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Personality Traits and Heterogeneous Adaptation to the Mental Health Effects of the Covid-19 Pandemic

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Personality Traits and Heterogeneous Adaptation to the Mental Health Effects of the Covid-19 Pandemic

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DEDICATORY

To my beloved moms.

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First of all, **to my moms Rosy and Alex** for their tireless support throughout my life. Thanks for all your love. This achievement is ours.

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Paúl Andrés Ponce

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Resumen

El presente trabajo analiza el efecto de la adaptación a lo largo del tiempo y de los rasgos de personalidad del modelo *Big-five* sobre dos dimensiones de salud mental: preocupaciones –entendida también como ansiedad– y depresión. Usando un modelo Logit ordernado generalizado encontramos que el tiempo transcurrido reduce el nivel de preocupaciones a la vez que incrementa el nivel de depresión. De igual forma, encontramos que el rasgo de neuroticismo tiene un impacto negativo sobre el nivel de salud mental en general, y sobre el aumento de la depresión a lo largo del tiempo. El rasgo de escrupulosidad tiene un impacto negativo sobre las preocupaciones, mientras que los rasgos de extroversión y escrupulosidad contribuyen a reducir el nivel de depresión.

Palabras clave: salud mental, preocupaciones, ansiedad, depresión, personalidad, cuarentena, Covid-19, adaptación.

Abstract

This work analyzes the effect of adaptation over time and of the *Big-five* personality traits model on two dimensions of mental health: worries –also understood as anxiety– and depression. Using a generalized ordered Logit model, we find that elapsed time reduces the level of worries, while contributing to an increased level of depression. Similarly, we find that the trait of neuroticism has a negative impact on the level of mental health in general, and on the increase in depression over time. The trait of conscientiousness has a negative impact on worries, while the traits of extraversion and conscientiousness help reduce the level of depression.

Keywords: mental-health, worries, anxiety, depression, personality, lockdown, Covid-19, adaptation.

1 Introduction

The Covid-19 pandemic has had a large negative effect on mental health (Brooks et al., 2020; Javed et al., 2020; Panchal et al., 2020; Singh et al., 2020). Indeed, mental health has been affected not only by the pandemic itself, but also by the contingent and extraordinary measures associated with it, like the imposition of lockdowns, suspension of transnational travel, closing of schools and offices, among others.

Given the persistent and/or recurring nature of the negative shock created by the pandemic and the associated response policies, a key question that has received attention recently concerns individuals' mental health response over time (see e.g. Daly and E. Robinson (2020)). This research aims at analyzing whether individuals show resilience or adaptation, bouncing back from the initial shock, or whether, on the contrary, the initial shock on mental health is exacerbated over time.

Figure 1 provides a first look at these dynamics using the daily average of the worries and depression indexes based on the survey responses reported by (Fetzer et al., 2020a). It shows that, as the number of days in confinement increases, the depression index grows and then stabilizes, while the worries index is declining over time. Thus, it seems that the dynamic of adaptation varies depending on the dimension of mental health considered.

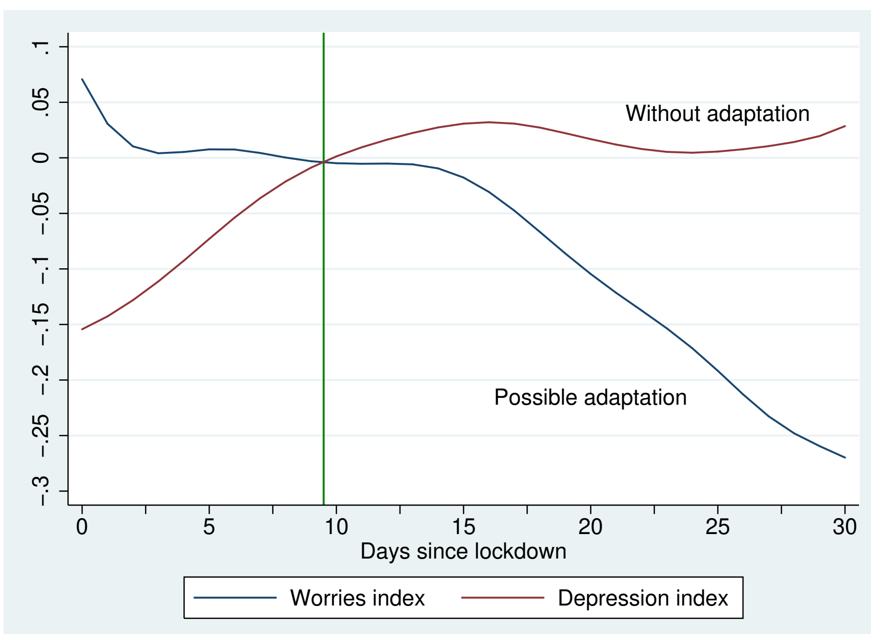


Figure 1: Worries and Depression Indexes by Day Since Lockdown

In this paper we analyze this question by exploiting the international variation generated by the times at which the pandemic struck different countries together with the individual variation generated by the times at which the individuals in each country responded to the global survey that we use. Furthermore, since mental health is a multidimensional concept, we study this response along two dimensions of mental health –worries and depression. More specifically, we analyze the effect of the number of days since the start of a lockdown on independent indexes of worries and depression. In addition, given that personality traits are associated with mental health (Kokko, Rantanen, and Pulkkinen, 2015; Rammstedt, 2007), the measurement of the effect of days is further conditioned on individuals' personality traits as defined by the *Big-five* model, i.e. extraversion, agreeableness, conscientiousness, neuroticism, and openness to experiences.

Our analysis uses the survey responses reported by the project *Global Behaviors and Perceptions in the COVID-19 Pandemic* (Fetzer et al., 2020a). This international survey focused on the behaviors and perceptions of people regarding the pandemic. By relating these data to the database provided by the *Coronavirus Government Response Tracker* of Oxford University (Hale et al., 2020a), which provides country-level data, we are able to construct a measure of time elapsed that is comparable across countries.

Our preferred econometric specification estimates a generalized ordered logit model that explicitly considers the fact that our dependent variables take a limited set of hierarchical values, and also that the odds ratio between categories does not remain constant. For comparison, we also estimate an OLS model and a mixed-effects ordered logit.

We find that, as the number of days increases, the depression index tends to rise as well. In the case of worries, however, we find an effect in the opposite direction, favoring adaptation. These results may be related to the fact that worries are affected by uncertainty, which has tended to partially resolve over time, independently of confinement. We also find that neuroticism (negative emotionality and nervousness) has a negative impact on the level of mental health in general, and on the increase in depression over time. Conscientiousness (constraints and control of impulses) has a negative impact on worries, while extraversion (sociability, and positive emotionality) and conscientiousness help to reduce the level of depression.

Our work contributes to the literature by first measuring the effect of time elapsed on two specific dimensions of mental health: Worries and depression, thus evaluating the adaptation hypothesis on these dimensions. Second, it contributes to the literature by analyzing the differential effects of personality traits on the adjustment mechanisms for each dimension of mental health.

The paper is organized as follows. In Section 2 we review the related literature, with an examination of some relevant works on Covid-19 and mental health, the dimensions of mental health analyzed, the mechanisms available to face negative shocks, and their relationship with the adaptation process and the personality traits. In Section 3 we look at the econometric models used, while Section 4 describes the data used. In Section 5 we present the main results, and Section 6 provides a robustness analysis. Section 7 concludes.

2 Literature review

The Covid-19 pandemic represents a systemic and sustained shock with profound impacts throughout the world. A key aspect that has received increased interest and concern is the impact of the pandemic, and specifically lockdowns, on people's mental health. The pandemic generates a state of heightened levels of health-related risk along with increased uncertainty and ambiguity. Lockdowns add to these effects by imposing restrictions on individuals' normal lives, economic activity and, particularly, social contact. As a consequence, recent research shows a consistent negative effect on individuals' emotional well-being throughout the world (Van Babel et al., 2020; Brooks et al., 2020; Javed et al., 2020; Panchal et al., 2020; Singh et al., 2020).

For instance, Serafini et al. (2020) argue that during the Covid-19 outbreak, various psychological problems that affect mental health have emerged. These include anxiety, depression, frustration, uncertainty and stress. These authors also summarize the most relevant psychological reactions to the Covid-19 infection including pervasive anxiety, frustration and boredom, and disabling loneliness. These factors feed back from heightened-risk elements such as inadequate supplies and information, together with a constant reduction in psychological resilience.

Several papers also highlight that the mental-health impact of the Covid-19 pandemic varies across different population groups and geographical areas. Courtney et al. (2020) analyzed the impact on depression and anxiety among children and adolescents, while Hagerty and L. Williams (2020) focused on brain styles and their interaction with the need for human connection to explain the mental health consequences of Covid-19 from a psychiatric perspective. Hagerty and L. Williams (2020) characterized the brain's biotypes with the aim of conceptualizing how they contribute to mental-health dysfunction. Given the restrictions on social interaction, "these brain styles could be determinative of how individuals' experience the pandemic from a mental-health perspective" (p. 2). The authors found that people with an anhedonic brain style face a threat to their core need for human connection during COVID-19, while individuals with a ruminative brain style could experience an increased need for social support. Also, individuals with a threat dysregulation brain style face a risk due to deficits in human connection. Sharifi and Khavarian-Garmsir (2020) and Rubin and Wessely (2020) studied the impact of quarantines on cities using different analytical perspectives.

Building upon this research, Xiang et al. (2020) concludes that mental health care needs to be developed urgently. Likewise, Van Babel et al. (2020) argue that several actions must be implemented to mitigate the potentially devastating effects of Covid-19. For example, identifying credible sources to share public health messages, promoting cooperative behavior, emphasizing messages focused on protecting others, among other measures that should be carried by political and community leaders. Meanwhile, International Red Cross (2020) highlights the necessity to increase the mental health and psychosocial support worldwide, with emphasis on more affected and unequal communities.

Although Covid-19 constitutes a negative shock to individuals' mental-health that requires broad-based responses, it is important to note that people also have at their disposal mechanisms to fight negative shocks. Indeed, the literature mentions some endogenous and exogenous mechanisms through which a person may reduce the impact of negative shocks. Among these mechanisms, resilience, locus of control and some personality traits appear as factors that help cope with negative situations (Daly and E. Robinson, 2020; Henry and Mõttus, 2020; Johnston, Kung, and Shields, 2020; Buddelmeyer and Powdthavee, 2016).

First, Daly and E. Robinson (2020) found an increase in distress in the U.S. during the Covid-19 crisis. However, the large initial rise in distress is followed by a drop in the weeks following the start of the crisis. The authors propose that resilience is the factor that explains this dynamic of the response to the shock caused by the pandemic. However, resilience implies a heterogeneous response *throughout* the shock, particularly a *limited* negative response to the initial shock along with better adaptation thereafter. In this research we focus on the process of adaptation over time, i.e. following the initial shock, we ask how mental health evolved considering the number of days that passed thereafter.

Thus, there exists a difference between Daly and E. Robinson (2020) and us regarding the approach used to identify the mechanisms to face negative shocks. While they followed up on the behavior of distress analyzing eight waves of the 'Understanding America Study (UAS)', we analyze the surveyed sample by Fetzer et al. (2020a) only for one period. Daly and E. Robinson (2020) identify neuroticism as a factor that causes less resilience. We share this finding that neuroticism negatively affects both mental health measures in our estimates. However, more generally, we found differences on the effects of personality traits on adjustment depending on the dimension of mental health considered as outcome.

In the same line, Johnston, Kung, and Shields (2020) found that non-cognitive skill is the best predictor of resilience. This skill is measured by self-efficacy, that also reduces the psychological effects of a negative earning shock. Buddelmeyer and Powdthavee (2016) showed that people with strong internal locus of control are psychologically insured against own and others' serious illnesses or injuries. But, the authors also mention that this characteristic is not enough to face the majority of other life events.

