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EXPLORING THE IMPACT OF MENTAL HEALTH ON INDIVIDUAL OUTCOMES: AN INSTRUMENTAL VARIABLES APPROACH USING SHARE DATA

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Abstract

The aim of this dissertation is to investigate the economic implications of mental health, focusing on its impact on labor market performance during the COVID-19 pandemic. Utilizing datasets such as SHARE and OxGRT, the study employs IV-Probit to address known endogeneity issues of mental health measures, using a sample of working older adults from 24 European countries (and Israel) during the pandemic, and novel instrumental variables related to the pandemic. Findings, consistent with the literature, indicate that poor mental health is significantly associated with reduced working hours. No association is found with increased working hours.

Abstract

L'obiettivo di questa tesi è indagare le implicazioni economiche della salute mentale, con focus particolare riguardo gli impatti sulla performance individuale nel mondo del lavoro durante la pandemia di COVID-19. Attraverso l'uso dei dataset SHARE e OxGRT, questo studio si avvale della metodologia IV-Probit per affrontare note problematiche di endogeneità attraverso innovative variabili strumentali collegate alla pandemia. Il campione è costituito da adulti partecipanti attivamente al mondo del lavoro durante la pandemia, provenienti da 24 paesi europei e Israele. I risultati, consistenti con la letteratura, mostrano una associazione significativa tra peggiore salute mentale e una riduzione delle ore lavorative. Nessuna associazione significativa è emersa tra salute mentale e aumento delle ore di lavoro.

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1 Introduction

The Western World awoke to the importance of mental well-being in the aftermath of World War II, which proved the need for research and intervention in the study and care of mental conditions, alongside physical health. This newfound awareness culminated in the founding of the World Health Organization (WHO) in 1948, which acknowledged mental health as a key aspect of overall well-being. Nowadays, the rise of ditigal platforms has increased information accessibility and aided in the creation of digitized public spaces for the exploration and discussion of mental health. Nevertheless, prejudice and misunderstanding are rampant, proving the necessity for further efforts in understanding and de-stigmatizing in this realm.

The COVID-19 pandemic has further underscored the urgency of understanding and addressing the economic and social ramifications of mental health. During this time, risk factors for worsened mental health such as social isolation, job loss, pervasive uncertainty, and routine disruption have affected the global population on an unprecedented scale (WHO, 2022), impacting all demographics. This heightened focus on mental well-being makes the present study not only timely but also critical in informing policy decisions aimed at mitigating the pandemic's long-term impact on individual and societal well-being.

Mental health has profound implications on economic and social outcomes, affecting labor market participation, social interactions, and even the accumulation of social capital. Furthermore, negative shocks to individual mental health have the potential for long lasting detrimental impacts on both the individual and the surrounding community. Despite its significance, the subject remains under-researched, particularly in the context of its broader societal implications. A key challenge has been the difficulty in establishing causal relationships between mental conditions and individual outcomes, often due to data limitations. For this reason, the COVID-19 pandemic offers an unparalleled opportunity for data-driven insights.

This dissertation aims to explore the impact of mental health on individual outcomes, specifically focusing on labor market performance. Utilizing datasets such as the Survey of Health, Ageing and Retirement in Europe (SHARE) and the Oxford Government Response Tracker (OxGRT), this study employs a combination of Instrumental Variables and Probit methods, known as IV-Probit, to provide a comprehensive analysis. The sample includes 25 countries (Austria, Belgium, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Israel, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Romania, Slovenia, Spain, Sweden, and Switzerland) and focuses on working older adults.

The next chapters are structured as follows. Chapter 2 lays the groundwork by defining mental health, discussing the epidemiology of the most common disorders, and exploring the mental health impact of COVID-19. Chapter 3 delves into an extensive literature review, identifying the prevalent topics and methodological approaches in studying the effects of mental health on individual outcomes, and highlights the main identification challenge: the endogeneity of mental health measures with respect to any individual outcome. Chapter 4 introduces the key datasets and variables that will be employed in the analytical models. Chapter 5 provides the rationale behind the identification strategy and introduces the candidate instrumental variables essential for establishing causality. Chapter 6 presents the various iterations of the models and their respective results, alongside rigorous validity testing. Finally, Chapter 7 summarizes the findings and offers concluding remarks.

By integrating these elements, this dissertation aims to contribute to a deeper understanding of the complexities involved in studying mental health and its implications on individual outcomes, thereby providing valuable insights for both policy and future research.

2 Mental Health

Increasingly recognized as a crucial factor for well-being, mental health carries significant economic implications that are often overlooked in favor of more easily quantified conditions, such as physical health. Nevertheless, recent events such as the COVID-19 pandemic shed light on the importance of psychological welfare.

Mental health is an economically relevant phenomenon with far-reaching implications that extend beyond individual well-being. Poor mental health often leads to reduced productivity, increased absenteeism, and higher turnover rates in the workplace, directly impacting an organization's bottom line (OECD/EU (2018), OECD/EU (2022)). Furthermore, it places a significant burden on healthcare systems through increased medical costs and utilization of services. The indirect costs, such as loss of income due to disability and the ripple effects on families and communities, further amplify its economic relevance and far outweigh the direct healthcare costs (OECD/EU (2022), WHO (2022)). Therefore, investing in mental health not only enhances individual quality of life but also has the potential for significant economic returns, framing it as a key opportunity in the context of social capital accumulation.

This chapter aims to shed light on the definitions, statistics and dynamics of the topic, with the aim of providing the reader with comprehensive and up to date knowlege in this realm.

2.1 Defining Mental Health

Mental health can be defined as a state of psychological well-being which allows people to cope with demands of life, realize their abilities, learn and work well while contributing to their community. It represents a crucial feature of personal and collective socio-economic develpoment, involving psychological, emotional and social welfare, and affecting how people think, feel and act. Being mentally healthy goes beyond the mere absence of clinically relevant conditions, it encompasses self-esteem, resilience, relationships. Conditions that affect mental health include mental disorders, psychosocial disabilities and mental states associated with impaired functioning, or risk of self-harm. Those affected by these conditions are more likely to report lower mental well-being.

Mental health is dynamic and is affected by the interplay of biological factors, environmental conditions and individual experiences. Biological factors such as genetics or substance abuse can create vulnerabilities in all stages of life, but events that occur during developmentally sensitive periods are particularly impactful. Harsh childhood experiences in the form of bullying, physical or psychological abuse and poor health can have long lasting negative consequences on an individual's mental condition. On the other hand, mental resilience can be promoted through building social and emotional skills, providing youths with positive interactions, safety and community as well as quality education. Thus, mental health can be thought of as a continuum ranging from an optimal state of well being, to debilitating states of great suffering and emotional pain (WHO, 2022).

When dealing with circumstances that can exacerbate mental ill-health, a distinction can be made between local factors which affect individuals, families and communities on a small scale, and global or systemic factors which generate vulnerabilities for the entire population. Among the latter we find key threats such as economic crises, disease outbreaks, humanitarian emergencies, displacement and climate crisis related events, as well as sociocultural and geopolitical factors such as infrastructure, inequality, social stability and environmental quality.

Although exposure to risk factors undermines mental health, most at-risk people will not develop conditions, while many without known risk factors will develop them. In this perspective, encouraging protective factors strenghtens resilience in the population. On the individual plane, building strong social and emotional skills, a solid sense of self-worth and healthy habits such as keeping physically active are key in generating resilient individuals. Other individual protective factors include a nurturing and supportive family environment from a very young age, decent working conditions and a cohesive social network. On the structural level, protective factors manifest in economic security, easy and equal access to services, social protection, qualitable infrastructure and economic security, as well as social integration and contained inequality.

2.2 Global Epidemiological Overview

Mental health conditions are prevalent in the population, with about one in eight people worldwide living with a mental disorder (WHO, 2022). Heterogeneity in their distribution emerges according to age, gender and other individual characteristics. Overall, disorders related to anxiety and depression are the most common, and suicide accounts for more than one out of one hundred deaths (WHO, 2022). Still, seeking help for mental health conditions is hindered by low mental health literacy, poor service quality, high cost of care, fear of stigma and discrimination, making for underdiagnosis of all conditions.

Worldwide, mental health conditions are severely underserviced due to lack of information and research, as well as deficient provision of resources and services. On average, less than 2% of healthcare budgets are dedicated to mental health, and out of that more than 70% of mental health expenditure in middle-income countries is dedicated to psychiatric hospitals (WHO, 2022). Furthermore, professionals such as psychiatrists and psychologists are scarce relative to the population, and gaps in service coverage are amplified by quality and cost of care across countries. Additionally, measurement of mental health condition is hampered by incomplete data, outdated information and cross-cultural differences in the conceptualization and tracking of conditions.

The most commonly occurring mental conditions are anxiety disorders, which have a prevalence rate of about 4%, followed closely by depressive disorders at 3.8%. Developmental disorders and Attention Deficit Hyperactivity Disorder (ADHD) are also significant, contributing to an additional 1.4% and 1.1% of cases, respectively (WHO, 2022). A higher percentage of the population is diagnosed in high-income countries, followed in order by middle and low-income countries (WHO, 2022). On average, people with severe mental conditions die 10-20 years prematurely with respect to the general population (Chesney et al., 2014) and at great individual and societal cost. This section presents current statistics on the global prevalence and diversity of mental health conditions, with a particular emphasis on the OECD region prior to the COVID-19 pandemic. Before delving into a data-driven discussion on this subject, it is essential to first clearly define the two most pertinent categories of mental disorders under consideration: anxiety and depressive disorders.

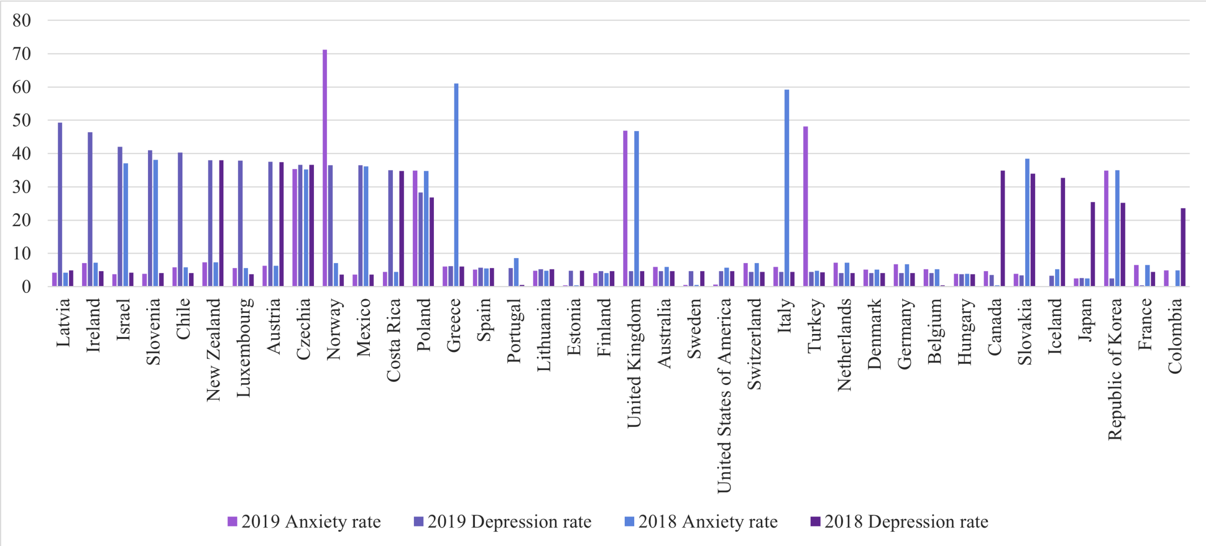


Figure 2.1: Prevalence of anxiety and depression disorders per 100 inhabitants, 2018-2019. Source: Global Burden of Disease Study 2019 (GBD 2019), available from https://vizhub.healthdata.org/gbd-results/.

2.2.1 Anxiety Disorders

Anxiety disorders involve excessive and prolonged feelings of worry, fear, or nervousness that negatively affect an individual's ability to function. According to the Fifth Edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), they are classified as follows: separation anxiety disorder, selective mutism, specific phobia (related to animals, natural environment, blood, injection, injuries, specific situations or other), social phobia, panic disorder, panic attacks, agoraphobia, generalized anxiety disorder (GAD). Comorbidity of anxiety disorders is most common with depression and substance abuse (DSM-5, WHO (2022)).

The symptomatology includes physical symptoms that often include but are not limited to heart palpitations, muscle tension, and gastrointestinal discomfort. Behavioral symptoms manifest as avoidance behaviors, such as evading places or situations that trigger anxiety. On a psychological level, patients experience a heightened state of arousal and hyper-vigilance, frequently leading to intrusive thoughts and emotional distress. These symptoms are not static but interact in a dynamic fashion, often exacerbating each other in a vicious cycle that hampers the quality of life for the affected individual.

2.2.2 Depressive Disorders

According to the DSM-5 the main categories of depressive disorders are: major depressive disorder (MDD), persistent depressive disorder (dysthymia), bipolar depression, depressive disorder as a consequence of other medical conditions, and substance induced depressive disorder. For the disorder to be clinically relevant, the DSM-5 criteria must be met alongside functional impairment. Depressive disorders are often comorbid with anxiety disorders and substance abuse.

Core symptoms of this category include depressed mood, characterized by feelings of hopelessness, despair and sadness, and a significant loss of interest or pleasure in activities, also known as anhedonia. Depressive disorders are also characterized by the presence of cognitive symptoms such as reduced concentration, indecisiveness, feelings of worthlessness and guilt, and suicidal ideation. In addition, physiological symptoms may manifest through changes in appetite and weight, disturbed sleep, psychomotor issues in the form of agitation or retardation, and fatigue. Finally, an affected individual may show affective manifestations such as a lack of emotional responsiveness and irritability.

2.2.3 Heterogeneity Determinants of Mental Health Conditions

Factors which generate heterogeneity in mental health measurement and statistics are gender, age, socio-economic status, ethnicity, geographic location, cultural background, sexual orientation. Furthermore, different diagnostic criteria and data collection methods complicate cross-country comparison. For instance, cultural background adds a layer of complexity in the case of stronger stigma towards mental illness, which makes symptoms less readily identifiable and individuals more prone to masking their conditions. To further exemplify the complexity from the interplay of the aforementioned factors, the reader may consider the fact that worldwide about 4% of people live with anxiety disorders, but this number increases to 10% for working age women in the Americas (WHO, 2022).

In this analysis, two of the most poignant determinants of heterogeneity are gender and cohort.

Gender differences. Women and men often display different prevalence rates and patterns of mental health issues. On average, women are more likely to be diagnosed with mood and anxiety disorders, such as depression and generalized anxiety disorder, while men are more prone to be diagnosed with substance abuse and externalizing disorders like conduct disorder (WHO, 2022). Worldwide, 13.5% of women live with a mental disorder, as opposed to 12.5% of men (WHO, 2022). Factors such as pregnancy increase the risk of all mental conditions, especially depression. Woody et al. (2017) find increased prevalence of symptoms in women from low and middle income countries in the perinatal period. Alexandrino-Silva et al. (2012) analyze symptomatic subtypes of depression and their relation to gender. For the most symptomatic classes of the disorders, they find women reporting more inhibition and disturbances to sleeping and eating patterns, and hypersomnia. Men reported more psychomotor retardation and agitation.

