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COVID-19 and mental health: natural experiments of the costs of lockdowns*

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Abstract

The COVID-19 pandemic has profoundly impacted the world, affecting not only physical health and the economy but also mental well-being. This chapter provides an investigation of the causal link between lockdown measures –a significant public health intervention– and mental health. Our examination begins with an overview of the mental health landscape across various countries prior to the COVID-19 pandemic. We then summarize key insights from a range of surveys, reviews, and meta-analyses concerning the pandemic's effect on mental health. Further, we delve into a detailed analysis of three noteworthy studies that employ natural experiments to investigate the effects of lockdowns on mental health in different countries. Despite their differing research designs, these studies converge on the conclusion that lockdowns have had a detrimental impact on mental health. The intensity of this effect, however, varies among different population groups. This suggests that lockdown measures have affected certain segments of the population more profoundly than others.

JEL Codes: I1, J1.

Keywords: COVID-19, mental distress, natural experiments.

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Introduction

A summary on the consequences of the COVID-19 pandemic. The COVID-19 pandemic, as a severe health crisis, had an extraordinary global impact. Reflected starkly in the annual death toll, **Figure 1** illustrates a disconcerting leap from approximately 57.9 million worldwide estimated deaths in 2019 to around 63.2 million in 2020, and a further rise to about 69.2 million in 2021. This remarkable escalation underscores the devastating health implications brought on by the pandemic.

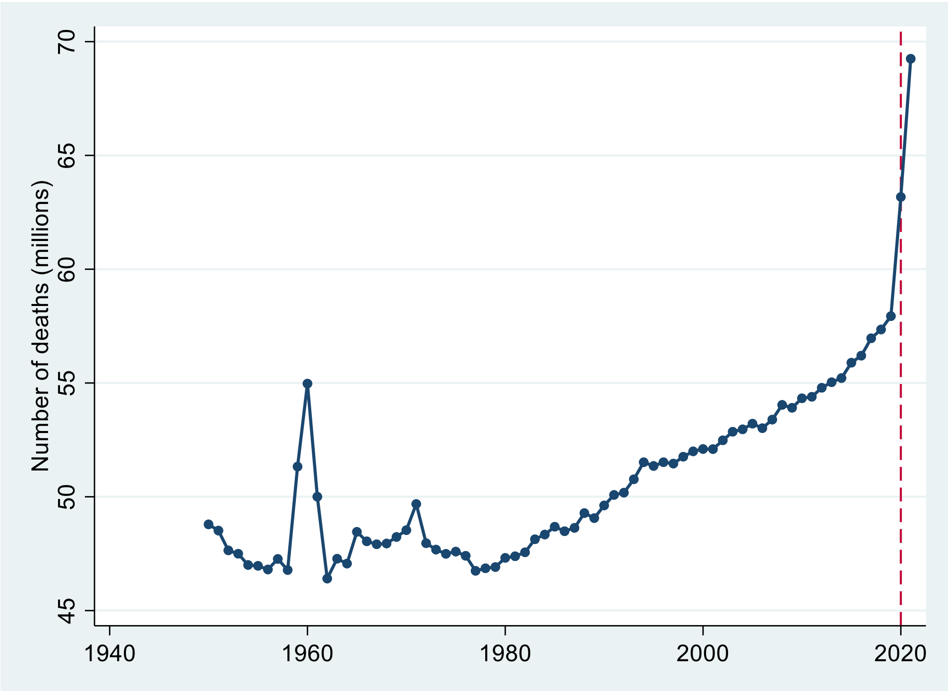


Figure 1. Worldwide annual deaths, 1950-2021. *Note: Number of deaths over a given period. Refers to annual civil calendar years from 1 January to 31. Source: Own elaboration using data from (Ritchie & Mathieu, 2023) (https://ourworldindata.org/grapher/number-of-deaths-per-year and https://ourworldindata.org/grapher/number-of-deaths-per-year) and United Nations Population Division (2022) (https://population.un.org/wpp/Download). The code to produce Figure 1 is openly available in Harvard Dataverse, at https://doi.org/10.7910/DVN/K4OW35.*

Yet, the challenges were not confined to health alone. The pandemic became a catalyst for the most severe global economic crisis observed in over a century. This crisis was primarily a consequence of the stringent public health measures, such as mobility restrictions and lockdowns that were indispensably enforced to contain the virus (World Bank, 2022, p.1). As documented in the World Development Report (2022), such measures resulted in a considerable contraction of economic activity in nearly 90% of countries in 2020, outpacing the effects of the two world wars, the Great Depression, the 1980s' emerging economy debt crises, and the 2007-09 global financial crisis (World Bank, 2022, Figure O.1).

In 2020, the global economy experienced an estimated shrinkage of 3 percent (IMF, 2021; World Bank, 2021), as cited in the Human Development Report (2022), which also notes that this economic downturn had far-reaching social repercussions; for the first time in a generation, there was a notable increase in global poverty levels (Mahler et al., 2022). Thus, the COVID-19 pandemic demonstrated both its profound and pervasive socio-economic impacts together with its catastrophic health effects.

While the pandemic's immediate effects were most visibly seen in the increase in deaths and the decline in economic activity, a major impact has been found on mental health. The uncertainty and fear surrounding personal and family health risks, coupled with economic instability, have taken a toll on global mental health (UNDP, 2022). Stringent public health measures, including mobility restrictions and lockdowns, further exacerbated this issue.

Surveys, reviews, and meta-analyses have examined the impact of the COVID-19 pandemic on mental health. A notable systematic review and meta-analysis considering variation in treatment levels by Salanti et al. (2022) of 43 longitudinal studies involving 331,628 participants drew two primary conclusions. Firstly, depression and anxiety symptoms generally worsened within the initial two months of the pandemic, with a standardized mean difference of −0.39 (95% credible interval [−0.76, −0.03]). Secondly, the pandemic's repercussions and its containment measures affected different population groups variably.

In their extensive literature survey, Banko-Ferran et al. (2023) synthesized the COVID-19 pandemic's effects on mental health. They first reviewed the impact of lockdowns (e.g., Altindag et al., 2022), school closures (e.g., Blanden et al., 2021), economic hardship (e.g., Kämpfen et al., 2020), remote work (e.g., Bertoni et al., 2021), and vaccine distribution (e.g., Perez-Arce et al., 2021). They summarised the evidence showing that the increases in mental distress were not uniformly distributed across different demographic groups. These were particularly concentrated among women (e.g., Oreffice & Quintana-Domeque, 2021); young adults (e.g., Giuntella et al., 2021); essential workers (e.g., Quintana-Domeque et al., 2021); ethnic minorities (e.g., Proto & Quintana-Domeque, 2021); and individuals with certain personality traits (e.g., Staneva et al., 2022).

In another insightful review that also offers policy recommendations, Aknin et al. (2022) pinpointed three significant findings. First, psychological distress heightened during the pandemic's early phase. Second, younger individuals, women, and those with children under the age of 5 were the groups witnessing the most significant surge in psychological distress. Third, higher levels of psychological distress were linked to proximity to or experiencing COVID-19 infection, financial uncertainties brought about by the pandemic, and increased time spent on home-schooling, chores, or consuming COVID-19 news.

Lastly, the Human Development Report (2022) substantiates that within the initial year of the COVID-19 pandemic, there was an alarming rise in the global prevalence of depression and anxiety by over 25% (WHO, 2022b). This mental health crisis was unevenly shouldered, with women, ethnic minorities, and younger individuals bearing a disproportionate burden.

In summary, the literature on the mental health ramifications of the COVID-19 pandemic points to two consistent findings. First, the pandemic has negatively affected mental health, at least in the immediate aftermath. Second, the severity of these effects has varied across sociodemographic groups. The question of whether these effects are short-lived or long-lasting remains debated among researchers. Some suggest that the effects are transient (e.g., Pierce et al., 2021), while others argue for more enduring impacts (e.g., Quintana-Domeque & Proto, 2022).