Pulkkinen and Caspi (2002) considered various additional elements that affect the dynamics of psychological well-being. The authors find that features such as community reallocation, social comparisons, coping strategies, among others, influence adaptation to different life circumstances. However, these factors are not necessarily adjustable in the short-term. On the contrary, we focus on adaptation as a fast mechanism to cope with the effects of the pandemic, confinement and deep uncertainty suffered during this year.

Personality traits are also identified as factors that help cope and adapt to difficult situations. In this line, Bucher, Suzuki, and Samuel (2019) found that "lower levels of neuroticism and higher levels of extraversion, agreeableness, conscientiousness, and openness were associated with more favorable outcomes" (p. 51). That is to say, personality represents one of the key underlying mechanisms in the process of mental adaptation.

Beyond these results, however, it is important to consider that mental health is a multidimensional concept and hence negative shocks may have different effects on each of these dimensions. Furthermore, the same factors related to resilience and adaptation may also have a different relation with each dimension of mental health. It is thus necessary to delimit the elements of mental health that we analyze in this paper.

But, first it is necessary to mention what are the dimensions of mental health. Headey, Kelley, and Wearing (1993) found four dimensions of mental health: Life Satisfaction, Positive Affect, Anxiety and Depression. Also, they recommend the need of measured it separately, also avoiding mixed measures. Since this date, literature in the field have a generalized use of this four dimensions.

In this study we focus on two particular dimensions of the set of mental health: *worries* and *depression*. In particular, we use as outcome variables a worries index and a depression index. The worries index is a formulation by Fetzer et al. (2020c).[1] The depression index provides a criteria-based diagnostic of depressive disorders and a valid measure of depression severity. It is formulated based on a battery of questions from the "Patient Health Questionnaire (PHQ)", where its PHQ-9 module refers to depression. There are several references that confirm the psychological properties of this measure (see e.g. Kroenke, Spitzer, and J. Williams (2001); Manea, Gilbody, and McMillan (2012)).[2]

As mentioned above, personality is one of the key factors that affect the individuals' ability to cope with negative shocks. However, considering the multidimensionality of mental health, it remains to analyze how this effect may vary across dimensions. We next turn to this point.

The Big-Five personality model is a standard measure to summarize the main personality aspects, called *traits*. Gosling, Rentfrow, and Swann (2003) mention that the Big-Five framework provides a classification of individual differences of personality into five broad and empirically derived domains. These domains are: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experiences.[3] Their opposite domains are: introversion, antagonism, lack of direction, emotional stability and close-mindedness (Appelt et al., n.d.).[4]

Following Oliver, Naumann, and Soto (2008), extraversion refers to energy and enthusiasm, and implies an *energetic approach* that includes aspects such as sociability, activity, assertiveness, and positive emotionality. Agreeableness refers to altruism and affection, with a *prosocial and communal orientation* combining traits like altruism, tender-mindedness, trust, and modesty. Conscientiousness refers to constraints and control of impulses, focused on *socially prescribed impulse control* following norms and rules, and planning, organizing, and prioritizing tasks. Neuroticism refers to *negative emotionality* and nervousness, constrasted against emotional stability by feeling anxious, nervous, sad, and tense. Finally, Openness refers to originality and open-mindedness, focusing on describing the depth and complexity of an individual's *mental and experiential life* (Oliver, Naumann, and Soto, 2008).

Analyzing the relationship between personality traits and mental health, we found that this connection can be expressed in many ways. For example, one approach for mental health treatment lies on the design of treatments based on personality traits, where neuroticism is

[1] There are another measures of this dimension like e.g. the index used from the German Socio-Economic Panel (SOEP) that was used on the work of Rammstedt (2007).

[2] The construction process of each index is described in the Appendix.

[3] These five traits also can be found with the acronym 'OCEAN' for openness, conscientiousness, extraversion, agreeableness and neuroticism (Oliver, Naumann, and Soto, 2008).

[4] Sometimes neuroticism is measured by its inverse: emotional stability. We use neuroticism throught this paper.

usually the most stable predictor (Hopwood et al., 2008). Another approach considers the existence of relationships between most of the Big-Five traits at non-trivial levels with mental health. Mu et al. (2016) proposed the 'barometer hypothesis', which argues that there may exist a barometer of general feelings of positivity or negativity behind both mental-health and personality. They found that, in line with their hypothesis, the optimal model included both personality traits and mental health latent factors. Also, Kokko, Rantanen, and Pulkkinen (2015) establishes that in adulthood, personality traits and mental well-being are highly linked, and that "low neuroticism and high extraversion were most strongly associated with mental well-being; the other traits had less consistent links" (p.156). More generally, personality traits have different levels and directions of association with mental health. In this study we are particularly interested in how these traits are related to worries and depression, and the dynamics of adaptation to a negative shock in each of these domains.

Regarding the worries index, Rammstedt (2007) studied the correlations between personality and ten domains of worries and twelve domains of satisfaction. Considering for the domain of personality internal and external locus of control as well as optimism, the author found that satisfaction and individual worries are highly related to personality. But, society-oriented worries are explained by personality to a lower degree. In particular, Rammstedt (2007) found that although aggregated worries were unaffected by personality, individual worries were correlated with the individual's personality. Indeed, personality, conjugated with emotional stability, optimism and external locus of control accounted for 23% of the variance on worries and satisfaction.

Rammstedt (2007) also found that neurotics do not tend to worry more than emotionally stable individuals. As we will see, this result contrasts with our estimates presented in section 4, where we consistently find a negative effect of neuroticism on the worries index, i.e. neuroticism increases the level of worries. Even, though it has no statistical significance, the negative effect remains when days since lockdown are mediated by neuroticism.

Specht, Egloff, and Schmukle (2011) found in their study that personality had the capacity to predict some of the objective major life events and then change as a reaction to these events. Thus, the authors concluded that personality can change throughout life especially in young and old ages, partly in response to social changes and new experiences. For this reason, we develop a robustness analysis within section 4, with the aim of estimating whether the time under confinement can affect the personality traits.

Wehner, Schils, and Borghans (2016) analyze the relationship between low emotional stability and mental ill-health along with the possible substitution effect between conscientiousness and emotional stability. They found that a higher degree of conscientiousness mitigates the negative relationship between low emotional stability and mental health. On the contrary, an individual with low emotional stability (i.e. high neuroticism) and low degree of conscientiousness is more likely to experience mental ill-health (Wehner, Schils, and Borghans, 2016).[5]

Moreover, adaptation can be an effective mechanism to cope with negative shocks that affect mental health. Crum et al. (2017) provides an interesting study in this line. They find that adopting a stress-is-enhancing mindset can improve "cognitive, emotional, and physiological attributes that may contribute to adaptive responses over the long-run" (Crum et al., 2017:p.13). This finding is in line with our hypothesis that adaptation drives better mental health over time. Hence, it could be an interesting research question to capture a person's mindset, and then measure its relationship with adaptive mechanisms used to face the affectations caused by the pandemic.

There is also evidence that points out that, as the days pass since the start of the confinement, individuals adjust their behaviors and beliefs such that their mental health stabilizes or improves. This adjustment process can be called *adaptation*, like Daly and E. Robinson (2020) establish in their work. The authors show that the levels of distress initially rose due to the pandemic, but then showed a significant decline thanks to mental adaptation and resilience.

Other works, however, show that, as time goes by, individuals suffer a (further) deterioration of their mental health. For example, Fetzer et al. (2020c) states that people who perceive an insufficient public and government response to the pandemic, suffered lower mental well-being. In particular, they found that "respondents' pessimistic beliefs about their fellow citizens' and government's response to COVID-19 are related to lower mental well-being, particularly in terms of their anxieties and worries specific to the COVID-19 pandemic" (Fetzer et al., 2020c:p. 8).

Fetzer et al. (2020c) also argue that people rely on a fast response by governments as a mechanism to cope with the uncertainty derived from the crisis. And finally, they mention that nationwide lockdown measures have an impact on citizens' confidence on their government, but the effects on well-being are less consistent.

These findings are relevant for our work. On the one hand, the results presented in section 4 contrast with those of Fetzer et al. (2020c). On the other hand, our results complement

[5] For a more detailed discussion on the relationship between economics and personality, see Heckman (2011) and Heckman, Jagelka, and Kautz (2019).

their results by showing that, under lockdown, people can achieve mental well-being through a mechanism of mental adaptation, sometimes mediated by personality traits or gender of the individuals.

Therefore, adaptation plays a key role in explaining the set of reactions shown by people during and after lockdowns. However, as we show below, its role is not uniform because some dimensions of mental health worsen after the confinements, while others seem to improve.

The indicator of adaptation in the present work corresponds to the number of days elapsed after the start of the quarantine in each country, in the context of the Covid-19 pandemic. In this sense, it is important to mention that references to short and medium-term correspond to a low and high number of days, respectively. This means that the temporal variation is compressed in a short window frame.

Although the time-horizon based on the number of days may not sound very intuitive, it is worth noting that the pandemic has extended for almost a year. This is why economic predictions and the actions of society itself have been adjusted and remain in constant configuration to mitigate the difficulties of the 'new normality'.

The contribution of our work lies in analyzing the effect of days in quarantine on people's mental health (worries and depression), also considering the importance that the personality traits of each individual have.

3 Methodology

Following the literature on resilience and adaptation we propose that, after the negative shock to mental health caused by the Covid-19 pandemic, as time goes by individuals may adjust their behavior to recover –or at least not further worsen– their emotional stability. We consider, however, that this effect may vary across mental health dimensions, particularly in the context of the Covid-19 pandemic, where long lockdowns may be understood as a sustained shock with potentially increasing negative effects on mental health.

If the adjustment process favored by the passing of days is statistically significant, it is possible that there is a period of individual adaptation that leads to better levels of mental health. For this study, this would mean lower rates of worries and depression. We thus consider two specific hypotheses.

The first one implies that the number of days elapsed since the start of a quarantine has a significant effect on people's mental health, after controlling for socio-demographic characteristics and other covariates of interest. In particular, a negative coefficient implies an adaptation process associated with less worries and lower depression.

Our second hypothesis, is that some dimensions of personality help reduce the levels of worries and depression. Previous psychological literature shows that personality plays a key role in resilience and adaptation (Daly and E. Robinson, 2020; Henry and Mõttus, 2020). We also analyze this and ask what dimensions of personality are related to lower levels of worries and depression and whether they contribute to adaptation over time.

We propose several econometric models to estimate these relationships for each dimension of mental health analyzed (worries and depression). But, first it is necessary to explain some details about the expected results.

Regarding worries, the time in confinement is expected to be associated with a reduction in the index. That is to say, as the number days following a lockdown increase, mental health associated with worries is gradually improving, returning to pre-pandemic levels. Or, at the very least, this dimension of mental health does not deteriorate. This process is considered an *adaptation process* of the individual to cope with the complications imposed by the pandemic.

For the depression index and related to the studies of Fetzer et al. (2020c) and Serafini et al. (2020), it is presumed that the time in confinement is associated with an *increase* in the level of depression. In the best scenario, we expected that this variable would not have a significant effect on the level of depression such that there is no increased emotional draining. The process of adaptation is likely more limited in the case of depression. Whether we consider the effects of a prolonged lockdown or a diminished income due to the economic impact of the pandemic, or personal losses occurred in this period, depression tends to aggravate over time.

Thus, the effect of the number of days varies depending on the mental health dimension that we consider. This provides a possible reconciliation between two opposing lines of research regarding the mental health impact of the Covid-19 pandemic. First, some of the recent literature about mental health in the time of Covid-19 finds that people are adapting to the new context (Daly and E. Robinson, 2020). But, there is actually an argument more commonly found that the pandemic generates a negative impact on mental health derived from uncertainty, lockdown measures, trust in government and neighbors, among others (Fetzer et al., 2020c).