Cohort specificity. A study by Bell (2014) challenges the belief of a U-shaped life course trajectory in mental health, using data from the British Household Panel Survey, arguing that previous literature had not properly separated age, period, and cohort effects. Key findings show that mental health does not follow U-shaped trajectory, instead, it increases throughout life, slowing down in mid-life, and worsening again in old age. Cohort effects also play a role, with more recent cohorts showing worse mental health. On average, youths and older adults suffer most from mental conditions; WHO (2022) data shows that around 8% of children aged 5-9 and 14% of adolescents ages 10-19 live with a mental condition. For adults 70 years and older, around 13% live with a mental disorder (excluding dementia), mostly in the form of depressive and anxiety disorders. Within this age category, affected women are 14.2% and men 11.7%.

The analysis of a nationally representative survey in the United States done by Kessler et al. (2005) shows that the median age for onset is 11 years for anxiety disorders, 20 years for substance abuse and 30 years for mood disorders. Overall, three fourths of all lifetime conditions have onset before 24 years of age.

In the older population, depression is associated with emotional suffering and increased suicidal ideation, and a risk factor for disability and mortality (Zenebe et al. (2021), Vieira et al., (2014)). Many of the risk factors for depression are associated with increased age, such as social isolation, traumatic life events, functional decline, loss of independence and onset of medical conditions. Depression in older adults is associated with events such as falls, strokes, functional impairment, activity limitations (Vieira et al., 2014). A study on geriatric depression in the public community long-term care system by Morrow-Howell et al. (2008) found that 40% of the sample was consistently depressed over a year of observations, with comorbidity of medical, functional and psychosocial conditions. A review of 42 studies by Zenebe et al. (2021) placed the prevalence of depression in the elderly population at 40.78% in developing countries, a considerably higher statistics than the 17.05% found in developed countries; the authors also point out that depression is often undiagnosed.

A similar picture can be drawn for anxiety disorders in older adults. A study by Schaub and Linden (2000) on the German population found a weighted overall prevalence of anxiety of 4.3% for individuals aged 70-84 years old, higher than the 2.3% observed in the group aged 85-103. Interestingly, this study also found no relation between anxiety and cognitive status or socio-economic status.

In a particularly alarming trend, data from the World Health Organization (WHO) in 2022 indicate that individuals over the age of 70 experience a suicide rate more than double that of their younger counterparts.

2.3 COVID-19's Mental Burden

The COVID-19 pandemic has had a profound impact on mental health (Pieh et al. (2021), Deng et al. (2021), Wang et al. (2020), Lakhan et al. (2020), Adams-Prassl et al. (2022)), manifesting in distinct but interconnected local and global threats. At the local level, individuals have reported higher rates of anxiety, depression and stress related symptoms, driven by exposure to risk factors such as social isolation, disruption to daily activities and heightened uncertainty. A 2021 study by Pieh et al. in the United Kingdom revealed that four weeks post-lockdown, 52% of participants screened positive for a common mental disorder, while 28% showed signs of clinical insomnia. Interestingly, younger individuals exhibited worse mental health outcomes compared to older adults, despite being less physically vulnerable to the virus. The likely factors contributing to this discrepancy include uncertainties in employment status and greater disruptions to daily routines. Wang et al. (2020) compared respondent scores for the Impact of Event Scale-Revised (IES-R) and the Depression, Anxiety and Stress Scale (DASS-21) at the beginning of pandemic restrictions, and four weeks after. Findings show that individuals reported higher average scores in the first round relative to the second one, although average scores above clinically relevant cutoffs were detected in both. Additionally, a paper by Adams-Prassl et al. (2022) examines the impact of state-wide stay-at-home orders on mental health in the United States finding a significant reduction in self-reported mental health by 0.083 standard deviations. This effect is entirely driven by women, leading to an estimated 61% increase in the gender gap in mental health.

On a broader, structural scale, the pandemic has significantly compromised healthcare delivery, a disruption of particular impact for those with pre-existing mental health conditions (WHO, 2022). Overall, this has had a disproportionate impact on vulnerable and disadvantaged populations, further widening existing inequalities. Public health emergencies of this kind can be platforms for change, driving improvement of public services and structural investments in the name of public interest, focused on education, prevention and effective treatment aimed at rehabilitation.

The prevalence rate of all forms of depression, anxiety, stress, sleep problems, and psychological distress in general population increased during the pandemic (Lakhan, 2020). The most palpable stressor is fear of the health implications of the virus, a concern that was particularly acute during the periods of maximum uncertainty surrounding its nature and transmission. Contracting the virus introduces an additional layer of adversity, encompassing not just the physical symptoms, but also the psychological toll linked to the illness and its potential long-term effects. Additionally, the emotional burden of bereavement adds yet another dimension to the mental health landscape. Public health containment measures, such as distancing and quarantining, imposed social isolation and loneliness on many, generating feelings of helplessness and putting strain on the individual's relationships. Loss of routine and abrupt change to daily activities has negatively impacted the youth and the older component of the populations (WHO, 2022).

COVID-19 exacerbated uncertainty for the work force, causing spikes in unemployment and plunging many into financial adversity. Both unemployment and poverty are known risk factors for mental health conditions, and global projections for extreme poverty have been revised upwards in light of the pandemic (Lakner et al., 2020).

Negative coping mechanisms for psychological distress and symptoms of anxiety and depression may include resorting to alcohol, drugs and other addictive behavior, including but not limited to technology aided gambling, gaming and excessive use of social media.

This chapter has provided a comprehensive overview of mental health, emphasizing its impact and far-reaching economic and societal implications. It argues that mental health is not merely a matter of individual well-being but a critical factor that impacts productivity, healthcare costs, and social capital. This chapter also highlights how the COVID-19 pandemic has further exacerbated mental health issues, particularly among vulnerable populations. Given these extensive consequences, there is an urgent need to understand the causal impact of mental health on individual and societal outcomes. In the following chapter, I will define the research question and expand on relevant literature.

3 Framing the Research Question

Building upon the previous chapter's exploration of mental health, this chapter aims to frame the research question and provide a comprehensive and pertinent literature review. While there exists an extensive body of literature on mental health, both as an isolated subject and as a determinant of individual outcomes, much of this research is limited to correlational analyses. These studies often fall short of addressing the methodological challenges inherent in establishing a causal relationship between mental health conditions and individual outcomes.

Among the most commonly examined topics related to mental health are:

1. **Labor Market Participation.** Including employment status, job performance, hours worked, wages, and self-rated satisfaction.

2. **Loneliness.** Including social disconnectedness and isolation.

3. **Community Involvement.** Including civic participation and elective activities.

4. **Social Networks.** Measured by size and quality, self-reported satisfaction, frequency of social interaction, isolation, and perceived loneliness.

Additional outcomes may include behavioral ones such as the likelihood of substance use, financial stability, and educational ones like dropout rates, attainment, attendance, and performance.

Data collection for mental well-being is typically conducted using standardized questionnaires and scales, including Beck Depression Inventory (BDI), Generalized Anxiety Disorder 7 (GAD-7), Patient Health Questionnaire 9 (PHQ-9), Center for Epidemiological Studies-Depression Minus Loneliness (CES-D-ML), These assessments are commonly administered via assisted face-to-face interviews or through computerized adaptive testing interviews (CATI).

Observations made by the interviewer about the context and the respondent can be integrated to provide a more comprehensive understanding of the individual's state.

The existing literature on the topic is fragmented in both topics and methods, primarily due to challenges in sourcing appropriate data for investigation and different diagnostic tools employed to assess mental well-being in subjects. A frequently utilized dataset for this line of research is the Survey of Health, Ageing and Retirement in Europe (SHARE). This dataset provides a wealth of variables that are highly relevant to this study, thus the following literature review is particularly focused in its applications in researching mental health. Detailed information about SHARE, as well as other datasets employed in this dissertation, will be available in Chapter 3.

3.1 Mental Health and Labor Market Outcomes

The relationship between mental health and labor market outcomes is intricate, which may explain why existing research on the subject is limited and largely focuses on correlational findings. Labor market conditions encompass a wide range of factors, including job security, work-life balance, income levels, self-assessed job satisfaction, social support, and employment status. Additionally, specific working conditions—such as remote versus in-person work—and skill mismatches can influence an individual's mental well-being. In turn, these mental health states can also impact labor market outcomes by affecting individual productivity, likelihood of labor market participation, or type of occupation. Therefore, the relation between mental health and labor market conditions is affected by reverse causality. Some of the literature focuses on delineating the effect of labor market characteristics on mental conditions, as shown in a review by Rönnblad et al. (2019), who investigated the effects of precarious employment on mental health, and mostly found very low quality evidence of negative effects of temporary employment or unpredictable work hours on mental health, and moderate quality of evidence was found for perceived job insecurity having adverse effects on mental health.

In the same field of literature, an example of the many correlational studies is in Nadinloyi et al.'s (2013). The authors explore the correlation between job satisfaction and mental health among employees in two industrial firms. They assess individual conditions using Birfield's Job Satisfaction Scale and the Ruth Questionnaire and Scale. The study employs multiple regression analysis, t-tests, and Pearson correlation coefficients as its methodology. However, it does not address the potential issue of reverse causality between job satisfaction and mental well-being, thereby limiting the interpretation of the results to correlational rather than causal relationships.

Conversely, a second branch of the literature, more aligned with my work, explores the impact of mental health on labor market outcomes. In contrast to the method employed by Nadinloyi et al. (2013), Banerjee et al. (2017), Frijters et al. (2014) and Frijters et al. (2010) tackle endogeneity issues in two different ways. Banerjee et al. (2017) explore the impact of psychiatric disorders on labor market performance by utilizing a structural equation model that incorporates a latent index for mental health. This index is formulated based on symptoms from four specific psychiatric conditions (major depression, panic attacks, social phobia, and generalized anxiety disorder) as well as demographic, socioeconomic, and health-related variables. To address endogeneity, the study employs a Multiple Indicator and Multiple Cause (MIMIC) model, with the aid of covariance instruments. The findings reveal that mental illness negatively influences both employment rates and labor force participation. The study estimates that improving mental health could potentially increase employment for 3.5 million people and reduce absenteeism costs by approximately $21.6 billion. Frijters et al. (2010) focus on the impact of mental health on employment status. Mental health is measured as an index based on the Short-Form General Health Survey (SF-36) answers. To tackle endogeneity concerns, their preferred specification is an Instrumental Variable (IV) Probit model, using the death of a close friends as an instrument for mental health. The paper finds that a one standard deviation decline in mental health leads to a drop in the probability of labor market participation by around 19 percentage points. Finally, Frijters et al. (2014) also measures mental well-being with the SF-36 Survey and exploits the death of a close friend as an instrument, however the method of choice is an Instrumental Variables Fixed Effects (IV-FE) model applied to high-quality Australian panel data spanning 10 waves. Results prove that mental health has a substantial negative impact on employment, with a one standard deviation in mental health leading to a 30 percentage point reduction in the likelihood of being employed.

3.2 Mental Health and Loneliness

The body of literature exploring the relationship between loneliness and mental health faces the same methodological challenges, including issues of reverse causality, unobserved variables, and measurement errors in the independent variable. Studies in this domain can be categorized into three distinct groups: 1) pre-pandemic studies that largely fall short in adequately addressing endogeneity concerns; 2) research leveraging pandemic-related data to investigate the link between loneliness and mental health; 3) a subset of papers employing more rigorous methodologies to provide credible insights into the relationship.

Fokkema et al. (2012) employ a cross-country comparative approach to analyse loneliness among older adults. Health variables include perceived health, functional limitations, and problems with seeing or hearing, all measured on a 5-point scale ranging from 'excellent' to 'poor.' The study utilizes hierarchical logistic regression to explore the factors contributing to varying levels of loneliness across countries. The dependent variable, 'loneliness,' is assessed through a single-item measure derived from the CES-D (depression) scale. The findings indicate that countries with older populations, a higher proportion of women, and a greater number of unpartnered older adults tend to report elevated levels of loneliness. However, the unaddressed endogenous relationship between physical and mental health limits the causal interpretation of the results.

A paper by Alves et al. (2014) aims at understanding the predictors of feelings of loneliness in middle-aged and older adults in Portugal through logistic regression analysis using survey data (socio-demographic variables, residence characteristics, measures of health). They find that variables such as age, gender, marital status, living arrangements, region, type of housing, professional status and income are all significantly associated with feelings of loneliness.

Niedzwiedz et al. (2016) investigate the relationship of loneliness and household wealth in older adults, focusing on the mediating role of social participation. Mental well-being is measured with the R-UCLA loneliness scale, and household wealth is measured by the sum of financial and real assets, minus liabilities. The authors recognize the limitations of a cross-sectional logistic regression study, and find that lower household wealth is associated with higher levels of loneliness. They also identify social participation as a key mediating factor, noting that certain forms of social engagement are particularly effective in alleviating loneliness.

Logistic regression is also the tool of choice in Jarach et al. (2021), which uses SHARE data to investigate the relation between loneliness and the reversion of frailty in older Europeans. Loneliness is measured with the UCLA-L scale, and social isolation is measured with a custom index. Multinomial logistic regression is used to compute relative risk ratios for changing frailty status according to levels of social isolation and loneliness. Their findings indicate that both loneliness and social isolation are significantly linked to the increased risk of individuals transitioning from a robust to a frail or pre-frail state.

Loneliness may also have an association with cognitive impairment, as analysed by Luchetti et al. (2019), which investigate the relationship between loneliness and cognitive impairment using data from SHARE. To assess cognitive performance, they utilize the memory and verbal fluency tasks provided by SHARE, while employing the R-UCLA scale to gauge loneliness. The researchers opt for Cox regression hazard models to analyse the time-to-event relationship from baseline predictors to the onset of cognitive issues. Sensitivity analyses reinforce the robustness of their findings, revealing that loneliness is a significant predictor of cognitive impairment, even after adjusting for variables such as age, sex, education, and depressive symptoms.

Lee et al. (2020) focus on exploring loneliness among older adults in the Czech Republic. They employ the UCLA-L scale to measure loneliness and use the EURO-D scale to evaluate mental and emotional health. While the study aims to understand the relationship between mental and physical health, its methodology is limited to regression analysis, analysis of variance (ANOVA), and descriptive statistics, without addressing the aforementioned endogeneity issues.

Hajek and König (2022) employ SHARE longitudinal data and utilize linear fixed-effects regression to account for unobservable variables while investigating the factors associated with loneliness in older Europeans. Their analysis reveals that loneliness intensifies with factors such as aging, alterations in marital status, reductions in log income, deteriorating self-assessed health, and functional decline. Interestingly, they found no correlation between changes in chronic diseases and shifts in loneliness levels.

