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# Income insecurity and mental health in pandemic times[☆]

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ABSTRACT

This paper contributes to the literature on the impact of the COVID-19 outbreak on mental health by providing novel evidence of its interaction with labor market conditions and the long-term persistence of these effects. We run four waves of a large-scale representative survey in Spain between April 2020 and April 2022, and benchmark our data against a decade of pre-pandemic information. We document an increase in the share of individuals reporting depressive feelings from 16% prior to the pandemic to 46% in April 2020. We show that this effect is more pronounced for women, younger individuals and those with unstable incomes. We apply machine learning techniques, mediation analysis and event studies to document the role of the labor market as an important driver of these effects. Our results are crucial for the design of targeted policies that proof useful in overcoming the long lasting consequences of the pandemic.

## 1. Introduction

Economic insecurity and financial worries can significantly impact individuals' mental health. While previous research has established that recessions can be detrimental to mental well-being, most studies have focused on economic-driven recessions (see Hiilamo et al., 2021; Bellés-Obrero and Vall Castelló, 2018, for recent surveys). This paper presents novel evidence on the mental health impact of the Covid-19 outbreak, a crisis with non-economic origins but severe impacts on labor markets as well as on the daily life's of individuals.

We obtain our results from a new longitudinal survey data set assembled during the pandemic. The first observations were collected early during the most severe lock-down measures at onset, allowing us to capture the initial shock of the pandemic. We are also able to identify the long term effects and the persistency of the effects with three further waves. An important aspect of our study is that we can match our data to four pre-pandemic surveys dating back to 2009, which allows us to estimate the deviations caused by the pandemic from long-term trends.

Most of our results are obtained by estimating event-study models, which allow to precisely quantify the impact of the pandemic on mental health outcomes across time and for different socio-demographic groups defined by characteristics that have been identified in the literature as having substantial within-group differences (gender, age, education, occupation and household income). We document an important and persistent deterioration of mental health conditions relative to the pre-pandemic baseline. To shed light on the mechanisms, mediation analysis models confirm that the mental health impact of the pandemic is greater for those experiencing income insecurity due to unstable employment conditions, which disproportionately affects women, but also creates important inequalities across age groups.

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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, studies providing information on the persistence of the mental health 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. This feature is particularly important when analyzing effects across different groups, as it allows us to disentangle the impact of this shock from pre-existing differences across cohorts. Furthermore, by benchmarking our survey questions to be comparable to pre-pandemic data on the same mental health dimensions, we are able to estimate the change brought about by COVID19 vis-a-vis the pre-pandemic situation (while previous studies are only able to capture the situation during the pandemic).

Second, we document the underlying mediators that drive the observed differences across socio-economic groups, which is a relevant task for the design of public sector interventions mitigating the exposure of vulnerable individuals. For example, we show important differences in psychological well-being between men and women throughout the crisis.[2] 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, a result which highlights the importance of targeted policy interventions and it has not been documented before.

Part of the recent literature on the labor market impact of the pandemic has focused on identifying heterogeneous effects across subgroups of the population given that not all economic activities were equally affected (see Stantcheva (2022) for an overview; Immel et al. (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.[3] Therefore, we contribute to this literature by showing that those differential labor market impacts triggered important heterogeneous mental health effects.

Respondents are asked throughout the survey to self-assess their general and mental health. Although we do not detect any impact on general health, we do report a substantial and 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).

We provide evidence for an unequal impact of the pandemic on mental health across demographic groups. We first show that women, young individuals, and those with unstable employment are much more likely to self-report worse mental health outcomes. We apply machine learning methods which corroborate, in a non-parametric 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.

By exploiting the longitudinal dimension of the panel, 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.[4]

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

*Survey design.* 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 relationship with panelists secures reliable

[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 et al., 2020), the UK (Proto and Quintana-Domeque, 2021; Etheridge and Spantig, 2022), Germany (Huebener et al., 2021), and Turkey (Altindag et al., 2022). Results for Spain are provided by Jacques-Aviñó et al. (2020) and Codagnone et al. (2020).