We estimate models for each index separately. In each case, we incorporate variables that reflect individuals' perception of their own health status and their personality traits from the Big-Five model. Personality variables are included as dummies for each personality trait so as to allowing the inclusion of interaction terms between these dummies and the variable *days since lockdown*.

Recall that for both indexes a higher value means greater worries/anxiety or depression. Also, it is important to note a key distinction between the two indexes. In the case of the worries index, it is a measure developed by the authors of the survey (Fetzer et al., 2020b; Fetzer et al., 2020c), and there have been no efforts to validate it. Thus, it is possible to find less parsimonious results in this dimension. The depression index, however, refers to a standard questionnaire generally applied to diagnose this condition in a patient. For the Global Survey of COVID-19, the authors made a small adaptation by not including the question about suicide, so the index is constructed with 8 questions (Fetzer et al., 2020b). Yet, we expect that component-wise comparisons would be more consistent in this dimension.

For our proposed estimations, note that both indexes are constructed as the aggregation of their respective components, which are categorical variables. Therefore, the indexes are not fully continuous variables and the hierarchy represented by their values makes them ordinal variables. Personality traits are also constructed as categorical variables whose values follow a hierarchical order. As a consequence of this structure, the functional form of the model to be estimated is not trivial, and thus we use several alternatives.

3.1 Estimation by Ordinary Least Squares – OLS

Let Φ be a function of covariates defined as:

$$\Phi = \beta_1 days_{i,t} + \beta_2 days_{i,t}^2 + \delta_{\mathbf{1}} \mathbf{x_o} + \gamma_{\mathbf{1}} \mathbf{x_p} + \gamma_{\mathbf{2}}(\mathbf{x_p} \times days) + \delta_3(x_o^s \times days), \quad (1)$$

where *days* is a continuous variable that refers to days since lockdown, $\mathbf{x_o}$ is a vector of other covariates that includes age, education, gender (female) and health status (poor, fair, good, and excellent). $\mathbf{x_p}$ is a vector with dummy variables that captures the five dimensions of the Big-Five personality test, and x_o^s refers to a subset from $\mathbf{x_o}$ corresponding to a gender indicator variable.[6]

Hence, the OLS estimation is given by the following equation:

$$y_{i,j,t}^h = \beta_0 + \Phi_{i,t}(\cdot) + a_j + b_k + \mu_i, \quad (2)$$

where $y_{i,j,t}^h$ is the mental health dimension outcome and $h \in \{worries, depression\}$. We include country fixed effects a_j and date fixed effects b_k.[7]

[6]We include only an interaction term with *female* for parsimony.

[7]Note that date fixed effects correspond to the actual date of the survey and not to *days since lockdown*.

3.2 Estimation by Mixed-Effects Ordered Logit – MEOLOGIT

As Rabe-Hesketh and Skrondal (2012) points out, the entities used as observation units often *fall into groups or clusters*, such that it is necessary to design models that allow for within-cluster correlations. Ordinary regression models assume that the residuals are independent, therefore do not align with within-cluster dependence assumptions. In this way, although ordinary regression shows incorrect standard errors, multilevel models can overcome this issue (Rabe-Hesketh and Skrondal, 2012). For this reason, it is important to note that the sample used in this study is composed by individuals nested within countries. Therefore, a natural next step is to incorporate the two-levels of nesting explicitly. Thus, we estimate a Multilevel Mixed-Effects Ordered Logit –MEOLOGIT– model, which incorporates nesting explicitly, considering the categorical nature of the dependent variables and providing adjusted standard errors that add precision to the coefficients (Rabe-Hesketh and Skrondal, 2012; Smithson and Merkle, 2014).

For the estimation of the MEOLOGIT model and following StataCorp (2013) and Agresti (2010), we have as starting point a two-level model with J independent clusters, conditional on a set of fixed effects $\mathbf{x}_{ij}$, a set of cutpoints κ, and a matrix $\mathbf{z_{ij}u_j}$ of random effects. The cumulative probability of the response being in a category higher than m is given by:

$$Pr(y_{ij} > m|\mathbf{x}_{ij}, \kappa, \mathbf{u}_j) = H(\mathbf{x}_{ij}\beta + \mathbf{z}_{ij}\mathbf{u}_j - \kappa_m)$$

for $j = 1, ..., J$ clusters. Each cluster j has n_j observations and M is the number of possible outcomes. $H(\cdot)$ is the logistic cumulative distribution function that represents cumulative probability.

The vector $\mathbf{x}_{ij}$ are the covariates for the fixed effects, analogous to the covariates of a standard logistic regression model, with regression coefficients (fixed effects) β. Also, $\mathbf{x}_{ij}$ does not contain a constant term because its effect is absorbed into the cutpoints.[8]

Our estimating equation for MEOLOGIT is thus:

$$Pr(y_{i,j,t} > m|\mathbf{\Phi}_{i,j,t}, \kappa, \mathbf{u}_j) = H(\mathbf{\Phi}_{i,j,t} + \mathbf{z}_{ij}\mathbf{u}_j - \kappa_m). \tag{3}$$

[8] An introduction to multilevel models for limited dependent variables is provided by Smithson and Merkle (2014). And, an analysis of ordered response models with a different approach is provided by Riedl and Geishecker (2014).

3.3 Estimation by Generalized Ordered Logit – GOLOGIT

Agresti (2010) recommends to avoid linear regression models for ordinal response scores. Among various limitations, the author explains that an "ordinary regression approach does not account for 'ceiling effects' and 'floor effects,' which occur because of the upper and lower limits for the ordinal response variable. Such effects can cause ordinary regression modeling to give misleading results." (Agresti, 2010:p. 5).

Remembering that our outcome variables –the worries and depression indexes– are ordinal variables (each category or level of the index represents a hierarchy), it seems necessary to implement a non-linear estimation with a different functional form. The natural option is an Ordered Logit –OLOGIT– model, which we estimate first. Yet, this model assumes that the odds ratio is constant across categories. Indeed, according to R. Williams (2016), "if the assumptions of the model are met, the odds ratios will stay the same regardless of which of the collapsed logistic regressions is estimated" (p. 3). To evaluate this assumption we conducted a *Brant's test* (Brant, 1990), where we found that the assumptions of the model are not satisfied (R. Williams, 2016). For this reason, we prefer the generalized version of the ordered logistic regression, which relaxes the assumptions of the OLOGIT.

For the estimation of a Generalized Ordered Logit Model –GOLOGIT– and based on R. Williams (2006), we have the general formula:

$$P(y_i > m) = g(X\beta_m) = \frac{\exp(\beta_{0m} + X_i\beta_{1m})}{1 + \{\exp(\beta_{0m} + X_i\beta_{1m})\}},\ m = 1, 2, ..., M-1,$$

where M is the number of categories of the ordinal dependent variable.[9] Then, the GOLOGIT estimation is specified as follows:[10]

$$P(y_{i,t} > m) = \frac{\exp(\beta_{0m} + \Phi_m(\cdot) + a_j + b_k)}{1 + \{\exp(\beta_{0m} + \Phi_m(\cdot) + a_j + b_k)\}},\ m = 1, 2, ..., M-1 \tag{4}$$

Having described the econometric models to be used, in the next section we provide a look at the datasets analyzed.

[9]Following R. Williams (2006), the probabilities that Y will take on each of the values M are given by:

$$\begin{aligned} P(Y_i = 1) &= 1 - g(X_i\beta_1) \\ P(Y_i = m) &= g(X_i\beta_{m-1}) - g(X_i\beta_m),\ m = 2, ..., M-1 \\ P(Y_i = M) &= g(X_i\beta_{M-1}). \end{aligned}$$

The formulas for the OLOGIT estimation are the same, except that in OLOGIT the β's are the same for all values of m (Long and Freese, 2014).

[10]The worries index has five categories and the depression index has four categories.

4 Data description

The main dataset used is the "Global Behaviors Perceptions Data" that comes from the "Measuring Worldwide COVID-19 Attitudes and Beliefs" project (Fetzer et al., 2020a). This project is sponsored by 12 different international institutions, and the survey responses were collected starting in March 20th, 2020. The aim of the survey was to "explore how beliefs about citizens' and government's response to the COVID-19 pandemic, and the actions taken by governments, affected mental well-being" (Fetzer et al., 2020c:p: 1). With a total number of 111,225 respondents from 58 countries, this paper considers only responses received between March 20th and April 7th, in line with Fetzer et al. (2020c), who were in charge of the survey.

The auxiliary dataset used in the paper is the "Oxford Policy Tracker" -OPT-, compiled by Hale et al. (2020a). This country level daily-panel captures various measures related to government policies in response to the COVID-19 pandemic. These policies, are categorized from general to specific (regional) level, and from mandatory to suggested (Hale et al., 2020b). In the present work we consider only general policies for all country-residents in each day.

Importantly, while the survey data covers only 19 days, we can extend the time variation comparing the survey dates to the dates when a lockdown was established. We use OPT to identify the dates when countries entered lockdown measures and then, comparing this to the date of the survey's response, we obtain the number of days elapsed since lockdown for each individual as our main explanatory variable.

Since *days since lockdown* is the main independent variable for the models that we implement, we restrict the sample to non-negative values. The dropped observations include residents of countries where, according to OPT, no lockdown has been imposed throughout the period, and residents who live in countries where, at the survey's response date, no policy referred to lockdown has been imposed. Also, with the aim of obtaining inference on the *female* variable, we dropped 743 observations that answer 'other' in the 'gender' question. Because we are considering observations that appear at different points in time, the low number of observations in original categories within categorical covariates limits valid inference.

Variable	Abs. Freq.	Rel. (%)	Variable	Mean	Std. Dev.
Age (18-29)	21,596	26.30	Age[a]	39.05	13.00
Age (30-64)	57,175	69.62	Education[a]	16.33	4.83
Age (65+)	3,350	4.08	Worries[b]	13.98	3.09
Educ yrs (0-10)	9,197	11.20	Depression[b]	13.86	5.17
Educ yrs (11-18)	47,315	57.62			
Educ yrs (19+)	25,609	31.18			
			Trait	Low (%)	High (%)
Males	36,442	44.38	Extraversion	53.95	46.05
Females	45,679	55.62	Agreeableness	49.65	50.35
Health=Poor	1,229	1.50	Conscient.	46.52	53.48
Health=Fair	13,366	16.27	Neuroticism	48.32	51.68
Health=Good	42,899	52.24	Openness	49.75	50.25
Health=Excellent	24,627	29.99			

[a] In the regressions presented in section 4 we use the continuous variable.

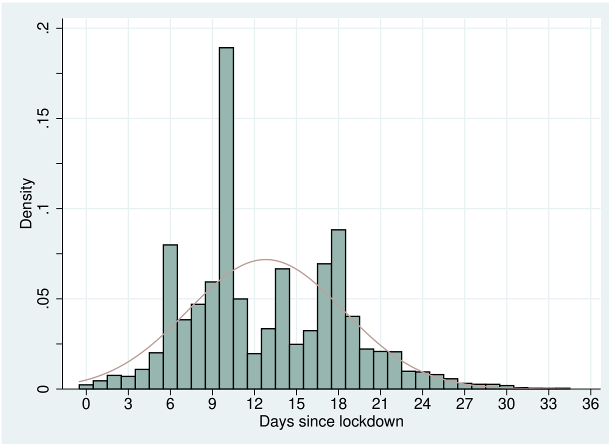
[b] In the regressions presented in section 4 we use the standardized index.