The focus of this chapter. This chapter aims to examine the causal effect of lockdowns, a stringent public health measure, on mental health.[1] While the COVID-19 pandemic might be the most recent, it surely will not be the last. Therefore, understanding the implications of lockdowns on mental distress is critical. As highlighted in the Human Development Report (2022), without psychological resilience, mental distress can escalate into mental disorders, and these are linked with detrimental outcomes, such as poor educational attainment (e.g., Brännlund et al., 2017), diminished workplace productivity (e.g., Bubonya et al., 2017), poverty (e.g., Callander & Schofield, 2018), premature and excess mortality (e.g., Saxena, 2018), and overall poor health.

We focus our attention on studies that utilize *natural experiments*. While we do not anticipate randomly allocating individuals to pandemics or lockdown measures anytime soon, policy decisions or natural events sometimes create 'as good as random' variations in exposure to pandemics or containment measures. These situations are known as natural experiments (Angrist & Krueger, 1999), and their goal is to simulate randomized experiments where researchers manipulate exposure to the treatment or intervention to investigate the causal effect of interest. Under certain conditions, natural experiments enable us to distinguish causation, 'when changing a feature of the world leads to a change in some other feature of the world', from association, 'when two features of the word tend to move together', (de Mesquita & Fowler, 2021).

[1] Our focus in this chapter is on mental distress. For a comprehensive review of the pandemic's impact on self-harm, subjective well-being, loneliness, and social connection, in addition to psychological distress, readers are encouraged to refer to Aknin et al. (2022).

Numerous studies have attempted to quantify these effects (see the list in Appendix A), but our analysis primarily concentrates on three works: Adams-Prassl et al. (2022), Altindag et al. (2022) and Serrano-Alarcón et al. (2022), published in three economics journals with different scope: *Economic Policy*, a journal focused on informing policymaking, *Health Economics*, a field journal in health economics, and *American Economic Journal: Applied Economics*, the top journal in applied economics.

We have chosen these three studies due to their varied geographical scope (encompassing the USA, England and Wales in the UK, and Turkey), their distinct data sources (ranging from primary online survey data to secondary nationally representative data), their different mental health measures (from subjective wellbeing indicators to somatic indicators of mental distress) and their unique identification strategies (which include difference, difference-in-differences, and regression discontinuity design), among other selection criteria.

Before delving into our review of these studies, it is crucial to understand the pre-pandemic state of mental health and the inherent complexities of measuring mental health. While it may seem that such a consideration is only relevant for descriptive research, it is equally critical for causal inference. By grasping the distinct domains of mental health, we can better comprehend how they may be influenced, either positively or negatively, by various shocks or interventions.

Mental health before the pandemic and its measurement

Mental health before the onset of the COVID-19 pandemic. Prior to the pandemic, one in every eight individuals globally, approximately 970 million people, suffered from a mental health disorder (UNDP, 2022). Pre-pandemic prevalence rates across 186 countries (Dattani et al., 2021; Institute of Health Metrics and Evaluation, 2019) indicated that 3.8% (SD = 1.2) suffered from anxiety disorders, while depressive disorders affected 3.6% (SD = 0.8) of the population.[2]

Figure 2 and **Figure 3** present scatter plots of anxiety and depressive disorders' pre-pandemic prevalence rates across countries, juxtaposed against their per capita income. Intriguingly, the relationship between a country's income per capita and mental health varies based on the specific mental health measure. Anxiety disorders are more prevalent in wealthier countries — across 186 countries, a 1 log point increase in GDP per capita corresponds to an increase in the prevalence of anxiety disorders by 0.47 percentage points (SE = 0.17). Conversely, poorer countries witness a higher prevalence of depressive disorders — a 1 log point increase in GDP per capita is associated with a decrease in the prevalence of depressive disorders by 0.35 percentage points (SE = 0.16). Despite these differences, income differences across countries account for a similar percentage of the variance in the prevalence of anxiety and depressive disorders, 13% and 15% respectively.

[2] The list of 186 countries includes the following: Bermuda (a British Overseas Territory, not a sovereign nation), Micronesia (while there is a country known as the Federated States of Micronesia, "Micronesia" is more generally a subregion of Oceania composed of thousands of small islands), Puerto Rico (a territory of the United States, not a sovereign nation), and Taiwan (while it functions as a sovereign state in many aspects, its status is complex due to its unique political situation). All the estimates in this section are weighted by population size: that is, each country's observation is weighted by the size of its population.

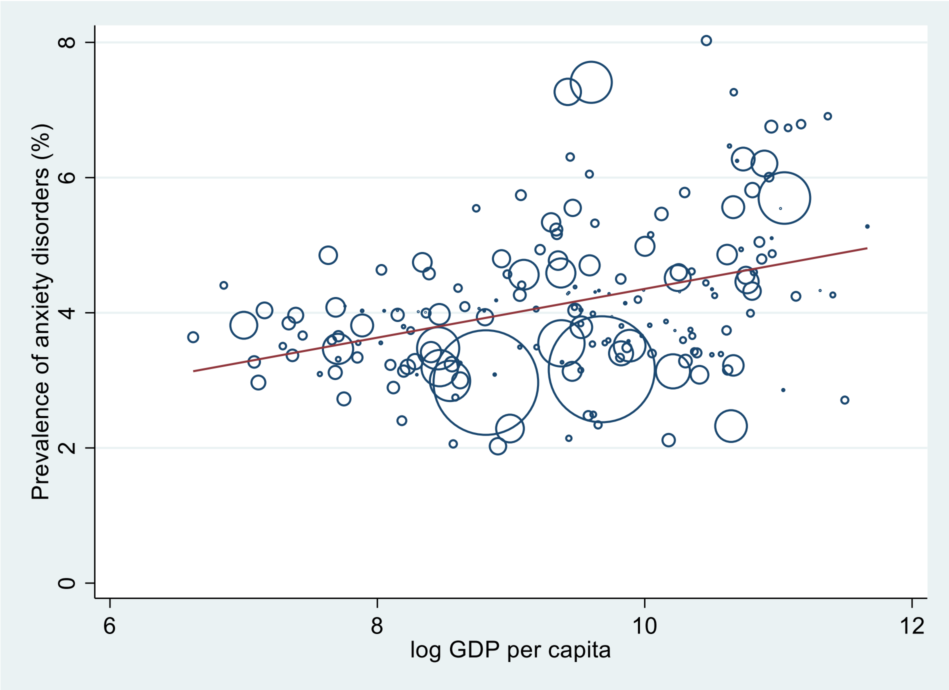


Figure 2. Anxiety disorders and income per capita across countries in 2019. *Note: Log GDP per Capita is the natural logarithm of GDP per Capita, PPP, constant 2017 international $. The size of each circle is proportional to the country's population size. Own elaboration using data from Dattani et al., (2021) (https://ourworldindata.org/mental-health and https://ourworldindata.org/grapher/anxiety-disorders-prevalence-vs-gdp?tab=table), Institute of Health Metrics and Evaluation (2019) (http://ghdx.healthdata.org/gbd-results-tool), and World Development Indicators - World Bank (https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators). The red line represents the OLS fitted regression line. The code to produce Figure 2 is openly available in Harvard Dataverse, at https://doi.org/10.7910/DVN/K4OW35.*