[2] Other papers documenting heterogeneous mental health effects of the pandemic, but along different dimensions than us are Blay Benzaken et al. (2023) for forcibly displaced individuals, Li et al. (2022) for parents, Shields-Zeeman and Smit (2022) for part-time workers, and for differences along the income distribution.

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

[4] 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. Similarly, our documented COVID-driven changes in income can lead to changes in lifestyle behaviors which, in turn, can impact mental health outcomes (see, for example, Renzo et al. (2020)).

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 h,[5] while subsequent waves required additional time to re-contact the maximum number of individuals from the first wave. In April '20, 1097 individuals were surveyed. In July '20, 2000 individuals answered the survey, 795 of whom were from the first wave (72%). In July '21, 2014 individuals answered the survey, 74% (1273 individuals) of whom were from the second wave from the second survey. In April '22, 2002 individuals answered the survey, 74% (1498) of whom were from the third survey. Overall, 24% (475) answered the four waves.

*Attrition.* We find that attrition is mostly random. 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. We identify for each wave of the survey, how many individuals answered the previous wave (first and second; second and third; third and fourth). For each wave, 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, being young people less likely to answer the following survey (relative to middle aged people).[6] In order to get unbiased estimators, we need that the waves of the survey do not differ in terms of the socio-demographics and economic characteristics that can affect mental health. The first four columns of Table A3 shows that this assumption holds in the final sample that we use in our analysis.

*Spanish setting.* 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 8008 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.[7] These measures controlled the spread of the virus, but they also had a strong impact on the labor market (see Fig. 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 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 Fig. 1, during the fourth and last wave of our survey, in April '22, mortality was at stable and relatively low levels, all restrictions had been lifted and employment was higher than in pre-pandemic times.

[5] 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.

[6] As a robustness check, we perform the same analysis identifying the individuals that answered the fourth waves of the survey. Results are reported in column (4) of Table A1.

[7] 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.

### 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[8]:

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?"
   - "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

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

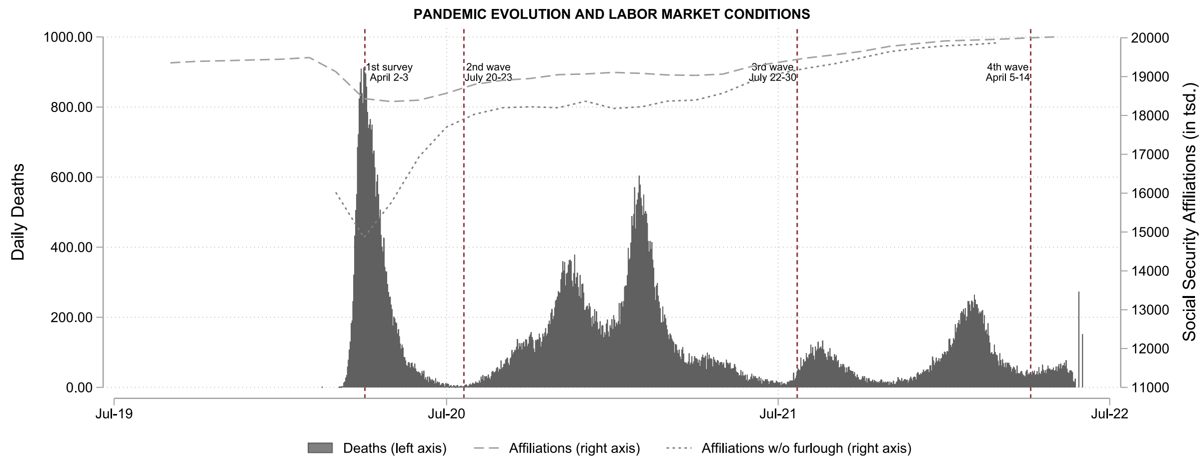



**Fig. 1.** Survey timing and pandemic evolution. Notes: The figure shows the daily observation of cases (left axis). Source: World Health Organization. Vertical lines indicate the timing of our survey. The right axis measures social security affiliations including and excluding furlough policies. Data source: INE (*Instituto Nacional de Estadística*, National Statistics Institute - Spanish Statistical Office.