In the second category of research papers on loneliness, the following studies were chosen for their use of pandemic-related data. The first study by Atzendorf et al. (2022) examines the mental well-being of retired adults in various European countries during the COVID-19 pandemic, with a specific focus on loneliness and depression. The researchers utilized the SHARE Corona Survey, supplemented by the Oxford Government Response Tracker (OxGRT), to gather data on individual feelings of loneliness and depression with respect to pre-pandemic times, and on the stringency of epidemic control measures. Their methodological approach involved multi-level binary logistic regression models that incorporated both individual and country-level variables. The authors find significant differences between countries in the prevalence of increased feelings of depression and loneliness, particularly for the oldest in the sample. Specifically, the number of deaths explains 32.4% of the country variance in depression and 20.7% in loneliness. The second study, conducted by Arpino et al. (2022), assesses the effects of the COVID-19 pandemic on loneliness in older adults. It specifically explores how variables such as childlessness and lack of a partner contribute to feelings of loneliness. The researchers chose to use the most recent wave of the SHARE dataset for their analysis. Employing a logistic model, they focused on the binary outcome variable of 'loneliness.' Their findings reveal that 11.6% of respondents felt lonelier during the pandemic, while the overall prevalence of depression rose by 0.8%. Being childless or unpartnered was a significant risk factor for increased feelings of loneliness.

Finally, a paper by Santini et al. (2020) stood out by addressing endogeneity in the analysis of the relationship between social disconnectedness, perceived isolation, and symptoms of depression and anxiety in older adults using longitudinal data from the National Social Life, Health, and Aging Project (NSHAP) in the USA. The method of choice is a random intercept cross-lag panel model with maximum likelihood estimation. According to the authors, this approach aims to establish whether the associations might have been obtained spuriously based on stable third variable traits that were not controlled for. The authors also acknowledge the potential for measurement error, noting that results could vary if mental health was assessed through clinical evaluations rather than screening tools. Additionally, they recognize unaccounted-for confounders like stressful life events or a family history of mental disorders. Their findings indicate that social disconnectedness leads to perceived isolation, which subsequently predicts depression and anxiety. To address concerns of reverse causality, the authors also explored the reverse relationships between variables and found evidence supporting bi-directional influences.

3.3 Mental Health and Social Capital

Mental health and social capital are linked by a mutually reinforcing relationship, creating a cycle that affects both individual and collective well-being. Poor mental health can hinder an individual's ability to accumulate social capital by reducing productivity and limiting social engagement. Conversely, a lack of social capital can exacerbate mental health issues due to diminished social support, community cohesion, and access to quality information. Additionally, societal stigma and economic disadvantages associated with low social capital further impact mental well-being.

In their 2012 study, Sirven and Debrand employ panel data from the SHARE and SHARE-LIFE surveys to explore the causal relationships between social capital and health in an older European population. The authors employ a comprehensive set of baseline health indicators, encompassing both physical dimensions (such as poor self-rated health, limitations in Activities of Daily Living (ADL), General Activity Limitations Indicator (GALI), mobility restrictions, and low grip strength) and mental aspects (such as depressive symptoms and cognitive impairment). Given the bidirectional causality between mental health and overall well-being, addressing endogeneity is crucial for establishing the causal implications of their findings. While acknowledging the merits of an Instrumental Variables (IV) approach, the authors express reservations about its ability to accurately assess the impact of social capital on health when using various social capital measures. Instead, they opt for a bivariate recursive probit model, incorporating lagged values of the dependent variables to account for endogeneity. The results suggest a reciprocal causal relationship between social capital and health. Specifically, past health status influences individual health in the following period, and the same relationship holds for social participation. The impact of health on social capital is found to be more substantial than the reverse, indicating that health may serve as a more potent driver for the accumulation or depletion of social capital.

Murayama et al. (2013) investigate the longitudinal effects of bonding and bridging social capital on self-rated health, depressive mood, and cognitive decline among older Japanese individuals. Utilizing panel data from the Hatoyama Cohort Study, the research focuses on social capital as the key independent variable, where bonding social capital is assessed based on the individual's perception of neighborhood and network homogeneity, while bridging social capital is assessed based on the individual's perception of network heterogeneity. The study finds that stronger perceived neighborhood homogeneity is inversely associated with poor self-rated health and depressive mood. However, neither bonding nor bridging social capital was significantly associated with cognitive decline. The authors employ logistic regression models to carry out their analysis, however they do not explicitly address the critical issue of endogeneity, particularly the problem of reverse causality between social capital and health outcomes.

Ehsan and De Silva (2015) present a systematic review that investigates the association between social capital and common mental disorders, such as depression, anxiety, and PTSD, using validated measurement tools. While the review includes a large number of studies, it does not directly tackle the issue of endogeneity in the methodologies of the reviewed works. Additionally, the authors note that the majority of the studies are situated in middle to high-income countries, limiting the generalizability of the findings to lower-income settings.

A paper focused on yet another high-income country is Riumallo et al. (2014), which explores the relation between social capital and both self-rated health and biological health in Chile using data from the Chilean National Health Survey (2009-2010). Using an IV approach with a variety of instruments, they define the dependent variable using a binary indicator of self-rated health, depression, hypertension or diabetes. Social capital is captured by a questionnaire inquiring about social support, generalized trust and neighborhood trust. The study uses recent crime victimization and aggregate social capital as instruments, and finds that all social capital indicators have an association with depression. Some social capital indicators are associated with self-rated health, hypertension and diabetes above age 45.

A paper by Landstedt et al. (2016) focuses on the longitudinal relationship between individual-level structural social capital, measured as civic engagement, and depressive symptoms from age 16 to 42 in Swedish men and women, using data from the Northern Swedish Cohort. Civic engagement is measured by a single-item question reflecting the level of engagement in clubs or organizations, and depressive symptoms are measured with an index. Methodologically, the authors employ cross-lagged structural equation models separated by gender in order to analyze the direction of associations between civic engagement and depressive symptoms. The directionality between social capital and mental health is established with the use of a cross-lagged structural equation model, which explains present values of the dependent with past values of the independent variable. Results show that both civic engagement and depressive symptoms are stable across time, with male civic engagement being inversely related to depressive symptoms in adulthood, while no such relationship is observed for women.

Finally, a paper by Cohen-Cline et al. (2018) explores the relationship between social capital and depression, utilizing a sample of same-sex twin pairs. Symptoms of depression are measured with the Patient Health Questionnaire (PHQ-2); social capital is conceptualized into cognitive and structural domains, with the former including sense of belonging, neighborhood social cohesion, trust and workplace connections, and the latter is measured through volunteerism, community participation, and social interaction. The twin design combined with a Poisson model offer an approach that controls for genetic and environmental confounders. However, this does not necessarily translate to solving the ever-present issue of reverse causality. Results show that all measures of cognitive social capital and neighborhood characteristics are associated with less depressive symptoms.

3.3.1 Mental Health and Social Networks

The topic of social capital is tightly linked with the nature of social networks since their quality serves as a critical dimension of social capital, shaping its effectiveness and impact on mental well-being. High-quality networks, characterized by strong, trust-based relationships, not only facilitate the exchange of valuable information but also provide emotional support and a sense of belonging. These factors contribute to a more robust form of social capital, which in turn positively influences mental health by building resilience and fostering self-esteem (WHO, 2022). Conversely, low-quality social networks, marked by weak ties and low levels of trust, can diminish social capital and exacerbate mental health issues. Therefore, the quality of one's social network is a pivotal factor in the symbiotic relationship between social capital and mental health. An individual's social network can be characterized by three key dimensions: the quantity of connections, the quality of those connections, and the geographical proximity to other network members.

Shiovitz-Ezra and Leitsch (2010) explores the associations between objective and subjective social network characteristics and their impact on loneliness in older adults. Mental health is measured with the R-UCLA scale, and subjective measures such as eyesight and hearing loss. The paper distinguishes between objective indicators like frequency of contact with social network members and subjective perceptions of social ties, such as the quality of marriage or familial relationships. Results show that a larger portion of the variance in loneliness perception is explained in the non-married sub-sample, 13%, relative to the married or cohabiting sub-sample, 7%. The empirical strategy of the paper involves the use of hierarchical linear regression models applied to a cross-section of the NSHAP dataset. This specification does not properly account for reverse causality: individuals who are lonely or have mental health issues might have fewer social interactions or perceive their social networks differently. In addition, the model does not adequately address likely omitted variable bias and simultaneity.

Another correlative paper is found in Gu (2020), which aims to explore the impact of neighborhood social networks on the mental well-being of women residents in a middle-class urban neighborhood in Seoul, South Korea. The study employs a phenomenological qualitative approach, an approach that translates to dialogical interviews to understand the pehonmenon, and focuses on 18 full-time or part-time housewives with children. Results are ambiguous and highly context specific, showing both positive and negative effects on the women's well-being.

Santini et al. (2021-B) investigates the moderating role of social network size in the relationship between formal social participation and mental health outcomes among older adults in Europe, focusing specifically on quality of life and symptoms of depression. The dataset of choice is SHARE (waves from 2011 and 2013) to investigate formal social participation and social network size, with their impact on quality of life and depressive symptoms. The moderating role of formal social participation is investigated through a linear regression model with two possible outcomes: quality of life, as measured by the CASP-12 scale, and depressive symptoms, measured with the EURO-D scale. Although results show that individuals with few social ties may benefit from social participation via a reduction in depressive symptoms and an increase in quality of life, the specification choices raise concerns analogous to those discussed for Shiovitz-Ezra and Leitsch (2010).

Finally, Coleman et al. (2022) examine how social networks prior to the pandemic influenced older adults in perceived risk of COVID-19, preventative behavior and mental health outcomes such as loneliness, depression and anxiety. The authors distinguish between bridging and bonding social capital. Specifically, bridging social capital refers to the benefits derived from a vast and diverse social network, while bonding social capital refers to the benefits derived from strong and close ties in a social network. The former manifests in weak ties, and is found to predict a higher perceived risk of COVID-19, as well as more preventative behaviors;

the latter is associated with less perceived COVID-19 risk, fewer precaution, but better mental health outcomes. The authors fit 60 models using ordinary least squares (OLS) regression for continuous outcome variables (risk perception, loneliness, stress), binomial regression for count outcomes (health precautions, depression, anxiety), and generalized linear models (GLM). To accredit causal interpretation of the results, controls for baseline mental health are included in the model. According to the authors, the use of a cross-lagged approach and the timing of data collection should mitigate concerns of reverse causation. Results show that mean density of the network, mean tie strength and strength of the weakest tie are significantly associated with loneliness. For depressive symptoms, lower values are associated with mean support functions received from the network, mean tie strength, and strength of the weakest tie. Finally, proportion of frequent contact, diversity, and strength of weakest tie are associated with lower anxiety, while network density is associated with higher anxiety, therefore suggesting that bonding capital can be negatively associated with mental health.

3.4 Summary and Implications

In this literature review I aimed to provide a comprehensive examination of the existing research on the interplay of mental well-being and various outcomes such as labor market participation, loneliness, and social capital (with additional focus on social networks). I have highlighted the methodological challenges in establishing a causal relationship between mental health and outcomes, particularly the issues of reverse causality and simultaneity. While some studies address these challenges with various methods, many fall short, proving the need for rigorous approaches in this field. By underlining the shortcomings of the literature in question, I have set the stage for the empirical analysis in the following chapters, with the aim of contributing to filling the gaps about the evidence of a causal link.

4 Datasets and Key Variables

The overarching question guiding this study is how mental health, as measured by various indicators, affects individual outcomes. To answer this question, I employ the Survey of Health, Ageing and Retirement in Europe (SHARE) dataset, which offers a rich array of pertinent variables, and the Oxford Government Response Tracker (OxGRT) dataset, which provides detailed information about the policy actions taken in response to, and the effects of, the pandemic. In this chapter, my objective is to provide a comprehensive background on the datasets utilized in this work, while also introducing the variables that serve as indicators of mental health and explaining the rationale behind their selection.

4.1 SHARE data

The primary dataset utilized in this study is SHARE, a cross-national, multidisciplinary panel database that collects data on health, socio-economic status, as well as social and family networks, specifically targeting individuals aged 50 and above. SHARE data is typically collected in biennial waves, with certain waves focusing on longitudinal tracking of a subset of the sample, referred to as SHARELIFE.

For this work's purpose, the most pertinent wave is the eighth, which is the latest publicly available at time of writing. Collection timing is of the utmost importance, since the main empirical strategy is an IV approach that relies on instruments connected to the pandemic. In the majority of participating countries, the initial interviews began towards the end of October 2019. By mid-November 2019, nearly all countries had initiated their regular fieldwork, with the exception of the French-speaking region of Belgium, where interviews began in December. The end of fieldwork was more synchronized across countries, as all concluded their final interviews by mid-March 2020 due to pandemic disruptions (Bergman and Börsch-Supan, 2021). The individual data collection period can be identified through the int_year and int_month, which signal the year and month of the questionnaire administration.

According to the SHARE Release Guide 8.0.0, the pandemic hit in the middle of data collection, disrupting activities in all participating countries. Eventually, fieldwork was suspendend in March 2020, when about 70% of all interviews had been conducted. In response, the SHARE Corona questionnaire was elaborated as a shortened version of the main questionnaire, collecting data on health and behavior, mental health, COVID-19 symptoms, healthcare, changes in work and economic situation and changes in social networks.

Data collection for the SHARE Corona Survey (SCS) began in June and concluded in August for the majority of countries. The only exception was the Austrian sub-sample, which began data collection in late July and completed it by the end of September. Similar to the main Wave 8 questionnaire, the variables int_year_ca and int_month_ca are used to identify the specific year and month when the SCS was administered to individuals.

Within the regular questionnaires of Wave 8, relevant thematic modules cover information about demographics, social networks, physical health, behavior, cognitive function, mental health, health care, employment and pensions, social support, activities, housing, income, financial transfers, consumption, assets and expectations. A strong feature of the SHARE dataset is heterogeneity of information on individuals, although tempered by the presence of a significant number of missing responses or incomplete modules for individual participants. The SCS is a considerably shorter questionnaire and, as a result, is less affected by missing or incomplete information. Within the SCS sample, a portion of the questionnaires was administered to individuals who had already taken part in Wave 8 fieldwork.

4.2 OxGRT data

The second source of data is the Oxford COVID-19 Government Response Tracker (OxGRT), a project aimed at collecting information on policy responses to the pandemic. This datset provides publicly available cross-national and cross-temporal tracking of government policies and interventions in response to the spread of COVID from January 2020 to December 2022. Detailed information on the dataset is available in Hale et al. (2023).

Indicators within the dataset broadly cover the following areas:

- **Closure and containment indicators**, to measure limitations with respect to gatherings, travel and workplaces.
- **Economic indicators**, to measure economic policies that provide financial support and debt relief.
- **Health indicators**, measuring policies such as contact tracing and mask requirements.
- **Vaccine indicators**, measuring their availability, distribution and mandates.
- **Miscellaneous indicators**, for those not fitting in the previous categories.