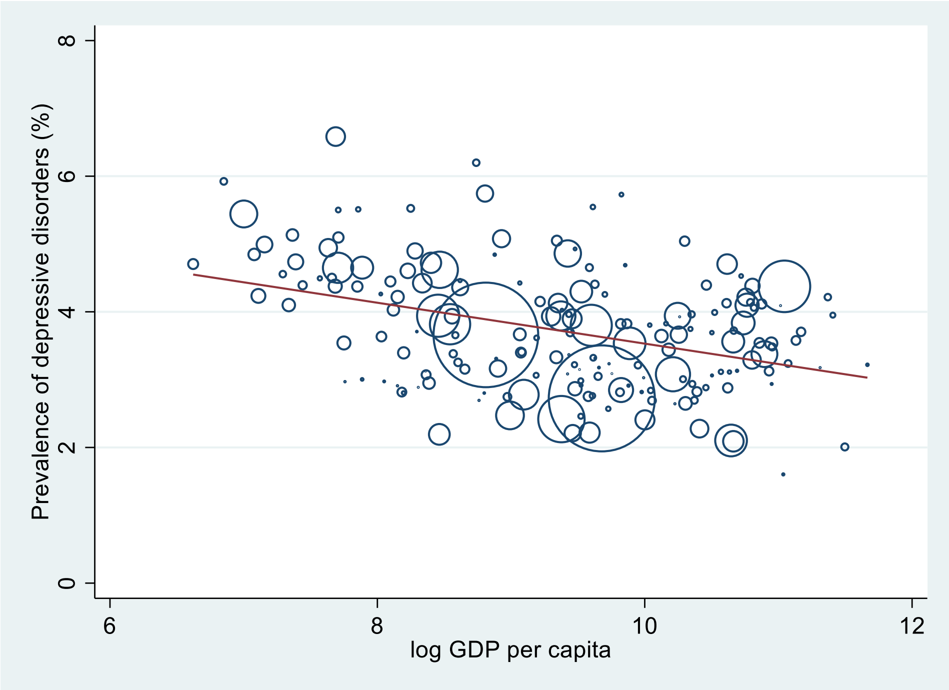


Figure 3. Depressive disorders and income per capita across countries in 2019. *Note: Log GDP per Capita is the natural logarithm of GDP per Capita, PPP, constant 2017 international $. The size of each circle is proportional to the country's population size. Own elaboration using data from Dattani et al., (2021) (https://ourworldindata.org/mental-health and https://ourworldindata.org/grapher/depressive-disorders-prevalence-vs-gdp-per-capita?tab=table), Institute of Health Metrics and Evaluation (2019) (http://ghdx.healthdata.org/gbd-results-tool), and World Development Indicators - World Bank (https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators). The red line represents the OLS fitted regression line. The code to produce Figure 3 is openly available in Harvard Dataverse, at https://doi.org/10.7910/DVN/K4OW35.*

The data depicted in **Figure 2** and **Figure 3** can be summarized by calculating the means for groups of countries based on their income levels. **Figure 2** reveals that among lower-income countries (defined as those with a log GDP per capita below 8), the prevalence of anxiety disorders is 3.7%, while in higher-income countries (log GDP per capita 10 or above), the prevalence of anxiety disorders further increases to 4.7%. Conversely, **Figure 3** displays a reversed gradient. In lower-income countries, the prevalence of depressive disorders is the highest at 4.9%, while this figure drops to 3.6% in higher-income countries.

Measuring mental health. As underscored in the Human Development Report (2022), quantifying mental wellbeing presents a significant challenge due to its encompassing nature, which extends beyond just the absence of mental disorders. According to the World Health Organization (WHO), mental health is "a state of well-being in which every individual realizes his or her own potential, can cope with the normal stress of life, can work productively and fruitfully, and is able to make a contribution to her or his community" (WHO, 2022a).

Figure 2 and **Figure 3** utilize two different metrics of mental wellbeing or health, leading to contrasting conclusions — one suggests a positive correlation between mental health and income across countries, the other a negative one. This basic example highlights one of the primary challenges in mental health and wellbeing research, namely, measurement. By 'measurement,' we refer both to capturing the various dimensions of mental health and ensuring accurate reporting of these aspects. Accuracy may be hindered by factors such as self-reporting biases, stigma effects that discourage seeking professional help, or lack of access to mental health services, among others (see UNDP, 2022; UNICEF, 2021).

Numerous measures of mental health exist, including the 7-item Generalized Anxiety Disorder questionnaire (GAD-7) and the 9-item Patient Health Questionnaire (PHQ-9). The GAD-7 is a seven-item, self-report anxiety questionnaire designed to assess the patient's health status over the previous 2 weeks. The questionnaire has been validated for use as both a screening tool and a severity measure in general populations (Löwe et al., 2008; Spitzer et al., 2006). The PHQ-9, derived from the depression section of the Patient Health Questionnaire by Spitzer et al. (1999), is a self-report measure of depression. It consists of nine items that align with the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) criteria for major depression, and has been widely used for depression screening in primary care and clinical settings (Kroenke et al., 2001; Kroenke & Spitzer, 2002). Our focus in this chapter however is on the three measures utilized by the studies under review — the 12-item General Health Questionnaire (GHQ-12), the 20-item Self-Reporting Questionnaire (SRQ-20), and the 5-item World Health Organization Well-being index (WHO-5). Table 1 provides the description of these metrics and summarizes their key strengths and weaknesses, while Appendix B includes their questionnaires.

Table 1. Three mental health metrics: description, strengths, and weaknesses.

Measure	Description	Strengths	Weaknesses
WHO-5 (Topp et al., 2015)	A short self-report measure of current mental well-being, focusing on positive mood, vitality, and general interest over the past two weeks.	- Quick and straightforward administration. - Validation across multiple settings and languages. - High sensitivity and specificity for detecting depression. - High clinimetric validity	- Relies on self-reporting. - Focuses on the recent two weeks, which may not capture long-term trends. - May not capture the full range of mental health concerns.
GHQ-12 (Goldberg et al., 1997)	A screening instrument for minor psychiatric disorders in community settings and non-psychiatric clinical settings, such as primary care or general practice.	- Short and easy to administer. - Versatile, not specific to any mental disorder. - Validated across many cultures and languages.	-Relies on self-reporting. - Focuses on recent past, which may not capture long-term trends. - Does not provide a clinical diagnosis. - It is based on the respondent's comparison of their present state to their usual or normal state of mental health, which can vary among individuals and limit the comparability of GHQ-12 scores.
SRQ-20 (Beusenberg et al., 1994)	A screening/case-finding instrument for mental disorders in primary healthcare settings. It consists of 20 yes/no questions about mental health status over the past month.	- Covers a broad range of mental health issues. - Widely used and validated across different cultures and languages	- Relies on self-reporting. - Focus on the past month, limiting the capture of long-term trends. - Does not provide a clinical diagnosis. - Binary yes/no format that may oversimplify mental health experiences. - Lack of differentiation between types of mental disorders.

On the causal effect of the COVID-19 pandemic and lockdown measures on mental health

Exploiting cross-sectional differences. When considering the impact of the COVID-19 pandemic and its associated containment measures on mental health within the general population, we encounter a fundamental question of causality. To address this question, we can employ the potential outcomes framework, also called the Rubin-Causal-Model (Imbens & Rubin, 2010), as a means of formalizing the notion of causal effect. Within this framework, the causal effect of the COVID-19 pandemic on an individual's mental health is defined as the difference between two potential outcomes each linked to a different sate of the world.[3] They are referred to as 'potential' outcomes because, for every individual, only one of the two outcomes is observed (*what is*). The other remains a counterfactual (*what would have been).* For example, if our interest relies on the impact of being exposed to the COVID-19 pandemic on individual mental health, the two potential outcomes are: the individual's mental health in a pandemic-affected world and their mental health in a scenario where the pandemic did not occur. Notably, at a given point in time, we can only observe the individual in one of the two worlds, with or without pandemic, and hence such a difference, the individual causal effect, cannot be observed. This is the key challenge in the field of causal inference. Although

[3] The standard potential outcomes framework employs the Stable Unit Treatment Value Assumption, or SUTVA (Imbens & Rubin, 2010). This assumption essentially precludes any interference between units and rules out variations in the treatment's effects across units. Under SUTVA, the potential outcomes for every individual are independent of the treatment status of other individuals. In practical terms, this implies that the mental health of individuals not exposed to lockdown would not be affected by the mental health status of others who were subjected to lockdown.

recovering individual causal effects is not feasible, we can still attempt to gain insights into average causal effects.

We will now introduce some notation to formalize the definition of causal effect for an individual i, as well as the type of average causal effect we can aim to learn about. Let Y_i represent the observed mental health score of individual i. We can express Y_i as follows:

$$Y_i = Y_i(0)(1 - D_i) + Y_i(1)D_i$$

Here, $Y_i(0)$ denotes the mental health score of individual i in a scenario where the pandemic does not occur, while $Y_i(1)$ represents the mental health score of individual i in a pandemic-affected world. D_i takes the value of 1 if individual i has been exposed to the pandemic, and 0 otherwise. Thus, the observed mental health score of individual i, denoted as Y_i, corresponds to $Y_i(1)$ if the individual was exposed to the COVID-19 pandemic, and $Y_i(0)$ if not. In addition to the previously mentioned standard missing data problem in causal inference (i.e., only one of the two potential outcomes is observed), things are more complicated in our context because *all* individuals were exposed to the COVID-19 pandemic ($D_i = 1$ for all i). Consequently, using cross-sectional information alone, we cannot make progress in determining the causal effect of the COVID-19 pandemic on mental health.