Table 1: Main sample: Descriptive statistics

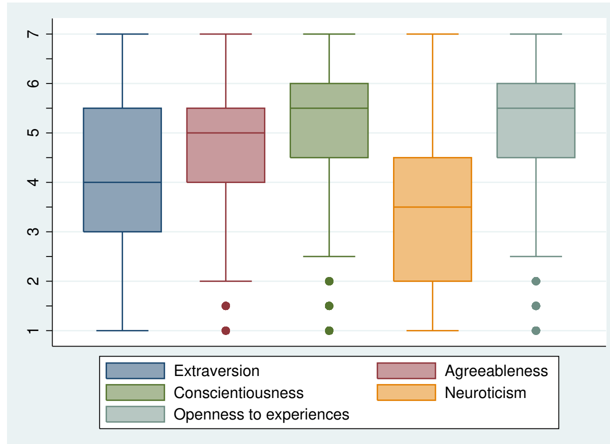
Additionally, considering the representativeness at the country level, we also restricted the sample to countries with at least 200 observations. The resulting dataset contains 82,121 observations and 41 countries.[11]

Table 1 provides descriptive statistics on the relevant variables. From the left panel we see that adults are the majority of the sample, while a quarter corresponds to young people and 4% to the elderly. Likewise, a little more than half of the sample has years of education corresponding to high-school and university education, while 31% have graduate level education and the remaining of the sample has an educational achievement corresponding to middle school or less. Females are the majority in the sample (56%). And a little more

[11] We also ran estimations including observations from China, India, South Korea, and Italy. Nevertheless, these countries were not considered in the core results because most of their participants had been several additional weeks in lockdown, relative to the remainder of the sample. Thus, the range of days since lockdown was wider and let to slightly less efficient estimates. Yet, the results are qualitatively similar if we include these countries. The results are available from the author upon request.



(a) Distribution of Days Since Lockdown



(b) Personality traits

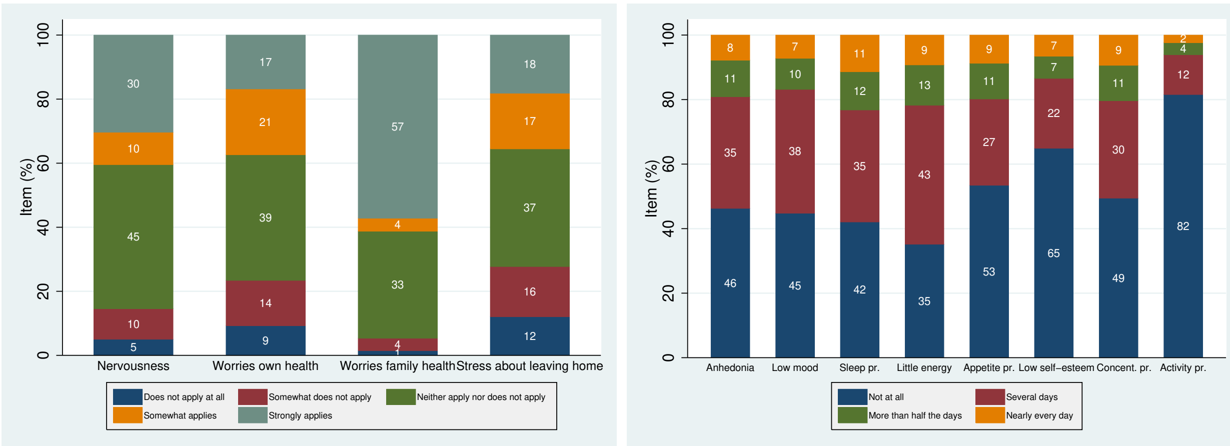
Figure 2: Distribution of Days Since Lockdown and Personality Traits

than 80% of individuals considered that their health was good or excellent at the date of the survey.

In the right top panel, Table 1 shows central tendency and dispersion measures for the variables included in the regressions described below. Finally, the right bottom panel provides information on the proportions of low and high personality traits. These variables are categorical according to the Big-five personality test. To generate dummy variables, we collapse the scale breaking the distribution into equal parts. This adjustment is not exact because the distribution has discrete values.

Figure 2 shows the distribution of responses by day since lockdown along with the distribution of personality traits. Panel 2(a) shows that individuals filled the survey mainly between 5 and 22 days after a lockdown. Panel 2(b) provided box plots of showing the distribution of each personality trait. Here, conscientiousness and openness to experiences show a higher median value, while neuroticism has the lower median as can be expected because it refers to a (generally) undesirable characteristic.

Figure 3 summarizes the relative frequencies of the responses for the worries and depression indexes, separated by their respective components. For the worries index (Panel 3(a)), there are four questions related to nervousness, worries about their own health, worries about their relatives' health, and stress about leaving home. Each question has five possible responses: "Does not apply at all", "Somewhat does not apply", "Neither applies nor does not apply", "Somewhat applies", and "Strongly applies". The questions are framed such that the last two options are associated with higher levels of worry. There is some degree of concern



(a) Components of Worries Index **(b)** Components of Depression Index

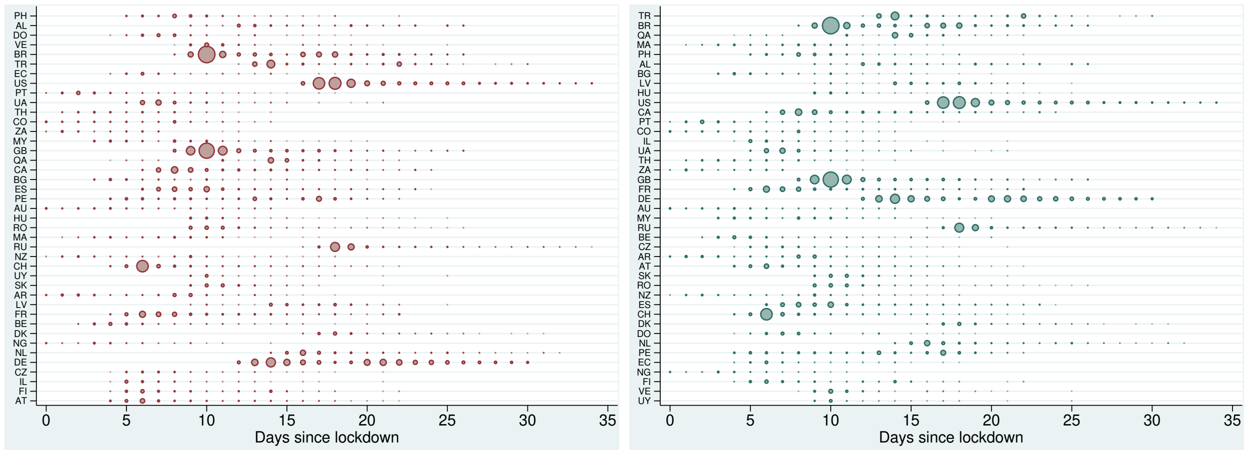
Figure 3: Components of Worries Index and Depression index

throughout the components but most importantly, more than 60% of responses show concern about the relatives' health, significantly higher than the 38% of individuals showing concern for their own health.

The depression index (Panel 3(b)) generally comprises 9 components, but Fetzer et al. (2020a) do not include the question about suicide attitudes that belongs to the PHQ-9 standard questionnaire. Thereby, from the question *How often have you been bothered by the following over the past 2 weeks?*, the individual needs to answer about: anhedonia (little pleasure in doing things), low mood, sleep problems, having little energy, appetite problems, low self-esteem, concentration problems and, development activities problems. Each question has four possible answers: "Not at all", "Several days", "More than half the days", and "Nearly everyday day". Responses associated with higher frequencies imply higher levels of depression.

Four components show a prevalence of depression signs of 20% or more: sleep problems, little energy, appetite problems, and concentration problems.[12] Across these components, more than 17% of people on average answered that they felt signs of depression at least for several days. If we consider this result as a symptom of moderate depression, our sample shows similar levels with those found by Ettman et al. (2020). These authors found that moderate depression symptoms raised from 5.7% before the pandemic to 14.8% during the pandemic, among a sample of U.S. adults. Thus, compared to standard levels, depression

[12]We label the depression index components following J. Robinson et al. (2017).



(a) Worries Index

(b) Depression Index

Figure 4: Responses by Index, Countries and Days Since Lockdown

look worse within our sample during the pandemic, as found by Fullana et al. (2020) and Fitzpatrick, Harris, and Drawve (2020).

Figure 4 provides a more detailed perspective on the worries (Panel 4(a)) and depression (Panel 4(b)) indexes. In each case, the vertical axis orders all 41 countries in the sample by their average value of the index for all the period from highest to lowest. The horizontal axis shows the number of days since a lockdown was introduced. The bubbles represent the existence of at least one observation on each country-day and their radius corresponds to the number of responses. As can be seen there is significant variation over time and across countries without a discernible pattern. This is important because the sample is not representative and thus there may be significant selection bias. For our research purposes, the main concern is that the survey captures responses regarding the worries and depression indexes that are driven by the order in which countries establish their lockdown policies. Figure 4 thus provides initial evidence that selection bias is not a major problem, but we return to this issue in section 6.

5 Results

We now turn to an analysis of the results. For the OLS model we present β's coefficients, while for GOLOGIT and MEOLOGIT we provide Odds-Ratios in order to get a better sense of the magnitude of the effect of each covariate on mental health. To implement the GOLOGIT estimation, we use the Stata package developed by R. Williams (2006).

Variables	OLS (β Coefficients) Worries	Depression	MEOLOGIT(OR)[a,b] Worries	Depression
days	-0.026***	0.011*	1.002	1.017*
days^2	0.001***	-0.0001	1.000*	1.000
age	-0.002*	-0.011***	0.995***	0.966***
educ	0.004**	-0.001	1.011***	1.002
female	0.252***	0.203***	1.654***	1.829***
health=2	-0.203***	-0.358***	0.600***	0.459***
health=3	-0.349***	-0.600***	0.442***	0.252***
health=4	-0.502***	-0.737***	0.329***	0.164***
extraversion	-0.003	-0.091***	0.989	0.758***
agreeableness	0.030	-0.033*	1.077*	0.900**
conscientiousness	0.079***	-0.136***	1.157***	0.657***
neuroticism	0.274***	0.323***	1.740***	2.681***
openness	-0.006	-0.003	0.992	0.982
extraversion×days	-0.0001	0.002	0.999	1.005
agreeableness×days	0.002	0.001	1.002	1.004
conscientiousness×days	-0.001	-0.0005	0.999	1.000
neuroticism×days	0.002	0.005**	1.003	1.007**
openness×days	0.002	0.001	1.004	1.002
female×days	-0.004	-0.004	0.992***	0.989***
intercept	4.118***	2.448***		
Fixed-effects	Country	Country		
Fixed-effects	Date of survey	Date of survey		
Sample size	82,121	82,121	82,121	82,121

[a] OR stands for Odds-Ratio.

[b] The cutpoints κ from the MEOLOGIT are not shown for ease of exposition.

Significance level: * p<0.05, ** p<0.01, *** p<0.001

Table 2: OLS and MEOLOGIT for Worries index and Depression index

To present comparable estimates between the three models implemented, we compressed each index into the same number of categories as the number of corresponding components. Thus, we collapse the worries index from 17 values into five categories (1 corresponds to a lower level of worries and 5 to a higher level of worries). Likewise, we collapse the depression index from 25 values into four categories (1 corresponds to a lower level of depression and 4 to a higher level of depression).

Table 2 shows the results of the estimation using ordinary least squares –OLS– and the mixed-effects ordered logit –MEOLOGIT– for each compressed index. Consider first OLS results in the left panel. The effect of the days on the worries index and on the depression index is presented in the first rows. *Days since lockdown* favors the adaptation of the individual by reducing their levels of worries, but it contributes to *worsening* depression. Specifically, one more day in quarantine implies a reduction of 0.026 points in the level of worries, while it increases the level of depression by 0.011 points. Also, the positive effect of days squared on worries implies that after around two weeks, the mental adjustment will occur less quickly.