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.[9]

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.[10]

### 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.[11]

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 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 against all the available pre-pandemic surveys. This final sample includes 6928 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. Fig. 2(a) illustrates the distribution of responses to the **general health** question[12] 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 be "very good" relative to pre-pandemic data.[13] 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.[14] Part of

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

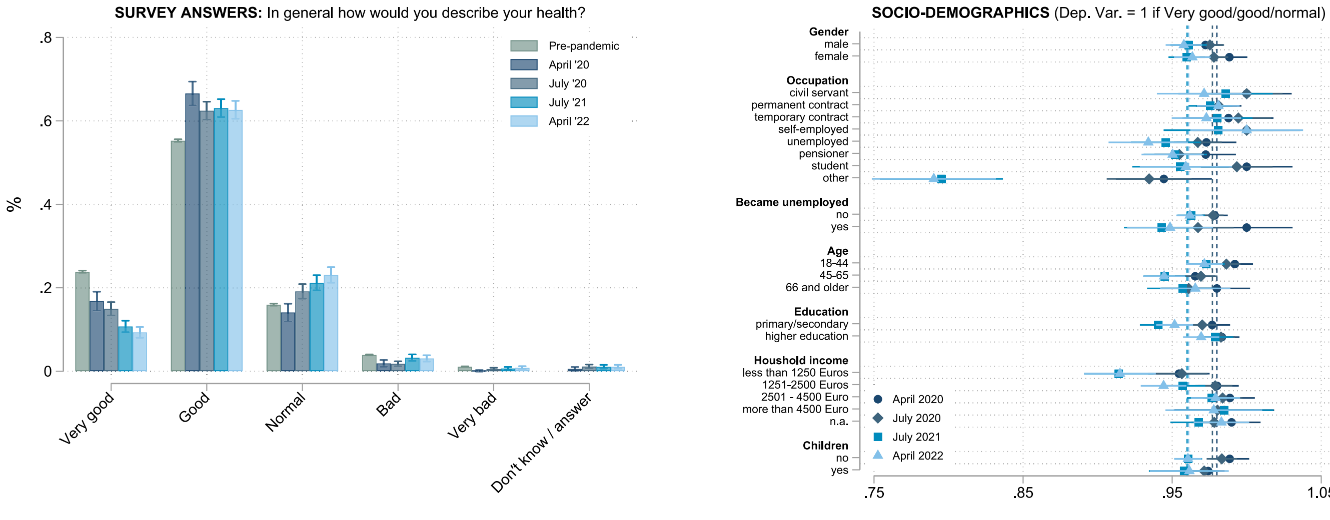
[10] None of the questions about outcomes were changed. Modifications affected mostly questions used in Foremny et al. (2020).

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

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

[13] 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.

[14] 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.




(a) Evolution over time

(b) Heterogeneity

**Fig. 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 = 1065), wave two (n = 1949), wave three (n = 1966) and wave four (n = 1948) of the survey. Panel (b) shows heterogeneous effects for wave one (n = 1065; dots), wave two (n = 1949; diamonds), wave three (n = 1966; squares) and wave four (n = 1954; 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 Eq. (1)). Dashed lines indicate the mean per wave. 95% confidence intervals indicated in the graphs.

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.[15]

Next, we turn to **mental health**. Fig. 3(a) similarly shows the distribution of responses to the question about feeling unhappy or depressed.[16] 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 (despite 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.[17] 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.[18] Figs. 2(b) and 3(b) show results for general and mental health, respectively. Dots

[15] 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).

