966; squares) and wave four (n=1,954; triangles) of the survey. In Panel b) positive outcomes of general health are coded as one (if the answer is very good, good or normal). It shows the effects by demographic groups (estimates of Equation (1)). Dashed lines indicate the mean per wave. 95% confidence intervals indicated in the graphs.



(a) Evolution over time

(b) Heterogeneity

Figure 3: *Mental health: feeling unhappy or depressed*

Notes: Panel a) combines the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), n=73,866) with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey. Panel (b) shows heterogeneous effects for wave one (n=1,065; dots), wave two (n=1,949; diamonds), wave three (n=1,966; squares) and wave four (n=1,954; triangles) of the survey. In Panel b) positive outcomes of mental health are coded as one (if the answer is not at all, no more than usual). It shows the effects by demographic groups (estimates of Equation (1)). Dashed lines indicate the mean per wave. 95% confidence intervals indicated in the graphs.

Figure 4: *Machine learning: random forest importance, feeling unhappy or depressed*

Notes: The figure shows the importance of different variables after running a random forest classification model for each wave of the survey. All importance values are expressed as shares of the most important determinant. The dependent variable is the positive outcomes of mental health (variable coded as one if the answer is not at all or no more than usual; zero otherwise)

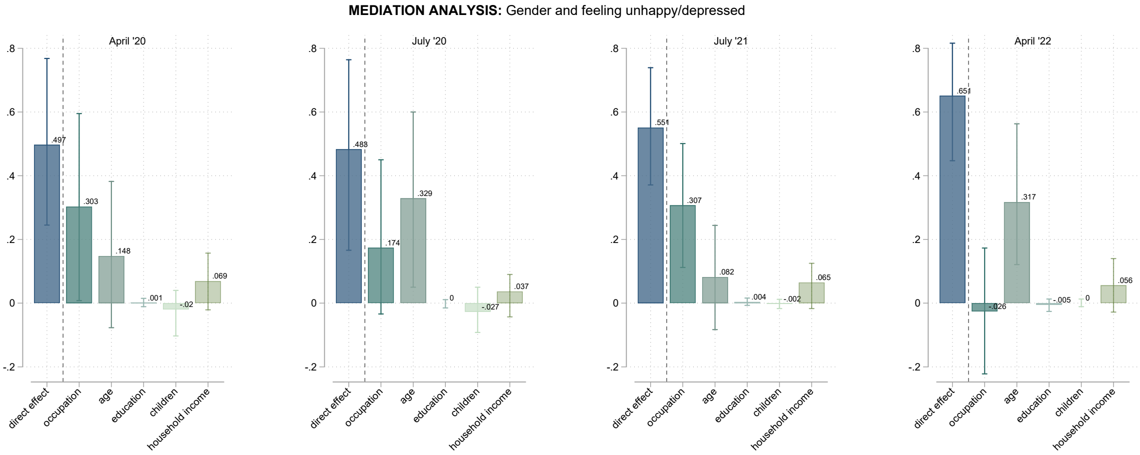
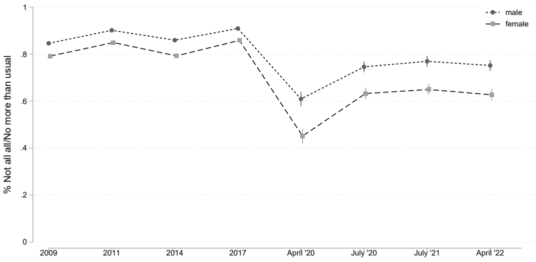
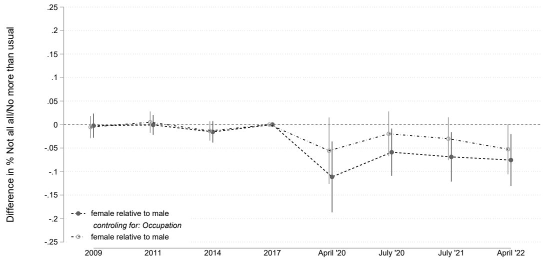


Figure 5: *Mediation analysis: Relative importance over the total effect of gender (feeling unhappy or depressed)*

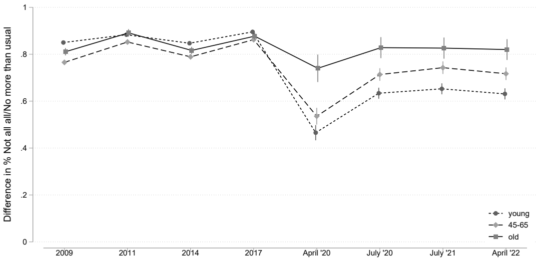
Notes: The figure shows the relative importance of direct effect of gender on mental health and the indirect effect of gender on mental health mediated through the effect that gender has on each potential mediator. 95% confidence intervals indicated in the graph.



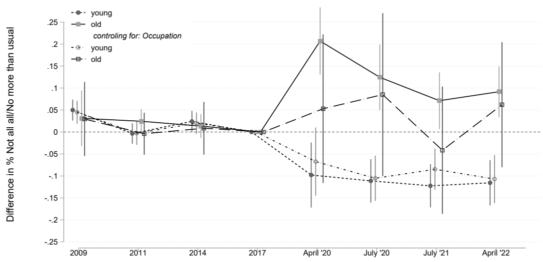
(a) Gender



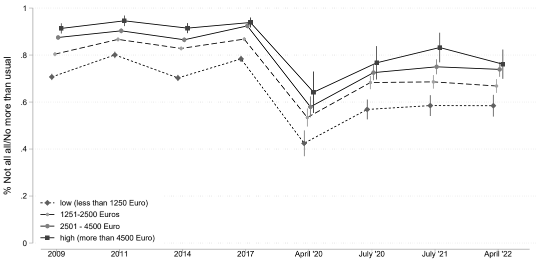
(b) Relative Difference (to Male)



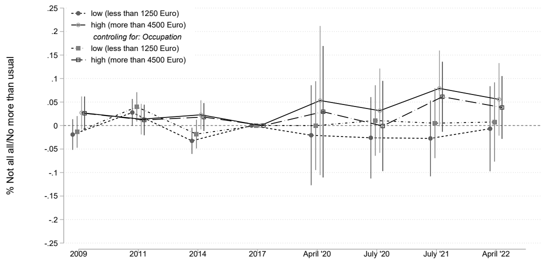
(c) Age



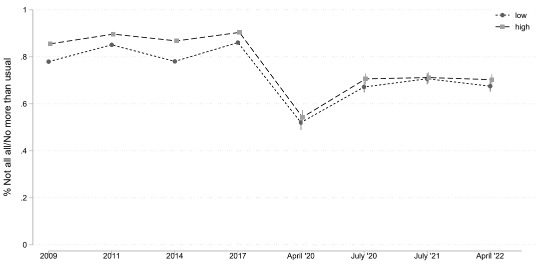
(d) Relative Difference (to 45-65)



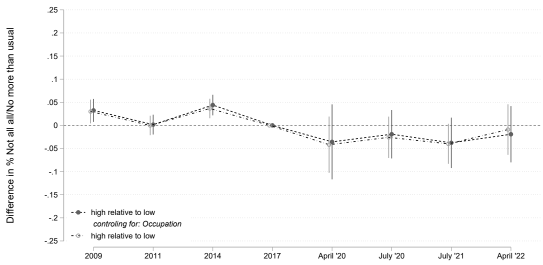
(e) Income



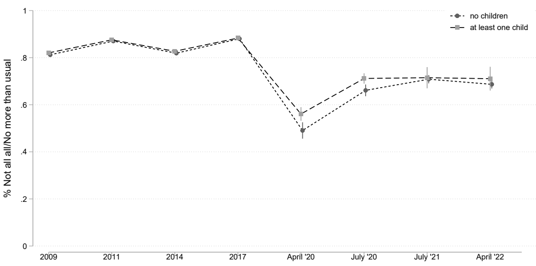
(f) Relative Difference (to 1251-4500)



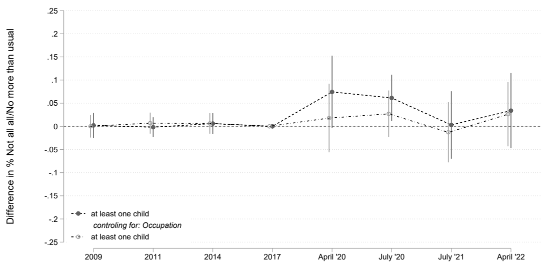
(g) Education



(h) Relative Difference (to low)



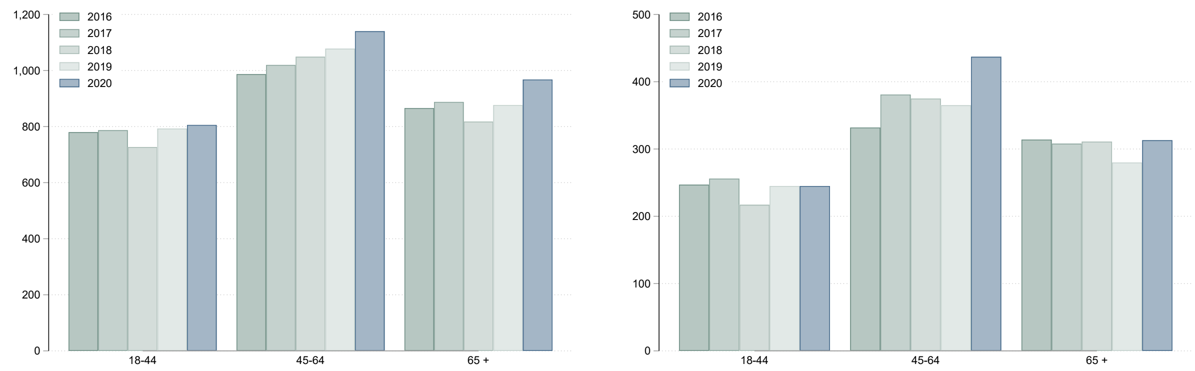
(i) Children



(j) Relative Difference (to no Child)

Figure 6: *Effects over time: mental health (feeling unhappy or depressed)*

Notes: These figures combine data from the Encuesta Nacional de Salud de España (ENS, Spanish National Health Survey) of 2009, 2011 and 2017, the European Health Survey (for the Spanish sample) of 2014 and 2009 with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of our survey (matched sample). Left panels (a/c/e/g/i) shows the evolution over time. Right panels (b/d/f/h/j) show results from equation (4) and (5). 95% confidence intervals for standard errors clustered at the cell-level indicated in the graphs.



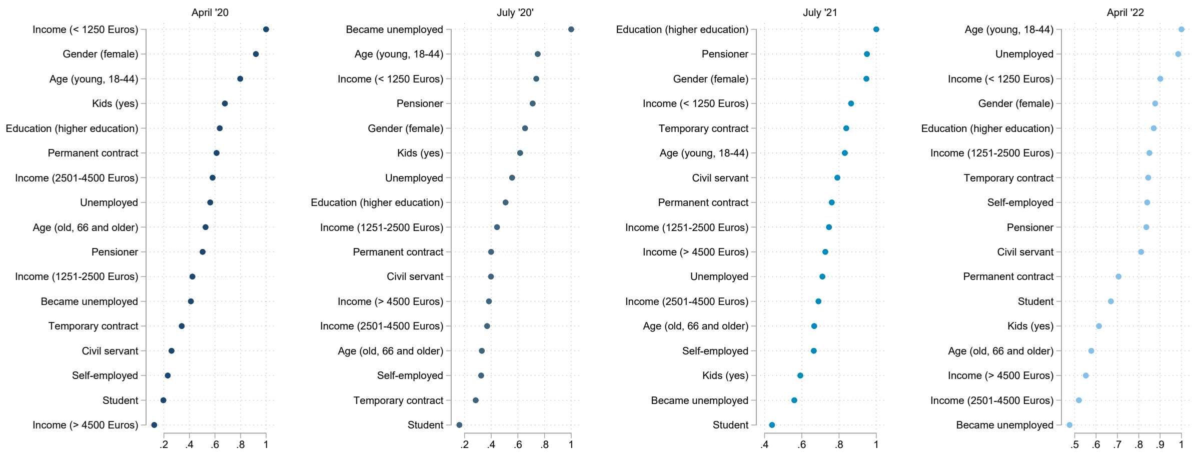
(a) Men (b) Women

Figure 7: *Number of suicides by age*

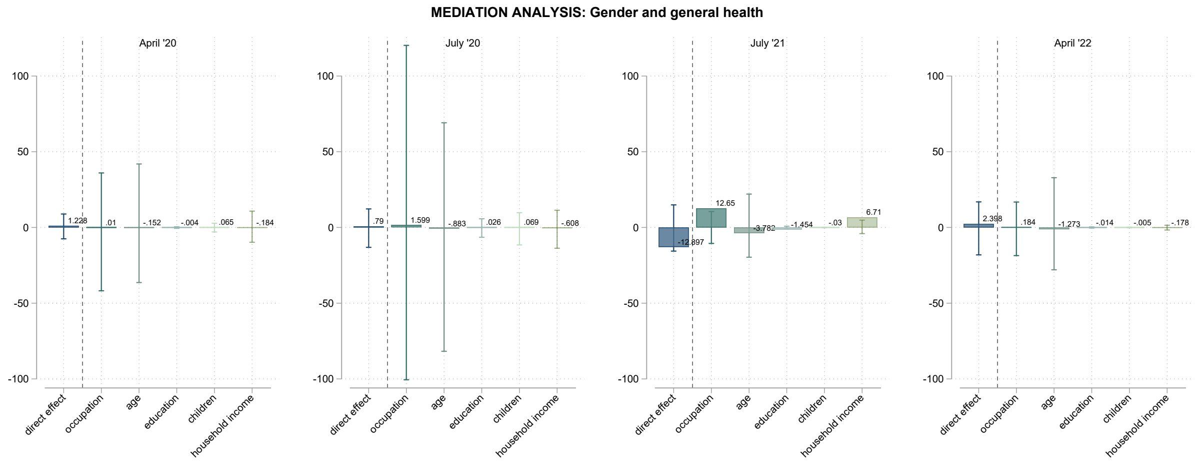
Notes: The figure shows the total number of suicides for men (panel a) and for women (panel b) in Spain by age bracket for each year from 2016 to 2020. Data comes from administrative sources; Mortality Registers collected by the National Institute of Statistics.