While we cannot find out the causal effect of the COVID-19 pandemic on mental health with cross-sectional information only, we can still make progress in understanding the causal effect of containment measures implemented during the pandemic. Let us consider the following notation: $Y_i(0)$ represents the mental health of individual i when not exposed to a lockdown, $Y_i(1)$ represents the mental health of individual i when exposed to a lockdown, and D_i takes the value of 1 if individual i is exposed to a lockdown and 0 otherwise.

It is evident that at any given time, an individual is either exposed or not exposed to a lockdown. As a result, the causal effect of being exposed to a lockdown on an individual's i

mental health during the COVID-19 pandemic, denoted as $Y_i(1) - Y_i(0)$, is not identified. Once again, only one potential outcome is observable for everyone. However, Adams-Prassl et al. (2022) addressed this issue by leveraging variations in lockdown measures across different states in the USA to identify the average causal effect of lockdowns on mental health among individuals exposed to lockdown measures.

Their approach involved comparing the average mental health among individuals exposed to lockdowns, denoted as $\mathbb{E}[Y_i|D_i = 1]$, with the average mental health among individuals not exposed to lockdowns, denoted as $\mathbb{E}[Y_i|D_i = 0]$, during the COVID-19 pandemic in the USA. Formally, this can be expressed as:

$$\mathbb{E}[Y_i|D_i = 1] - \mathbb{E}[Y_i|D_i = 0] =$$

$$\mathbb{E}[Y_i(1)|D_i = 1] - \mathbb{E}[Y_i(0)|D_i = 0] =$$

$$\mathbb{E}[Y_i(1) - Y_i(0)|D_i = 1] + \mathbb{E}[Y_i(0)|D_i = 1] - \mathbb{E}[Y_i(0)|D_i = 0]$$

This expression reveals that the average difference in mental health between individuals exposed to lockdowns and those unexposed to lockdowns is composed of three components.[4] Firstly, it includes the *average causal effect of lockdowns on mental health among individuals exposed to lockdowns*, denoted as $\mathbb{E}[Y_i(1) - Y_i(0)|D_i = 1]$. Secondly, it encompasses the average mental health among individuals exposed to lockdowns if they *had not been* exposed to lockdowns, represented as $\mathbb{E}[Y_i(0)|D_i = 1]$. Lastly, the last term is the average mental health among individuals not exposed to lockdowns, denoted as $\mathbb{E}[Y_i(0)|D_i = 0]$.

[4] To obtain the final expression one needs to add and subtract the *counterfactual* conditional mean $\mathbb{E}[Y_i(0)|D_i = 1]$, the average mental health among individuals exposed to lockdowns if they had not been exposed to lockdowns.

The first term, $\mathbb{E}[Y_i(1) - Y_i(0)|D_i = 1]$, is known as the *average treatment effect on the treated*. The difference between the second and last terms, $\mathbb{E}[Y_i(0)|D_i = 1] - [Y_i(0)|D_i = 0]$, represents the *selection bias*. Selection bias may arise due to systematic differences between states that enforced stay-at-home orders and those that did not. In other words, there could be various factors beyond stay-at-home orders that contribute to, fully explain, or even reverse the average differences in mental health across states.

Adams-Prassl et al. (2022) conducted a comparison between the average mental health of individuals in states with lockdown measures ($D_i = 1$) and individuals in states without lockdown measures ($D_i = 0$) in April 2020. After controlling for factors such as gender, household income, education, age, and marital status, they found that individuals in states with lockdown measures scored, on average, 0.067 standard deviations below those in states without lockdown measures (standard error = 0.036) on the WHO-5 Well-being index, a 5-item measure of psychological well-being.[5]

Exploiting differences over time. Based on our previous discussion, determining the causal effect of the COVID-19 pandemic on mental health solely through cross-sectional information is not possible. However, significant progress has been made by various studies in this regard by leveraging time variation. To incorporate the time dimension, we introduce new notation.

Let Y_{it} represent the observed mental health score of individual i at time t. We can express Y_{it} as follows:

[5] This estimate is the one after restricting the sample to respondents of the second wave who lived in states that did not have lockdowns measures in place at the time of the first data collection. See column 2 of Table 1 in Adams-Prassl et al. (2022). The estimate for the full sample is 0.083 (0.032). See column 1 of Table 1 in 1 in Adams-Prassl et al. (2022) .

$$Y_{it} = Y_{it}(0)(1 - D_i) + Y_{it}(1)D_i$$

Here, D_i takes the value of 1 if individual i is exposed to the pandemic, and 0 otherwise. $Y_{it}(0)$ represents the mental health of individual i when not exposed to the pandemic at time t, and $Y_{it}(1)$ represents the mental health of individual i when exposed to the pandemic at time t. In our context, since everyone was exposed to the pandemic, D_i is equal to 1 for all individuals. Therefore, we are compelled to compare mental health before and after the onset of the COVID-19 pandemic.

The difference in average mental health among individuals after and before the onset of the COVID-19 pandemic can be expressed as:[6]

$$\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 1, T_t = 0] =$$

$$\mathbb{E}[Y_{i1}(1)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] =$$

$$\mathbb{E}[Y_{i1}(1) - Y_{i1}(0)|D_i = 1, T_t = 1]$$

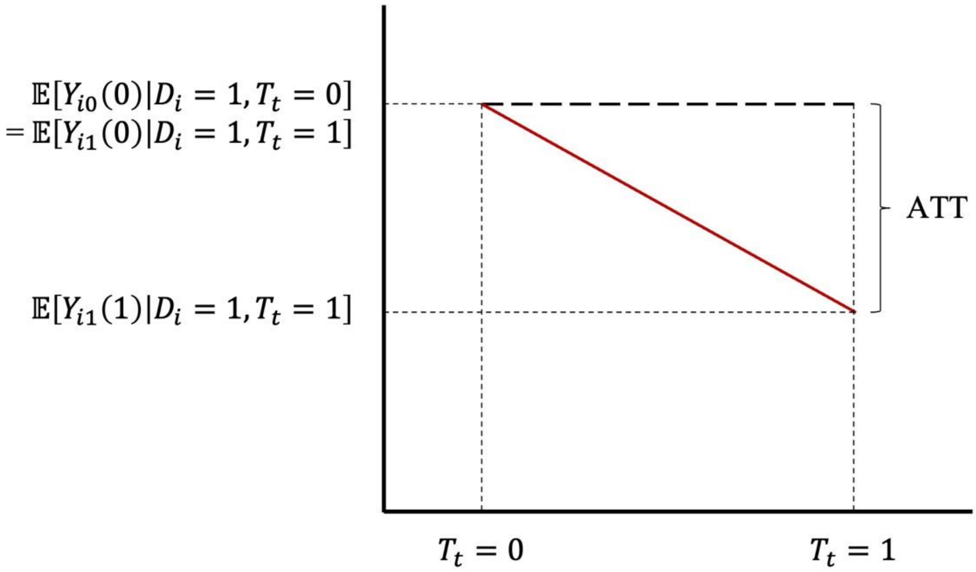
$$+\{\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0]\}$$

The first term represents the average causal effect of the pandemic among individuals affected by it (also known as the average treatment effect on the treated). The second term, in brackets, captures selection bias, taking the form of a time effect. It captures what would have been the average change in mental health between the pre-pandemic and pandemic periods among individuals affected by the pandemic, had the pandemic not occurred. If the time effect is zero, comparing the average mental health among individuals after and before the