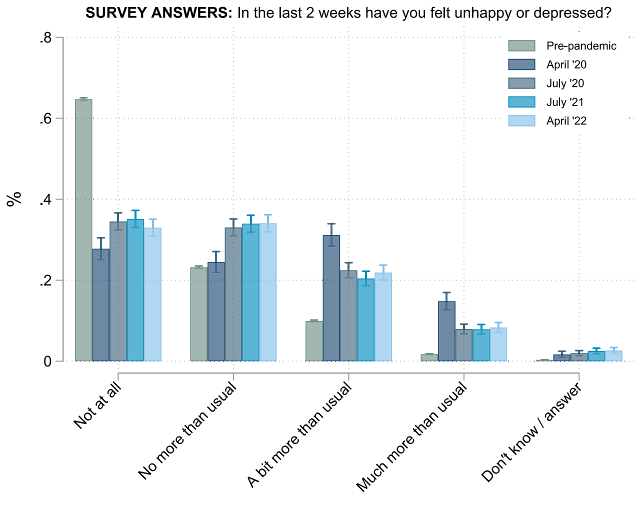
[16] The exact wording of the question is "*In the last two weeks, have you felt unhappy or depressed?*".

[17] 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.

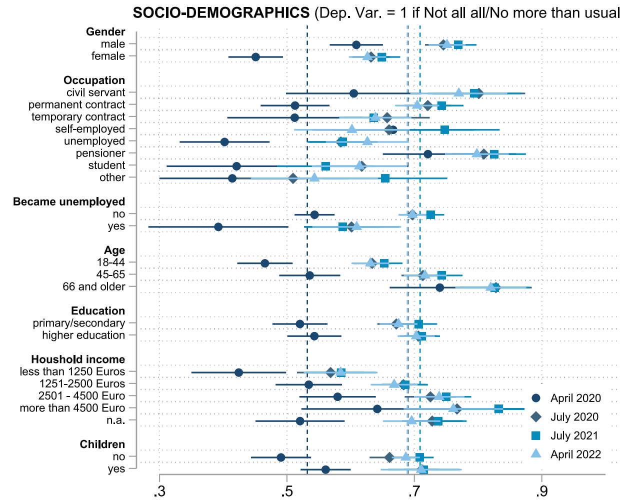
[18] As a first step, we document heterogeneity by estimating a linear probability model where we group positive outcomes and code them as a binary variable (see Table D1 in the appendix for the exact grouping of all variables used.):

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

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 $\beta_g$ 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.




(a) Evolution over time




(b) Heterogeneity

**Fig. 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 = 1065), wave two (n = 1949), wave three (n = 1966) and wave four (n = 1948) of the survey. Panel (b) shows heterogeneous effects for wave one (n = 1065; dots), wave two (n = 1949; diamonds), wave three (n = 1966; squares) and wave four (n = 1954; 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 Eq. (1)). Dashed lines indicate the mean per wave. 95% confidence intervals indicated in the graphs.

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.

Fig. 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).

Fig. 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 of reporting a good mental health status.[19]

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 1250 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.[20]

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.[21] 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.

Fig. 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 identifies gender as the most important determinant for reporting a good or bad mental health status, followed by living in a low-income household

[19] 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.

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

[21] 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).