Appendix

A. Graphs and tables



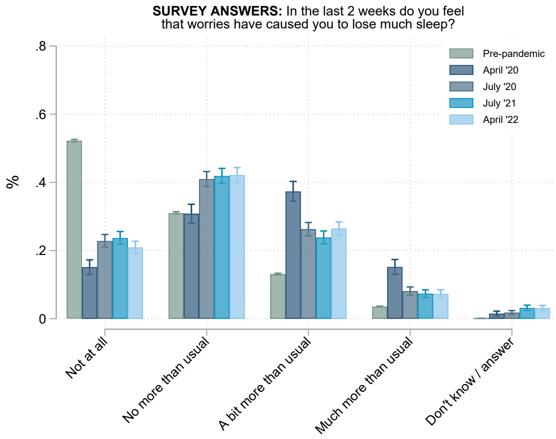
(a) Machine learning: random forest importance ranking



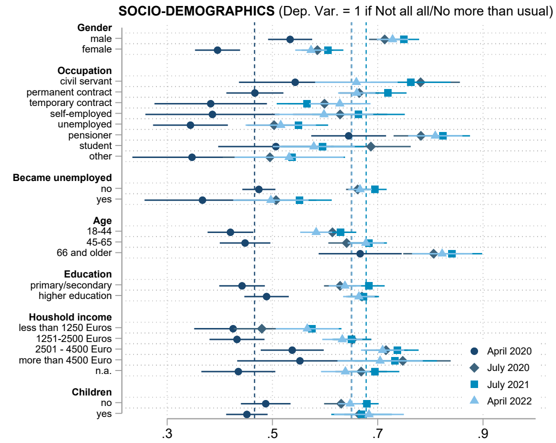
(b) Mediation analysis

Figure A1: *General health: Other results*

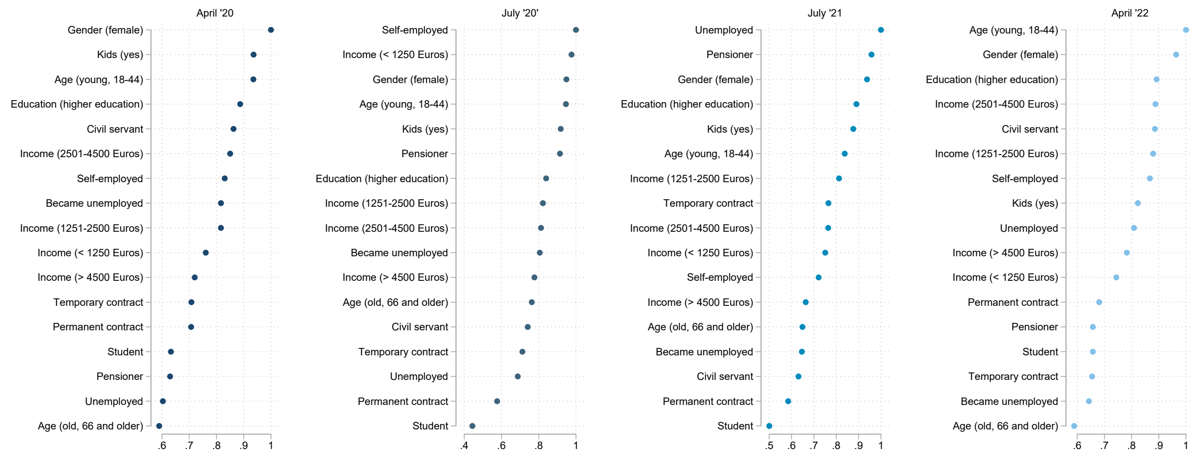
Notes: These figures use data from wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey (matched sample). Panel a) show the results of the machine learning estimation. The figures show the importance of different variables after running a random forest classification model for each wave of the survey. All importance values are expressed as shares of the most important determinant. The dependent variable is the positive outcomes of general health (variable coded as one if the answer is very good, good or normal; zero otherwise). Panel b) shows the results of the mediation analysis. The figures show the relative importance of direct effect of gender on health and the indirect effect of gender on health mediated through the effect that gender has on each potential mediator. 95% confidence intervals indicated in the graph.



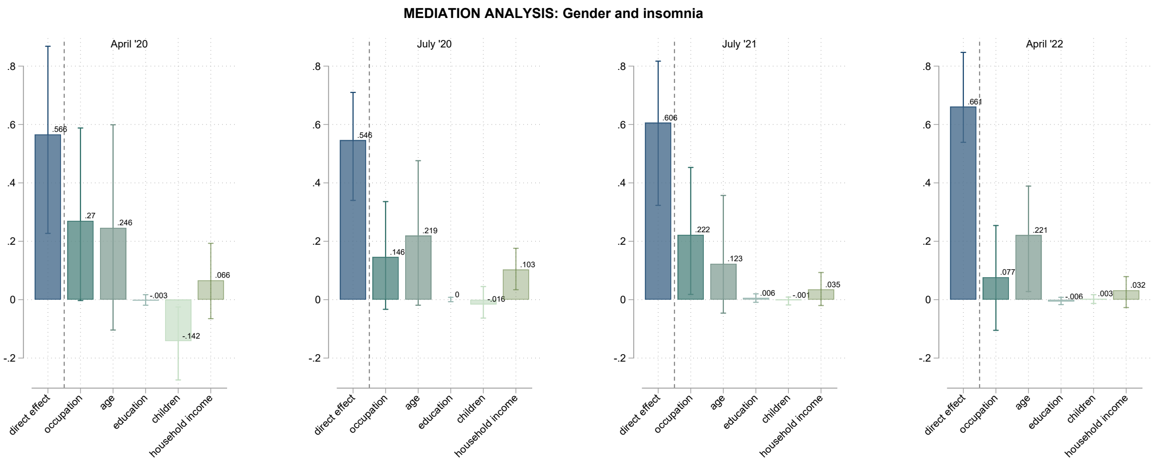
(a) Survey answers



(b) Heterogeneous effects



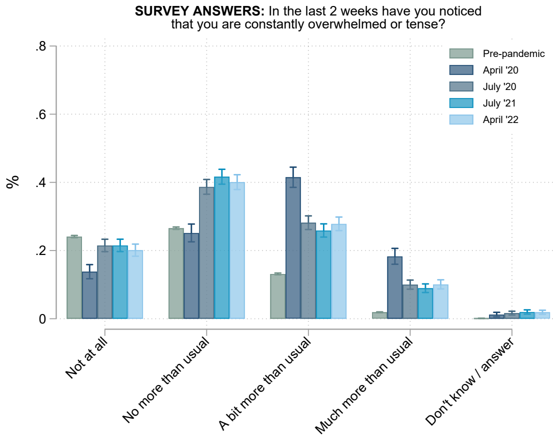
(c) Machine learning: random forest importance ranking



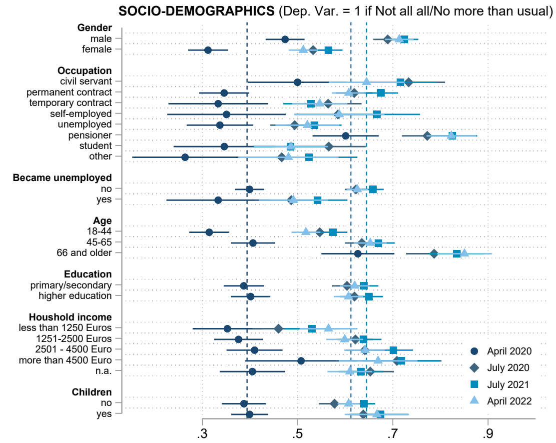
(d) Mediation analysis

Figure A2: *Mental Health - Other Dimensions - Insomnia*

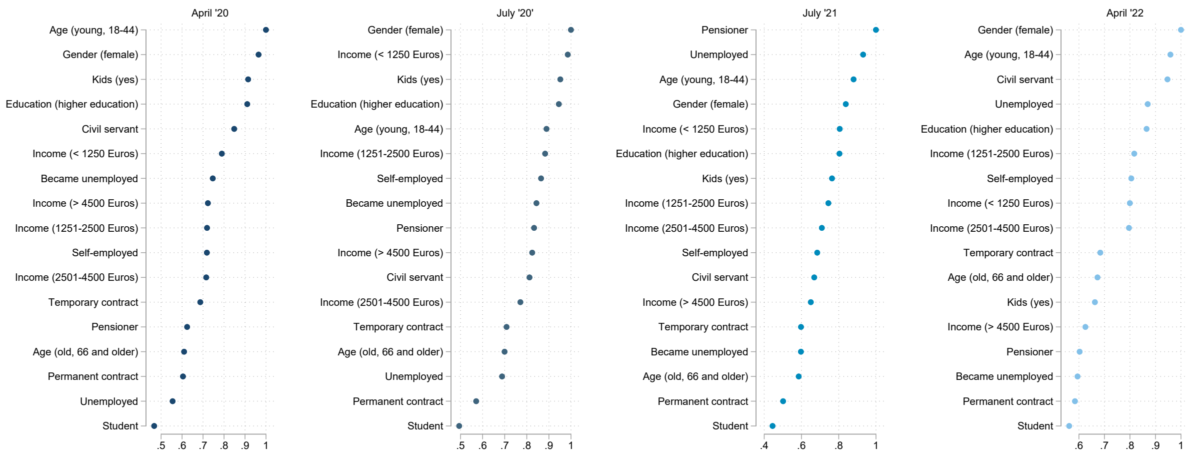
Notes: Panel a) combines the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey. Panel b) shows heterogeneous effects for wave one (dots), wave two (diamonds), wave three (squares) and wave four (triangles) of the survey. It shows the effects by demographic groups (estimates of equation (1)). Dashed lines indicate the mean per wave. Panel c) shows the results of the machine learning estimation obtained from applying a random forest algorithm. Panel d) shows the results of the mediation analysis. The positive outcomes of mental health are coded as one (if the answer is not at all or no more than usual; zero otherwise). 95% confidence intervals indicated in the graphs.



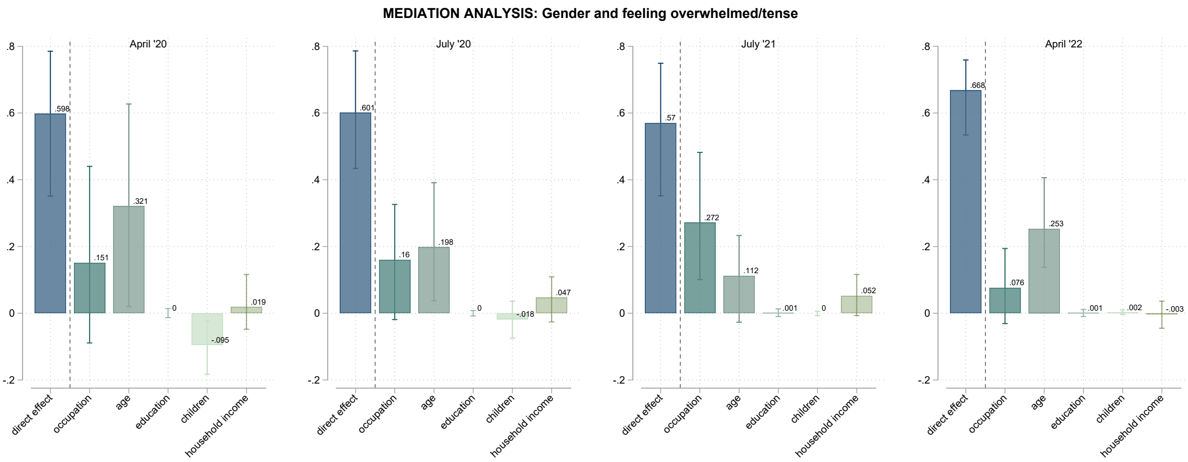
(a) Survey answers



(b) Heterogeneous effects



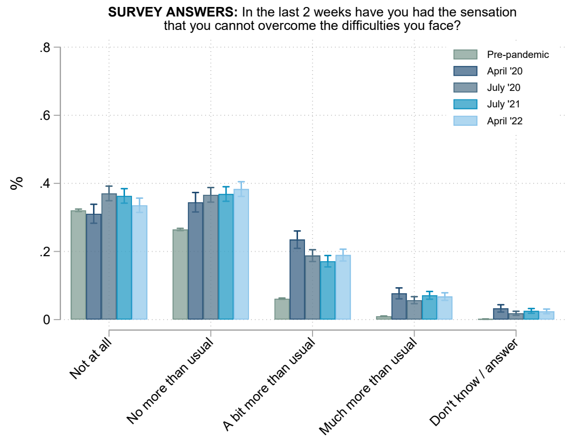
(c) Machine learning: Random Forest Importance ranking



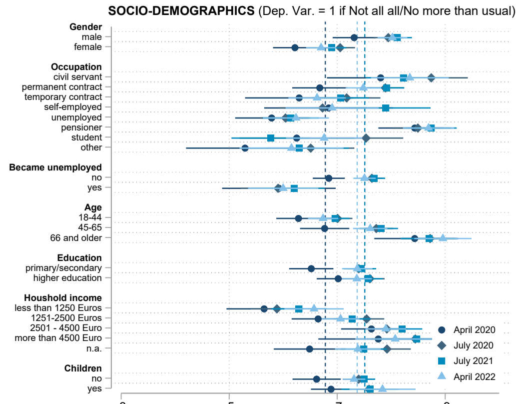
(d) Mediation analysis

Figure A3: *Mental Health - Other Dimensions - Overwhelmed/tense*

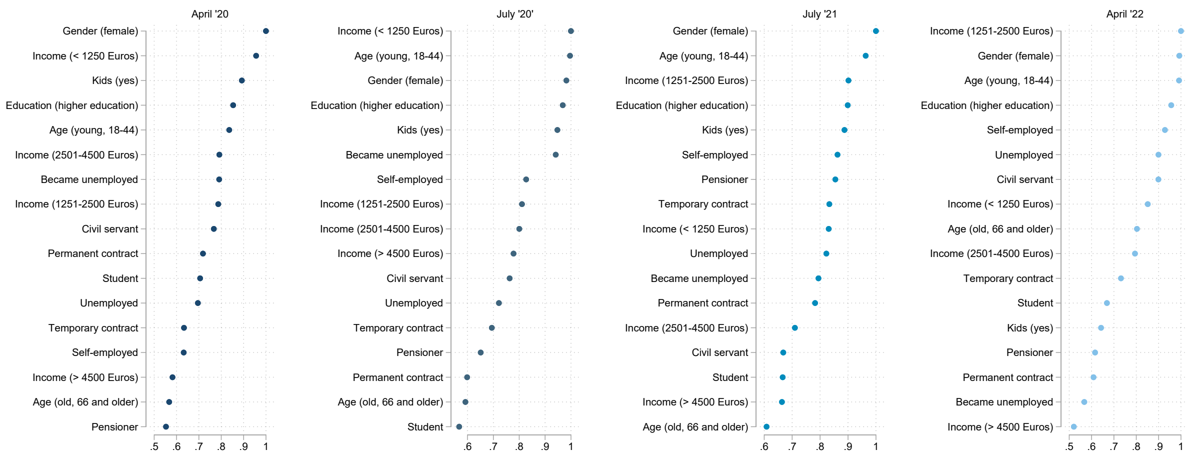
Notes: Panel a) combines the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey. Panel b) shows heterogeneous effects for wave one (dots), wave two (diamonds), wave three (squares) and wave four (triangles) of the survey. It shows the effects by demographic groups (estimates of Equation (1)). Dashed lines indicate the mean per wave. Panel c) shows the results of the machine learning estimation obtained from applying a random forest algorithm. Panel d) shows the results of the mediation analysis. The positive outcomes of mental health are coded as one (if the answer is not at all or no more than usual; zero otherwise). 95% confidence intervals indicated in the graphs.