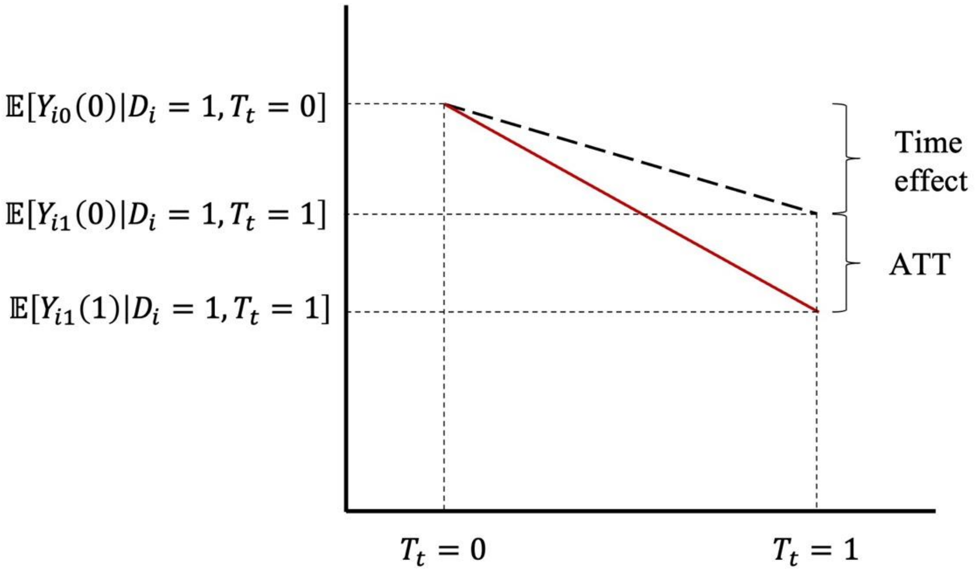
[6] To obtain the final expression one needs to add and subtract the *counterfactual* conditional mean $\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1]$, the average mental health at $T_t = 1$ among individuals exposed to lockdowns $D_i = 1$ if they had not been exposed to lockdowns.

onset of the COVID-19 pandemic reveals the average causal effect of the pandemic among individuals affected by it.

Figure 4 graphically represents the validity (panel A) or invalidity (panel B) of the time-difference research design. In panel A, where there is no time effect, $\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0]$ equals zero. As a result, $\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 1, T_t = 0]$ recovers the average treatment effect on the treated. In panel B, where a time effect exists, $\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0]$ is negative. Consequently, $\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 1, T_t = 0]$ becomes a biased measure of the average treatment effect on the treated.



Panel A. No time effect. Difference in means equals selection bias + average treatment effect on the treated.



Panel B. Time effect. Difference in means equals average treatment effect on the treated.

Figure 4. Identification of average treatment effect on the treated using a time-difference research design.

For example, using data from the UK Household Longitudinal Study, Proto and Quintana-Domeque (2021) find that mental distress, as measured by the GHQ-12, increased by 0.21 standard deviations [95% CI: 0.19, 0.23] when comparing individuals before (2017-2019) and after the onset of the COVID-19 pandemic (April 2020). Of course, if the time effect is different from zero, then this comparison does not give us the average causal effect of the pandemic among individuals affected by the pandemic. However, existing evidence shows that the time trends (time effects) cannot account for the increase in mental distress observed between before and after the onset of the pandemic (e.g., Banks & Xu, 2020).

Differences along two dimensions: multiple cross-sectional data. In their study, Adams-Prassl et al. (2022) compared the average mental health of individuals in USA states with lockdown measures to those in USA states without lockdown measures in April 2020. This allowed them to examine the average causal effect of these measures on individuals who were exposed to them during the COVID-19 pandemic. The findings of Adams-Prassl et al. (2022) strongly suggest that stay-at-home orders led to a significant reduction in mental health.

However, it is important to consider the possibility that states implementing stay-at-home orders differed from those that did not along dimensions relevant for mental health. If these differences exist, the difference will not capture just the effect of lockdowns but other state differences. Consequently, the reported reduction of 0.067 in mental health will capture both the average causal effect of stay-at-home orders on mental health among individuals subject to them and selection bias.

While Adams-Prassl et al. (2022) controlled for variables such as gender, household income, education, age, and marital status, there could still be numerous other factors, both observable and unobservable, that contribute to, fully explain, or even reverse the average gap in mental health across states.

Before delving into how Adams-Prassl et al. (2022) address this concern, let us formalize their analysis introducing the time dimension in the potential outcomes framework. The authors compared the average mental health among individuals in states under lockdown ($D_i = 1$) with individuals in states without lockdown ($D_i = 0$) during April 2020 ($T_t = 1$):[7]

$$\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 0, T_t = 1] =$$

$$\mathbb{E}[Y_{i1}(1)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1] =$$

$$\mathbb{E}[Y_{i1}(1) - Y_{i1}(0)|D_i = 1, T_t = 1]$$

$$+\{\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1]\}$$

[7] As before, to obtain the final expression one needs to add and subtract the *counterfactual* conditional mean $\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1]$, the average mental health at $T_t = 1$ among individuals exposed to lockdowns $D_i = 1$ if they had not been exposed to lockdowns.

The first term represents the average causal effect of the lockdown among individuals affected by the lockdown. The second term, in brackets, captures the selection bias, which now takes the form of a state effect. It captures what would have been the average difference in mental health between states with lockdown and states without lockdown after the onset of the pandemic, assuming the lockdown had not taken place. If the state effect is zero, the average mental health among individuals in states under lockdown ($D_i = 1$) and individuals in states without lockdown ($D_i = 0$) during April 2020 ($T_t = 1$) reveals the average causal effect of the lockdown among individuals affected by the lockdown.

Is there any evidence that $\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1] = 0$? While this represents a counterfactual difference that cannot be computed with the available information, we can make an identifying assumption based on observable factors. Let us assume that

$$\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1]$$
$$= \mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0, T_t = 0]$$

This assumption is known as the *parallel trends assumption* and is a key assumption in difference-in-differences analyses.[8] It states that the difference in average mental health between individuals exposed to lockdown measures and individuals not exposed to lockdown would have remain constant over time had the pandemic not occurred. If we set $T_t = 1$ for April 2020 and $T_t = 0$ for March 2020, what is the estimated $\mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0, T_t = 0]$?

[8] The other assumption in difference-in-differences analysis is that there are "no anticipation" effects. In words, the treatment (in this case being exposed to lockdown measures) has no effect prior its implementation. For a recent discussion on new advances in difference-in-differences strategies see Roth et al. (2023)

Adams-Prassl et al. (2022) find that the adjusted average difference in mental health in March 2020 between individuals in states where lockdown measures would be implemented in April 2020 and individuals in states where lockdown measures would not be implemented in April 2020 is essentially zero (0.007 standard deviations, SE = 0.035).[9] Therefore, they present compelling evidence countering the potential selection bias in the form of a state effect. Their findings indicate that the state effect is essentially zero, meaning that the observed reduction of 0.067 in mental health captures solely the average causal effect of stay-at-home orders on the mental health of individuals subject to those orders. Moreover, their research reveals that the effect is predominantly driven by women and persists even after accounting for factors such as financial worries, childcare responsibilities, and confirmed COVID-19 cases and deaths. **Figure 5** exemplifies their identification strategy.

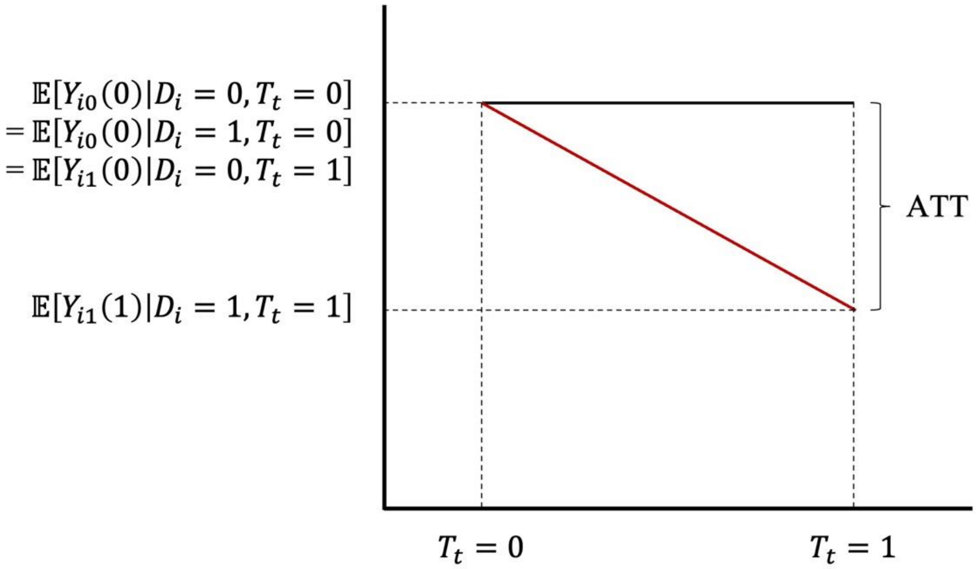


Figure 5. Identification of average treatment effect on the treated using a multiple cross-section time-difference research design.