Looking at personality traits, extraversion, agreeableness and conscientiousness are associated with lower levels of depression. Most importantly, neuroticism has a large negative and significant effect on both dimensions of mental health. Thus, an increase of one point on the neuroticism scale generates 0.27 and 0.32 additional points in the levels of worries and depression, respectively. In addition, age and better self-reported health states, significantly favor better mental health, while being a woman increases the level of both indexes by 0.25 and 0.20 points, respectively.

Furthermore, despite the lack of significance, when adaptation is mediated by neuroticism we found a positive effect on the worries index, i.e. it increases the level of worries. Then, neuroticism is a key element when analyzing the adaptation process that stabilizes mental health.

The right panel of Table 2 shows the results of the multilevel mixed-effects model. Days has a significant effect only for depression. Specifically, one more day in lockdown increases the probability of presenting a higher level of depression by 1.7%. The effect on worries, however, disappears.

Regarding depression, an additional point in the personality traits of extraversion, agreeableness, and conscientiousness reduces the probability of higher depression levels by 24%, 10%, and 34%, respectively. An additional point in neuroticism is associated with an increase of 168% in the probability of presenting higher levels of depression. Regarding worries, a more accentuated trait of agreeableness, conscientiousness, and neuroticism increases the probability of higher anxiety by 8%, 16%, and 74%, respectively.

Age and better self-reported health are significantly associated with a lower probability of presenting higher levels of worries or depression, while an additional year of education increases the probability of these conditions. Being a woman is also associated with higher likelihoods of worsened mental health.

Also, regarding adaptation, the effect of days mediated by being a woman reduces the probability of suffering higher levels of worries or depression by 1%, favoring the adaptation of the individual's mental health to the context of prolonged confinement. Also, for the depression index we found a significant effect of adaptation mediated by neuroticism. This effect shows an additional 0.7% of probability of an increase in the level of depression. The small magnitude could mean that, even in the presence of a mental stabilization process, a higher level of neuroticism exceeds the positive impact of adaptation mechanisms.

Following R. Williams (2016), we first implement an OLOGIT model with its corresponding *Brant* test. The χ^2 statistic was 1,693 with 285 freedom degrees in the case of the worries index. For the depression index, we obtained a χ^2 of 795.5 with 368 freedom degrees. Both of them had corresponding $p-values$ of 0.000. Thus, the evidence does not provide support to not reject the null hypothesis of proportional odds. For this reason, we use a GOLOGIT estimation.

Table 3 shows the results of the estimation of a generalized ordered logit –GOLOGIT– for the worries index. Days shows a consistent positive effect on the worries dimension in each of the cumulative logistic regressions. Thus, significantly, one more day in confinement reduces the probability of a higher level of worries by between 5% and 6% (binary logistic regressions 2 to 4).

As for personality traits, a higher point on the scale of conscientiousness increases the probability of a higher level of worries by between 15% and 21%. Meanwhile, neuroticism has a large and significant effect in the four cumulative regressions, more than doubling the level of worries in the case of the first regression.

Additionally, an extra year of education has a negative effect on the level of mental health, significantly increasing the probability of a higher level of the worries index by between 1% and 2%.

	GOLOGIT (Odds-Ratio)			
Variables	1 vs 2, 3, 4, 5	1 & 2 vs 3, 4, 5	1, 2, 3 vs 4 & 5	1, 2, 3, 4 vs 5
days	0.970	0.942**	0.953***	0.952***
days^2	1.001	1.001**	1.001**	1.001***
age	0.991***	0.993***	0.995***	1.000
educ	1.016*	1.014***	1.008**	1.003
female	1.907***	1.592***	1.576***	1.970***
health=2	1.087	0.929	0.697**	0.539***
health=3	0.735	0.738**	0.555***	0.346***
health=4	0.324***	0.472***	0.435***	0.276***
extraversion	1.121	0.979	0.988	0.966
agreeableness	1.128	1.062	1.085	1.011
conscientiousness	1.046	1.171*	1.150**	1.207***
neuroticism	2.623***	1.901***	1.626***	1.795***
openness	0.903	0.937	1.015	0.957
extraversion×days	0.992	0.999	1.000	1.004
agreeableness×days	1.008	1.006	1.002	1.006*
conscient.×days	1.000	0.995	1.000	0.999
neuroticism×days	1.005	0.999	1.004	1.007
openness×days	0.997	1.002	1.004	1.008*
female×days	0.989	0.994	0.994	0.983*
intercept	82.517***	22.332***	3.323***	0.607
Fixed-effects	Country	Country	Country	Country
Fixed-effects	Date of svy.	Date of svy.	Date of svy.	Date of svy.
Sample size	82,121	82,121	82,121	82,121

Significance level: * p<0.05, ** p<0.01, *** p<0.001

Table 3: GOLOGIT for Worries Index

Variables	GOLOGIT (Odds-Ratio) 1 vs 2, 3, 4	1 & 2 vs 3 & 4	1, 2, 3 vs 4
days	1.039*	1.043*	1.017
days^2	1.000	0.999*	1.000
age	0.967***	0.966***	0.965***
educ	1.003*	1.002	0.993
female	1.770***	1.853***	1.985**
health=2	0.529***	0.438***	0.420***
health=3	0.298***	0.235***	0.212***
health=4	0.193***	0.156***	0.135***
extraversion	0.764***	0.778***	0.717***
agreeableness	0.905*	0.903*	0.935
conscientiousness	0.660***	0.688***	0.760**
neuroticism	2.548***	3.027***	3.740***
openness	0.994	0.947	0.998
extraversion×days	1.004	1.003	1.011
agreeableness×days	1.004	1.003	0.997
conscientiousness×days	0.999	0.999	0.994
neuroticism×days	1.009***	1.009	1.004
openness×days	1.001	1.006	1.001
female×days	0.991	0.986*	0.983
intercept	4.310***	1.019	0.285**
Fixed-effects	Country	Country	Country
Fixed-effects	Date of survey	Date of survey	Date of survey
Sample size	82,121	82,121	82,121

Significance level: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4: GOLOGIT for Depression Index

Table 4 shows the results of the generalized ordered logit –GOLOGIT– for the depression index. In this case, and again highlighting the differentiated effect of the variable days on various dimensions of mental health, we find that one more day in lockdown *increases* the probability of a higher level of depression by 4%. In this case, adaptation as a resource to mitigate the mental affectation caused by the pandemic and subsequent confinement does not appear available. In addition, the effect of days mediated by neuroticism is consistent with the direction of the odds-ratio presented in the RHS panel of the table 2, implying an additional 1% in the probability of a higher depression index.

Among the personality traits, only openness to new experiences does not show a significant effect. While extraversion, agreeableness and conscientiousness are associated with a lower probability of suffering higher levels of depression, neuroticism leads to an increase of more than twice in the probability of extra levels of depression.

A better health status and an older age also promote better mental health by reducing the probability of higher levels of depression. Being a woman increases the probability of higher levels of depression.

The description of the results presented above show, in summary, three important findings that were observed in the three estimated models for each of the indexes. First, the number of days that have elapsed since the start of lockdown in each country has a significant effect reducing the level of worries and increasing the level of depression. Second, the traits of conscientiousness and neuroticism increase significantly the worries index. The traits of extraversion, agreeableness, and conscientiousness lead to a decrease in the level of depression in a significant way, while neuroticism generates a significant increase in the level of depression. Third, the effect of days mediated by the gender of the individual (female = 1) also contributes to *improving* mental health in both dimensions, while the effect of days mediated by neuroticism causes an increase in the probability of higher levels of depression.

For all this, we find that there is a differentiated effect in the adaptation that a person can achieve during confinement regarding the two mental health dimensions analyzed here. While the elapsed days help to stabilize or not worsen the level of worries, they also cause an increased level of depression. Likewise, personality traits can help reduce depression (or at least stabilize it), but also lead to an increment in the levels of anxiety.

6 Robustness analysis

In this section, we provide an analysis of two elements that might generate concern on the results shown above.

First, it is likely that the sample used for the estimates might suffer from selection bias. To address this issue, we analyze the distribution over *days since lockdown* of the worries and mental health indexes and also run a MEOLOGIT estimation where we evaluate more precisely the relationship between each personality trait and *days since lockdown*.

Second, we also carry out an analysis of the consistency of the results, including the whole sample regarding *days since lockdown* through a MEOLOGIT estimation.

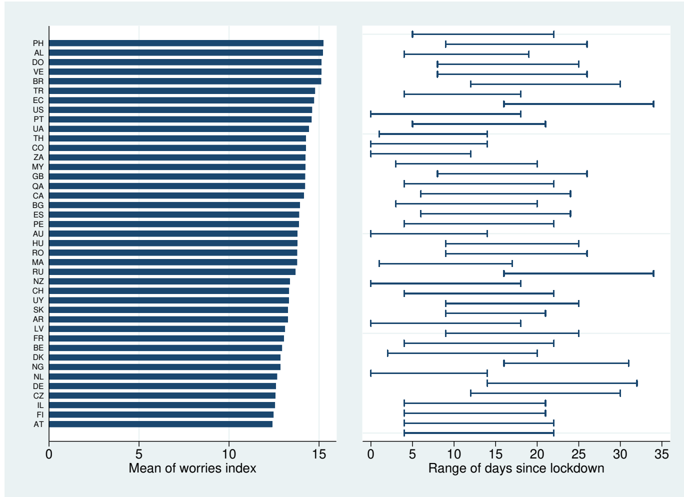
6.1 Selection bias

Recall that the sample constructed by the survey is not a representative one. A risk thereof is that it may suffer from significant selection bias, which may come from different sources. First, people with specific characteristics (e.g. more worried, anxious, depressed, or extroverted) may be those who answer the survey early on. This might lead to the observed correlations because the sample changes over time. Second, the survey's answers are concentrated soon after the quarantines began in various countries. Thus, a small number of observations towards the end of the range of days may be subject to increased measurement error. Third, the survey may be answered mostly by people from countries most affected by the pandemic. This might lead to the observed correlations if different countries have different baselines for mental health or personality traits. In this section, we briefly address these concerns by looking at the distribution of observations across countries and over time.

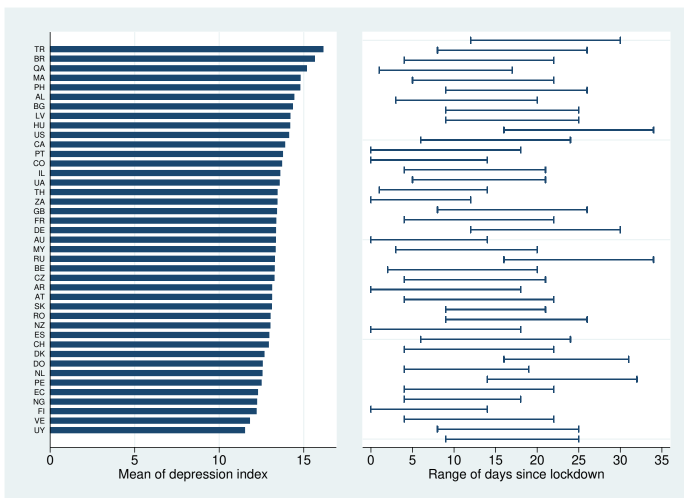
Clearly, these questions raise concerns at the country and individual level. We first address this issue at the country level and then move on the individual level. Figure 5 orders countries by the mean of the worries and depression indexes (LHS panels) and shows the range of days since lockdown with observations for each country, in the same order (RHS panels).[13]

The LHS panels in Figure 5 show that there is significant variation at the country level regarding the mean of each index. This would be problematic if we would capture individuals from different countries over a limited range of days. It would also be problematic if we would observe a pattern of the range of days with observations for each country in line with the order presented. As is clear from the RHS panels in Figure 5, neither of these concerns seems

[13]The RHS panels show similar information as Figure 4, except that we do not include bubbles to provide an easier visualization of the range of available observations.