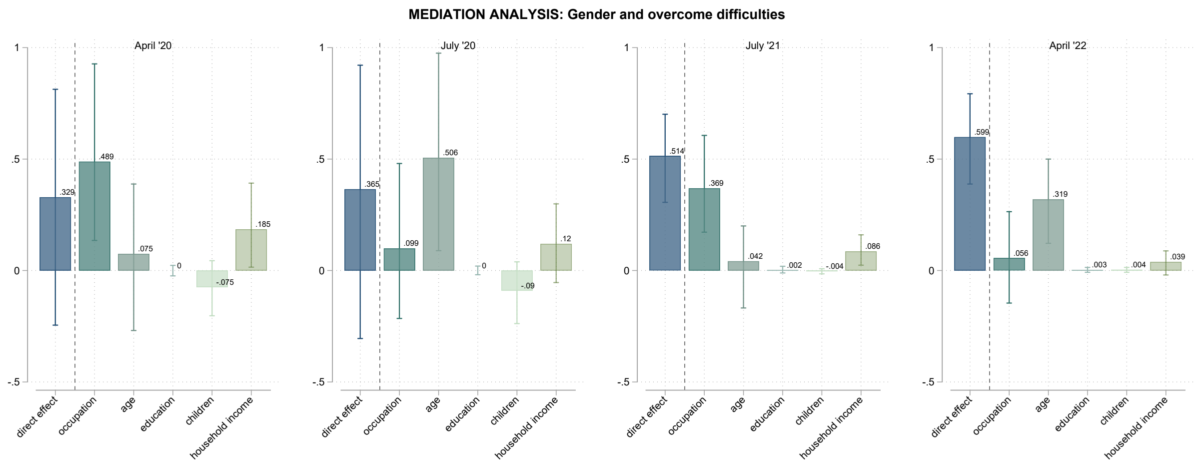
(a) Survey answers



(b) Heterogeneous effects



(c) Machine learning: Random Forest Importance ranking



(d) Mediation analysis

Figure A4: *Mental Health - Other Dimensions - Overcome difficulties*

Notes: Panel a) combines the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey. Panel b) shows heterogeneous effects for wave one (dots), wave two (diamonds), wave three (squares) and wave four (triangles) of the survey. It shows the effects by demographic groups (estimates of Equation (1)). Dashed lines indicate the mean per wave. Panel c) shows the results of the machine learning estimation obtained from applying a random forest algorithm. Panel d) shows the results of the mediation analysis. The positive outcomes of mental health are coded as one (if the answer is not at all or no more than usual; zero otherwise). 95% confidence intervals indicated in the graphs.

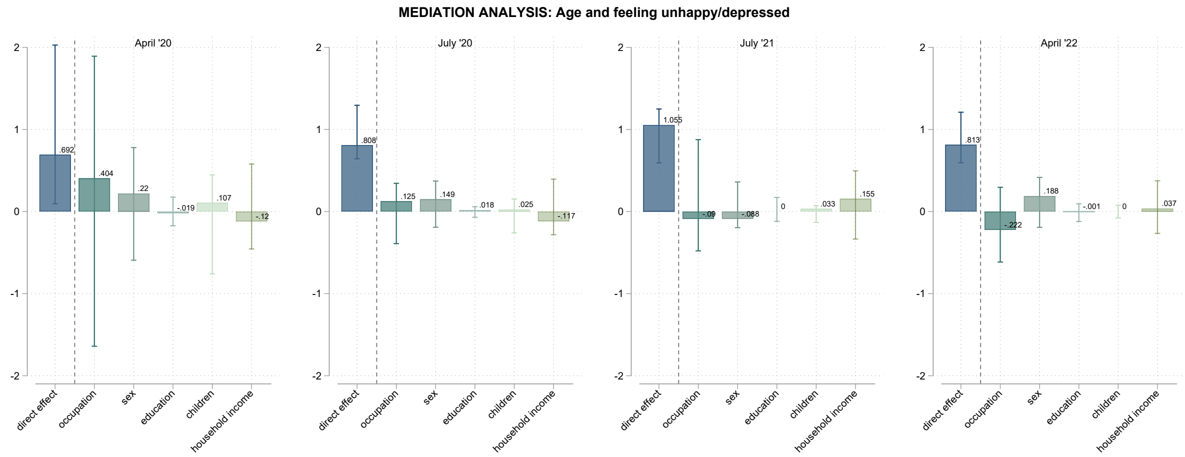
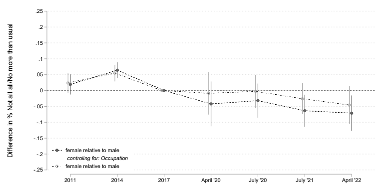
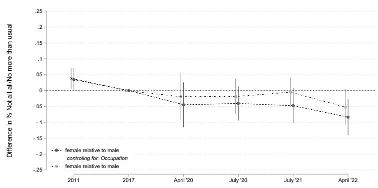


Figure A5: *Mediation analysis: Relative importance over the total effect of age (feeling unhappy or depressed)*

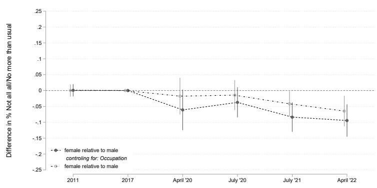
Notes: The figure shows the relative importance of direct effect of age on mental health and the indirect effect of age on mental health mediated through the effect that gender has on each mediator. Age is considered a continuous variable. 95% confidence intervals indicated in the graph.



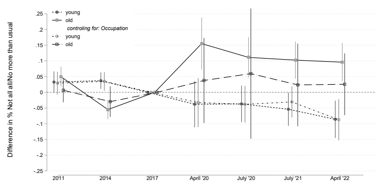
(a) Insomnia



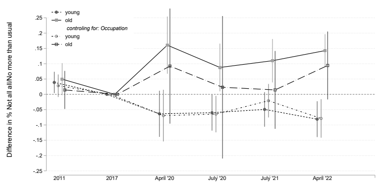
(b) Overwhelmed/tense



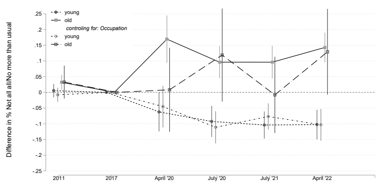
(c) Overcome difficulties



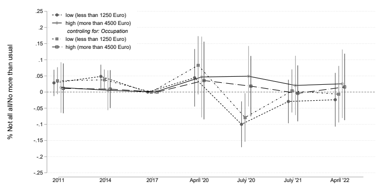
(d)



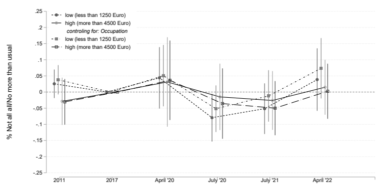
(e)



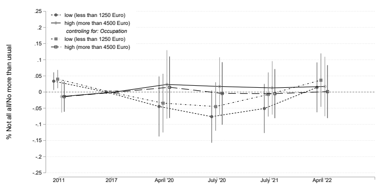
(f)



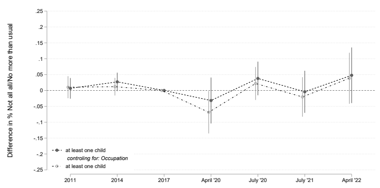
(g)



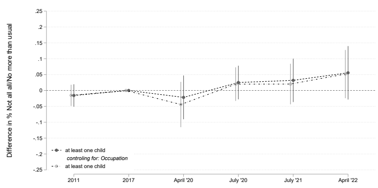
(h)



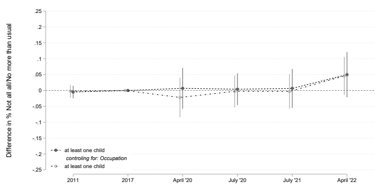
(i)



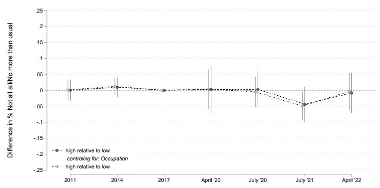
(j)



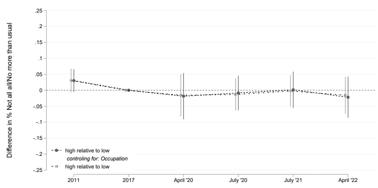
(k)



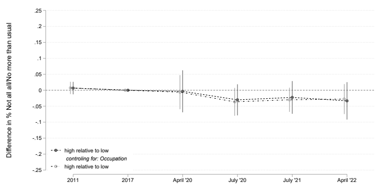
(l)



(m)



(n)



(o)

Figure A6: *Effects over time (other mental health dimensions)*

Notes: These figures use the matched data from pre-pandemic surveys (the National Health Survey (2011/12 and 2017) and European Health Survey (2009 and 2014), with wave one (n=1,065), wave two (n=1,949), wave three (n=1,966) and wave four (n=1,948) of the survey (matched sample). They show the results from Equations (4) and (5). The dependent variable is a positive mental health outcome (coded one if the answer is not at all or no more than usual; zero otherwise). The left column shows the result for insomnia, the column in the middle for feeling overwhelmed/tense and the column on the right for the ability to overcome difficulties. 95% confidence intervals for standard errors clustered at the cell-level indicated in the graphs.

Table A1: *Attrition between survey waves*

Dep.Var.	(1) 1st-2nd	(2) 2nd-3rd	(3) 3rd-4th	(4) 1st-2nd-3rd-4th
Gender	(relative to men)			
Female	-0.043	-0.012	-0.080***	0.001
	(0.031)	(0.022)	(0.021)	(0.008)
Age	(relative to 45-65)			
young	-0.083**	-0.095***	-0.090***	-0.085***
	(0.036)	(0.026)	(0.023)	(0.009)
old	0.114	0.084	0.048	0.030
	(0.082)	(0.064)	(0.057)	(0.022)
Household income	(relative to less than 1250 Euros)			
1251-2500 Euros	-0.013	0.025	0.073**	0.016
	(0.043)	(0.033)	(0.032)	(0.012)
2501 - 4500 Euros	-0.014	0.038	0.065*	0.037***
	(0.048)	(0.036)	(0.035)	(0.013)
more than 4500 Euros	-0.105	0.023	0.030	0.024
	(0.070)	(0.055)	(0.048)	(0.018)
n.a.	-0.033	0.034	0.034	0.004
	(0.048)	(0.036)	(0.034)	(0.012)
Education	(relative to high)			
low	-0.043	-0.032	-0.026	0.004
	(0.030)	(0.022)	(0.020)	(0.008)
Kids	(relative to no)			
yes	0.004	-0.014	-0.057**	-0.152***
	(0.033)	(0.025)	(0.029)	(0.008)
Occupation	(relative to civil servant)			
permanent contract	-0.034	0.001	0.021	-0.001
	(0.057)	(0.042)	(0.040)	(0.015)
temporary contract	-0.064	-0.056	0.029	-0.017
	(0.073)	(0.052)	(0.046)	(0.018)
self-employed	-0.128	-0.011	0.004	0.001
	(0.079)	(0.057)	(0.056)	(0.021)
unemployed	-0.063	0.017	0.022	-0.022
	(0.063)	(0.047)	(0.047)	(0.017)
pensioner	-0.171*	-0.031	-0.003	-0.007
	(0.088)	(0.069)	(0.063)	(0.024)
student	-0.060	-0.078	-0.047	-0.069***
	(0.077)	(0.057)	(0.055)	(0.020)
other	-0.132*	-0.005	0.063	0.000
	(0.075)	(0.059)	(0.059)	(0.021)
Region	(relative to Andalusia)			
Aragon	-0.003	0.064	0.039	0.006
	(0.090)	(0.063)	(0.060)	(0.023)
Asturias	-0.148	-0.031	-0.094	-0.050**
	(0.099)	(0.070)	(0.065)	(0.024)
Balearic Islands	-0.015	0.116	-0.095	0.009
	(0.098)	(0.078)	(0.073)	(0.028)
Canary Islands	-0.040	0.002	-0.194***	-0.015
	(0.074)	(0.057)	(0.053)	(0.019)
Cantabria	-0.008	-0.094	-0.264**	-0.037
	(0.135)	(0.110)	(0.107)	(0.037)
Castile and Leon	0.087	0.024	0.091*	0.041**
	(0.068)	(0.051)	(0.049)	(0.019)
Castile - La Mancha	0.034	-0.051	-0.039	-0.005
	(0.073)	(0.054)	(0.051)	(0.019)
Catalonia	0.016	-0.055	-0.059*	-0.014
	(0.048)	(0.036)	(0.034)	(0.012)
Valencian Community	-0.048	-0.036	-0.031	-0.016
	(0.054)	(0.039)	(0.037)	(0.014)
Extremadure	0.018	-0.015	-0.080	0.056**
	(0.096)	(0.079)	(0.073)	(0.028)
Galicia	-0.000	-0.032	0.006	-0.010
	(0.064)	(0.047)	(0.044)	(0.016)
Madrid	-0.032	-0.002	0.040	-0.009
	(0.051)	(0.037)	(0.034)	(0.013)
Murcia	-0.053	-0.048	-0.093	0.006
	(0.083)	(0.064)	(0.060)	(0.022)
La Rioja	0.040	-0.002	-0.175*	0.062
	(0.122)	(0.107)	(0.096)	(0.038)
Ceuta	-0.026	0.017	0.018	-0.020
	(0.073)	(0.052)	(0.049)	(0.018)
Melilla	0.013	0.026	-0.104	-0.020
	(0.163)	(0.116)	(0.096)	(0.036)
# Obs.	1,097	2,000	2,014	4,752

Notes: This table shows results of a linear probability model. The dependent variable is equal to 1 in column (1) if an individual participated in the first and in the second wave of the survey. In column (2) the dependent variable is equal to 1 if an individual participated in the second and in the third wave of the survey. In column (3) the dependent variable is equal to one if an individual answered the three waves of the survey. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table A2: *Sample characteristics*