In addition to daily country indicators, OxGRT aggregates them into composite measures to synthesise data and reduce complexity. A possible drawback of this approach is that individual components of an index may be more relevant to outcomes of analyses, and bias may be introduced through weighting choices that lead to the final indexes. As such, Hale et al. (2023) encourage researchers to carefully evaluate each index before integrating it in their work. The dataset offers four composite indexes where, for each indicator, a score is created by taking the ordinal value and subtracting half a point if the policy is general rather than targeted. Then, each score is rescaled to create an index ranging from 0 to 100. Index construction favors conservatism, choosing to assign a score of zero to any missing data indicator, and exclude country days where more than one indicator is missing. The resulting indexes are:

- **Government Response Index (GRI)**. Considers indicators for school closures, workplace closures, cancellation of public events, restrictions on gatherings, public transportations, stay at home orders, restrictions on internal movement, international travel controls, income support, debt relief for households, public information campaigns, testing policy, contact tracing, facial coverings, vaccination policy and protection of elderly people.
- **Stringency Index (SI)**. Considers indicators for school closures, workplace closures, cancellation of public events, restrictions on gatherings, public transportations, stay at home orders, restrictions on internal movement, international travel controls and public information campaigns.
- **Containment and Health Index (CHI)**. Considers indicators for school closures, workplace closures, cancellation of public events, restrictions on gatherings, public transporta-

tions, stay at home orders, restrictions on internal movement, international travel controls, public information campaigns, testing policy, contact tracing, facial coverings, vaccination policy and protection of elderly people.

- **Economic Support Index (ESI)**. Considers only indicators for income support measures and debt relief for households.

Notably, these indexes do not inform on the effectiveness of the government's response, nor do they capture demographic or cultural characteristics that may have affected the spread of the virus.

Comparing indexes, the GRI emerges as the most comprehensive, providing a multi-faceted measure of government restrictiveness in response to the COVID-19 pandemic, capturing both policies aimed at sustaining long-term citizen well-being and those that have immediate effects on daily life, routines, and social interactions. Unlike the SI, the GRI includes additional economic intervention indicators such as income support and household debt relief, as well as public health measures like testing policy, contact tracing, and facial coverings. It also considers policies aimed at protecting the elderly and vaccination strategies. Of these additional measures, facial coverings and testing policies are particularly relevant to the period of interest, as they have an arguably stronger influence on daily life and risk perception. Nevertheless, the addition of less relevant indicators in an already conservative index introduces undesirable variability in scores for the first months of the pandemic. As such, the SI is a more stable and relevant indicator of government reaction to the ongoing event. For ease of visualization, daily country level of the SI are plotted for a selected group of countries in Figure 4.1 and Figure 4.2, respectively.

The dynamic for SI leading up to August 2020 shows how some countries implemented restrictions from roughly mid-January, including Germany, Italy and Poland. Within each country's line there might be strong variability, with countries such as Germany and France exhibiting strong jumps in the index, and countries such as Italy maintaining a more sustained path.

Besides the various indexes, the database also provides data on the number of COVID-19 cases, deaths, and tests per million population. It is important to note that these specific metrics are not incorporated into the SI calculation, as the index is designed to exclusively evaluate

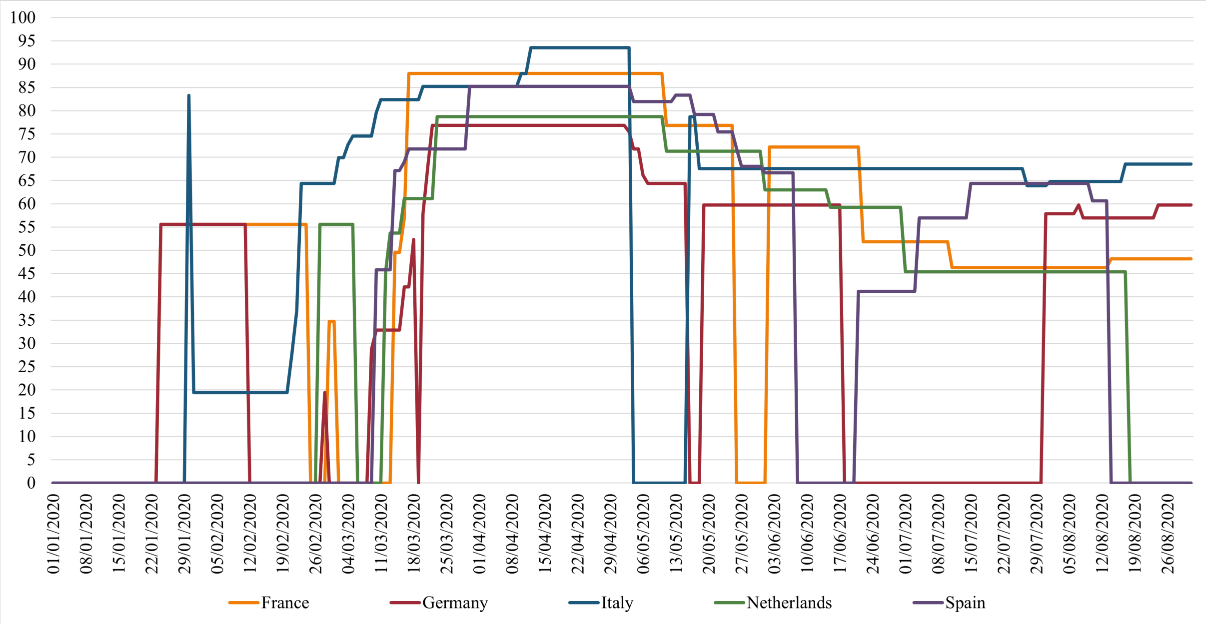


Figure 4.1: Evolution of the Stringency Index from January to August 2020. Country group A.

Source: OxGRT data elaboration.

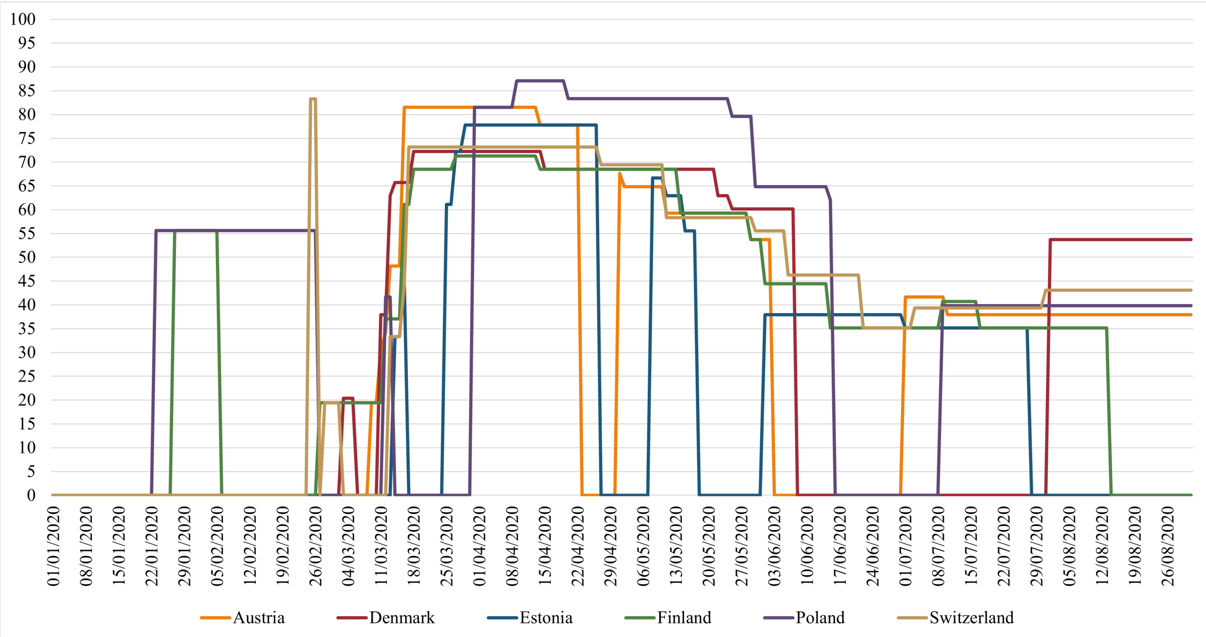


Figure 4.2: Evolution of the Stringency Index from January to August 2020. Country group B.

Source: OxGRT data elaboration.

governmental responses rather than the pandemic's statistical effects *per se*.

4.3 Mental Health Indicators

This study aims to quantify the impact of mental health on individual outcomes, making the accurate measurement and identification of mental well-being a critical component. In the existing literature, mental health is commonly assessed using clinical scales like the EURO-D for depression and the R-UCLA for loneliness. However, some studies lack access to these established methods and instead rely on ad-hoc indexes constructed from individual responses.

SHARE Wave 8 collects data on the EURO-D and R-UCLA scales up until March 2020. The R-UCLA Loneliness Scale is a widely recognized psychological instrument designed to assess subjective feelings of loneliness or social isolation. It provides a quantitative measure that can be used to gauge an individual's emotional well-being and social connectedness. It usually consists in 20 items, each rated on a Likert scale ranging from 1 (Never) to 4 (Often), resulting in scores that range from 20 to 80. Higher scores indicate greater feelings of loneliness or social isolation. The EURO-D scale is a standardized tool used for assessing depression in older adults. It consists of 12 items, each scored on a binary scale (0 or 1), with the total score ranging from 0 to 12. Higher scores indicate a greater severity of depressive symptoms. The items cover various aspects such as mood, pessimism, and fatigue. For further details on both scales and their scoring, see Table 9.1 a and Table 9.2 in the Appendix.

4.3.1 Measuring Mental Health in SHARE Corona Survey

The SCS does not include the R-UCLA nor the EURO-D scales; instead, it focuses on collecting more general questions about individual well-being over the past month. Additionally, it features questions designed to assess whether symptoms have become more or less prevalent compared to the period before the pandemic, totaling six questions on mental well-being that cover both loneliness and depressive symptoms.

The questionnaire focuses on three key indicators of mental well-being:

- Whether the respondent has experienced sadness or depression in the past month, with possible answers being 'yes' or 'no.'

- Whether the respondent has encountered sleep difficulties recently, with the options for response being ‘trouble with sleep or recent change in pattern’ or ‘no trouble sleeping.’
- The frequency with which the respondent feels lonely, offering the choices of ‘often,’ ‘some of the time,’ or ‘hardly ever or never.’

Additionally, if the individual answers in the affirmative for any of the previous items, they are asked to evaluate whether these symptoms are more, less, or about the same as before the outbreak of COVID-19.

An index for mental well-being can be constructed based on these questions, following the same criteria of the EURO-D and R-UCLA scales, whose scoring system assigns higher values to individuals exhibiting more severe symptoms. Specifically, affirmative responses to SCS questions about depression and sleep difficulties yield a score of +1, while negative responses result in a score of 0. For the loneliness question, scores are assigned as follows: 0 for ‘hardly ever,’ 1 for ‘some of the time,’ and 2 for ‘often.’ In the follow-up questions about symptom changes, a score of +1 is given if symptoms have worsened since the pandemic, -0.5 if they have improved, and 0 if they remain unchanged. The total individual scores can range from 0, indicating the absence of any symptoms, to 7, signifying the presence of all assessed symptoms along with a worsening of each since the onset of the COVID-19 pandemic. The resulting index variable is denominated `mh_ca` in the dataset, to signify its pertinence to models which derive some of the information from the SCS questionnaire.

4.4 Dependent Variables

In this section, I discuss the dependent variables of this empirical analysis. Specifically, I examine two key variables: `reduced_hours` and `increased_hours`, derived from the SHARE Corona Survey (SCS). These variables are binary in nature, taking on a value of 1 if the individual has either reduced or increased their working hours since the onset of the pandemic, respectively. The distribution of both in the final samples is reported in Table 4.1. For `reduced_hours`, about 16.6% of the sample has reduced work hours since the start of the pandemic, whereas around 14.4% has increased work hours.

The aim of the following chapters is to identify the effect of mental health on the probability of having reduced or increased work hours, while exploiting pandemic based instrumental

reduced_hours	**Freq.**	**Percent**	**Cum.**
0	1,916	83.41	83.41
1	381	16.59	100
Total	**2297**	**100**	

increased_hours	**Freq.**	**Percent**	**Cum.**
0	1,966	85.63	85.63
1	330	14.37	100
Total	**2296**	**100**	

Table 4.1: `reduced_hours` and `increased_hours` Distribution in SHARE Corona Survey.

variables to address the blatant endogeneity concerns.

4.5 Independent Variables

In the following section, I will introduce the independent variables that appear in the various models of this study. These variables are selected based on their relevance to the research questions and are supported by existing theoretical and empirical work. The sample tracks individuals who participated in both Wave 8 and SCS data collections, thereby possessing data availability as vast as possible. For ease of reference, Table 4.2 provides summary statistics and a quick description for dependent and independent variables.

The first category of variables captures demographic information. First, the variables `age` and `female` capture the age and gender of the respondent. Then, `rel_status` is a binary variable which signals if the individual is partnered and `isced97educ` captures level of education according to the 1997 International Standard Classification of Education (ISCED), a framework used to categorize and compare educational programs and their levels. This variable assigns 0 to “pre-primary education”, 1 to “primary education”, 2 to “lower secondary education”, 3 to “upper secondary education”, 4 to “post-secondary non-tertiary education”, 5 to “first stage of tertiary education”, and 6 to “second stage of tertiary education”.

The second category of variables is concerned with an individual’s social network. As outlined in Chapter 2, these variables serve as mediators in the relationship between mental health and other factors. The variables `child_SN`, `sibling_SN`, `parents_SN`, `friends_SN`, `helpers_SN` and `others_SN` specify the number and type of relationships within the respondent’s social network.

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
reduced_hours	Binary indicator for reduced work time since pandemic onset.	2297	0.1659	0.3720	0	1
increased_hours	Binary indicator for increased work time since pandemic onset.	2296	0.1437	0.3509	0	1
mh_ca	Mental health index.	2297	0.8296	1.3224	0	7
age	Age at time of interview.	2297	60.7266	5.4547	37	90
female	Gender.	2297	0.5908	0.4918	0	1
rel_status	Binary indicator for being partnered.	2297	0.7222	0.4480	0	1
isced97educ	ISCED-97 education level acquired.	2297	3.8633	1.1494	1	6
SN_contact	Average contact frequency with SN members.	2297	1.9304	0.9084	1	6
SN_proximity	Average physical distance from SN members.	2297	3.5358	1.6752	1	8
SN_closeness	Average emotional closeness from SN members.	2297	3.2523	0.5748	1	4
child_SN	Number of living children.	2297	0.8542	0.9523	0	7
sibling_SN	Number of living siblings.	2297	0.2773	0.5845	0	5
parents_SN	Number of living parents.	2297	0.1241	0.3588	0	2
friends_SN	Number of living friends.	2297	0.6670	1.0246	0	7
others_SN	Number of other SN members.	2297	0.1959	0.5513	0	6
log_inc_prre_ca	Logarithm of annual income pre-pandemic.	2297	7.5702	0.9219	-2.009	14.627
job_flex_ca	Binary indicator for having experienced flexible work modality since pandemic onset.	2297	0.3875	0.4873	0	1
ends_meet_ca	Ability to make ends meet since pandemic onset.	2297	3.1367	0.8703	1	4
diagnosed_ca	Binary indicator for having been diagnosed with a long-term condition since pandemic onset.	2297	0.0588	0.2352	0	1
ca_symptoms	Binary indicator for having experienced COVID-19 symptoms.	2297	0.0287	0.1671	0	1
longterm_condition	Binary indicator for being diagnosed with a long-term condition.	2297	0.4523	0.4978	0	1
health	Self-assessed health status.	2297	2.7902	0.9414	1	5
pain	Self-assessed pain level.	2297	0.3274	0.4694	0	1
bmi_cat	BMI category.	2297	2.9203	0.7888	1	4
flu_vax	Binary indicator for having received a seasonal flu vaccine in the last year.	2297	0.2138	0.4100	0	1
iadl_score	Instrumental Activities of Daily Living score.	2297	0.0805	0.5247	0	9
smoker	Binary indicator for being a smoker.	2297	0.1872	0.3902	0	1
alcohol	Binary indicator for heavy alcohol drinking.	2297	0.0814	0.2735	0	1
sport	Binary indicator for being physically active.	2297	0.9604	0.1951	0	1

Table 4.2: Summary Statistics of Dependent and Independent Variables.