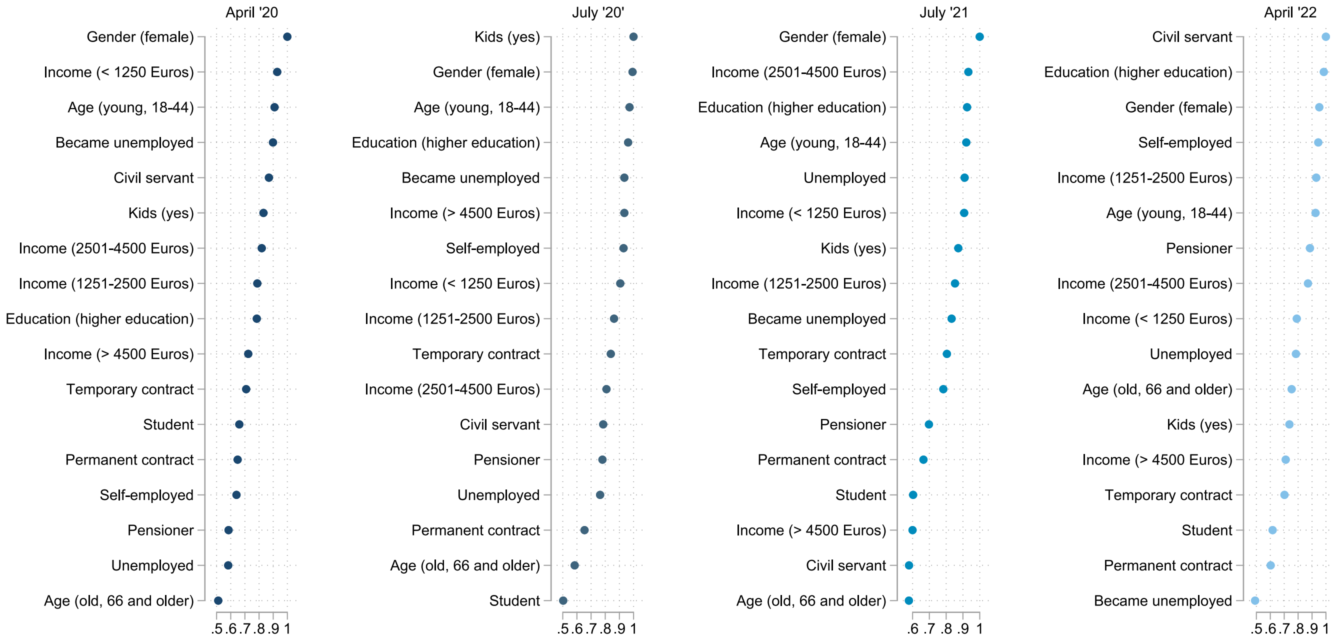



**Fig. 4.** Machine learning: random forest importance, feeling unhappy or depressed. Notes: The figure shows the importance of different variables after running a random forest classification model for each wave of the survey. All importance values are expressed as shares of the most important determinant. 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).

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.[22] 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 mediators 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).[23] This is 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 Eq. (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.[24]

[22] 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.

[23] We have selected these characteristics based on the evidence provided by the existing literature, as well as on the results of the machine learning exercise implemented in the previous section

[24] See Keele et al. (2015) and Gelbach (2016) for a detailed description of mediation analysis. In brief, mediation analysis estimates a simultaneous equations model. Eq. (2) estimates the direct effect of the various mechanisms on mental health, including all potential mediators and covariates (i.e. Eq. (1) with the addition of mediators as controls (Each regression includes the other potential mediators as control variables to alleviate the concern of potential confounding variables.)):

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

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).