Panel A:	**Original sample**				
	2009	2011/12	2014	2017	Survey
Gender					
Female	0.547	0.542	0.539	0.541	0.498
	(0.498)	(0.498)	(0.499)	(0.498)	(0.500)
Age					
18-24	0.0581	0.0597	0.0481	0.0473	0.120
	(0.234)	(0.237)	(0.214)	(0.212)	(0.325)
25-34	0.140	0.129	0.110	0.0989	0.157
	(0.347)	(0.336)	(0.313)	(0.299)	(0.364)
35-44	0.200	0.189	0.205	0.183	0.218
	(0.400)	(0.391)	(0.404)	(0.387)	(0.413)
45-54	0.173	0.171	0.181	0.182	0.198
	(0.378)	(0.377)	(0.385)	(0.386)	(0.399)
55-65	0.167	0.170	0.176	0.189	0.173
	(0.373)	(0.376)	(0.381)	(0.391)	(0.378)
66 and older	0.263	0.281	0.280	0.300	0.134
	(0.440)	(0.449)	(0.449)	(0.458)	(0.340)
Household income					
less than 1250 Euros	0.412	0.399	0.430	0.360	0.143
	(0.492)	(0.490)	(0.495)	(0.480)	(0.350)
1251-4500 Euros	0.351	0.314	0.320	0.367	0.583
	(0.477)	(0.464)	(0.467)	(0.482)	(0.493)
more than 4500 Euros	0.0454	0.0359	0.0526	0.0334	0.0681
	(0.208)	(0.186)	(0.223)	(0.180)	(0.252)
n.a	0.191	0.251	0.197	0.240	0.206
	(0.393)	(0.433)	(0.398)	(0.427)	(0.404)
Education					
primary/secondary	0.775	0.789	0.734	0.736	0.485
	(0.418)	(0.408)	(0.442)	(0.441)	(0.500)
higher education	0.225	0.211	0.266	0.264	0.515
	(0.418)	(0.408)	(0.442)	(0.441)	(0.500)
Occupation					
civil servent	0.0927	0.0399	0.0540	0.0499	0.0753
	(0.290)	(0.196)	(0.226)	(0.218)	(0.264)
permanent contract	0.200	0.214	0.227	0.236	0.321
	(0.400)	(0.410)	(0.419)	(0.425)	(0.467)
temporary contract	0.0773	0.0574	0.0630	0.0698	0.113
	(0.267)	(0.233)	(0.243)	(0.255)	(0.316)
self-employed	0.0774	0.0736	0.0834	0.0792	0.0556
	(0.267)	(0.261)	(0.277)	(0.270)	(0.229)
unemployed	0.109	0.128	0.134	0.111	0.143
	(0.311)	(0.334)	(0.341)	(0.314)	(0.350)
pensioner	0.256	0.265	0.293	0.296	0.163
	(0.437)	(0.441)	(0.455)	(0.457)	(0.369)
student	0.0328	0.0407	0.0328	0.0335	0.0764
	(0.178)	(0.197)	(0.178)	(0.180)	(0.266)
others	0.155	0.182	0.113	0.124	0.0529
	(0.362)	(0.386)	(0.317)	(0.329)	(0.224)
# Obs.	21,563	19,950	21,997	22,297	7,107

Continued on next page

Table A2 – *Continued from previous page*

Panel B:	**Matched sample**				
	2009	2011/12	2014	2017	Survey
Gender					
Female	0.525	0.525	0.525	0.525	0.496
	(0.499)	(0.499)	(0.499)	(0.499)	(0.500)
Age					
18-24	0.165	0.165	0.165	0.165	0.116
	(0.371)	(0.371)	(0.371)	(0.371)	(0.320)
25-34	0.160	0.160	0.160	0.160	0.156
	(0.366)	(0.366)	(0.366)	(0.366)	(0.363)
35-44	0.226	0.226	0.226	0.226	0.221
	(0.418)	(0.418)	(0.418)	(0.418)	(0.415)
45-54	0.190	0.190	0.190	0.190	0.200
	(0.392)	(0.392)	(0.392)	(0.392)	(0.400)
55-65	0.147	0.147	0.147	0.147	0.173
	(0.354)	(0.354)	(0.354)	(0.354)	(0.379)
66 and older	0.112	0.112	0.112	0.112	0.134
	(0.316)	(0.316)	(0.316)	(0.316)	(0.340)
Household income					
less than 1250 Euros	0.151	0.151	0.151	0.151	0.144
	(0.358)	(0.358)	(0.358)	(0.358)	(0.351)
1251-4500 Euros	0.578	0.578	0.578	0.578	0.586
	(0.494)	(0.494)	(0.494)	(0.494)	(0.493)
more than 4500 Euros	0.0579	0.0579	0.0579	0.0579	0.0632
	(0.234)	(0.234)	(0.234)	(0.234)	(0.243)
n.a	0.213	0.213	0.213	0.213	0.207
	(0.410)	(0.410)	(0.410)	(0.410)	(0.405)
Education					
primary/secondary	0.504	0.504	0.504	0.504	0.490
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
higher education	0.496	0.496	0.496	0.496	0.510
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Occupation					
civil servent	0.0696	0.0696	0.0696	0.0696	0.0745
	(0.255)	(0.255)	(0.255)	(0.255)	(0.263)
permanent contract	0.310	0.310	0.310	0.310	0.326
	(0.462)	(0.462)	(0.462)	(0.462)	(0.469)
temporary contract	0.107	0.107	0.107	0.107	0.112
	(0.309)	(0.309)	(0.309)	(0.309)	(0.316)
self-employed	0.0482	0.0482	0.0482	0.0482	0.0531
	(0.214)	(0.214)	(0.214)	(0.214)	(0.224)
unemployed	0.162	0.162	0.162	0.162	0.142
	(0.369)	(0.369)	(0.369)	(0.369)	(0.349)
pensioner	0.140	0.140	0.140	0.140	0.164
	(0.347)	(0.347)	(0.347)	(0.347)	(0.370)
student	0.107	0.107	0.107	0.107	0.0764
	(0.309)	(0.309)	(0.309)	(0.309)	(0.266)
others	0.0558	0.0558	0.0558	0.0558	0.0517
	(0.229)	(0.229)	(0.229)	(0.229)	(0.221)
# Obs.	19,164	17,797	19,699	20,048	6,928

Notes: The table shows summary statistics for the original data in Panel A and for the matched sample in Panel B. The table reports the mean and the standard deviation (in brackets).

Table A3: *Comparison with census data*

	(1) April '20	(2) July '20	(3) July '21	(4) April '22	(5) Census
Gender					
Female	0.490	0.496	0.499	0.497	0.485
Age					
18-24	0.108	0.115	0.116	0.120	0.0847
25-34	0.146	0.161	0.159	0.154	0.136
35-44	0.223	0.222	0.223	0.219	0.187
45-54	0.200	0.202	0.201	0.197	0.193
55-65	0.182	0.169	0.171	0.176	0.174
66 and older	0.141	0.132	0.130	0.134	0.225
Education					
primary/secondary	0.488	0.488	0.489	0.495	0.603
higher education	0.512	0.512	0.511	0.505	0.397
Occupation					
civil servent	0.0779	0.0780	0.0717	0.0719	0.0822
permanent contract	0.300	0.305	0.334	0.353	0.314
temporary contract	0.0770	0.0929	0.130	0.133	0.105
self-employed	0.0545	0.0549	0.0534	0.0503	0.0787
unemployed	0.175	0.172	0.133	0.103	0.0915
pensioner	0.173	0.160	0.161	0.166	0.163
student	0.0761	0.0800	0.0702	0.0791	0.0732
others	0.0676	0.0570	0.0463	0.0431	0.0925
Household Income					
mean	29.04	28.49	29.90	30.38	34.90
Income percentile					
less than 20	12.39	12.39	12.39	12.39	8.900
between 20 and 40	20.84	20.84	20.84	20.84	17
between 40 and 60	27.73	27.73	27.73	27.73	25.70
between 60 and 80	36.32	36.32	36.32	36.32	38.20
between 80 and 90	46.85	46.85	46.85	46.85	56
between 90 and 100	67.70	67.70	67.70	67.70	113
# Obs.	1,065	1,949	1,966	1,948	

Notes: 1) Census data on gender and age are from INE (January 2020). 2) Census data on education is from INE 2019. 3) The percentages across the different occupational categories in column (2) are calculated using information for employed individuals aged 16+ with respect to the overall population in this age group in Spain. This data is taken from the INE website and calculated using the Spanish Labor Force Survey of 2019. 4) The data on income distribution comes from the Spanish survey of household finances of 2017 (EFF, Banco de Espana). 5) In our survey, we ask the individuals about their household income providing different income brackets expressed in Euros per month (see question 18 in our survey). To compare the household income data from our survey, we assign to each bracket its mean value. For the individuals that select the lowest income bracket (500 Euro or less) we assigned the maximum value of this bracket, 500 Euro per month. For individuals that select the highest income bracket, (more than 8000 Euro), we assign the minimum value of this bracket, 8000 Euro per month. Then, we multiple the monthly household income by 12, and compute the percentile distribution.)

Table A4: *Heterogeneous effect on mental health (feeling depressed or unhappy)*

Dep.Var.	(1) 1st survey	(2) 2nd survey	(3) 3rd survey	(4) 4rth survey
Gender	(relative to men)			
Female	-0.079**	-0.054**	-0.066***	-0.083***
	(0.034)	(0.023)	(0.022)	(0.023)
Occupation	(relative to civil servant)			
permanent contract	-0.081	-0.054	-0.032	-0.032
	(0.063)	(0.038)	(0.038)	(0.040)
temporary contract	-0.047	-0.091*	-0.111**	-0.070
	(0.081)	(0.050)	(0.046)	(0.048)
self-employed	0.057	-0.138**	-0.049	-0.177***
	(0.085)	(0.057)	(0.055)	(0.061)
unemployed	-0.146**	-0.159***	-0.148***	-0.065
	(0.070)	(0.045)	(0.048)	(0.053)
pensioner	0.044	-0.097	0.017	-0.079
	(0.091)	(0.065)	(0.056)	(0.060)
student	-0.150*	-0.121**	-0.169***	-0.048
	(0.086)	(0.057)	(0.058)	(0.058)
other	-0.129	-0.238***	-0.090	-0.163**
	(0.083)	(0.060)	(0.063)	(0.068)
Age	(relative to 18-44)			
45-65	0.024	0.076***	0.045*	0.075***
	(0.040)	(0.027)	(0.024)	(0.026)
66 and older	0.101	0.178***	0.037	0.175***
	(0.089)	(0.065)	(0.055)	(0.057)
Household income	(relative to less than 1250 Euros)			
1251-2500 Euros	0.082*	0.072**	0.060	0.055
	(0.047)	(0.035)	(0.037)	(0.038)
2501-4500 Euros	0.106**	0.089**	0.101***	0.109***
	(0.053)	(0.037)	(0.038)	(0.040)
more than 4500 Euros	0.145**	0.098*	0.182***	0.113**
	(0.072)	(0.053)	(0.047)	(0.051)
n.a.	0.089*	0.130***	0.123***	0.097**
	(0.054)	(0.038)	(0.038)	(0.040)
Education	(relative to primary)			
Higher education	-0.016	0.008	-0.022	0.017
	(0.032)	(0.022)	(0.021)	(0.022)
Kids	(relative to no)			
yes	-0.020	-0.019	-0.029	0.002
	(0.037)	(0.025)	(0.030)	(0.033)
# Obs.	1,065	1,949	1,966	1,948

Notes: This table shows results of a linear probability model, where the dependent variables is equal to 1 if the individual reports good mental health (not at all or no more than usual; zero otherwise). All the control variables are included simultaneously. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table A5: *Heterogeneous effect on mental health (insomnia)*

Dep.Var.	(1) 1st survey	(2) 2nd survey	(3) 3rd survey	(4) 4th wave
Gender	(relative to men)			
Female	-0.077**	-0.070***	-0.087***	-0.103***
	(0.034)	(0.024)	(0.023)	(0.024)
Occupation	(relative to civil servant)			
permanent contract	-0.054	-0.093**	-0.033	0.037
	(0.063)	(0.040)	(0.040)	(0.045)
temporary contract	-0.132*	-0.132**	-0.165***	0.033
	(0.079)	(0.053)	(0.049)	(0.052)
self-employed	-0.143*	-0.140**	-0.105*	-0.072
	(0.086)	(0.058)	(0.059)	(0.064)
unemployed	-0.152**	-0.196***	-0.171***	-0.067
	(0.069)	(0.048)	(0.050)	(0.058)
pensioner	0.032	-0.098	-0.026	0.065
	(0.101)	(0.067)	(0.066)	(0.063)
student	-0.031	-0.032	-0.128**	0.038
	(0.087)	(0.057)	(0.059)	(0.062)
other	-0.127	-0.208***	-0.186***	-0.064
	(0.082)	(0.062)	(0.068)	(0.071)
Age	(relative to 18-44)			
45-65	0.049	0.025	0.015	0.082***
	(0.039)	(0.028)	(0.025)	(0.026)
66 and older	0.141	0.147**	0.096	0.143**
	(0.099)	(0.067)	(0.064)	(0.057)
Household income	(relative to less than 1250 Euros)			
1251-2500 Euros	-0.027	0.131***	0.033	0.024
	(0.046)	(0.035)	(0.037)	(0.039)
2501-4500 Euros	0.051	0.169***	0.092**	0.079*
	(0.052)	(0.038)	(0.038)	(0.041)
more than 4500 Euros	0.068	0.174***	0.088*	0.055
	(0.074)	(0.055)	(0.052)	(0.054)
n.a.	-0.006	0.153***	0.091**	0.048
	(0.053)	(0.039)	(0.039)	(0.041)
Education	(relative to primary)			
Higher education	0.018	-0.000	-0.037*	0.025
	(0.032)	(0.023)	(0.022)	(0.023)
Kids	(relative to no)			
yes	-0.112***	-0.012	-0.038	0.018
	(0.036)	(0.026)	(0.032)	(0.034)
# Obs.	1,065	1,949	1,966	1,948

Notes: This table shows results of a linear probability model, where the dependent variables is equal to 1 if the individual reports good mental health (not at all or no more than usual; zero otherwise). All the control variables are included simultaneously. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table A6: *Heterogeneous effect on mental health (overwhelmed/tense)*