(a) Worries Index

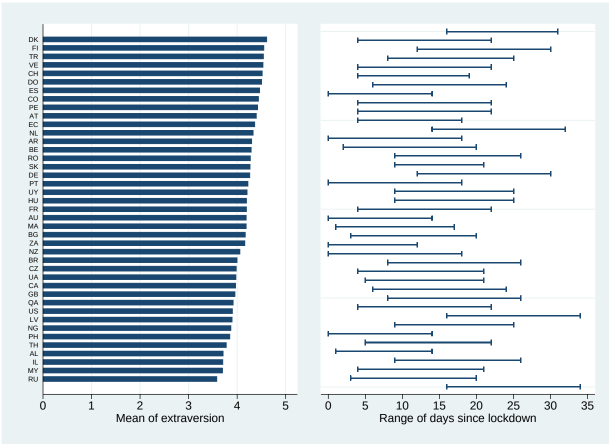


(b) Depression Index

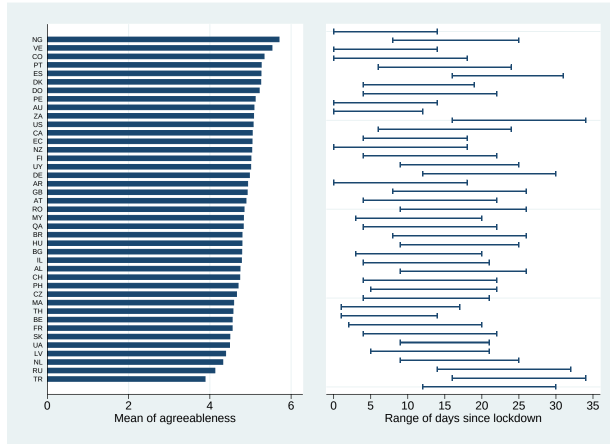
Figure 5: Mental Health Indexes and Range of Days Since Lockdown by Country

to apply. First, individuals within each country answer the survey during a wide range of days. Second, the survey includes responses from individuals in distinct countries at different times with respect to the days since lockdown and without a clear pattern.[14]

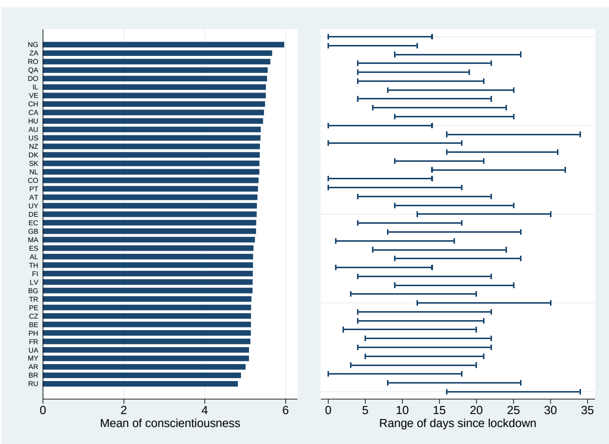
[14]Interestingly, China (not included in our analyses) shows the lowest value for the *worries index*. Given that China was the first country in the world to adopt lockdown measures –at least in the Wuhan region– this result provides additional support to our findings regarding worries. As the days in confinement pass, there is an adaptation of people's behavior that leads to better –or at least not worse– mental health measured by the worries index.



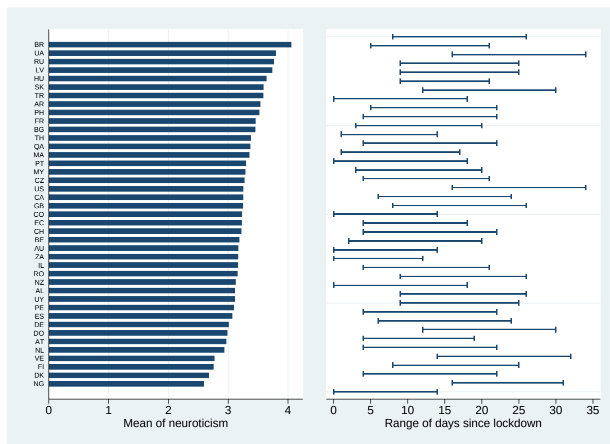
(a) Extraversion



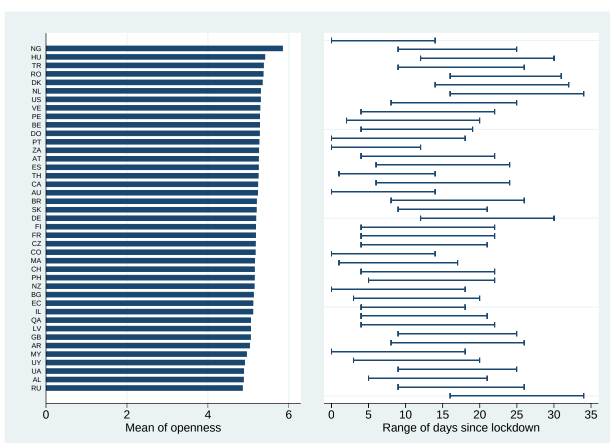
(b) Agreeableness



(c) Conscientiousness



(d) Neuroticism



(e) Openness to experiences

Figure 6: Personality Traits and Range of Days Since Lockdown by Country

Figure 6 provides a similar perspective for each of the five personality traits analyzed. With the exception of agreeableness, we confirm that there is no pattern at the country level associated with the order of each personality trait.

Therefore, it seems that the sample used, despite not being random or coming from a sample design, does not show patterns or trends in the variables of interest at the country level that might cause a bias in the estimators.

Yet, we might still face a bias coming from the individual dynamics. To evaluate this, we analyze whether there is a relationship between personality traits and the number of days since the start of confinement. The objective of this exercise is to determine if there is a relationship between time elapsed and personality traits. To estimate this relationship, let Ω be a function defined as follows:

$$\Omega = \beta_1 days + \beta_2 days^2 + \delta_{\mathbf{1}}\mathbf{x}, \tag{5}$$

where *days* is the same continuous variable that refers to days since lockdown, and $\mathbf{x}$ is the vector of other covariates that includes age, educ, female and auto-reported health status. We estimate this model by MEOLOGIT using the following equation:

$$Pr(y_{ij}^p > m|\mathbf{\Omega}_{ij}, \kappa, \mathbf{u}_j) = H(\mathbf{\Omega}_{ij} + \mathbf{z}_{ij}\mathbf{u}_j - \kappa_m). \tag{6}$$

In equation (6), the dependent variable is each personality trait measured as a categorical variable, i.e. the set of outcomes p includes extraversion, agreeableness, conscientiousness, neuroticism, and openness. Each trait takes values between 1 and 7 with intervals of 0.5. Also, as in equation (3), $\mathbf{\Omega}_{ij}$ corresponds to fixed-effects, $\mathbf{z}_{ij}\mathbf{u}_j$ corresponds to random-effects, and n_j observations are nested within the $j \in J$ countries.

Table 5 presents the results. It shows that there is no significant effect of the variable *days* on either extraversion, conscientiousness, neuroticism, or openness. Consistent with Figure 6, however, there is evidence that *days* does affect agreeableness. Therefore, with the exception of this trait, the number of days elapsed since the start of a quarantine does not influence personality traits, highlighting their stability. At the same time, it denotes that the estimates previously presented for these traits are robust.

The variable *days* has a significant effect in the case of agreeableness, with a magnitude implying that one more day in confinement reduces the probability of being agreeable by around 1.6%. This is important because the negative effect of agreeableness on depression may follow simply because agreeableness is falling over time. We have no additional mechanism to explain this effect and thus we simply conclude that agreeableness has no discernible effect on depression.

	MEOLOGIT(Odds-Ratio)[a,b]				
Variables	Extra.	Agree.	Consc.	Neuro.	Openn.
days	1.012	0.984*	0.993	1.001	1.010
days^2	1.000	1.001***	1.000	1.000	1.000
age	1.013***	1.025***	1.013***	0.968***	1.016***
educ	1.002	1.010***	1.017***	0.996**	0.998
female	1.493***	1.489***	1.219***	1.740***	1.702***
health=2	1.116*	1.200***	1.012	0.718***	1.041
health=3	1.443***	1.947***	1.167**	0.395***	1.216***
health=4	2.083***	3.536***	1.562***	0.203***	1.460***
Sample size	82,121	82,121	82,121	82,121	82,121

[a] The cutpoints κ from the MEOLOGIT estimation are not shown for simplicity.

[b] Personality traits are: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to New Experiences.

Significance level: * p<0.05, ** p<0.01, *** p<0.001

Table 5: MEOLOGIT Estimation for Personality Traits

In addition, the variables included as controls have a significant effect on each personality trait in the same direction in almost all regressions. A better self-perception of health is associated with a higher probability of extraversion, agreeableness, conscientiousness, and openness to new experiences, while it is associated with a *lower* probability of neuroticism. More generally, recalling that, unlike the other Big-Five traits, neuroticism denotes a negative nuance in the personality, it is expected that the explanatory variables change the direction of their effect when looking at this outcome. Indeed, considering age as an example, one additional year of age *reduces* the probability of being more neurotic by 3.2%, while it *increases* the other personality traits. It is worth noting that the variable female, however, is associated with higher probabilities in all personality traits, also including neuroticism. This seems to be a key element in explaining the lower levels of mental health experienced by women.

Moreover, Figure 7 shows the dynamics of each of the Big-Five personality traits over time. Three traits remain quite stable, while agreeableness and neuroticism present some

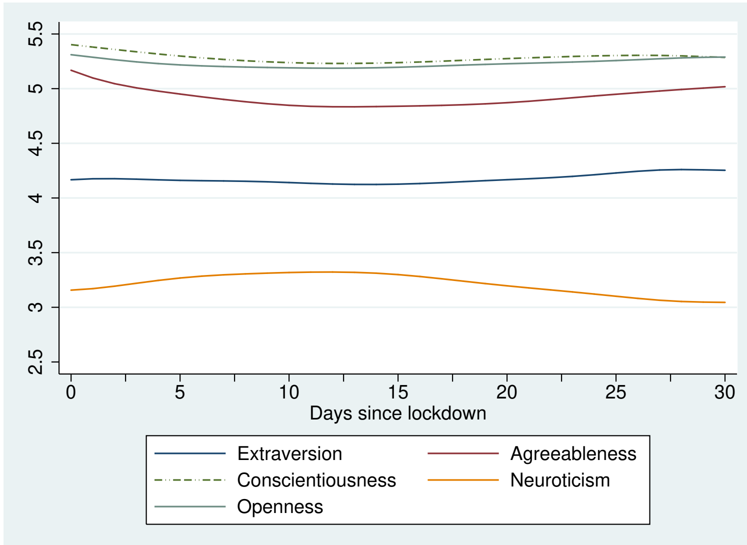


Figure 7: Personality Traits Over Days since Lockdown

variation. This finding explains, at least, that the personality traits have a weak relationship with the pass of time since the beginning of the lockdown.

In sum, we see that with the exception of agreeableness, the days elapsed since the beginning of the lockdown do not significantly affect the personality traits. Then, personality tends to remains stable during the period of analysis. Therefore, the incidence of the mechanism of adaptation follows a specific direction: starts since personality and goes towards the effects on times under lockdown and not the opposite, at least in the context of the COVID-19 pandemic.