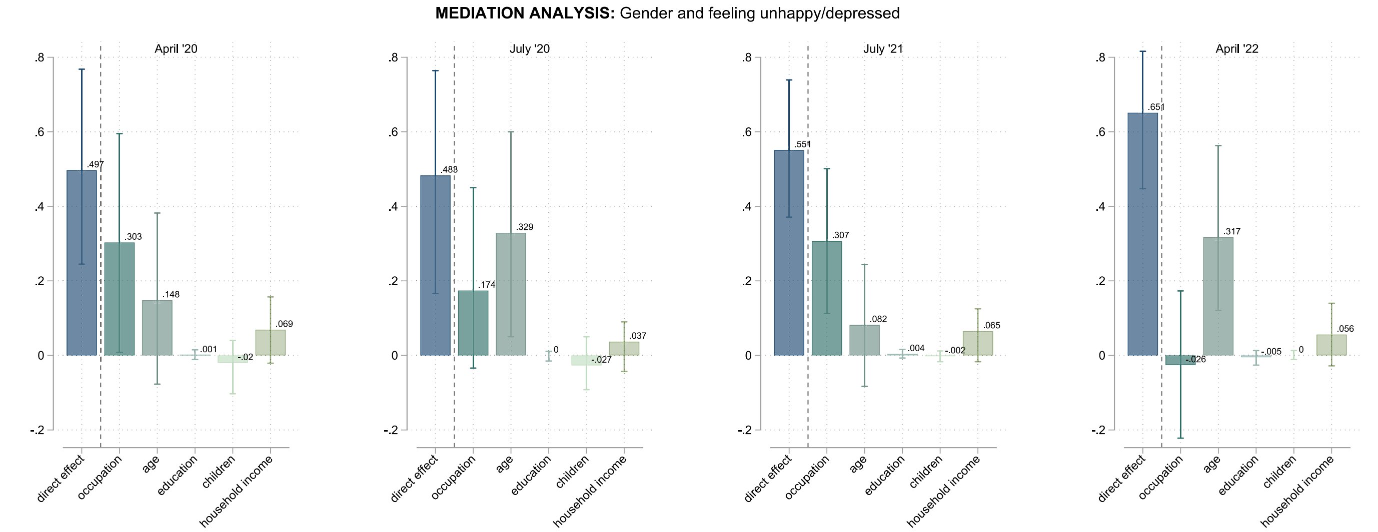



**Fig. 5.** Mediation analysis: Relative importance over the total effect of gender (feeling unhappy or depressed). Notes: The figure shows the relative importance of direct effect of gender on mental health and the indirect effect of gender on mental health mediated through the effect that gender has on each potential mediator. 95% confidence intervals indicated in the graph. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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.[25] 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. Fig. 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 a mediator for the gender effect on mental health. This is consistent with what we report in Fig. 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), $\beta_y$ correspond to the gap in mental health for group $g$ relative to the reference group before the pandemic and $\delta_y$ measure the evolution of the mental health gap during the pandemic. We include a full set of cell-level fixed effects $\gamma$ to our estimations.[26] 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.

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

The main difference between Eqs. (4) and (5) is that the latter controls for differences over time on the occupational status. In other

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A set of Eqs. (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 Eq. (3)

[25] These control variables are potential confounding variables. Our results show that when we control for them, the direct effect of gender gap on mental health persists, although it is of a smaller magnitude.

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

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 Fig. 6 show the evolution of each group over time, while panels on the right plot the estimates for each period according to Eqs. (4) and (5).[27]

Panels (a) and (b) of Fig. 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.[28] 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 Eqs. (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.[29] 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 conditions, in line with results from the mediation analysis.

Panels (c) and (d) of Fig. 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.[30] 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 Fig. 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.[31] 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 survey. 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 paper offers a novel perspective on the impact of Covid-19 on mental health in the Spanish population. We provide longitudinal evidence which sheds light on how gender and age has influenced mental well-being throughout the crisis. To achieve this, we conduct a large survey at four different points in time, including the peak of viral incidence (April '20) and various stages of the pandemic: a low-incidence scenario but with mobility restrictions (July '20), 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