The quality of respondent relations is captured by several variables. First, `SN_contact` provides information on contact frequency with other social network members, with values ranging from 1 (daily contact) to 7 (never). Next, `SN_proximity` gives the average geographical distance from others in the network, with values ranging from 1 (closest) to 7 (most spread out). Finally, `SN_closeness` is a measure of perceived emotional closeness to members of the network, with 1 being “Not very close” and 4 being “Extremely close”.

Another category of regressors provides information on labor market related factors. To capture financial stress, the variable `ends_meet_ca` details whether the individual struggles to make ends meet since the start of the pandemic; values range from 1, "With great difficulty", to 4 "Easily". Some additional variables come from the SCS, and as such can be included in models where the dependent variable has the same source. Specifically, `log_inc_pre_ca` provides the logarithm of monthly income before the start of the pandemic. Then, `job_flex_ca` signals whether the individual has experienced a change in work modality since the start of the pandemic, which serves as a proxy for occupation type.

The next set of control variables focuses on health and daily life. The binary variable `longterm_condition` indicates whether an individual has been diagnosed with a long-term medical condition. Self-assessed health and pain are captured by two variables: `health`, which ranges from 1 (Excellent) to 5 (Poor), and `pain`, a binary variable that signals the presence of daily pain. Body Mass Index (BMI) categories are represented by `bmi_cat`, with values from 1 (Underweight) to 4 (Obese). Functional status is measured using the Instrumental Activities of Daily Living (IADL) scale. The `iadl_score` variable, ranging from 0 to 9, assesses an individual's ability to perform complex tasks essential for independent living, such as managing finances and shopping. In both scales, a higher score signifies a lower level of functional independence.

The final set of control variables focuses on behavior. Binary variables like `smoker` and `alcohol` indicate whether the respondent is a smoker or a heavy drinker, respectively. Physical activity is captured by the binary variable `sport`. Additionally, `flu_vax` serves as a binary indicator for flu vaccination, which can also serve as a proxy for an individual's likelihood to receive the COVID-19 vaccine when available, as well as their trust in the healthcare system.

In summary, this chapter has provided an overview of the primary data sources that form the backbone of this research: SHARE Wave 8, the SHARE Corona Survey, and the Oxford Government Response Tracker. It has also delineated the key independent variable to capture mental health: a custom-built index called `mh_ca`. This index is inspired by scales commonly used in recent SHARE Waves and follows a similar logic. The introduction of this new variable addresses the absence of such scales in the SHARE Corona Survey, which serves as a crucial source for individual-level pandemic-related data. Finally, this chapter has provided an introduction to and description of dependent variables, as well as the selection on observables.

5 Identification Strategy

In this chapter, I outline the analytical frameworks and methodologies employed to address the research questions posited in this thesis. Specifically, I will detail the models estimated to assess the impact of mental health on various individual outcomes, drawing from SHARE Wave 8, SHARE Corona Survey, and the Oxford Government Response Tracker (OxGRT). The chapter will expand upon the econometric techniques used, and the rationale behind the choice of models.

5.1 Methodology: IV, Probit and IV-Probit

The main regressor of interest across all specifications is a self-reported measure of mental well-being. As such, it inherently introduces some degree of measurement error through biases and inaccuracies, as it captures only an imperfect measure of a respondent's true mental state. For instance, an individual having a particularly challenging day may have a propensity to report more severe symptoms, or it may be that two individuals with the same symptom severity score very differently on the chosen scale. Cultural factors can further complicate the issue, with some countries having stronger stigma that may incentivise underreporting. Moreover, the relationship between mental well-being and the dependent variables is fraught with endogeneity issues, as discussed in Chapter 2. These issues primarily manifest as reverse causality and simultaneity. For example, poor labor market conditions (e.g. mobbing, long work hours, low wages) can lead to deteriorating mental health due to stress or financial insecurity. At the same time, individuals with poor mental health may also struggle to maintain unemployment, or may perform worse. Additionally, labor market and mental health could influence each other simultaneously through feedback loops, where poor mental well-being leads to job loss, the stress of sudden unemployment worsens mental condition, creating a negative feedback loop.

To address endogeneity concerns, all models in this study will employ an Instrumental Variables (IV) approach to isolate the exogenous variation in mental well-being, allowing for a more accurate estimation of its impact on the dependent variables. Furthermore, since the dependent variables are dichotomous in nature, I will employ a variation of the IV method known as IV-Probit. In the following subsections I will provide an introduction to the methods of Instrumental Variables, Probit and IV-Probit.

5.1.1 Instrumental Variables

In the presence of endogenous variables, Ordinary Least Squares (OLS) estimation typically leads to inconsistent coefficient estimators. Consider a general model formulation as follows:

$$y = \beta_0 + \beta_1 \mathrm{MH} + \beta_2 x_2 + \cdots + \beta_k x_k + u, \tag{5.1}$$

where y is the dependent variable, MH represents an endognous measure of mental health, $(x_2, \ldots, x_k)$ are exogenous covariates, $(\beta_0, \beta_1, \ldots, \beta_k)$ are coefficients to be estimated, and u is the error term distributed as a $\mathcal{N}(0, \sigma^2)$.

If $Cov(MH, u) \neq 0$, then OLS estimation results in inconsistent estimates for the β_i coefficients. To address this issue with IV, an additional observable variable z_1, referred to as the instrument, must satisfy two conditions. First, z_1 must be uncorrelated with the model error term u:

$$Cov(z_1, u) = 0 \tag{5.2}$$

The second requirement concerns the relationship between the endogenous MH and the instrument z_1, as defined by the linear relation:

$$MH = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \cdots + \delta_k x_k + \theta_1 z_1 + e \tag{5.3}$$

where the dependent variable MH is the endogenous variable in Equation 5.1, $(x_1, \ldots, x_k)$ are exogenous variables, z_1 is the instrument, $(\delta_0, \delta_1, \ldots, \delta_k, \theta_1)$ are coefficients to be estimated, and e is an error term distributed as $\mathcal{N}(0, \sigma^2_{FS})$.

Specifically, the condition requires that z_1 is partially correlated with x_K once all the exogenous variables are accounted for:

$$\theta_1 \neq 0 \tag{5.4}$$

Both the endogenous and the instrument can be binary, continuous or discrete. If z_1 satisfies both conditions, it is a valid IV candidate for MH, and the IV estimator for β_1 is computed in the following manner:

$$\hat{\beta}_{1,\mathrm{IV}} = \frac{Cov(y, z_1)}{Cov(\mathrm{MH}, z_1)} \tag{5.5}$$

5.1.2 Two Stage Least Squares

When one or more valid instruments are available for the endogenous variable, Two Stage Least Squares (2SLS) estimation is commonly employed. The 2SLS procedure can be broken down into two stages:

- **First Stage.** In this stage, the endogenous variable MH is estimated using all the exogenous variables and the instruments. The first-stage equation is:

$$\mathrm{MH} = \pi_0 + \pi_1 x_1 + \pi_2 x_2 + \cdots + \pi_k x_k + \phi_1 z_1 + \phi_2 z_2 + \cdots + \phi_m z_m + v, \tag{5.6}$$

  where $(z_1, z_2, \ldots, z_m)$ are the instruments, $(x_1, \ldots, x_k)$ are exogenous regressors, and $(\pi_0, \pi_1, \ldots, \pi_k, \phi_1, \ldots, \phi_m)$ are parameters to be estimated. It is commonly assumed that the error term v is normally distributed, denoted as $\mathcal{N}(0, \sigma_v^2)$.

- **Second Stage.** Use the predicted values $\hat{MH}$ from the first stage to estimate the original equation:

$$y = \beta_0 + \beta_1 \hat{\mathrm{MH}} + \beta_2 x_2 + \cdots + \beta_k x_k + u. \tag{5.7}$$

  The 2SLS estimator for β_1 is then obtained from the estimation of this second stage regression, usually via OLS.

OLS standard errors of estimated coefficients in Equation (5.7) are not valid because they do not account for the presence of an additional estimation step to obtain $\hat{MH}$. Therefore, these standard errors must be corrected to reflect the two-stage nature of the estimation procedure. Common methods for adjusting the standard errors include bootstrapping or using heteroskedasticity-robust standard errors that take into account the estimation uncertainty from the first stage. Correcting second stage standard errors is crucial for valid statistical inference.

5.1.3 Probit

The Probit model is employed in scenarios where the dependent variable is binary, as in the case of `reduced_hours` and `increased_hours`. Unlike linear regression models, which often assume a continuous dependent variable, Probit is designed to handle dichotomous outcomes. It is particularly useful for estimating the probability of an event occurring as a function of several independent variables, and unlike the alternative Linear Probability Model (LPM) has outcomes bounded between 0 and 1. In this study, the Probit model offers insight into the effects of mental health and other covariates on the likelihood of observing an increase or decrease in working hours.

The model operates on the principle of the cumulative distribution function (CDF) of the standard normal distribution, transforming a linear combination of predictors to lie within the unit interval $[0,1]$. Mathematically, the Probit model can be expressed as:

$$P(y=1|\mathbf{X}) = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) \tag{5.8}$$

where Φ denotes the CDF of the standard normal distribution, and $\beta_0, \beta_1, \ldots, \beta_k$ are the parameters to be estimated.

In the Probit model, coefficients are estimated using Maximum Likelihood Estimation (MLE). Unlike OLS, coefficients are not directly interpretable as marginal effects. Instead, they indicate the change in the z-score or the number of standard deviations away from the mean of the underlying latent variable for a one-unit change in the predictor.

The likelihood function for the Probit model is given by:

$$L(\beta) = \prod_{i:y_i=1} \Phi(\beta' \mathbf{X} i)^{y_i} \prod_{i:y_i=0} (1 - \Phi(\beta' \mathbf{X}_i))^{(1-y_i)} \tag{5.9}$$

Here, $\mathbf{X}_i$ is the $n \times (k+1)$ matrix of independent variables for sample unit i, including a column of ones for the intercept, y_i is individual i dependent variable, and β is the $(k+1) \times 1$ vector of parameters to be estimated.

The associated log-likelihood function is given by:

$$\ell(\beta) = \sum_{i=1}^{n} \left[y_i \ln \Phi(\beta' \mathbf{X}_i) + (1 - y_i) \ln(1 - \Phi(\beta' \mathbf{X}_i)) \right] \tag{5.10}$$

The Probit estimator maximises Equation (5.10) to obtain consistent, asymptotically normal and efficient estimates of the coefficients. To interpret the coefficients, one often calculates the marginal effects:

$$\frac{\partial P(y=1|\mathbf{X})}{\partial x_j} = \phi(\beta' \mathbf{X}) \beta_j \tag{5.11}$$

where ϕ is the probability density function of the standard normal distribution. As such, the Probit coefficients themselves are not directly interpretable as the magnitude of the effect, although their associated marginal effects provide valuable insights into the impact of each predictor on the probability of the event of interest. That is, the sign of the effect is given by the sign of β_j.

For discrete regressors, the magnitude of the marginal effect is computed as the difference in predicted probabilities when the discrete variable x_j changes by one unit, ceteris paribus. Specifically:

$$P(y=1|x_j = a+1) - P(y=1|x_j = a) \tag{5.12}$$

5.1.4 IV-Probit

The dependent variables `reduced_hours` and `increased_hours` are binary in nature, making the Probit model a more appropriate choice for estimation compared to linear regression models. However, the relationship between mental health, MH, and these dependent variables is potentially endogenous. Given these concerns, a simple Probit model may yield biased and inconsistent estimates. To address both the binary nature of the dependent variables and the endogeneity of the MH variable, the modeling choice falls on the IV-Probit method. This approach combines the strengths of IV and Probit to provide consistent and efficient estimates in the presence of endogeneity and a binary dependent variable.

This method is essentially a two-stage process, where the first stage regresses the endogenous variable MH on the instrumental variables vector Z and the exogenous variables vector X

using OLS. In the second stage, the first stage predicted values replace MH in the Probit model to estimate the effects on the dependent variables `reduced_hours` and `increased_hours`.

The first and second stage equations can be represented as follows:

$$\text{First Stage:} \quad MH = \alpha + \mathbf{Z}\gamma + \mathbf{X}\delta + \varepsilon \tag{5.13}$$

where $\mathbf{Z}$ is an $n \times m$ matrix of instrumental variables, $\mathbf{X}$ is an $n \times k$ matrix of exogenous regressors, α, γ and δ are the column vectors of parameters to be estimated. The error term ε is assumed to follow a normal distribution with mean zero and variance σ^2.

$$\text{Second Stage:} \quad P(y = 1|\hat{MH}, \mathbf{X}) = \Phi\left(\beta_0 + \beta_1 \hat{MH} + \beta_2 x_2 + \cdots + \beta_k x_{k-1}\right) \tag{5.14}$$

where $\hat{MH}$ are the first stage predicted values for MH, $(x_2, \ldots, x_k)$ are the exogenous regressors in $\mathbf{X}$, and $\beta_0, \beta_1, \ldots, \beta_k$ are the parameters to be estimated in the second stage.

As in all IV-based methods, the relevance and exogeneity of the instruments in $\mathbf{Z}$ is essential. Second stage results are to be interpreted as in regular Probit applications, discussed above.

In STATA, IV-Probit can be estimated with a two-step approach or a Full Information Maximum Likelihood (FIML) procedure using the command `ivprobit`. For the former, the first stage residuals are obtained via OLS estimation, and plugged into a transformed second stage to be estimated with Probit (where the model error is decomposed into its endogenous and exogenous components, and rescaled so that the exogenous component has variance 1). The second method simultaneously estimates the first stage and the second stage using FIML, and assumes that the first and second stage errors follow a bivariate Normal distribution.