Dep.Var.	(1) 1st survey	(2) 2nd survey	(3) 3rd survey	(4) 4th survey
Gender	(relative to men)			
Female	-0.096***	-0.095***	-0.089***	-0.135***
	(0.033)	(0.024)	(0.023)	(0.024)
Occupation	(relative to civil servant)			
permanent contract	-0.136**	-0.091**	-0.025	-0.005
	(0.061)	(0.042)	(0.043)	(0.045)
temporary contract	-0.121	-0.111**	-0.141***	-0.030
	(0.078)	(0.054)	(0.051)	(0.052)
self-employed	-0.173**	-0.148**	-0.051	-0.082
	(0.086)	(0.060)	(0.061)	(0.064)
unemployed	-0.117*	-0.168***	-0.123**	-0.073
	(0.069)	(0.049)	(0.051)	(0.057)
pensioner	-0.023	-0.055	0.049	0.014
	(0.100)	(0.067)	(0.065)	(0.064)
student	-0.131	-0.098	-0.157***	-0.048
	(0.083)	(0.060)	(0.061)	(0.062)
other	-0.176**	-0.196***	-0.139**	-0.124*
	(0.078)	(0.063)	(0.068)	(0.071)
Age	(relative to 18-44)			
45-65	0.095**	0.070**	0.045*	0.102***
	(0.037)	(0.028)	(0.026)	(0.027)
66 and older	0.208**	0.146**	0.083	0.227***
	(0.099)	(0.067)	(0.061)	(0.058)
Household income	(relative to less than 1250 Euros)			
1251-2500 Euros	0.010	0.123***	0.061	-0.010
	(0.045)	(0.035)	(0.037)	(0.038)
2501-4500 Euros	0.020	0.121***	0.094**	0.010
	(0.050)	(0.039)	(0.039)	(0.040)
more than 4500 Euros	0.121*	0.152***	0.101*	0.020
	(0.072)	(0.056)	(0.052)	(0.053)
n.a.	0.061	0.168***	0.070*	0.026
	(0.051)	(0.039)	(0.040)	(0.040)
Education	(relative to primary)			
Higher education	-0.005	-0.012	-0.008	-0.005
	(0.031)	(0.023)	(0.022)	(0.023)
Kids	(relative to no)			
yes	-0.092***	-0.018	-0.001	0.024
	(0.035)	(0.026)	(0.032)	(0.034)
# Obs.	1,065	1,949	1,966	1,948

Notes: This table shows results of a linear probability model, where the dependent variables is equal to 1 if the individual reports good mental health (not at all or no more than usual; zero otherwise). All the control variables are included simultaneously. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table A7: *Heterogeneous effect on mental health (overcome difficulties)*

Dep.Var.	(1) 1st survey	(2) 2nd survey	(3) 3rd survey	(4) 4th survey
Gender	(relative to men)			
Female	-0.036	-0.032	-0.062***	-0.079***
	(0.032)	(0.021)	(0.021)	(0.022)
Occupation	(relative to civil servant)			
permanent contract	-0.090*	-0.058*	-0.009	-0.058
	(0.054)	(0.032)	(0.036)	(0.036)
temporary contract	-0.103	-0.103**	-0.068	-0.115***
	(0.074)	(0.045)	(0.044)	(0.044)
self-employed	-0.068	-0.194***	-0.025	-0.158***
	(0.079)	(0.052)	(0.051)	(0.056)
unemployed	-0.128**	-0.204***	-0.146***	-0.152***
	(0.063)	(0.041)	(0.046)	(0.049)
pensioner	0.084	-0.138**	0.059	-0.092*
	(0.073)	(0.060)	(0.051)	(0.055)
student	-0.113	-0.063	-0.177***	-0.068
	(0.080)	(0.050)	(0.057)	(0.053)
other	-0.177**	-0.169***	-0.138**	-0.177***
	(0.079)	(0.054)	(0.063)	(0.064)
Age	(relative to 18-44)			
45-65	0.030	0.094***	0.042*	0.070***
	(0.037)	(0.025)	(0.023)	(0.024)
66 and older	0.027	0.215***	0.013	0.189***
	(0.073)	(0.061)	(0.050)	(0.053)
Household income	(relative to less than 1250 Euros)			
1251-2500 Euros	0.078*	0.130***	0.047	0.011
	(0.047)	(0.034)	(0.035)	(0.037)
2501-4500 Euros	0.155***	0.149***	0.116***	0.077**
	(0.051)	(0.036)	(0.036)	(0.038)
more than 4500 Euros	0.164**	0.177***	0.140***	0.079
	(0.067)	(0.048)	(0.045)	(0.048)
n.a.	0.074	0.175***	0.083**	0.060
	(0.053)	(0.036)	(0.037)	(0.038)
Education	(relative to primary)			
Higher education	0.007	-0.016	-0.018	-0.012
	(0.031)	(0.020)	(0.020)	(0.021)
Kids	(relative to no)			
yes	-0.046	-0.048**	-0.027	0.022
	(0.035)	(0.023)	(0.029)	(0.030)
# Obs.	1,065	1,949	1,966	1,948

Notes: This table shows results of a linear probability model, where the dependent variables is equal to 1 if the individual reports good mental health (not at all or no more than usual; zero otherwise). All the control variables are included simultaneously. Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table A8: *Relative differences: feeling unhappy or depressed*

Panel A: Gender	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)
	Women (relative to men)						
April '20 (1st wave)	-0.107***	-0.111***	-0.056	-0.041	-0.126***	-0.065*	-0.052
	(0.037)	(0.038)	(0.036)	(0.036)	(0.035)	(0.037)	(0.037)
July '20 (2nd wave)	-0.063***	-0.059**	-0.020	-0.006	-0.071***	-0.033	-0.018
	(0.024)	(0.026)	(0.024)	(0.023)	(0.025)	(0.026)	(0.026)
July '20 (3rd wave)	-0.069***	-0.069**	-0.030	-0.020	-0.082***	-0.039*	-0.026
	(0.025)	(0.027)	(0.023)	(0.021)	(0.023)	(0.023)	(0.023)
April '22 (4th wave)	-0.075***	-0.076***	-0.052*	-0.035	-0.081***	-0.053**	-0.033
	(0.026)	(0.028)	(0.027)	(0.024)	(0.024)	(0.026)	(0.025)
Panel B: Age	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)
	Young (relative to 45-65)						
April '20 (1st wave)	-0.104***	-0.098***	-0.067*	-0.059	-0.094**	-0.066*	-0.053
	(0.038)	(0.038)	(0.039)	(0.041)	(0.037)	(0.040)	(0.043)
July '20 (2nd wave)	-0.113***	-0.111***	-0.105***	-0.107***	-0.108***	-0.109***	-0.105***
	(0.025)	(0.025)	(0.026)	(0.028)	(0.026)	(0.028)	(0.029)
July '21 (3rd wave)	-0.123***	-0.122***	-0.085***	-0.075***	-0.126***	-0.092***	-0.082***
	(0.026)	(0.025)	(0.024)	(0.023)	(0.024)	(0.026)	(0.027)
April '22 (4th wave)	-0.120***	-0.116***	-0.107***	-0.100***	-0.116***	-0.114***	-0.107***
	(0.028)	(0.026)	(0.028)	(0.027)	(0.026)	(0.028)	(0.028)
	Elderly (relative to 45-65)						
April '20 (1st wave)	0.189***	0.207***	0.053	0.048	0.248***	0.080	0.075
	(0.038)	(0.039)	(0.086)	(0.084)	(0.051)	(0.098)	(0.099)
July '20 (2nd wave)	0.100***	0.124***	0.085	0.090	0.132***	0.045	0.048
	(0.035)	(0.038)	(0.094)	(0.095)	(0.041)	(0.088)	(0.088)
July '21 (3rd wave)	0.068**	0.071**	-0.042	-0.043	0.075**	-0.035	-0.033
	(0.034)	(0.033)	(0.074)	(0.078)	(0.033)	(0.066)	(0.067)
April '22 (4th wave)	0.088***	0.092***	0.062	0.054	0.101***	0.049	0.043
	(0.030)	(0.029)	(0.072)	(0.071)	(0.032)	(0.060)	(0.059)
Panel C: Household income	(3a)	(3b)	(3c)	(3d)	(3e)	(3f)	(3g)
	Low (relative to 1251-4500)						
April '20 (1st wave)	-0.021	-0.021	-0.000	-0.014	-0.011	0.016	0.009
	(0.056)	(0.054)	(0.048)	(0.047)	(0.051)	(0.051)	(0.051)
July '20 (2nd wave)	-0.025	-0.026	0.011	-0.004	-0.034	0.010	-0.006
	(0.041)	(0.044)	(0.038)	(0.037)	(0.040)	(0.041)	(0.040)
July '21 (3rd wave)	-0.022	-0.027	0.005	-0.004	-0.028	0.012	0.002
	(0.036)	(0.041)	(0.038)	(0.034)	(0.037)	(0.040)	(0.038)
April '22 (4th wave)	-0.009	-0.007	0.008	-0.001	-0.015	0.004	-0.009
	(0.040)	(0.046)	(0.043)	(0.041)	(0.040)	(0.041)	(0.040)
	High (relative to 1251-4500)						
April '20 (1st wave)	0.041	0.053	0.029	0.037	0.016	0.001	0.002
	(0.083)	(0.081)	(0.071)	(0.069)	(0.076)	(0.072)	(0.072)
July '20 (2nd wave)	0.019	0.032	-0.001	-0.010	0.014	-0.003	-0.020
	(0.046)	(0.046)	(0.049)	(0.046)	(0.054)	(0.055)	(0.054)
July '21 (3rd wave)	0.071*	0.079*	0.061	0.072**	0.057	0.039	0.048
	(0.041)	(0.041)	(0.038)	(0.034)	(0.045)	(0.045)	(0.045)
April '22 (4th wave)	0.013	0.056	0.038	0.038	0.057	0.035	0.040
	(0.044)	(0.039)	(0.034)	(0.030)	(0.044)	(0.043)	(0.043)
Panel D: Education	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4g)
	Low (relative to high)						
April '20 (1st wave)	-0.021	-0.036	-0.042	-0.040	-0.034	-0.038	-0.030
	(0.043)	(0.041)	(0.031)	(0.033)	(0.036)	(0.034)	(0.036)
July '20 (2nd wave)	-0.009	-0.019	-0.026	-0.014	-0.019	-0.024	-0.007
	(0.027)	(0.027)	(0.023)	(0.022)	(0.025)	(0.025)	(0.026)
July '21 (3rd wave)	-0.038	-0.038	-0.040*	-0.034	-0.040*	-0.041*	-0.031
	(0.028)	(0.028)	(0.022)	(0.022)	(0.023)	(0.023)	(0.024)
April '22 (4th wave)	-0.016	-0.019	-0.009	0.001	-0.026	-0.014	-0.003
	(0.031)	(0.031)	(0.028)	(0.024)	(0.025)	(0.025)	(0.025)
Panel E: Children	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)	(5g)
	Yes (relative to no)						
April '20 (1st wave)	0.067*	0.074*	0.018	-0.012	0.080**	0.028	0.005
	(0.040)	(0.040)	(0.038)	(0.038)	(0.036)	(0.037)	(0.040)
July '20 (2nd wave)	0.048*	0.061**	0.027	-0.010	0.060**	0.038	0.006
	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)	(0.026)	(0.027)
July '21 (3rd wave)	0.003	0.003	-0.013	-0.022	0.003	-0.008	-0.014
	(0.037)	(0.037)	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)
April '22 (4th wave)	0.019	0.034	0.026	0.017	0.030	0.028	0.019
	(0.040)	(0.041)	(0.035)	(0.034)	(0.039)	(0.037)	(0.036)
cell FE	No	Yes	Yes	Yes[1]	No	No	No
cell-region FE	No	No	No	No	Yes	Yes	Yes[1]
t x occupation	No	No	Yes	Yes	No	Yes	Yes
t x categories	No	No	No	Yes	No	No	Yes

Notes: The table shows the point estimates of Equation 4 without cell fixed effects in column a). Columns b) to d) include cell fixed effects γ for combinations of groups of age, gender, education, occupation, income, and children; columns e) to g) add the region of residence (cell-region level). Columns c) and f) show results from Equation 5 controlling for occupation effects over time, while column d) and g) include simultaneously all interactions of group variables over time relative to the base year. [1] Cell-FE are colinear in this case with the dynamic interaction terms. Standard errors, clustered at the level of the FE, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1)