[9] By adjusted difference we mean the one resulting from controlling for gender, household income, education, age, and marital status in a linear regression setting. See column 3 of Table 1 in Adams-Prassl et al. (2022).

What if the estimated $\mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0, T_t = 0]$ is not zero? In such cases, it is possible to calculate a difference-in-differences estimate by subtracting the estimated difference in average mental health in March 2020 from the estimated difference in average mental health in April 2020. An example illustrating this situation is presented in **Figure 6**.

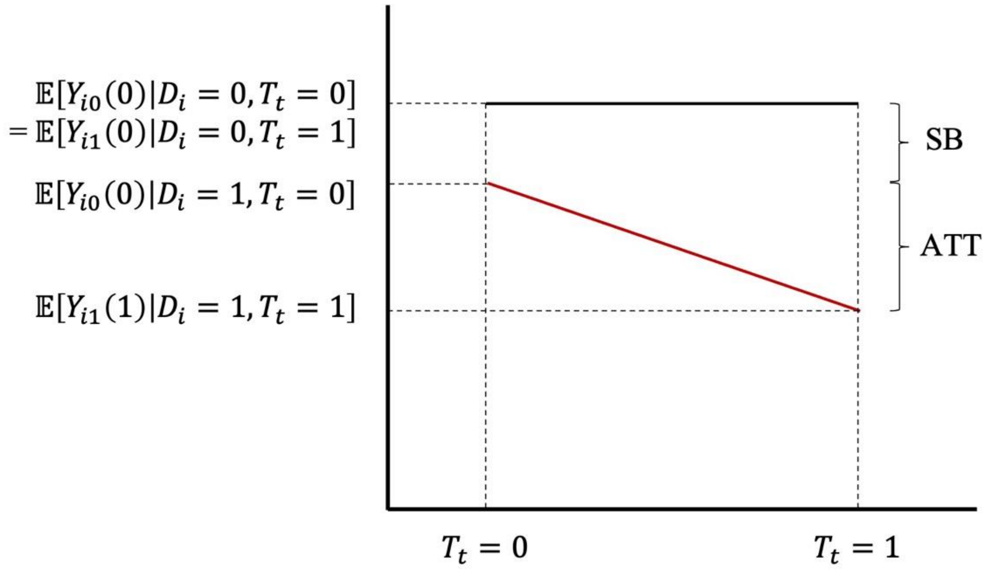


Figure 6. Identification of average treatment effect on the treated using a difference-in-differences research design.

The difference-in-differences estimand is expressed as

$$\{\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 0, T_t = 1]\}$$

$$-\{\mathbb{E}[Y_{it}|D_i = 1, T_t = 0] - \mathbb{E}[Y_{it}|D_i = 0, T_t = 0]\} =$$

$$\{\mathbb{E}[Y_{i1}(1)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1]\}$$

$$-\{\mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0, T_t = 0]\} =$$

$$\mathbb{E}[Y_{i1}(1) - Y_{i1}(0)|D_i = 1, T_t = 1] +$$

$$\{\mathbb{E}[Y_{i1}(0)|D_i = 1, T_t = 1] - \mathbb{E}[Y_{i1}(0)|D_i = 0, T_t = 1]\} -$$

$$\{\mathbb{E}[Y_{i0}(0)|D_i = 1, T_t = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0, T_t = 0]\}$$

Under the *parallel trends assumption*, the difference between the two differences in brackets is zero, and hence

$$\{\mathbb{E}[Y_{it}|D_i = 1, T_t = 1] - \mathbb{E}[Y_{it}|D_i = 0, T_t = 1]\}$$

$$-\{\mathbb{E}[Y_{it}|D_i = 1, T_t = 0] - \mathbb{E}[Y_{it}|D_i = 0, T_t = 0]\} =$$

$$\mathbb{E}[Y_{i1}(1) - Y_{i1}(0)|D_i = 1, T_t = 1]$$

Differences along two dimensions: longitudinal data. The standard difference-in-differences approach has also been used to examine the effect of easing lockdown measures on mental health in the UK. Serrano-Alarcón et al. (2022) exploited the different policy responses to COVID-19 in England and Scotland. Both countries pursued similar containment policies during the early months of the pandemic, but divergence began on May 13, 2020, when England ended its "Stay at Home" order, while Scotland sustained it until May 29, 2020. This occurred despite similar trajectories in the COVID-19 pandemic by the time England eased the restrictions. Utilising data from the UK Household Longitudinal Study, Serrano-Alarcón et al. (2022) found that the easing of restrictions in England by mid-May was associated with improved mental health, evidence by a reduction of 0.31 points ($p<0.10$) in the GHQ-caseness score, which ranges from 0 (indicating the best mental health state) to 12 (representing the worst mental health state).[10]

Ideally, the difference-in-differences identification strategy should be visualised clearly. A very remarkable feature of the study by Serrano-Alarcón et al. (2022) is its graphical

[10] Caseness scale (referred to as "GHQ-caseness" from now on), giving a point to each dimension with a score higher than 3, so that the score varies from 0 (best mental health state) to 12 (worst mental health state).

representation of their findings. Their Figure 2 (p. 289) offers visual evidence supporting the identification of the average causal effect of easing lockdown policies on the mental health of individuals affected by the easing of these policies. First, they provide evidence of parallel trends in average GHQ-caseness before the "Stay at Home" orders in England and Scotland began to differ, supporting the assumption of counterfactual parallel trends from May onwards had the policies not differed in England and Scotland. Second, they demonstrate that mental health improves in England in late May following the easing of restrictions on the 13th of May. Lastly, mental health also improves in Scotland in late June after restrictions were eased on the 26th of May, and the trends appear to become parallel once again in the time where both countries eased restrictions, in late June 2020 and late July 2020.

The authors also found that their results were driven by individuals with lower socioeconomic status, in terms of education or financial situation. These individuals benefited more from the end of the strict lockdown, whereas they experienced a larger decline in mental health where the lockdown was extended. In other words, it seems that easing the lockdown restrictions benefited those already disadvantaged in terms of education and financial difficulties more.

Differences at a given point in time between very similar groups of individuals. Having examined the impact of easing lockdown measures in the UK using a difference-in-differences approach, our attention now turns to another impactful study, by Altindag et al. (2022), that explores the causal effects of stay-at-home orders on mental health in a different context, namely Turkey. This study, in contrast, leverages a regression discontinuity design, exploiting the comparison between individuals just above and just below an age threshold. Individuals aged 65 or above were under curfew, while individuals aged 64 or below were exempt. The key identifying assumption is that individuals around the age cut-off have no systematic differences: individuals around the age cut-off are very similar in terms of observable and unobservable characteristics, other than for the treatment under analysis.

The study by Altindag et al. (2022) combined a natural experiment with the collection of primary survey data via phone interviews conducted between May 29 and July 4, 2020, focusing on approximately 1900 individuals born in Turkey, ranging in age from 59 to 70, who resided in urban areas where curfews were strictly enforced. Mental health was assessed using the SRH-20 scale, and participants were queried about mobility, their perception of being under curfew, demographic characteristics, and other relevant factors. The natural experiment arises with the implementation of the curfew orders, which began on March 21, 2020, accompanied by severe financial penalties for noncompliance, and the fact that individuals aged 65 or above (born in December 1959 or before) were under curfew, while individuals aged 64 or below (born after December 1959) were exempt. These strict curfew measures remained in effect until June 2020.

We now formalize and illustrate their regression discontinuity design (RDD) approach following Lee and Lemieux (2010). Let X_i be the measure of how many months before December 1955 individual i was born. If X_i is negative, the individual was born after December 1955; if positive, the individual was born before December 1955. Now, let $\varepsilon > 0$ denote a "small" number of months before December 1955, and $-\varepsilon$ represents the same number of months but after December 1955. Individuals born in or before December 1955 were subjected to the lockdown policy (under curfew), while those born after December 1955 were not (exempt of the curfew). Hence, the policy had a cut-off at $X_i = 0$. A RDD approach compares the average mental health status of these two groups to estimate the causal effect of the "being under curfew" on mental health at the cut-off, in this case, $X_i = 0$ (born in December 1955).