6.2 Consistency of the results

Another important question concerns the fact that we restrict our sample only to countries that were in lockdown at the moment of the survey. In this section we thus extend our sample to include all countries that were not in lockdown during the survey. This leads to a sample of 92,294 observations coming from 54 countries. This increase considers responses from China, India, Italy, and South Korea, where lockdowns were set early, but lifted at the moment of the survey, as well as responses from individuals in other countries where lockdown measures had not been implemented at the moment of the survey. In total, 10.69% of the whole sample was not facing confinement during the survey.

Variables	MEOLOGIT(Odds-Ratio)[a] Worries index	Depression index
lockdown	0.905**	1.035
days	0.993**	1.012***
days^2	1.000	1.000
age	0.996***	0.964***
educ	1.007***	1.004***
female	1.535***	1.566***
health=2	0.559***	0.451***
health=3	0.411***	0.254***
health=4	0.313***	0.162***
extraversion	1.017	0.807***
agreeableness	1.108***	0.937***
conscientiousness	1.142***	0.643***
neuroticism	1.729***	2.744***
openness	1.029	0.991
extraversion×days	0.998*	1.000
agreeableness×days	0.999	0.999
conscientiousness×days	1.000	1.002
neuroticism×days	1.002	1.002
openness×days	1.000	1.000
female×days	0.997**	1.001
Sample size	96,294	96,294

[a] There is not shown the cutpoints κ from MEOLOGIT estimation for simplicity of lecture.

Significance level: * p<0.05, ** p<0.01, *** p<0.001

Table 6: MEOLOGIT Estimation with the Whole Sample

Including these additional responses allows us to include in the models a dichotomous variable *lockdown* that refers to whether there has been a lockdown at the date of the survey response. A value of 1 means that individuals face lockdown measures.

Analyzing the results of Table 6 we see that the effect of *days* on both measures of mental health remains significant. Regarding the worries index, we observe the same adaptation effect that leads to an improvement in this dimension over time. Regarding the depression index, the significant odd-ratio of *days* implies that an additional day is associated with an increased probability of about 1% of having higher levels of depression.

Regarding the effect of being in lockdown, we see that it decreases by about 10% the probability of presenting higher levels of worries. This provides additional evidence favoring the existence of adaptation in this dimension of mental health. Yet, consistent with the specific effects of quarantines, this variable does not have a significant effect on the depression index.

Regarding personality traits, agreeableness, conscientiousness, and neuroticism raise the probability of having higher levels of anxiety. Neuroticism contributes greatly to a higher probability of higher levels of depression, while extraversion, agreeableness, and conscientiousness are associated with a reduction thereof.

Finally, *age* and *health* status support a reduction in the levels of both indexes (better mental health), while *educ* and particularly *female* contribute to a higher level of the indexes studied (worse mental health).

Summarizing, the differential effect of *days* on each mental health dimension remains, showing an adaptation process for the worries index, but no improvement on depression. Personality traits have also differentiated effects for each dimension except for neuroticism. This exercise thus provides supporting evidence for the results presented before.

7 Conclusions

The literature analyzing the impact of the Covid-19 pandemic on mental health has emphasized its negative initial effect and further deteriorating results (Fitzpatrick, Harris, and Drawve, 2020; Ettman et al., 2020). Yet, more recent research has found evidence that there may be a process of adaptation according to which individuals improve their mental health following the initial shock (Daly and E. Robinson, 2020). We argue that the two conclusions might be at play because mental health covers a wide spectrum of dimensions and thus time may have differential effects depending on the variable analyzed. Thus, our main finding was that individuals show some adaptation –or at least a stabilization– regarding an index of worries. But we found that depression tends to worsen over time.

Our observation that the level of the worries index decreases over time can be explained by the fact that the uncertainty shock is decreasing little by little. Yet, this is not the case for the mechanisms underlying depression as the pandemic effects on health as well as the confinement remain.

Furthermore, we showed that this result may be related to a differential effect of personality traits on each dimension of mental health, which may be a specific feature of the shock analyzed. For instance, although conscientiousness was associated with lower levels of depression, it was associated with *higher* levels of worries, probably indicating that in the current context people find it difficult to do one's work or duty well and thoroughly.

Most importantly, we found a large and consistent negative effect of neuroticism on both dimensions of mental health analyzed. This is consistent with Jylha and Isometsa (2006), who investigated the relationship between neuroticism and extraversion as personality traits and depression and anxiety. They found that neuroticism is strongly correlated with symptoms of depression and anxiety.

We also found that extraversion helped reduce the level of depression, a result that is consistent with Jylha and Isometsa (2006), who found that extraversion is correlated negatively with depression and anxiety.

Our results might be due to selection bias given the characteristics of the sample. We provided evidence that this bias is limited at the country and individual levels, except for the personality trait of agreeableness.

Yet, several questions remain. A key element is whether our results regarding personality traits are causal, i.e. whether variations in personality across individuals cause the observed variations in mental health. It is difficult to establish this given the available evidence because the literature is not clear on whether personality traits are constant over time. Based on the results on agreeableness, it might be the case that the pandemic affected not only individuals' mental health but also their personality.

We show that personality traits (except agreeableness) do not seem to vary during the time frame considered. Yet, even if this is the case, we do not have a baseline measure on pre-pandemic mental health to confirm it. Furthermore, it could also be the case that the initial shock of the pandemic already had an effect, possibly depending on different initial levels across countries, which we cannot observe. The literature does not provide a clear answer on this either. Kajonius and Mac Giolla (2017) analyzed 30 personality traits in 22 countries and found small differences across countries –what is known as the 'similarities hypothesis'–. But Bartram (2011) analyzed the scalar equivalence of the Big-Five model for over one million people from 31 countries. The author found that, cross-country differences of personality due to the metrics used actually represent true variation, and do not appear due to systematic instrument-related biases. Thus, according to this author, differences in personality between countries arise from cultural characteristics and not from the analytical tools used to measure personality.

Despite these caveats, our analysis contributes to extending the literature on the relationship between personality, mental health, and the mechanisms to face systemic shocks in the context of the Covid-19 pandemic. Furthermore, our results suggest that mental health interventions in the context of the Covid-19 pandemic could be targeted based on personality. In particular, because neuroticism is related to higher levels of depression as well as increased levels of depression over time, targeting neurotic individuals may contribute to reduce present and future levels of depression in the population.

From the results obtained and their implications, an interesting research niche is presented when the period of analysis of the pandemic –and perhaps of lockdowns– includes a larger number of days. Likewise, our analysis shows the importance of having panel data to monitor people over time and thus be able to refine the hypotheses and results found regarding their mental well-being. Also, the individual components of each index could be analyzed to get a better understanding of the mechanisms involved.

Our work contributes to creating a starting point to address a relevant question about the behavior and stability of mental health and personality when the pandemic has already lasted for several months and some restrictions that limit social interaction remain in place.

8 References

Agresti, Alan (2010). *Analysis of Ordinal Categorical Data*. 2nd. Wiley & Sons, Inc.: Hoboken, New Jersey.

Appelt, Kirstin et al. (n.d.). *NEO Personality Inventory-Revised (NEO PI-R)*. `http://www.sjdm.org/dmidi/NEO_PI-R.html`.

Bartram, Dave (2011). In: *Journal of Cross-Cultural Psychology* 44(1), pp. 61–83.

Brant, R. (1990). "Assessing proportionality in the proportional odds model for ordinal logistic regression". In: *Biometrics* 46.

Brooks, Samantha et al. (2020). "The psychological impact of quarantine and how to reduce it: rapid review of the evidence". In: *The Lancet* 395(10227), pp. 912–920.

Bucher, Meredith, Takakuni Suzuki, and Douglas Samuel (2019). "A meta-analytic review of personality traits and their associations with mental health treatment outcomes". In: *Clinical Psychology Review* 70, pp. 51–63.

Buddelmeyer, H. and N. Powdthavee (2016). "Can having internal locus of control insure against negative shocks? Psychological evidence from panel data". In: *Journal of economic behavior & organization* 122, pp. 88–109.

Courtney, Darren et al. (2020). "COVID-19 Impacts on Child and Youth Anxiety and Depression: Challenges and Opportunities". In: *The Canadian Journal of Psychiatry* 65(10), pp. 688–691.

Crum, Alia et al. (2017). "The role of stress mindset in shaping cognitive, emotional, and physiological responses to challenging and threatening stress". In: *Anxiety, Stress & Coping* 30(4), pp. 379–395.

Daly, Michael and Eric Robinson (2020). "Psychological distress and adaptation to the COVID-19 crisis in the United States". In: *Journal of Psychiatric Research*. `https://doi.org/10.1016/j.jpsychires.2020.10.035`.

Ettman, C. et al. (2020). "Prevalence of Depression Symptoms in US Adults Before and During the COVID-19 Pandemic". In: *JAMA Netw Open* 3(9). `https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2770146`.

Fetzer, Thiemo et al. (2020a). *Global Behaviors Perceptions Data*. `https://osf.io/3sn2k/files/`.

Fetzer, Thiemo et al. (2020b). "Measuring Worldwide COVID-19 Attitudes and Beliefs Project". In: *Measuring Worldwide COVID-19 Attitudes and Beliefs Project*. `https://osf.io/3sn2k/files/`.

Fetzer, Thiemo et al. (2020c). “Perceptions of an Insufficient Government Response at the Onset of the COVID-19 Pandemic are Associated with Lower Mental Well-Being”. In: *Measuring Worldwide COVID-19 Attitudes and Beliefs Project*. https://psyarxiv.com/3kfmh.

Fitzpatrick, K., C. Harris, and G. Drawve (2020). “Living in the midst of fear: Depressive symptomatology among US adults during the COVID-19 pandemic”. In: *Depression and Anxiety* 37, pp. 957–964.

Fullana, Miquel et al. (2020). “Coping behaviors associated with decreased anxiety and depressive symptoms during the COVID-19 pandemic and lockdown”. In: *Journal of Affective Disorders* 275, pp. 80–81.

Gosling, Samuel, Peter Rentfrow, and William Swann (2003). “A very brief measure of the Big-Five personality domains”. In: *Journal of Research in Personality* 37(6), pp. 504–528.

Hagerty, S. and L. Williams (2020). “The impact of COVID-19 on mental health: The interactive roles of brain biotypes and human connection”. In: *Brain, behavior, & immunity - health* 5(100078).

Hale, Thomas et al. (2020a). *Oxford COVID-19 Government Response Tracker*. www.bsg.ox.ac.uk/covidtracker.

Hale, Thomas et al. (2020b). “Variation in Government Responses to COVID-19. Version 7.0”. In: *Blavatnik School of Government Working Paper*. Avaible at: www.bsg.ox.ac.uk/covidtracker.

Headey, B., J. Kelley, and A. Wearing (1993). “Dimensions of mental health: Life satisfaction, positive affect, anxiety and depression”. In: *Social Indicators Research* 29, pp. 63–82.

Heckman, James (2011). In: *NBER* Working Paper 17378.

Heckman, James, Tomás Jagelka, and Timothy Kautz (2019). In: *NBER* Working Paper 26459.

Henry, S. and R. Mõttus (2020). “Traits and Adaptations: A Theoretical Examination and New Empirical Evidence”. In: *European Journal of Personality* 34, pp. 265–284.

Hopwood, C. et al. (2008). “Personality traits and mental health treatment utilization”. In: *Personality and mental health* 2(4), pp. 207–217.

International Red Cross (2020). *The importance of mental health and psychosocial support during COVID-19*. Ed. by Dick Clómen et al. https://www.icrc.org/es/document/una-crisis-dentro-de-una-crisis-mental-health-distress-rises-due-covid-19.

Javed, Bilal et al. (2020). “The coronavirus (COVID-19) pandemic’s impact on mental health”. In: *The International journal of health planning and management* 35(5), pp. 993–996.

Johnston, David, Claryn Kung, and Michael Shields (2020). “Who is Resilient in a Time of Crisis? The Importance of Financial and Non-Financial Resources”. In: *IZA Discussion Paper* 13720.