Table A9: *Relative differences: insomnia*

Panel A: Gender	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)
	Women (relative to men)						
April '20 (1st wave)	-0.058	-0.042	-0.009	-0.003	-0.040	0.002	0.005
	(0.039)	(0.036)	(0.034)	(0.035)	(0.034)	(0.037)	(0.037)
July '20 (2nd wave)	-0.048	-0.032	-0.003	0.011	-0.028	0.004	0.016
	(0.030)	(0.027)	(0.026)	(0.027)	(0.027)	(0.029)	(0.029)
July '21 (3rd wave)	-0.064**	-0.064**	-0.026	-0.016	-0.061**	-0.018	-0.011
	(0.027)	(0.026)	(0.025)	(0.024)	(0.025)	(0.026)	(0.026)
April '22 (4th wave)	-0.074***	-0.071**	-0.045	-0.028	-0.058**	-0.032	-0.015
	(0.028)	(0.028)	(0.030)	(0.028)	(0.027)	(0.028)	(0.028)
Panel B: Age	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)
	Young (relative to 45-65)						
April '20 (1st wave)	-0.042	-0.038	-0.033	-0.068	-0.032	-0.015	-0.043
	(0.038)	(0.037)	(0.040)	(0.042)	(0.037)	(0.040)	(0.041)
July '20 (2nd wave)	-0.041	-0.037	-0.038	-0.042	-0.027	-0.018	-0.019
	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.032)	(0.032)
July '21 (3rd wave)	-0.068**	-0.054**	-0.031	-0.020	-0.035	-0.002	0.010
	(0.031)	(0.027)	(0.025)	(0.026)	(0.028)	(0.029)	(0.029)
April '22 (4th wave)	-0.108***	-0.086***	-0.087***	-0.081**	-0.075***	-0.076**	-0.073**
	(0.032)	(0.030)	(0.033)	(0.032)	(0.029)	(0.031)	(0.031)
	Elderly (relative to 45-65)						
April '20 (1st wave)	0.157***	0.155***	0.038	0.022	0.171***	-0.027	-0.040
	(0.050)	(0.042)	(0.069)	(0.077)	(0.049)	(0.106)	(0.109)
July '20 (2nd wave)	0.104**	0.111***	0.060	0.053	0.109***	-0.024	-0.028
	(0.041)	(0.033)	(0.105)	(0.098)	(0.034)	(0.090)	(0.089)
July '21 (3rd wave)	0.096***	0.103***	0.024	0.022	0.104***	0.008	0.010
	(0.032)	(0.030)	(0.067)	(0.072)	(0.032)	(0.063)	(0.064)
April '22 (4th wave)	0.083**	0.096***	0.026	0.012	0.084**	-0.006	-0.020
	(0.032)	(0.031)	(0.050)	(0.050)	(0.034)	(0.053)	(0.052)
Panel C: Household income	(3a)	(3b)	(3c)	(3d)	(3e)	(3f)	(3g)
	Low (relative to 1251-4500)						
April '20 (1st wave)	0.038	0.044	0.083*	0.053	0.044	0.085*	0.052
	(0.046)	(0.045)	(0.046)	(0.048)	(0.048)	(0.050)	(0.051)
July '20 (2nd wave)	-0.109***	-0.100***	-0.079**	-0.091**	-0.108***	-0.082*	-0.097**
	(0.039)	(0.036)	(0.038)	(0.039)	(0.037)	(0.042)	(0.041)
July '21 (3rd wave)	-0.025	-0.029	0.003	-0.012	-0.010	0.029	0.010
	(0.035)	(0.034)	(0.034)	(0.033)	(0.036)	(0.041)	(0.039)
April '22 (4th wave)	-0.013	-0.024	-0.007	-0.012	-0.018	0.000	-0.007
	(0.041)	(0.042)	(0.044)	(0.044)	(0.042)	(0.048)	(0.046)
	High (relative to 1251-4500)						
April '20 (1st wave)	0.066	0.047	0.036	0.050	0.044	0.032	0.054
	(0.069)	(0.064)	(0.061)	(0.058)	(0.076)	(0.075)	(0.074)
July '20 (2nd wave)	0.061	0.049	0.018	0.020	0.021	-0.005	-0.001
	(0.053)	(0.048)	(0.048)	(0.048)	(0.062)	(0.064)	(0.064)
July '21 (3rd wave)	0.036	0.020	-0.004	0.015	-0.002	-0.035	-0.010
	(0.049)	(0.047)	(0.044)	(0.043)	(0.057)	(0.056)	(0.057)
April '22 (4th wave)	0.027	0.026	0.016	0.012	0.028	0.012	0.014
	(0.060)	(0.054)	(0.052)	(0.054)	(0.056)	(0.055)	(0.057)
Panel D: Education	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4g)
	Low (relative to high)						
April '20 (1st wave)	0.015	0.002	0.003	0.005	0.003	0.003	0.004
	(0.042)	(0.037)	(0.032)	(0.033)	(0.034)	(0.035)	(0.036)
July '20 (2nd wave)	0.010	0.003	-0.005	-0.012	0.003	-0.006	-0.013
	(0.032)	(0.028)	(0.024)	(0.026)	(0.027)	(0.027)	(0.027)
July '21 (3rd wave)	-0.041	-0.044	-0.049**	-0.049**	-0.041	-0.048*	-0.047*
	(0.030)	(0.028)	(0.023)	(0.024)	(0.026)	(0.026)	(0.026)
April '22 (4th wave)	-0.004	-0.008	-0.004	0.006	-0.004	0.004	0.015
	(0.034)	(0.032)	(0.030)	(0.026)	(0.027)	(0.027)	(0.027)
Panel E: Children	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)	(5g)
	Yes (relative to no)						
April '20 (1st wave)	-0.018	-0.032	-0.069**	-0.095***	-0.021	-0.066*	-0.085**
	(0.041)	(0.037)	(0.034)	(0.035)	(0.035)	(0.037)	(0.039)
July '20 (2nd wave)	0.052*	0.038	0.022	-0.001	0.035	0.016	0.001
	(0.031)	(0.027)	(0.026)	(0.026)	(0.027)	(0.030)	(0.030)
July '21 (3rd wave)	0.008	-0.004	-0.020	-0.028	-0.018	-0.036	-0.041
	(0.035)	(0.034)	(0.032)	(0.032)	(0.035)	(0.035)	(0.036)
April '22 (4th wave)	0.057	0.048	0.039	0.030	0.035	0.029	0.023
	(0.046)	(0.045)	(0.041)	(0.041)	(0.041)	(0.041)	(0.040)
cell FE	No	Yes	Yes	Yes[1]	No	No	No
cell-region FE	No	No	No	No	Yes	Yes	Yes[1]
t x occupation	No	No	Yes	Yes	No	Yes	Yes
t x categories	No	No	No	Yes	No	No	Yes

Notes: The table shows the point estimates of Equation 4 without cell fixed effects in column a). Columns b) to d) include cell fixed effects γ for combinations of groups of age, gender, education, occupation, income, and children; columns e) to g) add the region of residence (cell-region level). Columns c) and f) show results from Equation 5 controlling for occupation effects over time, while column d) and g) include simultaneously all interactions of group variables over time relative to the base year. [1] Cell-FE are co-linear in this case with the dynamic interaction terms. Standard errors, clustered at the level of the FE, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1)

Table A10: *Relative differences: overwhelmed/tense*

Panel A: Gender	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)
	Women (relative to men)						
April '20 (1st wave)	-0.042	-0.045	-0.019	-0.007	-0.025	-0.003	0.009
	(0.038)	(0.036)	(0.037)	(0.037)	(0.035)	(0.037)	(0.038)
July '20 (2nd wave)	-0.037	-0.041	-0.019	-0.007	-0.030	-0.004	0.013
	(0.029)	(0.027)	(0.028)	(0.028)	(0.029)	(0.031)	(0.031)
July '21 (3rd wave)	-0.040	-0.048*	-0.005	0.002	-0.048*	-0.004	0.005
	(0.027)	(0.028)	(0.024)	(0.024)	(0.026)	(0.027)	(0.027)
April '22 (4th wave)	-0.082***	-0.084***	-0.052*	-0.039	-0.083***	-0.054*	-0.038
	(0.028)	(0.029)	(0.029)	(0.028)	(0.026)	(0.028)	(0.028)
Panel B: Age	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)
	Young (relative to 45-65)						
April '20 (1st wave)	-0.046	-0.064*	-0.069	-0.089**	-0.058	-0.061	-0.078*
	(0.039)	(0.038)	(0.043)	(0.042)	(0.037)	(0.040)	(0.041)
July '20 (2nd wave)	-0.043	-0.060**	-0.065**	-0.063*	-0.072**	-0.066**	-0.063*
	(0.031)	(0.030)	(0.030)	(0.033)	(0.031)	(0.033)	(0.034)
July '21 (3rd wave)	-0.050	-0.049*	-0.021	-0.019	-0.060**	-0.027	-0.029
	(0.030)	(0.029)	(0.028)	(0.027)	(0.028)	(0.029)	(0.029)
April '22 (4th wave)	-0.089***	-0.081***	-0.079**	-0.068**	-0.093***	-0.091***	-0.081**
	(0.032)	(0.030)	(0.032)	(0.030)	(0.029)	(0.031)	(0.032)
	Elderly (relative to 45-65)						
April '20 (1st wave)	0.142***	0.161***	0.092	0.086	0.161***	0.041	0.038
	(0.047)	(0.048)	(0.096)	(0.099)	(0.053)	(0.113)	(0.115)
July '20 (2nd wave)	0.073*	0.088**	0.023	0.021	0.086**	-0.088	-0.093
	(0.042)	(0.040)	(0.118)	(0.114)	(0.041)	(0.095)	(0.093)
July '21 (3rd wave)	0.086**	0.110***	0.015	0.011	0.100***	0.011	0.004
	(0.036)	(0.036)	(0.065)	(0.066)	(0.032)	(0.070)	(0.070)
April '22 (4th wave)	0.119***	0.143***	0.094*	0.083	0.118***	0.054	0.041
	(0.028)	(0.027)	(0.056)	(0.057)	(0.033)	(0.059)	(0.059)
Panel C: Household income	(3a)	(3b)	(3c)	(3d)	(3e)	(3f)	(3g)
	Low (relative to 1251-4500)						
April '20 (1st wave)	0.042	0.044	0.051	0.031	0.065	0.048	0.025
	(0.051)	(0.048)	(0.048)	(0.048)	(0.048)	(0.051)	(0.051)
July '20 (2nd wave)	-0.090**	-0.079**	-0.052	-0.068*	-0.072*	-0.055	-0.069
	(0.041)	(0.038)	(0.037)	(0.036)	(0.041)	(0.045)	(0.044)
July '21 (3rd wave)	-0.057	-0.052	-0.012	-0.020	-0.034	-0.005	-0.006
	(0.039)	(0.040)	(0.040)	(0.040)	(0.039)	(0.043)	(0.042)
April '22 (4th wave)	0.025	0.039	0.074	0.062	0.048	0.074	0.061
	(0.048)	(0.049)	(0.047)	(0.047)	(0.042)	(0.046)	(0.045)
	High (relative to 1251-4500)						
April '20 (1st wave)	0.085	0.031	0.036	0.036	0.053	0.080	0.079
	(0.088)	(0.070)	(0.063)	(0.064)	(0.085)	(0.082)	(0.083)
July '20 (2nd wave)	0.047	-0.015	-0.036	-0.039	-0.027	-0.032	-0.038
	(0.059)	(0.052)	(0.055)	(0.055)	(0.069)	(0.072)	(0.071)
July '21 (3rd wave)	0.019	-0.026	-0.050	-0.048	-0.044	-0.070	-0.076
	(0.059)	(0.046)	(0.043)	(0.042)	(0.054)	(0.054)	(0.055)
April '22 (4th wave)	0.018	0.015	0.002	-0.000	-0.028	-0.043	-0.045
	(0.057)	(0.043)	(0.043)	(0.046)	(0.057)	(0.058)	(0.061)
Panel D: Education	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4g)
	Low (relative to high)						
April '20 (1st wave)	0.009	-0.019	-0.016	-0.011	-0.029	-0.010	-0.008
	(0.044)	(0.037)	(0.034)	(0.034)	(0.035)	(0.035)	(0.037)
July '20 (2nd wave)	0.010	-0.009	-0.013	-0.009	-0.012	-0.010	-0.001
	(0.034)	(0.028)	(0.026)	(0.028)	(0.029)	(0.030)	(0.030)
July '21 (3rd wave)	0.005	0.001	-0.002	0.003	0.008	0.010	0.020
	(0.032)	(0.029)	(0.025)	(0.025)	(0.026)	(0.026)	(0.027)
April '22 (4th wave)	-0.018	-0.022	-0.015	0.000	-0.032	-0.019	0.003
	(0.037)	(0.033)	(0.029)	(0.028)	(0.027)	(0.027)	(0.027)
Panel E: Children	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)	(5g)
	Yes (relative to no)						
April '20 (1st wave)	0.062	-0.022	-0.044	-0.075**	-0.029	-0.046	-0.069*
	(0.041)	(0.035)	(0.036)	(0.036)	(0.035)	(0.037)	(0.038)
July '20 (2nd wave)	0.111***	0.025	0.020	-0.002	0.034	0.027	0.009
	(0.031)	(0.027)	(0.027)	(0.027)	(0.029)	(0.031)	(0.032)
July '21 (3rd wave)	0.085**	0.032	0.020	0.018	0.018	0.009	0.011
	(0.037)	(0.035)	(0.032)	(0.032)	(0.035)	(0.035)	(0.035)
April '22 (4th wave)	0.113**	0.056	0.052	0.045	0.046	0.047	0.043
	(0.045)	(0.043)	(0.039)	(0.039)	(0.042)	(0.041)	(0.041)
cell FE	No	Yes	Yes	Yes[1]	No	No	No
cell-region FE	No	No	No	No	Yes	Yes	Yes[1]
t x occupation	No	No	Yes	Yes	No	Yes	Yes
t x categories	No	No	No	Yes	No	No	Yes

Notes: The table shows the point estimates of Equation 4 without cell fixed effects in column a). Columns b) to d) include cell fixed effects γ for combinations of groups of age, gender, education, occupation, income, and children; columns e) to g) add the region of residence (cell-region level). Columns c) and f) show results from Equation 5 controlling for occupation effects over time, while column d) and g) include simultaneously all interactions of group variables over time relative to the base year. [1] Cell-FE are co-linear in this case with the dynamic interaction terms. Standard errors, clustered at the level of the FE, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1)