Figure 7 shows the RDD idea graphically: using estimates $\mathrm{B}' = \mathbb{E}[Y_i|X_i = \varepsilon] = \mathbb{E}[Y_i(1)|X_i = \varepsilon]$ and $\mathrm{A}' = \mathbb{E}[Y_i|X_i = -\varepsilon] = \mathbb{E}[Y_i(0)|X_i = -\varepsilon]$ to approximate $\mathrm{B} = \lim_{\varepsilon\downarrow 0} \mathbb{E}[Y_i(1)|X_i = \varepsilon]$ and $\mathrm{A} = \lim_{\varepsilon\uparrow 0} \mathbb{E}[Y_i(0)|X_i = -\varepsilon]$. Then, one can use $\mathrm{B}' - \mathrm{A}'$ to estimate the causal effect $\mathrm{B} - \mathrm{A}$:

$$\mathrm{B} - \mathrm{A} = \lim_{\varepsilon\downarrow 0} \mathbb{E}[Y_i(1)|X_i = \varepsilon] - \lim_{\varepsilon\uparrow 0} \mathbb{E}[Y_i(0)|X_i = -\varepsilon] = \mathbb{E}[Y_i(1) - Y_i(0)|X_i = 0]$$

If compliance with the curfew is complete (100%), then this value represents the average treatment effect of the policy among individuals born in December 1955. Conversely, if compliance with the curfew is imperfect, it represents an intention to treat effect among this same group. Since these effects are for the group of individuals born in December 1955, these are *local* treatment effects, they are effects for the subpopulation of individuals born in December 1955 (the cut-off). A key assumption allowing the recovery of these causal effects is that individuals born just after December 1955 (those not targeted by the lockdown policy) provide a valid counterfactual for those born just before December 1955 (those targeted by the lockdown policy).[11]

[11] This is the continuity assumption. See Lee and Lemieux (2010).

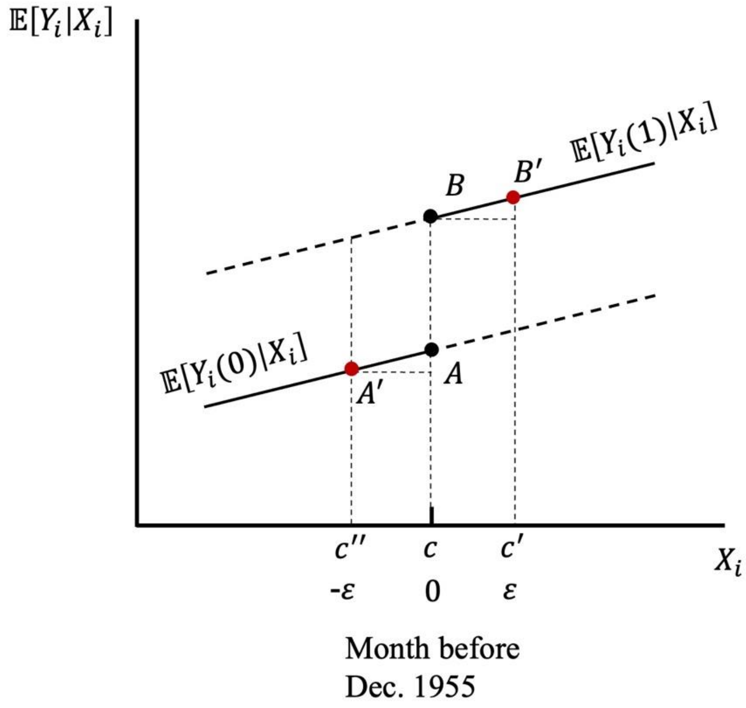


Figure 7. Identification of a local average treatment effect using a regression discontinuity research design.

The analysis by Altindag et al. (2022) reveals several interesting findings. As intended, the curfew measures resulted in reduced mobility, with individuals reporting approximately one fewer day outside in the previous week. However, unintended consequences emerged, as exposure to the curfew led to increased mental distress. Somatic indicators (which capture physical symptoms of anxiety and depression) increased by 0.18 standard deviations, while non-somatic symptoms (which represent more subjective assessments of anxiety and depression) increased by 0.16 standard deviations.

Comparing studies and understanding mechanisms. The difference-in-differences and regression discontinuity designs are both quasi-experimental methods that aim to identify causal effects, but they do so in distinctly different ways and rely on different key identifying assumptions. In the case of the difference-in-differences approach, the crucial assumption is the *parallel trends assumption*, which posits that, in the absence of the treatment (easing of lockdown in Serrano-Alarcón et al., 2022), the average mental health in the treatment and control groups (England and Scotland, respectively, in Serrano- Alarcón et al., 2022) would have followed the same trend over time. The strategy identifies the average causal effect of the treatment on the treated group, essentially providing an estimation of the lockdown easing's impact on the population affected by the easing of the restrictions (England).

The regression discontinuity design hinges on a different assumption, namely, the *continuity assumption*. This research design exploits a clear and distinct cut-off (in this case, age 65, born in December 1955) that separates the treatment group (those who are 65 or older) from the control group (those 64 or younger). Crucially, everything but the treatment and outcome must remain continuous at the cut-off. If so, this method effectively isolates the causal effect of the lockdown measures at the specific cut-off, giving us a local average treatment effect. In other words, the results obtained from this study particularly illuminate the lockdown's impact in Turkey on the mental health of those near the age of 65.

Table 2 provides a tabular comparison of the three studies that we have chosen. While Serrano-Alarcón et al. (2022) rely on secondary, longitudinal survey data (UK Longitudinal Household Survey), Adams-Prassl et al. (2022) and Altindag et al. (2022) collect primary, cross-sectional survey data. Both Adams-Prassl et al. (2022) and Altindag et al. (2022) effectively combine a natural experiment approach with the collection and analysis of primary survey data. While Adams-Prassl et al. (2022) exploit geographical variation in lockdown measures over time in the USA, supplementing their research with *online* survey data, Altindag et al. (2022) leverage discontinuity variation in exposure to lockdown in (urban) Turkey around the age of 65, underpinned by *phone* survey data. Under their corresponding identifying assumptions, they identify different causal effects. Adams-Prassl et al. (2022) identify an *average treatment effect on the treated*: the average causal effect of being exposed to lockdowns on mental health as measured by the WHO-5 on individuals exposed to lockdown measures in the USA. Altindag et al. (2022) identify a *local average treatment effect*: the average causal effect of being exposed to lockdowns on mental health as measured by the SRQ-20 on individuals exposed to lockdown measures around age 65 in Turkey.

Table 2. The causal effect of lockdowns: a comparison of three studies.

Study	Serrano-Alarcon et al. (2022)	Altindag, Erten, and Keskin (2022)	Adams-Prassl et al. (2022)
Country	England and Scotland	Turkey	USA
Data source	Understanding Society	Phone survey	Online survey
Data type	Longitudinal	Cross section	Repeated Cross Section
Sample size	A balanced sample of 9079 individuals: England (N = 8164), Scotland (N =915), followed over six waves	About 1900 observations	A total of 12,010 respondents first wave (N = 4,003), second wave (N = 4,000) third wave (N = 4,007)
Identification strategy	Difference-in-Differences	Regression Discontinuity Design	Difference (in Differences)
Measure	GHQ-12	SRQ-20	WHO-5
Finding and Magnitude	After the strict lockdown ended, mental health rebounded by approximately 31% with respect to the deterioration observed in the first months of the pandemic.	Exposure to the curfew results in a 0.18 standard deviation increase in somatic symptoms and a 0.16 standard deviation increase in non-somatic symptoms of mental distress	Lockdown measures lowered mental health by 0.067 standard deviations (standard error = 0.036) for respondents of the second wave who lived in states that did not have lockdown measures in place at the time of the first data collection
Heterogeneity	Effect stronger for individuals with lower socioeconomic status (education and financial situation)	–	Effect driven by women
Mechanism	Effect not accounted for by the evolution of the pandemic (COVID-19 cases and deaths). No evidence of a reduction in loneliness. No evidence of a negative effect on the probability of being employed. Evidence that the probability of working zero hours decreases by around 3 pp with the easing of restriction.	No evidence of effects on either employment or income. No evidence of effects on household conflict. Evidence of increase social and physical isolation.	The effect is not accounted for by financial worries, childcare responsibilities, and confirmed COVID-19 cases and deaths.