5.2 Selected Instruments

Candidate instrumental variables must serve as a source of exogenous variation in the endogenous variable that is otherwise unrelated to the outcome variable. That is, Z must contain instruments which affect MH but are unrelated to y. The COVID-19 pandemic offers an unprecedented opportunity to address the endogeneity issues in this branch of research.

Summary statistics for the three instrumental variables are shown in Table 5.1, and addi-

Variable	Obs	Mean	Std. Dev.	Min	Max
covid_death	2297	0.0674793	0.5808128	0	18
upto_month_avg_SI	2297	42.25638	5.149009	34.84262	58.863
upto_month_avg_newcasesperm	2297	14.25918	10.47381	1.535301	49.18575

Table 5.1: Instrumental Variables Summary Statistics.

tional summary statistics are available in the Appendix. In the following subsections I will introduce and expand upon each candidate instrumental variable.

5.2.1 COVID-19 Deaths

The first instrumental variable is motivated by the work of Frijters et al. (2010), which investigates the impact of mental health on employment status. In their study, they use the recent death of a friend as an instrument for a mental well-being index derived from the SF-36 survey. While SHARE Wave 8 lacks data on recent deaths within a respondent's social circle, the Corona Survey inquires whether the respondent is acquainted with anyone who has died due to COVID-19 and tracks the type of relation between the respondent and the deceased. These answers serve as the basis for the first instrument, `covid_death`.

The `covid_death` variable is constructed as a weighted sum to capture the emotional impact of COVID-19 related deaths on the respondent, with higher weights assigned to closer relationship categories. Specifically, the death of partners, parents, or children is given the highest weight of 4, reflecting their immediate familial ties to the respondent. Other household members and other relatives are assigned a weight of 3, acknowledging their close but somewhat less immediate relationship. Neighbors, friends, and colleagues are given a weight of 2, while caregivers and other individuals who do not fall into the aforementioned categories are assigned the lowest weight of 1. The `covid_death` variable thus serves as a nuanced measure of the emotional toll exerted by pandemic bereavement, weighted according to the closeness of the relationships affected. Unfortunately, information about the number of neighbors, friends and colleagues who died as a result of COVID-19 is grouped into a single category, leading `covid_death` to assign the same weight to the death of a colleague and that of a friend, while the latter could be considered more impacting on individual well-being. A limitation of the `covid_death` instrument is its sparse distribution: approximately 97% of the sample records a value of zero. Nevertheless, the instrument `covid_death` has a distinct advantage in that its influence on work choices is likely channeled exclusively through its impact on mental health, making it arguably exogenous.

5.2.2 Average Stringency Index

The second instrument is derived from the OxGRT database detailed in Chapter 3. Government-imposed restriction captured by the Stringency Index (SI) (see Figures 4.1 and 4.2) have a direct influence on individual daily routines and habits. This increased exposure to risk factors has been shown to elevate rates of anxiety, depression, and stress-related symptoms, as evidenced by aforementioned studies such as Pieh et al. (2021), Wang et al. (2020), and Adams-Prassl et al. (2022). The SI tracks, among other indicators, cancellation of public events, restrictions on public and private gatherings, public trasportation, stay at home orders, limitations on domestic movement, and public information campaigns. Therefore, it represents a valuable resource to track respondent exposure to risk factors for worsened mental health due to policy responses to the pandemic. Additionally, Atzendorf et al. (2022) use the SI from OxGRT to examine the evolution of feelings of loneliness and depression with respect to pre-pandemic times, lending credibility to its relevance as an instrument.

This second instrument is denoted as `upto_month_avg_SI` and is calculated as the average value of the Stringency Index (SI) from January 2020 up to the month in which the respondent's SCS interview took place, signaled by the variable `int_month_ca`. This formulation allows the instrument to exhibit variation both at the individual and country levels, capturing the nuanced impact of government policies across different jurisdictions.

5.2.3 Average Monthly New Cases

The Stringency Index does not include data on the number of COVID-19 cases per country, a statistic that was consistently highlighted in the media along with number of deaths and future projections. While this information may not have directly impacted the respondent's lived experience, it likely influenced their future expectations and risk perception. Consequently, it may correlate with mental health due to frequent exposure to reports of proximate adverse events.

The OxGRT dataset reports daily information on number of cases per million inhabitants. Based on that, the third and final candidate instrument `upto_month_avg_newcasesperm` is defined as the monthly average number of cases per million, computed up to the month of SCS interview. As such, the variable exhibits individual-by-country variation.

As long as the number of COVID-19 cases does not directly influence outcomes like working hours or social network satisfaction, it can be considered reasonably exogenous. Regarding working hours, the samples under consideration will specifically focus on individuals who were employed at the onset of the pandemic and have maintained their employment throughout, thereby minimizing the direct impact of case numbers on this particular outcome.

5.3 Concluding Remarks

This chapter has laid the groundwork for the empirical analyses that follow by introducing the econometric methods and strategies that will be employed. The use of IV-Probit models is not only methodologically sound but also relevant to the research questions at hand, particularly in addressing the endogeneity concerns associated with mental health variables. Additionally, the chapter has provided a comprehensive discussion on the candidate instrumental variables, elucidating their conceptual relevance and potential exogeneity. These methodological choices are designed to ensure that the forthcoming analyses are both robust and insightful, contributing to a nuanced understanding of the complex relationships between mental health and labor market participation.

6 Results

The present chapter is dedicated to presenting and discussing model results. In the following sections, I will discuss sample selection criteria and composition, estimation results, and their integrity for causal inference. For simplicity, the model where `reduced_hours` is the dependent variable will be referred to as 'Model 1,' while the model with `increased_hours` as the dependent variable will be designated as 'Model 2'. The aim is to interpret results in the context of the broader research branch, offering insight into the effect of the COVID-19 pandemic on various aspects of well-being, and thereby labor market outcomes.

6.1 Samples

The sample is limited to individuals who are present in both Wave 8 and the Corona Survey, identified by their unique `mergeid`. Additionally, the sample includes only those respondents who are either employed or self-employed, excluding homemakers, unemployed and permanently sick or disabled individuals whose data for having reduced (or increased) work might include activities typically outside of the labor force. To further isolate the effect of mental health on work outcomes, the sample is narrowed to include only individuals who did not suffer job loss as a consequence of the pandemic. Units whose covariate data is missing are removed, leaving a sample with complete information on all involved variables.

The final samples amount to 2,297 individuals in Model 1, and 2,296 individuals in Model 2. Both samples see a predominant amount of partnered individuals (72%) and, as can be expected in a sample of older adults, women account for 59% of units. Ages range from 37 to 90, and average at 60.73 years old. Summary statistics, complete with a quick description of each variable, are reported in Table 4.2. For additional information on sample country composition, and instrumental, dependent and independent variables summary statistics in both samples, please refer to Tables 9.3, 9.4, 9.5, 9.6, 9.7, and 9.8 in the Appendix. Except for a single unit, the summary statistics for both samples are virtually identical.

6.2 Tests For Instrument Validity

In the following section, I will outline the specific tests employed to evaluate the validity of the instruments used in the models. Ensuring instrument validity is crucial for the causal interpretation of model estimates. The tests will address both instrument relevance and, where applicable, exogeneity.

6.2.1 Relevance

As previously outlined in Section 4.1, for an instrument to be considered relevant, it must satisfy the condition specified by Equation 5.4. In the context of linear IV models, relevance is typically assessed using the first-stage F-statistic for the null hypothesis that the instrument coefficients are zero. While a rule of thumb suggests that instruments are considered strong when F>10, this criterion can be further refined using Stock and Yogo critical values.

The Stock and Yogo critical values provide a more nuanced assessment of instrument strength, tailored to the specific model conditions. If the statistic exceeds the critical value, instruments can be considered relevant. In the case of having one endogenous variable and a number of instruments ranging from 1 to 3, critical values will behave as shown in Table 6.1.

Maximal IV Size	**z = 1**	**z = 2**	**z = 3**
10%	16.38	8.96	7.03
15%	9.66	5.53	4.60
20%	6.66	4.58	3.95

Table 6.1: Stock and Yogo Critical Values for 1 Endogenous Variable

Maximal IV Size represents the willingness to tolerate a specific rate of test failure, i.e. of rejection of a true null hypothesis. A lower maximal IV size makes the test more stringent, but reduces the power of the test, whereas a higher size increases test power but makes it less stringent. For example, a maximal IV size of 25% is less stringent than a rate of 10%.

It is essential to note that utilizing Stock and Yogo's critical values for assessing instrument strength in an IV Probit framework may introduce inferential inaccuracies, as these values are originally derived under the linearity assumptions inherent to Two-Stage Least Squares (2SLS) models.

6.2.2 Exogeneity

In the context of both linear IV and nonlinear IV Probit models, the exogeneity of the instruments is a fundamental assumption that underpins the validity of the causal interpretation of the estimated parameters. In a linear IV model, tests like the Sargan-Hansen are commonly used to assess instrument exogeneity in overidentified models.

The Sargan test operates under the null hypothesis that the instruments are exogenous, meaning the overidentifying restrictions are valid. It relies on an auxiliary regression of the model residuals on all the exogenous variables and the instruments. The test statistic is computed as an $N \times R^2$ from the auxiliary regression, where N is sample size and R^2 is the regression's coefficient of determination, and follows a chi-squared distribution with degrees of freedom equal to the number of overidentifying restrictions. A rejection of the null hypothesis entails that the instruments are not valid. However, failing to reject the null does not necessarily confirm the instruments' exogeneity.

In nonlinear models like IV Probit, the testing procedures are less straightforward due to the complexities introduced by the nonlinear estimation techniques. The Amemiya-Lee-Newey (ALN) minimum chi-square statistic is a specific test statistic used in the context of nonlinear IV to assess the validity of the instruments. Essentially, it is the nonlinear counterpart of the Sargan-Hansen test. The ALN statistic tests the null hypothesis that the instruments are uncorrelated with the error term in the main equation. Similarly to Sargan-Hansen, if the null is rejected instruments are deemed invalid.

It is worth noting that STATA's `ivprobit` command does not directly support the ALN test via the `overid` command when using the maximum likelihood estimator. Therefore, the test statistics will be computed using models specified with the `twostep` estimator option.

6.3 Model 1 Results Analysis: Reduced Working Hours

The first model addresses the question of whether a change in mental health, as measured by the `mh_ca` index, causes a reduction in working hours for employed individuals who did not suffer job loss since the start of the pandemic.

Estimation results are reported in Table 6.2, using robust standard errors. Column 1 reports multiple Probit estimation results. Based on prior literature and economic theory, worsening mental health (i.e. a higher `mh_ca` value) is generally expected to have a negative impact on labor market outcomes. In the context of the model, one would initially expect `mh_ca` to have a positive and significant coefficient, indicating that a decline in mental health would increase the probability of reducing work hours. However, the results in column 1 show a positive but not statistically significant coefficient, possibly attributable to endogeneity issues biasing the estimates. This underscores the need for an IV-Probit approach, as discussed in the previous chapter.

6.3.1 Instrument Validity

Table 6.3 reports OLS estimation results for first stages, using various instrumental variables combinations. Three IV Probit specifications pass the Stock and Yogo critical values thresholds for 10% maximal IV size. Specifically, the model featuring the instruments `upto_month_avg_SI` and `covid_death`, as displayed in column 3, yields an F-statistic of 19.97, surpassing the critical threshold of 8.96. Likewise, the column 4 model incorporating `upto_month_avg_newcasesperm` and `covid_death` has an F-statistic of 11.54, also exceeding the threshold of 8.96. Lastly, in column 5 the model utilizing all three instruments achieves an F-statistic of 13.6, above the critical value of 7.03. Additionally, the model in column 1 passes the Stock and Yogo critical values for 15% maximal IV size, with an F-statistic of 15.39 and a threshold value of 9.66.

Comparing the first stage F-statistics across instrument composition, it becomes evident that the most relevant instruments are `upto_month_avg_SI` and `covid_death`. Given that models with more relevant instruments are generally preferable, the version with two instruments (`upto_month_avg_SI` and `upto_month_avg_newcasesperm`) in column 2, is the least robust choice.

Amemiya-Lee-Newey statistics are computed for the second stages of the three most robust models, to assess the validity of the overidentifying restrictions. Their values can be found at the bottom of Table 6.2. A rejection of the null implies endogeneity of the instruments. For the model that includes `upto_month_avg_SI` and `covid_death` (shown in column 4), the p-value is 0.0701, suggesting that the null is not rejected at 5% confidence. The model in column 6 performs worse, with an associated p-value of 0.028, rejecting the null at 5%.

On the other hand, the model displayed in column 5 has a p-value of 0.1516, which does not lead to a rejection of the null. This suggests that the `covid_death` variable serves as a relevant and exogenous instrument for mental health. Therefore, the models in columns 3, 4 and 5 emerge as the most reliable, featuring both relevant and exogenous instruments.

However, upon closer examination, the model in column 5 raises some concerns. The first stage (column 4 of Table 6.3) clearly indicates that the relevance of the instrument is primarily driven by `covid_death`. The second stage presents a non-significant but negative coefficient for `mh_ca`, accompanied by overall higher standard errors. For this reason, the preferred model appears to be the one in column 4 of Table 6.3, which includes `upto_month_avg_SI` and `covid_death` as instruments.

Focusing on this latter model, the coefficient on `mh_ca` is positive, but not statistically significant at any level. Moreover, the associated standard error is alarmingly large relative to other specifications. In fact, models in columns 2 and 3 (Table 6.2) use a different set of instruments, but both show similar effects of `mh_ca` and much smaller and stable standard errors. The difference of column 4 with respect to models in columns 2 and 3 is the absence of `covid_death` in the set of instrumental variables. In fact, as noted in Subsection 5.2.1, this instrument is fatally affected by the sparsity of its distribution, which introduces excessive noise in estimation.

In summary, the preferred model is that of column 2 of Table 6.2, whose first stage is reported in column 1 of Table 6.3. Based on test results, `upto_month_avg_SI` stands out as the most valid instrument, undoubtedly relevant and reasonably exogenous. On the other hand, `upto_month_avg_newcasesperm` lacks the necessary relevance with respect to `mh_ca`, while `covid_death`'s sparse distribution fatally affects the instrumented variable's second stage estimates.

6.3.2 Interpretation

The first stage is indicative not only of instrument strenght, but also of significant determinants of the `mh_ca` index. Looking closer, some findings are consistent with previously reviewed literature. For instance, being female is correlated with poorer mental health, while being in a partnership is linked to the most substantial improvement in mental well-being among all exogenous variables.

Next, `SN_proximity` is the only social network indicator strongly associated with mental health, with a positive coefficient signaling that a more spread out social network is associated with worse conditions. Other factors like contact frequency (`SN_contact`) and emotional closeness (`SN_closeness`) do not significantly affect `mh_ca`. Finally, number of relationships by type do not significantly affect the endogenous variable.

Financial stability since the pandemic's onset, as measured by `ends_meet_ca`, has a positive effect on mental well-being, signaled by a negative coefficient. Job flexibility, measured with a binary indicator of having the possiblity of working from home, presents a positive coefficient. This is possibly driven by an increase in loneliness due to reduced daily face-to-face interactions with coworkers.