Table A11: *Relative Differences: overcome difficulties*

Panel A: Gender	(1a)	(1b)	(1c)	(1d)	(1e)	(1f)	(1g)
	Women (relative to men)						
April '20 (1st wave)	-0.066**	-0.061*	-0.018	-0.007	-0.056*	-0.012	0.000
	(0.032)	(0.033)	(0.029)	(0.029)	(0.032)	(0.035)	(0.035)
July '20 (2nd wave)	-0.046*	-0.037	-0.015	0.004	-0.037	-0.014	0.007
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
July '21 (3rd wave)	-0.078***	-0.084***	-0.042**	-0.030	-0.100***	-0.065***	-0.050**
	(0.024)	(0.024)	(0.020)	(0.019)	(0.021)	(0.022)	(0.022)
April '22 (4th wave)	-0.089***	-0.094***	-0.065***	-0.049**	-0.096***	-0.069***	-0.051**
	(0.025)	(0.026)	(0.024)	(0.022)	(0.024)	(0.025)	(0.025)
Panel B: Age	(2a)	(2b)	(2c)	(2d)	(2e)	(2f)	(2g)
	Young (relative to 45-65)						
April '20 (1st wave)	-0.066**	-0.062*	-0.045	-0.056	-0.069**	-0.054	-0.064
	(0.031)	(0.032)	(0.034)	(0.035)	(0.034)	(0.038)	(0.040)
July '20 (2nd wave)	-0.089***	-0.093***	-0.111***	-0.121***	-0.110***	-0.122***	-0.130***
	(0.025)	(0.025)	(0.026)	(0.027)	(0.026)	(0.028)	(0.029)
July '21 (3rd wave)	-0.103***	-0.104***	-0.077***	-0.068***	-0.115***	-0.100***	-0.090***
	(0.025)	(0.022)	(0.021)	(0.022)	(0.023)	(0.024)	(0.025)
April '22 (4th wave)	-0.106***	-0.103***	-0.103***	-0.090***	-0.113***	-0.123***	-0.110***
	(0.026)	(0.024)	(0.026)	(0.024)	(0.026)	(0.028)	(0.028)
	Elderly (relative to 45-65)						
April '20 (1st wave)	0.161***	0.170***	0.008	0.002	0.163***	-0.032	-0.038
	(0.037)	(0.038)	(0.068)	(0.068)	(0.042)	(0.079)	(0.081)
July '20 (2nd wave)	0.094***	0.096***	0.119	0.125	0.076**	0.050	0.053
	(0.026)	(0.026)	(0.075)	(0.076)	(0.033)	(0.077)	(0.080)
July '21 (3rd wave)	0.083***	0.096***	-0.008	-0.013	0.081***	-0.008	-0.016
	(0.028)	(0.026)	(0.062)	(0.067)	(0.027)	(0.065)	(0.067)
April '22 (4th wave)	0.128***	0.143***	0.129*	0.121*	0.119***	0.098*	0.089
	(0.025)	(0.024)	(0.070)	(0.069)	(0.027)	(0.055)	(0.055)
Panel C: Household income	(3a)	(3b)	(3c)	(3d)	(3e)	(3f)	(3g)
	Low (relative to 1251-4500)						
April '20 (1st wave)	-0.035	-0.045	-0.034	-0.041	-0.042	-0.038	-0.046
	(0.048)	(0.047)	(0.046)	(0.045)	(0.048)	(0.050)	(0.050)
July '20 (2nd wave)	-0.075*	-0.076*	-0.045	-0.065*	-0.076**	-0.044	-0.066*
	(0.039)	(0.041)	(0.038)	(0.037)	(0.037)	(0.041)	(0.040)
July '21 (3rd wave)	-0.033	-0.051	-0.008	-0.013	-0.047	-0.018	-0.017
	(0.038)	(0.039)	(0.035)	(0.033)	(0.036)	(0.038)	(0.037)
April '22 (4th wave)	0.019	0.015	0.037	0.034	0.018	0.041	0.034
	(0.038)	(0.039)	(0.042)	(0.039)	(0.038)	(0.043)	(0.041)
	High (relative to 1251-4500)						
April '20 (1st wave)	0.009	0.024	0.015	0.020	0.029	0.036	0.041
	(0.057)	(0.054)	(0.048)	(0.049)	(0.058)	(0.058)	(0.057)
July '20 (2nd wave)	0.014	0.017	-0.004	-0.004	0.018	0.010	0.005
	(0.043)	(0.046)	(0.049)	(0.047)	(0.056)	(0.057)	(0.056)
July '21 (3rd wave)	0.018	0.013	-0.005	0.000	0.008	-0.007	-0.009
	(0.040)	(0.042)	(0.039)	(0.037)	(0.042)	(0.042)	(0.041)
April '22 (4th wave)	0.002	0.017	0.001	0.000	0.017	0.000	-0.001
	(0.044)	(0.047)	(0.042)	(0.040)	(0.043)	(0.044)	(0.046)
Panel D: Education	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4g)
	Low (relative to high)						
April '20 (1st wave)	0.008	-0.003	-0.006	-0.009	-0.006	-0.007	-0.009
	(0.035)	(0.033)	(0.027)	(0.029)	(0.032)	(0.032)	(0.033)
July '20 (2nd wave)	-0.021	-0.030	-0.036	-0.033	-0.022	-0.029	-0.021
	(0.026)	(0.025)	(0.022)	(0.022)	(0.024)	(0.024)	(0.025)
July '21 (3rd wave)	-0.029	-0.023	-0.030	-0.021	-0.015	-0.018	-0.003
	(0.027)	(0.026)	(0.019)	(0.019)	(0.022)	(0.021)	(0.022)
April '22 (4th wave)	-0.043	-0.033	-0.028	-0.011	-0.027	-0.020	0.002
	(0.030)	(0.030)	(0.024)	(0.021)	(0.024)	(0.024)	(0.025)
Panel E: Children	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)	(5g)
	Yes (relative to no)						
April '20 (1st wave)	0.032	0.007	-0.022	-0.034	-0.010	-0.031	-0.038
	(0.033)	(0.033)	(0.032)	(0.033)	(0.032)	(0.035)	(0.037)
July '20 (2nd wave)	0.025	0.004	-0.003	-0.037	-0.003	-0.005	-0.034
	(0.026)	(0.025)	(0.026)	(0.025)	(0.024)	(0.025)	(0.026)
July '21 (3rd wave)	0.017	0.006	-0.003	-0.006	-0.017	-0.015	-0.015
	(0.032)	(0.031)	(0.028)	(0.028)	(0.030)	(0.030)	(0.031)
April '22 (4th wave)	0.057	0.050	0.046	0.040	0.046	0.051	0.049
	(0.037)	(0.036)	(0.030)	(0.029)	(0.036)	(0.035)	(0.035)
cell FE	No	Yes	Yes	Yes[1]	No	No	No
cell-region FE	No	No	No	No	Yes	Yes	Yes[1]
t x occupation	No	No	Yes	Yes	No	Yes	Yes
t x categories	No	No	No	Yes	No	No	Yes

Notes: The table shows the point estimates of Equation 4 without cell fixed effects in column a). Columns b) to d) include cell fixed effects γ for combinations of groups of age, gender, education, occupation, income, and children; columns (e) to (g) add the region of residence (cell-region level). Columns c) and f) show results from Equation 5 controlling for occupation effects over time, while column d) and g) include simultaneously all interactions of group variables over time relative to the base year. [1] Cell-FE are co-linear in this case with the dynamic interaction terms. Standard errors, clustered at the level of the FE, in parenthesis. *** p<0.01, ** p<0.05, * p<0.1)

B. Survey

Instructions

Survey without Interruptions

- This survey should be completed only once, **without interruptions**.
- If you close the survey while answering it, you will not be able to open it again.
- To complete the survey correctly **you will need 15 minutes**.
- We recommend that you access the survey when you have enough time to answer it.

Personal Questions

- In this survey there are some questions of a personal nature.
- Don't worry, your responses are anonymous and the only purpose of this study is to create statistics based on the opinions of the participants.
- If any topic makes you uncomfortable, we apologize and remind you that you may leave the survey at any time.

Introduction

We are a group of researchers working at a public university in Spain. We are carrying out this study impartially and independently of any government or public body.

We want to understand citizens' opinions about the exceptional situation we are currently living through.

For this study to be reliable, it is important that you respond with total sincerity and that you read the questions carefully before answering.

Questions

1. **What gender do you identify as?**

male	1
female	2

2. **How old are you?**

(numerical response)

3. **How old is your partner or spouse?**

I don't currently have a partner or spouse	0
Less than 20	1
20-29	2
30-39	3
40-49	4
50-59	5
60-69	6
70-79	7
80-99	8
90 or older	9

4. **How old is your mother?**
5. **How old is your father?**

20-29	2
30-39	3
40-49	4
50-59	5
60-69	6
70-79	7
80-99	8
90 or older	9
She/he is deceased	10

6. **How old is your maternal grandmother?**
7. **How old is your maternal grandfather?**
8. **How old is your paternal grandmother?**
9. **How old is your paternal grandfather?**

40-49	4
50-59	5
60-69	6
70-79	7
80-99	8
90 or older	9
She/he is deceased	10

10. **How many children do you have?**

I don't have children	97
1	1
2	2
3	3
4	4
5 or more	5

11. **How many of your children currently live with you?**

None	97
1	1
2	2
3	3
4	4
5 or more	5

12. **What is the highest level of education you have completed?**

(Recode response)

13. **What was your occupational status one month ago?**

Employed full-time with a temporary contract	1
Employed full-time with a permanent contract	2
Employed part-time with a temporary contract	3
Employed part-time with a permanent contract	4
Official/civil servant	5
Self-employed	6
Unemployed	7
Student	8
Retired	9
Unable to work	9
Other	10

14. **What is your occupational status today?**

Employed full-time with a temporary contract	1
Employed full-time with a permanent contract	2
Employed part-time with a temporary contract	3
Employed part-time with a permanent contract	4
Official/civil servant	5
Self-employed	6
Unemployed	7
Student	8
Retired	9
Unable to work	9
Other	10

15. **What is your current working arrangement?**

I am working from home and I have maintained my standard work schedule	1
I am working from home and I have flexibility to organize my work schedule	2
I have to go into work, but with more flexibility and/or a different schedule than the rest of the year	3
I have to go into work, and I have maintained my standard work schedule	4

16. **In which Autonomous Community do you reside?**

(Recode response)

17. **Where would you place yourself on the political spectrum?**

Extreme left	0
Left	1
Center left	2
Center right	3
Right	4
Extreme right	5
Prefer not to answer	6

18. a) **What is your individual monthly income?**
b) **What is your monthly household income?**

500 €or less
501-750

1001-1250
1251-1500
1501-1750
1751-2000
2001-2250
2251-2500
2501-2750
2751-3000
3001-3250
3251-3500
3501-3750
3751-4000
4001-4250
4251-4500
4501-4750
4751-5000
5001-5250
5251-5500
5501-5750
5751-6000
6001-6250
6251-6500
6501-6750
6751-7000
7001-7250
7251-7500
7501-7750
7751-8000
More than 8000
Prefer not to answer

19. **In general how would you describe your health?**

Very good	1
Good	2
Normal	3
Bad	4
Very Bad	5
I don't know	98
Prefer not to answer	99

20. **Do you have any illness or chronic health problem?**

Yes	1
No	2
Prefer not to answer	99

21. **In the last 2 weeks do you feel that worries have caused you to lose much sleep?**
22. **In the last 2 weeks have you noticed that you are constantly overwhelmed or tense?**
23. **In the last 2 weeks have you had the sensation that you cannot overcome the difficulties you face?**
24. **In the last 2 weeks have you felt unhappy or depressed?**

Not at all	1
No more than usual	2
A bit more than usual	3
Much more than usual	4
I don't know	98
Prefer not to answer	99

25. **Are you (or have you been) infected with COVID-19?**

Yes, definitely, I have been tested and it came back positive	1
I think so based on my symptoms and the opinion of a doctor	2
No	3
Prefer not to answer	99

26. **Do you have any family member or close friend who is(or has been) infected with COVID-19?**

Yes, definitely, they have been tested and it came back positive	1
I think so based on their symptoms and the opinion of a doctor	2
No	3
Prefer not to answer	99

27. **In your opinion, since the appearance of COVID-19 up to today, how many confirmed cases of COVID-19 are there in your Autonomous Community?**

(numerical response)

28. **In your opinion, since the appearance of COVID-19 up to today, how many confirmed cases of COVID-19 are there in Spain?**

(numerical response)

29. **In your opinion, in Spain, for every 100,000 inhabitants, how many have been confirmed to have COVID-19 up to now?**

(numerical response) (of every 100,000 inhabitants)

30. **The fatality rate of COVID-19 is defined as the proportion of people infected by COVID-19 who die. In your opinion, what is the fatality rate of COVID-19 in Spain?**

(numerical response) (% of people infected with COVID-19)

Reliability Check

Before moving to the next set of questions, we would like to ask you about the answers you have provided up to now. It is critical for our study that we only include answers from respondents who have paid attention to the questions. No matter how you answer, this will not affect in any way the payment you will receive for answering this survey.

32. **With total sincerity, can we use your answers or should we discard them because you have answered without paying attention?**

Yes, I have paid attention to all the questions and I think you should use my answers in your study	1
No, I have not paid the attention needed to the questions and I think you should not use my answers in your study	2

Treatment

Treatment 1

Video with information about the fatality rate by age

Treatment 2

Video with information about the accumulated incidence for every 100,000 inhabitants by Autonomous Community

Post-treatment

33. **In your opinion, since the appearance of COVID-19, how many total confirmed cases of COVID-19 will there be up to tomorrow in Spain?**

    (numerical response) confirmed cases

34. **In a week's time, since the appearance of COVID-19, how many total confirmed cases of COVID-19 will there be in Spain?**

    (numerical response) confirmed cases

35. **In the Autonomous Community in which you reside, how many total confirmed cases of COVID-19 for every 100,000 residents do you think have been accumulated during the last 14 days up to tomorrow?**

    (numerical response) confirmed cases for every 100,000 residents

36. **If tomorrow in Spain 100 additional people who are 90 years old or older are infected with COVID-19, how many of these people do you think will die?**

    (response between 0-100) people

37. **What do you think will be your general health status in 2 weeks?**

Very good	1
Good	2
Normal	3
Bad	4
Very Bad	5
I don't know	98
Prefer not to answer	99

38. **Personally, in terms of health, what is your main current concern?**

My health status	1
The health of my family and friends	2
I am not worried about my health of the health of my family and friends	3
I don't know	98
Prefer not to answer	99

39. **As of today, at what age do you think a 65 year old woman will die?**

(numerical response) years old

40. **As of today, at what age do you think a 65 year old man will die?**

(numerical response) years old

41. **Now think about the budget of the public sector and how you think it should be distributed between different spending functions. What percentage of spending do you think should be assigned to each of the following functions?**

    The percentages should sum up to 100 and you should assign the highest values to the functions which you consider to have the greatest importance for citizens [The order of the categories is random]

Defense	(response between 0-100)
Education	(response between 0-100)
Health	(response between 0-100)
Housing	(response between 0-100)
Pensions	(response between 0-100)
Transportation	(response between 0-100)
Public safety	(response between 0-100)
Social services	(response between 0-100)
Labor	(response between 0-100)

42. **Which of the following statements best expresses your opinion regarding the health care system in our country?**

In general the health care system works fairly well	1
The health care system works well, although some changes are needed	2
The health care system needs fundamental changes, although some things work well	3
Our health care system is so poor that it needs to be completely overhauled	4
I don't know	98
Prefer not to answer	99

43. **[One of the three questions is shown randomly in each treatment group]**
    Statement A: Suppose that the Government plans to implement new health measures in order to be prepared to minimize the impact on the health of the population if a similar situation to the current one were to happen in the future. These measures have the objective to find a VACCINE in order to immunize the population. In order to carry out this investment in public health additional resources are required which would be obtained through a new tax.

    What amount per month (in Euros) would you be willing to pay in order to carry out this improvement of the health care system?

(numerical response) Euros per month

Statement B: Suppose that the Government plans to implement new health measures in order to be prepared to minimize the impact on the health of the population if a similar situation to the current one were to happen in the future. These measures have the objective to find new MEDICAL TREATMENTS for the infected population. In order to carry out this investment in public health additional resources are required which would be obtained through a new tax.

What amount per month (in Euros) would you be willing to pay in order to carry out this improvement of the health care system?

(numerical response) Euros per month

Statement C: Suppose that the Government plans to implement new health measures in order to be prepared to minimize the impact on the health of the population if a similar situation to the current one were to happen in the future. These measures have the objective to increase the number of ICU BEDS available in the health care system. In order to carry out this investment in public health additional resources are required which would be obtained through a new tax.

What amount per month (in Euros) would you be willing to pay in order to carry out this improvement of the health care system?

(numerical response) Euros per month

44. **Do you think, in general, that you can trust the majority of people or that people are never prudent enough in their treatment with others ?**
Use a scale of 0 to 10, where 0 means 'People are never prudent enough' and 10 means 'The majority of people can be trusted.'