Source: Adams-Prassl et al. (2022), Altindag, Erten, and Keskin (2022), and Serrano-Alarcon et al. (2022).

Why do lockdowns affect mental health? There could be numerous reasons why exposure to lockdowns affects mental health, including fear, changes in time allocation, income fluctuations, and increased conflict (including abuse and other forms of violence). First, lockdowns may escalate fear and concern among the population, due to a perceived heightened risk of contracting the virus (for oneself and loved ones), or in anticipation of economic contractions. Second, lockdowns may disproportionately increase domestic tasks for women. Third, lockdowns may adversely affect economic activity and income opportunities. Lastly, lockdowns may elevate the likelihood of household conflict.

Determining the exact mechanisms at play is a Herculean task, particularly as different mechanisms may operate concurrently and interact with each other. Collectively, the three studies underscore the uneven effects of lockdowns on mental health across various sociodemographic groups: age (in Turkey), gender (in the USA), and socioeconomic status (in the UK).

This heterogeneity in effects could shed light on the pathways from lockdowns to mental health. However, the fact that different characteristics are found to be more (or less) relevant in different countries does not mean that these are the only relevant factors in those countries. Different studies use varied identification strategies. For instance, in Turkey, age is a key factor due to the age-based lockdown, which the research design exploits to establish the average causal effect of (targeted) lockdown exposure on mental health among individuals aged 65.[12]

In Turkey, Altindag et al. (2022) provide compelling evidence that, at least among individuals around 65, increased physical and social isolation contributed to a decline in mental health. In the UK, Serrano-Alarcón et al. (2022) observed that easing lockdown restrictions appeared to benefit individuals of lower socioeconomic status the most. This observation aligns with the reduction in the fraction of individuals working zero hours as lockdown restrictions were eased. Finally, Adams-Prassl et al. (2022) found that the mental health cost of lockdowns was particularly concentrated among women, echoing many studies that highlighted the gender

[12] By average causal effect of (*targeted*) lockdown we mean an *intention*-to-treat effect.

inequality consequences of the COVID-19 pandemic (e.g., Oreffice & Quintana-Domeque, 2021).

Conclusions

In this chapter, we assessed the status of mental health across countries before the onset of the COVID-19 pandemic, summarized the key findings of prior studies on the COVID-19 pandemic and mental health based on existing surveys, reviews, and meta-analyses, and focused on the methodologies and results of three notable studies which exploit natural experiments in three different countries.

Although the identification methods differ, these studies aim to ascertain the impact of lockdown measures on mental health. By juxtaposing these rigorous, yet distinct research designs, we piece together a more nuanced understanding of how lockdown measures have influenced mental health across various contexts and population subsets.

The two key takeaways from these studies are: first, lockdowns have negatively affected mental health; second, the intensity of these effects varies across sociodemographic groups. In other words, lockdowns have inflicted unequal negative effects on the population.

We conclude with two significant points: one methodological and the other economic. Methodologically, these studies underscore the importance of acknowledging heterogeneity when assessing causality. We believe that machine learning methods will significantly contribute to future work on causality analysis (Chernozhukov et al., 2018; Knaus et al., 2021). Economically, the management of pandemic lockdowns highlights a key concept: the existence of trade-offs. The weight of evidence suggests that while lockdowns have been effective in mitigating virus spread and saving lives, they have also imposed substantial mental health costs. Like the benefits, the toll of lockdowns is diverse, affecting different population segments to varying degrees. This interplay between benefits and costs is crucial, providing invaluable insights for policymakers. As they navigate decisions in potential future pandemics, they must remain aware of these intricate trade-offs, aiming to strike an optimal balance between protecting public health and preserving mental well-being.

It is crucial that rigorous public health measures like lockdowns are balanced with the implementation of robust mental health support policies. These could include a variety of services such as mental health call centers and telehealth services, as highlighted by Altindag et al. (2022), and as implemented by the "la Caixa" Foundation and the Galatea Foundation to support health professionals (Atalyar, 2021). Providing these resources is pivotal in safeguarding and enhancing mental health during any future health crises.

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Appendix A

List of selected studies

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Appendix B

The 12-item General Health Questionnaire (GHQ-12)[13]

Here are some questions regarding the way you have been feeling over the last few weeks. For each question, please tick the box next to the answer that best describes the way you have felt.

Have you recently?

1. Been able to concentrate on what you're doing?

- Better than usual
- Same as usual
- Less than usual
- Much less than usual

2. Lost much sleep over worry?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

3. Felt you were playing a useful part in things?

- More so than usual
- Same as usual
- Less useful than usual
- Much less useful

4. Felt capable of making decisions about things?

- More so than usual
- Same as usual
- Less so than usual
- Much less capable

[13] Note that a license fee is required for including GHQ-12 in your questionnaire as a researcher. For more detailed information, please refer to: https://eprovide.mapi-trust.org/instruments/general-health-questionnaire.

5. Felt constantly under strain?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

6. Felt you couldn’t overcome your difficulties?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

7. Been able to enjoy your normal day-to-day activities?

- More so than usual
- Same as usual
- Less so than usual
- Much less than usual

8. Been able to face up to your problems?

- More so than usual
- Same as usual
- Less so than usual
- Much less able

9. Been feeling unhappy and depressed?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

10. Been losing confidence in yourself?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

11. Been thinking of yourself as a worthless person?

- Not at all
- No more than usual
- Rather more than usual
- Much more than usual

12. Been feeling reasonably happy, all things considered?

- More so than usual
- About same as usual
- Less so than usual
- Much less than usual

SELF-REPORTING QUESTIONNAIRE (SRQ)[14]

The following questions are related to certain pains and problems, that may have bothered you in the last 30 days. If you think the question applies to you and you had to describe the problem in the last 30 days, answer YES. On the other hand, if the question does not apply to you and you did not have the problem in the last 30 days, answer NO.

1. Do you often have headaches?	yes/no
2. Is your appetite poor?	yes/no
3. Do you sleep badly?	yes/no
4. Are you easily frightened?	yes/no
5. Do your hands shake?	yes/no
6. Do you feel nervous, tense or worried?	yes/no
7. Is your digestion poor?	yes/no
8. Do you have trouble thinking clearly?	yes/no
9. Do you feel unhappy?	yes/no
10. Do you cry more than usual?	yes/no
11. Do you find it difficult to enjoy your daily activities?	yes/no
12. Do you find it difficult to make decisions?	yes/no
13. Is your daily work suffering?	yes/no
14. Are you unable to play a useful part in life?	yes/no
15. Have you lost interest in things?	yes/no
16. Do you feel that you are a worthless person?	yes/no
17. Has the thought of ending your life been on your mind?	yes/no
18. Do you feel tired all the time?	yes/no
19. Do you have uncomfortable feelings in your stomach?	yes/no
20. Are you easily tired?	yes/no

The World Health Organisation- Five Well-Being Index (WHO-5)[15]

[14] SRQ-20 is generally available for use free of charge for clinical and research purposes. The user guide and questionnaire can be accessed at this link: https://apps.who.int/iris/bitstream/handle/10665/61113/WHO_MNH_PSF_94.8.pdf

Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks. Notice that higher numbers mean better well-being.

Example: If you have felt cheerful and in good spirits more than half of the time during the last two weeks, put a tick in the box with the number 3 in the upper right corner.

Over the last two weeks:	All the time	Most of the time	More than half of the time	Less than half of the time	Some of the time	At no time
1. I have felt cheerful and in good spirits	5	4	3	2	1	0
2. I have felt calm and relaxed	5	4	3	2	1	0
3. I have felt active and vigorous	5	4	3	2	1	0
4. I woke up feeling fresh and rested	5	4	3	2	1	0
5. My daily life has been filled with things that interest me	5	4	3	2	1	0

[15] The WHO-5 is free of charge and does not require permission to use. Additionally, it has been translated into more than 30 languages. For more information, please visit: https://www.corc.uk.net/outcome-experience-measures/the-world-health-organisation-five-well-being-index-who-5/