Jylha, Pekka and Erkki Isometsa (2006). In: *Depression and Anxiety* 23, pp. 281–289.

Kajonius, P. and E. Mac Giolla (2017). In: *PLOS ONE* 12(6).

Kokko, K., J. Rantanen, and L. Pulkkinen (2015). “Associations between Mental Well-being and Personality from a Life Span Perspective”. In: *Personality and Well-being Across the Life-Span*. Ed. by Marek Blatný. Palgrave Macmillan: London, UK, pp. 134–159.

Kroenke, K., R. Spitzer, and J. Williams (2001). “The PHQ-9: validity of a brief depression severity measure”. In: *Journal of General Internal Medicine* 16(9), pp. 606–613.

Long, Scott and Jeremy Freese (2014). *Regression Models for Categorical Dependent Variables Using Stata*. 3rd. STATA Press: College Station, Texas.

Manea, Laura, Simon Gilbody, and Dean McMillan (2012). “Optimal cut-off score for diagnosing depression with the Patient Health Questionnaire (PHQ-9): a meta-analysis”. In: *CMAJ* 184(3), E191–E196.

Mu, Wenting et al. (2016). “Generality or Specificity? Examining the Relation between Personality Traits and Mental Health Outcomes Using a Bivariate Bi-factor Latent Change Model”. In: *European Journal of Personality* 30(5), pp. 467–483.

Oliver, John, Laura Naumann, and Christopher Soto (2008). “Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, and Conceptual Issues”. In: *Handbook of Personality. Theory and Research*. Ed. by John Oliver, Richard Robins, and Lawrence Pervin. 3rd. The Guilford Press: New York, NY, pp. 114–158.

Panchal, Nirmita et al. (2020). *The Implications of COVID-19 for Mental Health and Substance Use*. Tech. rep. `https://www.kff.org/coronavirus-covid-19/issue-brief/the-implications-of-covid-19-for-mental-health-and-substance-use/`.

Pulkkinen, L. and A. Caspi (2002). “Personality paths and successful development: An overview”. In: *Paths to successful development: Personality in the life course*. Ed. by L. Pulkkinen and A. Caspi. Cambridge University Press: Cambridge, UK, pp. 1–16.

Rabe-Hesketh, Sophia and Anders Skrondal (2012). *Multilevel and Longitudinal Modeling Using Stata*. 3rd. StataCorp: College Station: Texas.

Rammstedt, Beatrice (2007). “Who worries and who is happy? Explaining individual differences in worries and satisfaction by personality”. In: *Personality and Individual Differences* 43(6), pp. 1626–1634.

Riedl, Maximilian and Ingo Geishecker (2014). “Keep it simple: estimation strategies for ordered response models with fixed effects”. In: *Journal of Applied Statistics* 41(11), pp. 2358–2374.

Robinson, J. et al. (2017). “Why are there discrepancies between depressed patients’ Global Rating of Change and scores on the Patient Health Questionnaire depression module? A qualitative study of primary care in England”. In: *BMJ Open* 7(4).

Rubin, G. J. and S. Wessely (2020). “Coronavirus: the psychological effects of quarantining a city”. In: *BMJ Opinion* 368(m313).

Serafini, G. et al. (2020). “The psychological impact of COVID-19 on the mental health in the general population”. In: *Quarterly Journal of Medicine* 113(8), pp. 531–537.

Sharifi, A. and A. R. Khavarian-Garmsir (2020). “The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management”. In: *The Science of the Total Environment* 749(142391).

Singh, Shweta et al. (2020). “Impact of COVID-19 and lockdown on mental health of children and adolescents: A narrative review with recommendations”. In: *Psychiatry Research* 293(113429).

Smithson, Michael and Edgar Merkle (2014). *Generalized linear models for categorical and continuous limited dependent variables*. Chapman & Hall - CRC: Boca Raton, FL.

Specht, J., B. Egloff, and S. Schmukle (2011). “Stability and change of personality across the life course: The impact of age and major life events on mean -level and rank- order stability of the Big Five”. In: *Journal of Personality and Social Psychology* 101(4), pp. 862–882.

StataCorp (2013). *Stata 13 Base Reference Manual*. College Station, TX.

Van Babel, Jay et al. (2020). “Using social and behavioural science to support COVID-19 pandemic response”. In: *Nature Human Behaviour* 4, pp. 460–471.

Wehner, Caroline, Trudie Schils, and Lex Borghans (2016). “Personality and Mental Health: The Role and Substitution Effect of Emotional Stability and Conscientiousness”. In: *IZA Discussion Paper* 10337.

Williams, Richard (2006). “Generalized ordered logit/partial proportional odds models for ordinal dependent variables”. In: *The Stata Journal* 6(1), pp. 58–82.

Williams, Richard (2016). “Understanding and interpreting generalized ordered logit models”. In: *The Journal of Mathematical Sociology* 40(1), pp. 7–20.

Xiang, Yu-Tao et al. (2020). “Timely mental health care for the 2019 novel coronavirus outbreak is urgently needed”. In: *The Lancet Psychiatry* 7(3), pp. 228–229.

9 Appendix

9.1 Countries in the sample

In Table A1 we list all the countries that integrate the sample used for the estimations.

Table A1: List of countries

Code	Name	Code	Name	Code	Name
AL	Albania	EC	Ecuador	PH	The Philippines
AR	Argentina	ES	Spain	PT	Portugal
AT	Austria	FI	Finland	QA	Qatar
AU	Australia	FR	France	RO	Romania
BE	Belgium	GB	United Kingdom	RU	Russia
BG	Bulgaria	HU	Hungary	SK	Slovak Republic
BR	Brazil	IL	Israel	TH	Thailand
CA	Canada	LV	Latvia	TR	Turkey
CH	Switzerland	MA	Morocco	UA	Ukraine
CO	Colombia	MY	Malaysia	US	United States
CZ	Czech Republic	NG	Nigeria	UY	Uruguay
DE	Germany	NL	Netherlands	VE	Venezuela
DK	Denmark	NZ	New Zealand	ZA	South Africa
DO	Dominican Republic	PE	Peru		

Codification for the countries corresponds to the ISO 3166 alpha-2 code.

9.2 Construction of indexes to measure mental health

In this section we describe each of the questions used to construct the worries and depression indexes, according to Fetzer et al. (2020b).

9.2.1 Worries Index

The survey provides five questions for this dimension of mental health. But, following Fetzer et al. (2020c) –and also confirmed with our own calculations– the second component is not used to generate the index because it has some statistical inconsistencies that break the efficiency of the index and the models. The five questions are listed below.

1. I am nervous when I think about current circumstances.
2. I am calm and relaxed. [reversed coded]
3. I am worried about my health.
4. I am worried about the health of my family members.
5. I am stressed about leaving my house.

The 5-point scale to answer all of these questions is:

1. Does not apply at all.
2. Somewhat does not apply.
3. Neither applies nor does not apply.
4. Somewhat applies.
5. Strongly applies.

The worries index is generated as the sum of each component (excluding component 2). Thus, if a person answered "Neither applies nor does not apply" in all questions, a score of 12 would be assigned. Higher values of the index indicate higher levels of worries. In the estimation, the index is standardized.

9.2.2 Depression Index

The survey provides eight questions for this dimension of mental health.

How often have you been bothered by the following over the past 2 weeks?:

1. Little interest or pleasure in doing things?

2. Feeling down, depressed, or hopeless?
3. Trouble falling or staying asleep, or sleeping too much?
4. Feeling tired or having little energy
5. Poor appetite or overeating?
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down?
7. Trouble concentrating on things, such as reading the newspaper or watching television?
8. Moving or speaking so slowly that other people could have noticed? Or so fidgety or restless that you have been moving a lot more than usual?

The 4-point scale to answer all of these questions is:

1. Not at all.
2. Several days.
3. More than half the days.
4. Nearly every day.

The depression index is generated as the sum of each component. For example, if a person answered "Several days" to all questions, a score of 16 would be assigned. Higher values of the index indicate higher levels of depression. In the estimation, the index is standardized.

9.3 Construction of personality traits

The personality traits were generated based on the 10 questions included in the survey. Half of the questions express positive conditions while the other half express negative conditions. Therefore, one question in each trait needs to be reverse-coded to have the variable in the same range and scale. The questions are listed below.

To which extent do the following questions apply to you? I see myself as...

- Extraversion:
  - Extroverted, enthusiastic
  - Reserved, quiet [reverse-coded].
- Agreeableness:
  - Critical, quarrelsome [reverse-coded].
  - Sympathetic, warm.
- Conscientiousness:
  - Dependable, self-disciplined.
  - Disorganized, careless [reverse-coded].
- Neuroticism:
  - Anxious, easily upset.
  - Calm, emotionally stable [reverse-coded].
- Openness to experiences:
  - Open to new experiences, complex
  - Conventional, uncreative [reverse-coded].

The 7-point scale to answer each question is:

1. Disagree strongly.
2. Disagree moderately.
3. Disagree a little.
4. Neither agree nor disagree.
5. Agree a little.
6. Agree moderately.

7. Agree strongly.

Personality traits are generated as the average value of each domain. For example, if a person answered "Disagree moderately" in the two questions that refer to extraversion, her average is 2, so she has a low degree of extraversion. Based on this process, a score is generated for each dimension of personality. Then, looking at the distribution, we identify the median to generate dummy variables for each personality trait, which is what we use in the main models. We use the full categorical variables to evaluate their relationship with *days since lockdown* in the robustness subsection in Section 4.

9.4 Additional Estimations

In this section, we present the results of the estimations using ordinary least squares –OLS– and the mixed-effects ordered logit –MEOLOGIT–, as a complement to the results shown in Table 2. In particular, while in section 5 we compress the worries and depression indexes into 4 and 5 categories, respectively, here we use the indexes without restriction. That is to say, the outcome variables have their complete range with 17 categories for the worries index and 25 categories for the depression index.

We do not provide a detailed interpretation of the results. The key point is that they are very similar to the results shown in the main text, thus providing justification for our analysis based on the restricted worries and depression indexes. Most importantly, the differential effect of *days since lockdown* on the two mental health indexes remains.

	OLS (β Coefficients)		MEOLOGIT(OR)[a,b]	
Variables	Worries	Depression	Worries	Depression
days	-0.025**	0.015*	1.000	1.016*
$days^2$	0.001**	-0.0002	1.000	1.000
age	-0.002*	-0.016***	0.996***	0.965***
educ	0.004*	0.00003	1.010***	1.004**
female	0.274***	0.272***	1.670***	1.802***
health=2	-0.246***	-0.443***	0.571***	0.465***
health=3	-0.423***	-0.754***	0.409***	0.259***
health=4	-0.585***	-0.947***	0.305***	0.165***
extraversion	0.002	-0.124***	0.986	0.755***
agreeableness	0.029	-0.046*	1.077*	0.900**
conscientiousness	0.089***	-0.190***	1.183***	0.646***
neuroticism	0.287***	0.441***	1.711***	2.592***
openness	-0.011	-0.006	0.987	0.966
extraversion×days	-0.001	0.002	1.000	1.005*
agreeableness×days	0.002	0.001	1.002	1.002
conscientiousness×days	-0.001	-0.00005	0.999	1.001
neuroticism×days	0.002	0.005*	1.004	1.007**
openness×days	0.002	0.001	1.004	1.002
female×days	-0.005	-0.005	0.991***	0.992***
intercept	0.568**	1.142***		
Fixed-effects	Country	Country		
Fixed-effects	Date of survey	Date of survey		
Sample size	82,121	82,121	82,121	82,121

[a] OR stands for Odds-Ratio.

[b] The cutpoints κ from the MEOLOGIT are not shown for ease of exposition.

Significance level: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A2: OLS and MEOLOGIT for ordinal indexes