Lastly, health indicators such as being recently diagnosed with a condition (`diagnosed_ca`), reporting worse self-rated health and having pain are all significantly associated with worse `mh_ca` scores.

Second stage estimates provide insight into what caused individuals to reduce working hours since the start of the pandemic. As expected, age has a positive impact on the probability of having reduced work time. Higher education levels, likely partially indicative of the nature of one's occupation, are associated with a lower likelihood of cutting back on work hours. Surprisingly, being in a partnership is linked with a higher probability of having reduced work time, as indicated by the positive coefficient.

Although social network variables do not show significant effects in the second stage, job flexibility stands out with a positive and significant coefficient. This is possibly explained by two co-occurring effects: an actual reduction in work hours and an individual perceived decrease in work time due to the elimination of commuting and other routine work related actions.

Health indicators like self-rated health and self-reported pain do not significantly influence the likelihood of reducing work hours. Interestingly, a recent diagnosis of a long-term condition is associated with a negative coefficient. This counterintuitive result could be explained by anticipatory behavior, where employees may avoid reducing work hours following a diagnosis.

Finally, but most importantly, `mh_ca` has a positive coefficient of 0.452, significant at the 5% level. Compared to other covariate coefficients, the effect is substantial. A one unit increase in `mh_ca` is associated with an average marginal effect of approximately 12.8% on the probability of having reduced work since the start of the pandemic, ceteris paribus. Second stage marginal

VARIABLES	(1) Probit reduced_hours	(2) IV Probit reduced_hours	(3) IV Probit reduced_hours	(4) IV Probit reduced_hours	(5) IV Probit reduced_hours	(6) IV Probit reduced_hours
mh_ca	0.0271	0.452**	0.540***	0.124	-0.223	0.196
	(0.0246)	(0.192)	(0.149)	(0.186)	(0.266)	(0.204)
age	0.0111*	0.0136**	0.0137**	0.0120*	0.00825	0.0126**
	(0.00622)	(0.00570)	(0.00547)	(0.00499)	(0.00692)	(0.00498)
female	-0.0354	-0.143*	-0.163**	-0.0606	0.261***	-0.0791
	(0.0707)	(0.0802)	(0.0705)	(0.0562)	(0.0558)	(0.0561)
rel_status	0.104	0.264***	0.295***	-0.408***	-0.00204	-0.398***
	(0.0837)	(0.0971)	(0.0728)	(0.108)	(0.142)	(0.0725)
isced97educ	-0.0669**	-0.0582**	0.0189	0.0198	0.00987	0.0228
	(0.0309)	(0.0296)	(0.0287)	(0.0250)	(0.0314)	(0.0306)
SN_contact	0.00540	0.00321	0.00610	0.00515	0.00792	0.00501
	(0.0509)	(0.0497)	(0.0499)	(0.0512)	(0.0488)	(0.0498)
SN_proximity	0.0255	-0.00929	-0.0177	0.0183	0.0672***	0.0126
	(0.0268)	(0.0313)	(0.0289)	(0.0253)	(0.0310)	(0.0315)
SN_closeness	0.0236	-0.00707	0.0657	0.0175	0.0380	0.0130
	(0.0620)	(0.0594)	(0.0507)	(0.0631)	(0.0615)	(0.0504)
child_SN	-0.0265	-0.0227	0.00232	0.00712	-0.0244	-0.0261
	(0.0359)	(0.0333)	(0.0302)	(0.0302)	(0.0302)	(0.0355)
sibling_SN	-0.0289	-0.0304	-0.0297	0.00672	0.0188	-0.0306
	(0.0587)	(0.0531)	(0.0510)	(0.0527)	(0.0586)	(0.0575)
parents_SN	0.0430	0.0392	-0.0110	0.0435	0.0392	0.0436
	(0.0880)	(0.0798)	(0.0663)	(0.0659)	(0.0853)	(0.0660)
friends_SN	0.0139	0.0193	0.0201	0.0154	0.00907	0.0165
	(0.0387)	(0.0357)	(0.0320)	(0.0320)	(0.0381)	(0.0384)
others_SN	-0.0692	-0.0701	-0.0664	0.0205	-0.0585	-0.0717
	(0.0608)	(0.0572)	(0.0535)	(0.0531)	(0.0531)	(0.0530)
log_inc_pre_ca	0.0944**	0.0560	0.0255	0.0284	0.0449	0.0823*
	(0.0450)	(0.0459)	(0.0309)	(0.0458)	(0.0312)	(0.0464)
job_flex_ca	0.321***	0.218**	0.180*	0.307***	0.128**	0.293***
	(0.0728)	(0.0988)	(0.0941)	(0.0575)	(0.0705)	(0.0578)
ends_meet_ca	-0.194***	-0.0724	-0.203***	-0.172***	-0.214***	-0.153**
	(0.0442)	(0.0842)	(0.0414)	(0.0629)	(0.0555)	(0.0700)
diagnosed_ca	0.172	-0.0477	0.445***	0.127	0.275*	0.419***
	(0.134)	(0.178)	(0.164)	(0.139)	(0.164)	(0.139)
ca_symptoms	0.351*	0.220	0.153	0.330*	0.381**	0.311*
	(0.182)	(0.196)	(0.183)	(0.183)	(0.185)	(0.183)
longterm_condition	-0.196***	-0.167**	-0.151**	0.0298	0.00870	0.0320
	(0.0737)	(0.0746)	(0.0721)	(0.0595)	(0.0598)	(0.0595)
health	0.0533	-0.0377	-0.0601	0.207***	0.0985*	0.204***
	(0.0410)	(0.0577)	(0.0334)	(0.0332)	(0.0330)	(0.0578)
pain	-0.0319	-0.115	-0.132*	-0.0515	0.190***	0.174***
	(0.0755)	(0.0789)	(0.0716)	(0.0616)	(0.0618)	(0.0616)
bmi_cat	-0.136***	-0.0817	-0.0633	-0.0668*	-0.0740**	-0.120**
	(0.0431)	(0.0523)	(0.0352)	(0.0350)	(0.0353)	(0.0489)
flu_vax	-0.144*	-0.168**	-0.166**	-0.153*	-0.110	0.0818
	(0.0810)	(0.0743)	(0.0715)	(0.0823)	(0.0916)	(0.0813)
iadl_score	0.0546	0.0250	0.0164	0.0494	0.0509	0.0531
	(0.0599)	(0.0629)	(0.0464)	(0.0461)	(0.0463)	(0.0628)
smoker	-0.0659	-0.0422	-0.0344	-0.0308	-0.0375	-0.0299
	(0.0867)	(0.0807)	(0.0698)	(0.0861)	(0.0842)	(0.0857)
alcohol	-0.0627	-0.0394	-0.0118	-0.00845	-0.0248	-0.0553
	(0.120)	(0.108)	(0.0932)	(0.0934)	(0.0939)	(0.117)
sport	-0.0488	-0.0385	-0.0335	0.112	-0.0423	0.111
	(0.164)	(0.159)	(0.155)	(0.145)	(0.145)	(0.145)
Constant	-1.464**	-1.605***	-0.320	-1.537**	0.736	-1.580***
	(0.608)	(0.564)	(0.597)	(0.582)	(0.688)	(0.607)
Observations	2,297	2,297	2,297	2,297	2,297	2,297
First Stage Instruments:						
upto_month_avg_SI		X	X	X		X
upto_month_avg_newcasesperm			X		X	X
covid_death				X	X	X
Degrees of overidentification		0	1	1	1	2
Amemiya-Lee-Newey χ^2 stat			1.551	3.281	2.056	7.153
Prob $>\chi^2$			0.2129	0.0701	0.1516	0.028

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.2: Estimation Results for `reduced_hours`.

VARIABLES	(1) OLS mh_ca	(2) OLS mh_ca	(3) OLS mh_ca	(4) OLS mh_ca	(5) OLS mh_ca
age	-0.00609	-0.00740	-0.00556	-0.00831*	-0.00653
	(0.00500)	(0.00500)	(0.00501)	(0.00499)	(0.00500)
female	0.286***	0.284***	0.281***	0.260***	0.279***
	(0.0567)	(0.0565)	(0.0566)	(0.0561)	(0.0565)
rel_status	-0.400***	-0.389***	-0.408***	-0.412***	-0.400***
	(0.0735)	(0.0733)	(0.0732)	(0.0735)	(0.0729)
isced97educ	0.0149	0.0183	0.0196	0.0103	0.0220
	(0.0254)	(0.0255)	(0.0251)	(0.0253)	(0.0253)
SN_contact	0.0116	0.00798	0.0145	0.00705	0.0118
	(0.0502)	(0.0501)	(0.0502)	(0.0502)	(0.0501)
SN_proximity	0.0760***	0.0774***	0.0704***	0.0674***	0.0715***
	(0.0256)	(0.0255)	(0.0254)	(0.0254)	(0.0254)
SN_closeness	0.0684	0.0667	0.0668	0.0615	0.0656
	(0.0511)	(0.0510)	(0.0508)	(0.0510)	(0.0507)
child_SN	0.00116	0.00201	0.00724	0.00728	0.00776
	(0.0303)	(0.0304)	(0.0304)	(0.0304)	(0.0304)
sibling_SN	0.00258	-0.000235	0.00713	0.0186	0.00498
	(0.0534)	(0.0532)	(0.0530)	(0.0526)	(0.0529)
parents_SN	-0.0129	-0.0118	-0.00345	0.00237	-0.00278
	(0.0665)	(0.0667)	(0.0663)	(0.0665)	(0.0664)
friends_SN	-0.0274	-0.0280	-0.0303	-0.0206	-0.0307
	(0.0321)	(0.0321)	(0.0322)	(0.0321)	(0.0322)
others_SN	0.0226	0.0209	0.0207	0.0284	0.0195
	(0.0539)	(0.0538)	(0.0534)	(0.0534)	(0.0533)
log_inc_pre_ca	0.0378	0.0281	0.0287	0.0433	0.0216
	(0.0313)	(0.0312)	(0.0309)	(0.0312)	(0.0308)
job_flex_ca	0.106*	0.102*	0.112*	0.128**	0.109*
	(0.0582)	(0.0586)	(0.0578)	(0.0580)	(0.0581)
ends_meet_ca	-0.195***	-0.200***	-0.200***	-0.216***	-0.203***
	(0.0415)	(0.0416)	(0.0408)	(0.0414)	(0.0411)
diagnosed_ca	0.445***	0.445***	0.418***	0.423***	0.418***
	(0.145)	(0.145)	(0.140)	(0.140)	(0.140)
ca_symptoms	0.162	0.155	0.121	0.135	0.116
	(0.185)	(0.185)	(0.185)	(0.186)	(0.184)
longterm_condition	0.0241	0.0264	0.0293	0.00867	0.0309
	(0.0601)	(0.0600)	(0.0599)	(0.0602)	(0.0599)
health	0.202***	0.199***	0.207***	0.197***	0.205***
	(0.0336)	(0.0336)	(0.0334)	(0.0332)	(0.0333)
pain	0.190***	0.189***	0.175***	0.190***	0.174***
	(0.0623)	(0.0623)	(0.0620)	(0.0622)	(0.0620)
bmi_cat	-0.0715**	-0.0694**	-0.0669*	-0.0737**	-0.0654*
	(0.0355)	(0.0354)	(0.0352)	(0.0355)	(0.0352)
flu_vax	0.0903	0.0871	0.0850	0.0988	0.0827
	(0.0688)	(0.0686)	(0.0685)	(0.0689)	(0.0684)
iadl_score	0.0542	0.0520	0.0550	0.0503	0.0533
	(0.0464)	(0.0466)	(0.0464)	(0.0466)	(0.0466)
smoker	-0.0202	-0.0199	-0.0312	-0.0376	-0.0307
	(0.0702)	(0.0702)	(0.0692)	(0.0695)	(0.0693)
alcohol	-0.0128	-0.0112	-0.00885	-0.0249	-0.00776
	(0.0935)	(0.0936)	(0.0940)	(0.0945)	(0.0941)
sport	0.0351	0.0373	0.112	0.0706	0.112
	(0.152)	(0.152)	(0.145)	(0.145)	(0.146)
upto_month_avg_SI	0.0220***	0.0245***	0.0213***		0.0232***
	(0.00560)	(0.00600)	(0.00556)		(0.00594)
upto_month_avg_newcasesperm		0.00414		-0.000613	0.00306
		(0.00293)		(0.00273)	(0.00290)
covid_death			0.233***	0.238***	0.230***
			(0.0481)	(0.0496)	(0.0479)
Constant	-0.392	-0.400	-0.419	0.761	-0.425
	(0.580)	(0.581)	(0.578)	(0.498)	(0.579)
Observations	2,297	2,297	2,297	2,297	2,297
F(m, n-(k+1))	15.39	8.34	19.97	11.54	13.6
Prob >F	0.0001	0.0002	0.0000	0.0000	0.0000
R-squared	0.123	0.124	0.133	0.127	0.134

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.3: First Stage Estimation Results for `reduced_hours`.

effects can be found in Table 9.9 of the Appendix.

6.4 Model 2 Results Analysis: Increased Work Hours

The second and final model explores the relationship between changes in mental health, as measured by the `mh_ca` index, and an increase in work hours since the onset of the COVID-19 pandemic, specifically among older working adults.

Much like the first model, a simple multiple Probit estimator is insufficient for establishing causality due to the presence of endogeneity. Therefore, a more appropriate IV Probit estimator is applied using the same instrument combinations seen in Model 1. Results are reported in Tables 6.4 and 6.5, along with F-statistics for instrument relevance and Amemiya-Lee-Newey (ALN) minimum chi-square statistics for instrument exogeneity in overidentified models.

The initial multiple Probit estimation, shown in column 1 of Table 6.4, reports no significance for the `mh_ca` coefficient. Formulating expectations in the case of `increased_hours` is less straightforward than in the case of `reduced_work`. For instance, one might expect to observe a higher likelihood of having increased work time if mental conditions are particularly good. However, the model's focus on pandemic-era data and individual behavior does not allow for differentiation between those who may have benefited from changes in routine and increased isolation, and those who may have been adversely affected. Therefore, the most likely outcome is that of no effect at all of mental conditions, instrumented with pandemic related variables, on the dependent. In simpler terms, while deteriorating mental health may lead to reduced work hours, improved mental well-being does not necessarily translate into increased work effort. Alternatively, it is possible that any change in mental health could affect work patterns, making this line of inquiry worthwhile.

6.4.1 Instrument Validity

The relevance testing for this model yields similar conclusions to those drawn in Model 1. Specifically, the instruments `upto_month_avg_SI` and `covid_death` emerge as the most relevant, while the inclusion of `upto_month_avg_newcasesperm` tends to lower the F-statistics.

In terms of the ALN tests for instrument exogeneity, the instruments perform better in this model compared to Model 1. Notably, none of the specifications result in a rejection of the null hypothesis, with p-values ranging from 0.6327 in column 5 to 0.8898 in column 4.