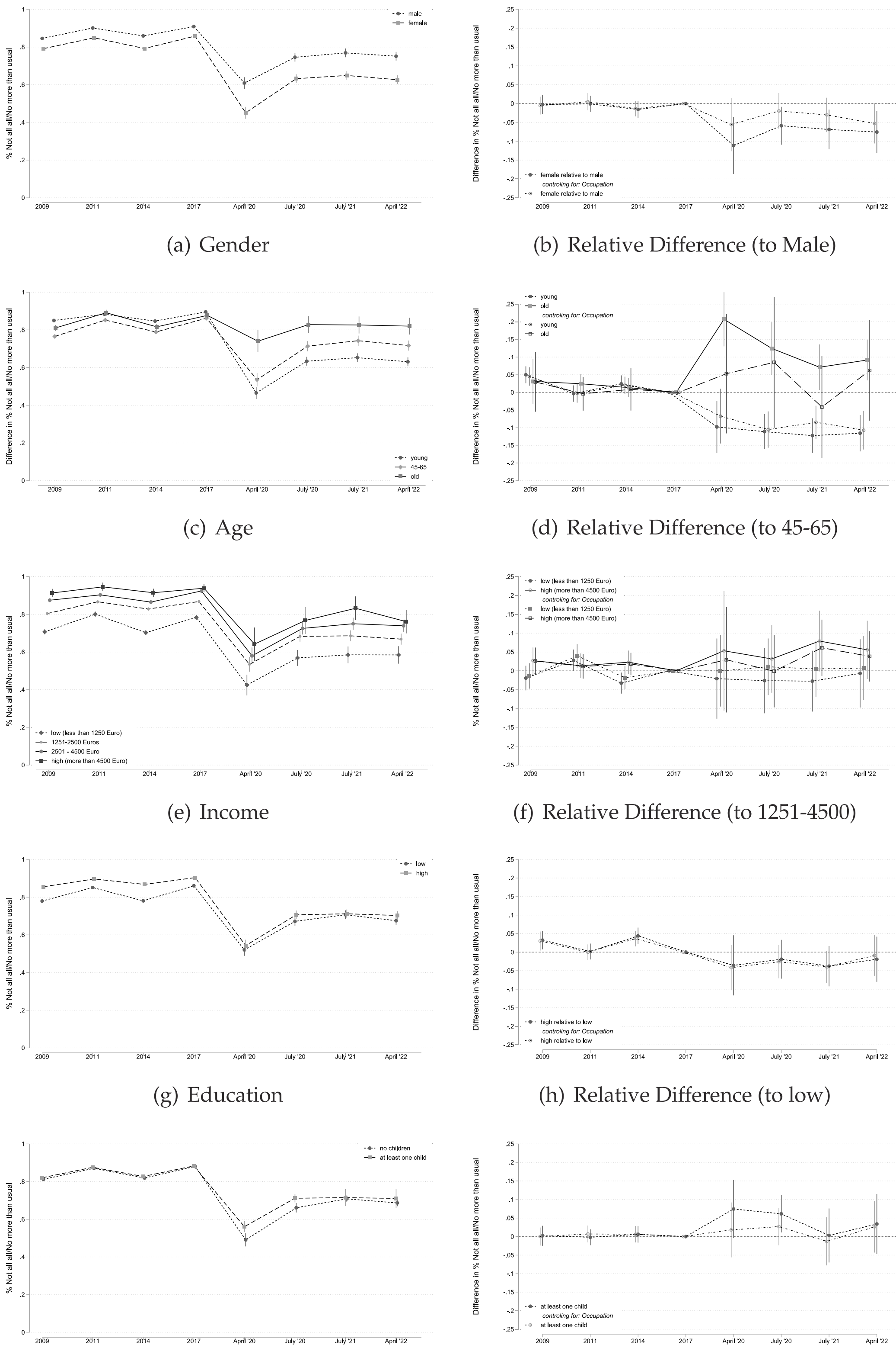
[27] Table A8 in the appendix shows the point estimates for various specifications and combinations of fixed effects. The graphs correspond to columns (b) and (c) in the table, which also shows OLS results (column a), a model controlling for all group trends in a dynamic way (column d), and estimations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

[28] 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).

[29] 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.

[30] 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.

[31] 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).




(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)

**Fig. 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 = 1065), wave two (n = 1949), wave three (n = 1966) and wave four (n = 1948) 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 Eqs. (4) and (5). 95% confidence intervals for standard errors clustered at the cell-level indicated in the graphs.