0 People are never prudent enough	0
1	1
2	2
3	3
4	4
5	5
6	6
7	7
8	8
9	9
10 The majority of people can be trusted	10
I don't know	98
Prefer not to answer	99

45. **Personally how much do you trust the president of the Government, Pedro Sánchez?**

a lot	1
a moderate amount	2
a little	3
not at all	4
I don't know	98
Prefer not to answer	99

46. **Given the health situation we are currently in, have you planned to perform any voluntary activity to help your neighbors?**

Yes	1
No	2

47. **In your opinion how important is it that citizens comply with the measures of the state of alarm declared by the government? Use a scale of 1-8 where 1 means "Complying is not important at all" and 8 means "Complying is very important."**

(response between 1-8)

48. **In your opinion when do you think the current confinement measures will end?**

Within one week	1
In one or two weeks	2
In three or four weeks	3
In May	4
In June	5
In July	6
In August	7
In September	8
After September	9

C. Summary of the surveys

Table C1: *Questions across waves*

Variable(s)	Waves			
	April '20	July '20	July '21	April '22
Socio-demographics				
Gender	1	1	1	1
Age	2	2	2	2
Partner age	3	3	3	3
Mother/Father age	4/5	4/5	4/5	4/5
Maternal grandmother/grandfather age	6/7	6/7	6/7	6/7
Paternal grandmother/grandfather age	8/9	8/9	8/9	8/9
Children	10	10	10	10
Children at home	11	11	11	11
Children's age		50	50	50
Living with partner now			13X	13X
Use of time now			13B2	13B2
Partner's use of time now			13B21	13B21
Living with partner March-May 2020			12B	12B
Use of time March-May 2020			13B	13B
Use of time March-May 2020			13B1	13B1
Children's learning		51	51	51
Children's future career		52A	52A	52A
Education	12	12	12	12
Labor market status Feb'20/today	13/14	13/14	13/14	13/14
Working arrangement	15	15	15	15
Back physically to work place		15A	15AA	15A
Region of residence	16	16	16	16
Political ideology	17	17	17	17
Individual/Household monthly income	18a/18	18a/18	18a/18	18a/18
Health				
General health	19	19	19	19
Chronic health problem	20	20	20	20
Mental health:insomnia	21	21	21	21
Mental health:overwhelmed, tense	22	22	22	22
Mental health:problem to overcome difficulties	23	23	23	23
Mental health:unhappy, depressed	24	24	24	24
Infected with covid19	25	25	25	25
Relative infected with covid19	26	26	26	26
Treatment block				
Confirmed cases of covid19 in your region	27			
Confirmed cases of covid19 in Spain	28			
Confirmed cases of covid19 in Spain per 100,000 inhab.	29			
Covid19 fatality rate in Spain	30			
Reliability check	31	31	31	31
Video information treatment: fatality rate / incidence by regions / control				
Covid19 cases in Spain tomorrow Spain	32			
Covid19 cases in Spain in a week Spain	33			
Covid19 cases per 100,000 inhab in your region tomorrow	34			
Covid19 Fatality rate in Spain for people 90 years old	35			
Health outcomes				
General health in two weeks	36	36	36	36
Health main current concern	37	37	37	37
Today life expectancy woman/man	38/39			
Public finance				
Composition expenditure budget	40	40	40	40
Opinion regarding health care system	41	41	41	41
Willingness to pay - health improvement: vaccine / medical treatments / ICU beds	42	42	42	42
Willingness to pay - recovery: EU / Spain / Region		52	52	52
Fair tax, 5 countries, different income		53	53	53
Fair grant allocation, different families		54	54	54
Trust and behavior				
General trust	43	43	43	43
Trust in the president	44	44	44	44
Management of the regional government		44B	44B	44B
Voluntary activity	45			45
Important compliance by people	46			
Expected end confinement measures	47			
Present worry: Covid19 vs. Ukraine				67
Past/present/future worry: Covid19 vs. Ukraine				68

D. Merge with previous survey data

Table D1: Description of physical and mental health variables

	Year				
Question	2009	2011	2014	2017	2020
General health (P19)	*How would you rate your health status in the last 12 months?*				
Positive answers [1] Negative answers [0]	Very Good Good Normal Bad Very Bad				
Depression (P24)	*How frequently did you feel miserable, disheartened and depressed during the last weeks?*	*In the last two weeks have you felt unhappy or depressed?*	*How frequently did you feel miserable, disheartened and depressed during the last weeks?*	*In the last two weeks have you felt unhappy or depressed?*	
Positive answers [1] Negative answers [0]	Never Very rarely Sometimes + Almost always Always	Not at all No more than usual A bit more than usual Much more than usual	Never Several days More than half of the days Almost every day	Not at all No more than usual A bit more than usual Much more than usual	Not at all No more than usual A bit more than usual Much more than usual
Insomnia (P21)	n.a.	*How frequently did your worries make you lose some sleep?*	*Did you experience problems to fall asleep, keep sleeping or because of sleeping too much?*	*How frequently did your worries make you lose some sleep?*	
Positive answers [1] Negative answers [0]		Not at all No more than usual A bit more than usual Much more than usual	Never Several days More than half of the days Almost every day	Not at all No more than usual A bit more than usual Much more than usual	Not at all No more than usual A bit more than usual Much more than usual
Overwhelmed (P22)	n.a.	*Did you feel overwhelmed or in tension?*	n.a.	*Did you feel overwhelmed or in tension?*	
Positive answers [1] Negative answers [0]		Not at all No more than usual A bit more than usual Much more than usual		Not at all No more than usual A bit more than usual Much more than usual	Not at all No more than usual A bit more than usual Much more than usual
Difficulties (P23)	n.a.	*Did you feel that you could not overcome difficulties?*	n.a.	*Did you feel that you could not overcome difficulties?*	
Positive answers [1] Negative answers [0]		No more than usual A bit more than usual Much more than usual		No more than usual A bit more than usual Much more than usual	No more than usual A bit more than usual Much more than usual

2018

2018/1, Boadway, R.; Pestieau, P.: "The tenuous case for an annual wealth tax"
2018/2, Garcia-López, M.À.: "All roads lead to Rome ... and to sprawl? Evidence from European cities"
2018/3, Daniele, G.; Galletta, S.; Geys, B.: "Abandon ship? Party brands and politicians' responses to a political scandal"
2018/4, Cavalcanti, F.; Daniele, G.; Galletta, S.: "Popularity shocks and political selection"
2018/5, Naval, J.; Silva, J. I.; Vázquez-Grenno, J.: "Employment effects of on-the-job human capital acquisition"
2018/6, Agrawal, D. R.; Foremny, D.: "Relocation of the rich: migration in response to top tax rate changes from spanish reforms"
2018/7, García-Quevedo, J.; Kesidou, E.; Martínez-Ros, E.: "Inter-industry differences in organisational eco-innovation: a panel data study"
2018/8, Aastveit, K. A.; Anundsen, A. K.: "Asymmetric effects of monetary policy in regional housing markets"
2018/9, Curci, F.; Masera, F.: "Flight from urban blight: lead poisoning, crime and suburbanization"
2018/10, Grossi, L.; Nan, F.: "The influence of renewables on electricity price forecasting: a robust approach"
2018/11, Fleckinger, P.; Glachant, M.; Tamokoué Kamga, P.-H.: "Energy performance certificates and investments in building energy efficiency: a theoretical analysis"
2018/12, van den Bergh, J. C.J.M.; Angelsen, A.; Baranzini, A.; Botzen, W.J. W.; Carattini, S.; Drews, S.; Dunlop, T.; Galbraith, E.; Gsottbauer, E.; Howarth, R. B.; Padilla, E.; Roca, J.; Schmidt, R.: "Parallel tracks towards a global treaty on carbon pricing"
2018/13, Ayllón, S.; Nollenberger, N.: "The unequal opportunity for skills acquisition during the Great Recession in Europe"
2018/14, Firmino, J.: "Class composition effects and school welfare: evidence from Portugal using panel data"
2018/15, Durán-Cabré, J. M.; Esteller-Moré, A.; Mas-Montserrat, M.; Salvadori, L.: "La brecha fiscal: estudio y aplicación a los impuestos sobre la riqueza"
2018/16, Montolio, D.; Tur-Prats, A.: "Long-lasting social capital and its impact on economic development: the legacy of the commons"
2018/17, Garcia-López, M. À.; Moreno-Monroy, A. I.: "Income segregation in monocentric and polycentric cities: does urban form really matter?"
2018/18, Di Cosmo, V.; Trujillo-Baute, E.: "From forward to spot prices: producers, retailers and loss averse consumers in electricity markets"
2018/19, Brachowicz Quintanilla, N.; Vall Castelló, J.: "Is changing the minimum legal drinking age an effective policy tool?"
2018/20, Nerea Gómez-Fernández, Mauro Mediavilla: "Do information and communication technologies (ICT) improve educational outcomes? Evidence for Spain in PISA 2015"
2018/21, Montolio, D.; Taberner, P. A.: "Gender differences under test pressure and their impact on academic performance: a quasi-experimental design"
2018/22, Rice, C.; Vall Castelló, J.: "Hit where it hurts – healthcare access and intimate partner violence"
2018/23, Ramos, R.; Sanromá, E.; Simón, H.: "Wage differentials by bargaining regime in Spain (2002-2014). An analysis using matched employer-employee data"

2019

2019/1, Mediavilla, M.; Mancebón, M. J.; Gómez-Sancho, J. M.; Pires Jiménez, L.: "Bilingual education and school choice: a case study of public secondary schools in the Spanish region of Madrid"
2019/2, Brutti, Z.; Montolio, D.: "Preventing criminal minds: early education access and adult offending behavior"
2019/3, Montalvo, J. G.; Piolatto, A.; Raya, J.: "Transaction-tax evasion in the housing market"
2019/4, Durán-Cabré, J.M.; Esteller-Moré, A.; Mas-Montserrat, M.: "Behavioural responses to the re)introduction of wealth taxes. Evidence from Spain"
2019/5, Garcia-López, M.A.; Jofre-Monseny, J.; Martínez Mazza, R.; Segú, M.: "Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona"
2019/6, Domínguez, M.; Montolio, D.: "Bolstering community ties as a means of reducing crime"
2019/7, García-Quevedo, J.; Massa-Camps, X.: "Why firms invest (or not) in energy efficiency? A review of the econometric evidence"
2019/8, Gómez-Fernández, N.; Mediavilla, M.: "What are the factors that influence the use of ICT in the classroom by teachers? Evidence from a census survey in Madrid"
2019/9, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "The long-run redistributive power of the net wealth tax"
2019/10, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "Building(s and) cities: delineating urban areas with a machine learning algorithm"

2019/11, Bordignon, M.; Gamalerio, M.; Slerca, E.; Turati, G.: “Stop invasion! The electoral tipping point in anti-immigrant voting”

2020

2020/01, Daniele, G.; Piolatto, A.; Sas, W.: “Does the winner take it all? Redistributive policies and political extremism”
2020/02, Sanz, C.; Solé-Ollé, A.; Sorribas-Navarro, P.: “Betrayed by the elites: how corruption amplifies the political effects of recessions”
2020/03, Farré, L.; Jofre-Monseny; J., Torrecillas, J.: “Commuting time and the gender gap in labor market participation”
2020/04, Romarri, A.: “Does the internet change attitudes towards immigrants? Evidence from Spain”
2020/05, Magontier, P.: “Does media coverage affect governments’preparation for natural disasters?”
2020/06, McDougal, T.L.; Montolio, D.; Brauer, J.: “Modeling the U.S. firearms market: the effects of civilian stocks, crime, legislation, and armed conflict”
2020/07, Veneri, P.; Comandon, A.; Garcia-López, M.A.; Daams, M.N.: “What do divided cities have in common? An international comparison of income segregation”
2020/08, Piolatto, A.: “'Information doesn't want to be free': informational shocks with anonymous online platforms”
2020/09, Marie, O.; Vall Castello, J.: “If sick-leave becomes more costly, will I go back to work? Could it be too soon?”
2020/10, Montolio, D.; Oliveira, C.: “Law incentives for juvenile recruiting by drug trafficking gangs: empirical evidence from Rio de Janeiro”
2020/11, Garcia-López, M.A.; Pasidis, I.; Viladecans-Marsal, E.: “Congestion in highways when tolls and railroads matter: evidence from European cities”
2020/12, Ferraresi, M.; Mazzanti, M.; Mazzarano, M.; Rizzo, L.; Secomandi, R.: “Political cycles and yardstick competition in the recycling of waste. evidence from Italian provinces”
2020/13, Beigelman, M.; Vall Castelló, J.: “COVID-19 and help-seeking behavior for intimate partner violence victims”
2020/14, Martínez-Mazza, R.: “Mom, Dad: I’m staying” initial labor market conditions, housing markets, and welfare”
2020/15, Agrawal, D.; Foremny, D.; Martínez-Toledano, C.: “*Paraísos fiscales*, wealth taxation, and mobility”
2020/16, Garcia-Pérez, J.I.; Serrano-Alarcón, M.; Vall Castelló, J.: “Long-term unemployment subsidies and middle-age disadvantaged workers’ health”

2021

2021/01, Rusteholz, G.; Mediavilla, M.; Pires, L.: “Impact of bullying on academic performance. A case study for the community of Madrid”
2021/02, Amuedo-Dorantes, C.; Rivera-Garrido, N.; Vall Castelló, J.: “Reforming the provision of cross-border medical care evidence from Spain”
2021/03, Domínguez, M.: “Sweeping up gangs: The effects of tough-on-crime policies from a network approach”
2021/04, Arenas, A.; Calsamiglia, C.; Loviglio, A.: “What is at stake without high-stakes exams? Students' evaluation and admission to college at the time of COVID-19”
2021/05, Armijos Bravo, G.; Vall Castelló, J.: “Terrorist attacks, Islamophobia and newborns’health”
2021/06, Asensio, J.; Matas, A.: “The impact of ‘competition for the market’regulatory designs on intercity bus prices”
2021/07, Boffa, F.; Cavalcanti, F.; Piolatto, A.: “Ignorance is bliss: voter education and alignment in distributive politics”

2022

2022/01, Montolio, D.; Piolatto, A.; Salvadori, L.: “Financing public education when altruistic agents have retirement concerns”
2022/02, Jofre-Monseny, J.; Martínez-Mazza, R.; Segú, M.: “Effectiveness and supply effects of high-coverage rent control policies”
2022/03, Arenas, A.; Gortazar, L.: “Learning loss one year after school closures: evidence from the Basque Country”
2022/04, Tassinari, F.: “Low emission zones and traffic congestion: evidence from Madrid Central”
2022/05, Cervini-Plá, M.; Tomàs, M.; Vázquez-Grenno, J.: “Public transportation, fare policies and tax salience”
2022/06, Fernández-Baldor Laporta, P.: “The short-term impact of the minimum wage on employment: Evidence from Spain”

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