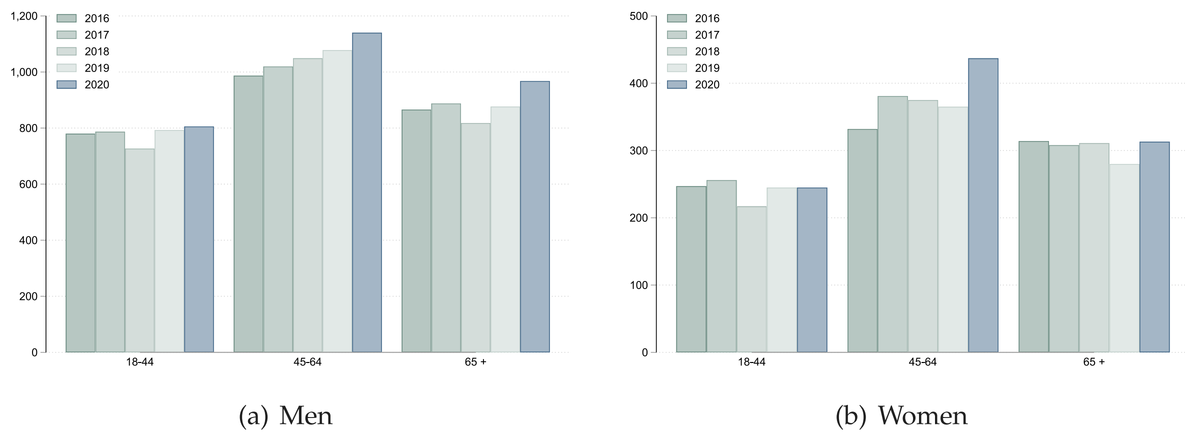



**Fig. 7.** Number of suicides by age. Notes: The figure shows the total number of suicides for men (panel a) and for women (panel b) in Spain by age bracket for each year from 2016 to 2020. Data comes from administrative sources; Mortality Registers collected by the National Institute of Statistics.

previous surveys to precisely quantify the deviations from long-term trends in the existing mental health gaps driven by the outbreak of the virus.

Our findings reveal a significant decline in all mental health outcomes compared to the pre-pandemic situation. Taking only the results of our first wave, we document quantitatively similar results compared to other studies in the literature, which document the short-term effects of the pandemic on mental health in Spain: while we find that 46% of the Spanish population report being depressed in April 2020, Codagnone et al. (2020) show that 43% of the population in Italy, Spain and the UK are at high risk of stress, anxiety and depressions during the same month. However, we document that this outcome is not evenly distributed across socio-economic groups. We observe that women and younger individuals are particularly likely to report negative mental health effects. This result is consistent with the short-run effects documented by Jacques-Aviñó et al. (2020). We then advance on these results and show that this effect is mediated by labor market conditions, which on average are less stable for this part of the population. Importantly, our results highlight the persistence of those gaps, even in the low-incidence contagion scenario. While our objective is to shed light on the labor market as one specific mediator, we acknowledge that this dimension is only one out of many determining the mental health status of the population. In this paper, we focus on the role of the observable characteristics collected as part of our survey for this purpose, leave the evaluation of other potential determinants, which is outside the scope of the paper, for future research.

Our results are policy relevant, as they emphasize the need for targeted interventions to support the most affected populations and mitigate the long-term impact of negative shocks on mental health. 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. Fig. 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. Our study demonstrates that the adverse impact of crises and recessions on mental health is largely concentrated among individuals in vulnerable situations. To avoid some of the psychological costs of potential future crisis, it is essential to consider the benefits of stable social assistance programs along these dimensions. While not all parts of society can be sheltered against unemployment during a crisis, properly defined welfare programs can mitigate the economic consequences of job loss. In addition, appropriately designed labor market reforms could help to reduce the level of vulnerability among people with precarious conditions by limiting the use of short-term contracts, which are concentrated within the most vulnerable groups.

## CRediT authorship contribution statement

**Dirk Foremny:** Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Pilar Sorribas-Navarro:** Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Judit Vall Castelló:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

## Data availability

The authors do not have permission to share data.

## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ehb.2024.101351.

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