However, the sparse distribution of `covid_death` continues to introduce distortion in the standard errors for models that include it as an instrument. Given this, and the lack of relevance of `upto_month_avg_newcasesperm`, the model presented in columns 2 of Table 6.4 and 1 of Table 6.3 is deemed to be the most reliable for this analysis. This model utilizes only `upto_month_avg_SI` as an instrument, and possesses an F-statistic of 15.14, which exceeds the Stock and Yogo critical value of 9.66 for a 15% maximal IV size, thereby leading to a rejection of the null hypothesis of instrument irrelevance. Furthermore, the ALN statistics do not raise any concerns about instrument exogeneity, solidifying the credibility of this model. Figure 6.1 provides point estimates and confidence intervals of second stage results for the preferred iteration of Model 1 and Model 2, ordered by magnitude of estimated coefficients.

6.4.2 Interpretation

In the first stage of the analysis, the findings mirror those of Model 1. However, the second stage reveals some distinct patterns. Among health-related variables, only self-rated health emerges as significant, displaying a negative coefficient. This suggests that individuals who rate their health poorly are less likely to have increased their working hours since the pandemic began. Neither self-reported pain levels nor recent diagnoses of long-term conditions significantly influence the outcome.

For financial covariates, while financial stability as measured by `ends_meet_ca` is not significant, the logarithm of pre-pandemic income shows a positive and significant relationship with increased working hours. This implies that individuals with higher incomes prior to the pandemic are more likely to have increased their work hours.

None of the social network covariates are significant. On the other hand, education level is positively and significantly associated with `increased_hours`, while age is negatively associated with it.

Most notably, the mental health index (`mh_ca`) is not significant at any level, reinforcing the initial hypothesis that mental health conditions have a less pronounced effect on the likelihood of increasing work hours compared to reducing them.

	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	IV Probit	IV Probit	IV Probit	IV Probit	IV Probit
VARIABLES	increased_hours	increased_hours	increased_hours	increased_hours	increased_hours	increased_hours
mh_ca	0.0294	0.332	0.292	0.357***	0.374**	0.346**
	(0.0266)	(0.256)	(0.258)	(0.134)	(0.154)	(0.136)
age	-0.0176***	-0.0135*	-0.00727	-0.0129*	-0.0126*	-0.0131*
	(0.00680)	(0.00791)	(0.00496)	(0.00682)	(0.00497)	(0.00686)
female	0.0343	-0.0493	-0.0378	0.280***	-0.0613	-0.0536
	(0.0752)	(0.102)	(0.0562)	(0.0562)	(0.0834)	(0.0809)
rel_status	-0.108	0.0222	-0.389***	-0.407***	-0.411***	-0.400***
	(0.0881)	(0.147)	(0.0729)	(0.0727)	(0.0731)	(0.0725)
isced97educ	0.0946***	0.0859**	0.0879**	0.0198	0.0846***	0.0218
	(0.0328)	(0.0348)	(0.0342)	(0.0321)	(0.0251)	(0.0322)
SN_contact	-0.0548	-0.0514	-0.0524	0.0129	0.00591	0.0108
	(0.0547)	(0.0547)	(0.0499)	(0.0540)	(0.0539)	(0.0541)
SN_proximity	0.000395	-0.0224	-0.0192	0.0705***	-0.0265	0.0713***
	(0.0281)	(0.0332)	(0.0254)	(0.0253)	(0.0299)	(0.0252)
SN_closeness	0.0417	0.0188	0.0227	0.0681	0.0145	0.0174
	(0.0658)	(0.0655)	(0.0507)	(0.0504)	(0.0628)	(0.0629)
child_SN	0.0283	0.0261	0.00246	0.00780	0.00778	0.00825
	(0.0361)	(0.0351)	(0.0302)	(0.0302)	(0.0302)	(0.0348)
sibling_SN	0.0471	0.0380	0.00565	0.0372	0.0356	0.0112
	(0.0619)	(0.0621)	(0.0532)	(0.0529)	(0.0524)	(0.0528)
parents_SN	-0.0735	-0.0646	-0.0126	-0.00404	0.00138	-0.00346
	(0.0926)	(0.0887)	(0.0897)	(0.0875)	(0.0873)	(0.0660)
friends_SN	0.0739*	0.0736*	0.0745**	0.0731*	-0.0190	-0.0290
	(0.0383)	(0.0379)	(0.0320)	(0.0320)	(0.0372)	(0.0374)
others_SN	0.0828	0.0672	0.0210	0.0657	0.0646	0.0665
	(0.0576)	(0.0594)	(0.0591)	(0.0571)	(0.0530)	(0.0530)
log_inc_pre_ca	0.178***	0.148**	0.154**	0.143***	0.0444	0.145***
	(0.0526)	(0.0607)	(0.0310)	(0.0522)	(0.0541)	(0.0307)
job_flex_ca	0.166**	0.117	0.103*	0.114**	0.108	0.111*
	(0.0734)	(0.0880)	(0.0874)	(0.0574)	(0.0770)	(0.0578)
ends_meet_ca	0.0337	0.0970	0.0890	-0.202***	-0.217***	0.0989*
	(0.0495)	(0.0693)	(0.0708)	(0.0536)	(0.0411)	(0.0409)
diagnosed_ca	-0.130	-0.258	-0.242	0.416***	-0.280*	0.416***
	(0.145)	(0.171)	(0.144)	(0.139)	(0.152)	(0.150)
ca_symptoms	-0.393*	-0.416**	-0.415*	-0.419**	0.135	-0.418**
	(0.227)	(0.210)	(0.184)	(0.184)	(0.185)	(0.209)
longterm_condition	-0.0503	-0.0476	-0.0482	0.0298	0.00952	-0.0454
	(0.0748)	(0.0720)	(0.0596)	(0.0595)	(0.0598)	(0.0713)
health	-0.108**	-0.160***	0.200***	0.207***	-0.164***	-0.162***
	(0.0423)	(0.0538)	(0.0559)	(0.0331)	(0.0441)	(0.0438)
pain	0.183**	0.106	0.118	0.0952	0.192***	0.0989
	(0.0762)	(0.107)	(0.106)	(0.0839)	(0.0618)	(0.0841)
bmi_cat	0.0221	0.0447	-0.0704**	-0.0678*	-0.0748**	0.0468
	(0.0442)	(0.0461)	(0.0470)	(0.0430)	(0.0430)	(0.0432)
flu_vax	0.0534	0.0172	0.0224	0.0879	0.102	0.0859
	(0.0815)	(0.0854)	(0.0861)	(0.0802)	(0.0808)	(0.0680)
iadl_score	0.0150	-0.000689	0.0519	-0.00183	0.0502	0.0532
	(0.0570)	(0.0536)	(0.0545)	(0.0509)	(0.0462)	(0.0512)
smoker	-0.0357	-0.0237	-0.0205	-0.0320	-0.0276	-0.0316
	(0.0900)	(0.0849)	(0.0861)	(0.0841)	(0.0690)	(0.0845)
alcohol	-0.180	-0.159	-0.164	-0.155	-0.151	-0.00788
	(0.139)	(0.135)	(0.0931)	(0.0935)	(0.130)	(0.0935)
sport	-0.170	-0.155	-0.158	-0.141	0.0708	-0.142
	(0.169)	(0.168)	(0.169)	(0.144)	(0.170)	(0.144)
Constant	-1.646***	-1.768***	-0.403	-1.772***	0.743	-0.412
	(0.633)	(0.595)	(0.605)	(0.567)	(0.495)	(0.592)
Observations	2,296	2,296	2,296	2,296	2,296	2,296
First Stage Instruments:						
upto_month_avg_SI		X	X	X		X
upto_month_avg_newcasesperm			X		X	X
covid_death				X	X	X
Degrees of overidentification		0	1	1	1	2
Amemiya-Lee-Newey χ^2 stat			0.216	0.019	0.228	0.357
Prob $>\chi^2$			0.6424	0.8898	0.6327	0.8364

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.4: Estimation Results for `increased_hours`.

VARIABLES	(1) OLS mh_ca	(2) OLS mh_ca	(3) OLS mh_ca	(4) OLS mh_ca	(5) OLS mh_ca
age	-0.00610	-0.00737	-0.00556	-0.00826*	-0.00651
	(0.00500)	(0.00500)	(0.00501)	(0.00499)	(0.00500)
female	0.286***	0.284***	0.281***	0.260***	0.279***
	(0.0567)	(0.0565)	(0.0566)	(0.0561)	(0.0565)
rel_status	-0.398***	-0.388***	-0.407***	-0.410***	-0.399***
	(0.0735)	(0.0733)	(0.0732)	(0.0735)	(0.0729)
isced97educ	0.0152	0.0184	0.0198	0.0106	0.0222
	(0.0254)	(0.0255)	(0.0251)	(0.0253)	(0.0253)
SN_contact	0.0100	0.00656	0.0130	0.00550	0.0104
	(0.0503)	(0.0502)	(0.0503)	(0.0502)	(0.0502)
SN_proximity	0.0761***	0.0774***	0.0705***	0.0675***	0.0716***
	(0.0256)	(0.0255)	(0.0254)	(0.0254)	(0.0254)
SN_closeness	0.0697	0.0680	0.0681	0.0631	0.0669
	(0.0511)	(0.0510)	(0.0508)	(0.0510)	(0.0507)
child_SN	0.00170	0.00251	0.00777	0.00786	0.00827
	(0.0303)	(0.0304)	(0.0304)	(0.0304)	(0.0304)
sibling_SN	0.00850	0.00554	0.0130	0.0249	0.0108
	(0.0537)	(0.0535)	(0.0533)	(0.0527)	(0.0531)
parents_SN	-0.0136	-0.0125	-0.00413	0.00154	-0.00347
	(0.0666)	(0.0667)	(0.0663)	(0.0665)	(0.0664)
friends_SN	-0.0258	-0.0264	-0.0286	-0.0189	-0.0290
	(0.0322)	(0.0322)	(0.0322)	(0.0321)	(0.0322)
others_SN	0.0227	0.0210	0.0208	0.0284	0.0196
	(0.0539)	(0.0538)	(0.0534)	(0.0533)	(0.0533)
log_inc_pre_ca	0.0382	0.0287	0.0290	0.0437	0.0222
	(0.0314)	(0.0312)	(0.0309)	(0.0312)	(0.0308)
job_flex_ca	0.108*	0.103*	0.114**	0.129**	0.110*
	(0.0582)	(0.0586)	(0.0578)	(0.0580)	(0.0581)
ends_meet_ca	-0.197***	-0.202***	-0.202***	-0.218***	-0.205***
	(0.0415)	(0.0417)	(0.0409)	(0.0414)	(0.0411)
diagnosed_ca	0.443***	0.443***	0.416***	0.421***	0.416***
	(0.145)	(0.145)	(0.139)	(0.140)	(0.140)
ca_symptoms	0.162	0.154	0.121	0.134	0.116
	(0.185)	(0.185)	(0.185)	(0.186)	(0.184)
longterm_condition	0.0247	0.0269	0.0299	0.00950	0.0314
	(0.0601)	(0.0600)	(0.0599)	(0.0602)	(0.0599)
health	0.202***	0.199***	0.207***	0.198***	0.205***
	(0.0336)	(0.0336)	(0.0334)	(0.0332)	(0.0333)
pain	0.192***	0.190***	0.177***	0.192***	0.176***
	(0.0624)	(0.0623)	(0.0620)	(0.0622)	(0.0620)
bmi_cat	-0.0724**	-0.0703**	-0.0678*	-0.0747**	-0.0663*
	(0.0355)	(0.0354)	(0.0352)	(0.0355)	(0.0352)
flu_vax	0.0932	0.0900	0.0879	0.102	0.0856
	(0.0688)	(0.0686)	(0.0685)	(0.0689)	(0.0684)
iadl_score	0.0539	0.0517	0.0546	0.0500	0.0530
	(0.0463)	(0.0465)	(0.0463)	(0.0465)	(0.0465)
smoker	-0.0209	-0.0205	-0.0319	-0.0383	-0.0314
	(0.0702)	(0.0702)	(0.0692)	(0.0695)	(0.0693)
alcohol	-0.0127	-0.0111	-0.00873	-0.0246	-0.00767
	(0.0935)	(0.0936)	(0.0941)	(0.0946)	(0.0941)
sport	0.0347	0.0369	0.111	0.0706	0.112
	(0.152)	(0.152)	(0.145)	(0.145)	(0.145)
upto_month_avg_SI	0.0218***	0.0243***	0.0212***		0.0230***
	(0.00560)	(0.00601)	(0.00556)		(0.00594)
upto_month_avg_newcasesperm		0.00405		-0.000674	0.00297
		(0.00293)		(0.00273)	(0.00290)
covid_death			0.233***	0.238***	0.230***
			(0.0481)	(0.0496)	(0.0479)
Constant	-0.386	-0.394	-0.413	0.755	-0.419
	(0.580)	(0.581)	(0.578)	(0.498)	(0.579)
Observations	2,296	2,296	2,296	2,296	2,296
F(m, n-(k+1))	15.14	8.19	19.83	11.55	13.49
Prob >F	0.0001	0.0003	0	0	0
R-squared	0.124	0.124	0.134	0.128	0.134

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6.5: First Stage Estimation Results for `increased_hours`.

6.5 Discussing Limitations

In discussing the limitations of the models, two key issues warrant attention. First, the merging of SHARE Wave 8 and SCS data has a significant impact on sample composition. Due to the varying progress levels of Wave 8 fieldwork across countries at the time of halt, there are substantial gaps in the data for certain nations. For example, Estonia is overrepresented in the sample (14.76%) and Spain is underrepresented (0.61%), which raises questions about the generalizability of the results. Even though the SCS provides much more balanced country representation, the impossibility to track all units across the two data sources limits sample balance.

Additionally, when interpreting the results of both Model 1 and Model 2, it is crucial to note that the IV estimations yield Local Average Treatment Effects (LATE) rather than Average Treatment Effects (ATE). This means that the estimated effects are specific to the subpopulation for whom the instruments (`upto_month_avg_SI` and `covid_death`) actually influence mental well-being (`mh_ca`). Therefore, results cannot necessarily be generalized to the overall population, but are localized to the compliers in the sample. In the context of this study, the complier group consists of older adults who remained employed throughout the pandemic, and whose mental well-being is actually influenced by the government containment measures as tracked by the OxGRT Stringency Index.

While some findings may be applicable to other demographic groups, such as relatively younger working adults, they are not directly transferable to populations like teens or pre-teens, who have different behavioral dynamics, or even very young working adults. According to other literature, these latter groups, along with older adults and at-risk populations, are among the most affected by mental health issues (WHO, 2022).

6.6 Robustness Checks

An issue that warrants specific scrutiny is the potential endogeneity of certain regressors, particularly those related to social networks and financial status. Specifically, social network and financial covariates may be affected by reverse causality issues.

To address this concern and mitigate the risk of endogeneity, I estimated Model 1 and Model

2 employing a reduced set of covariates, which excluded the following potentially problematic controls: `SN_contact`, `SN_proximity`, `SN_closeness`, `child_SN`, `parents_SN`, `friends_SN`, `others_SN`, `log_inc_pre_ca`, `job_flex_ca` and `ends_meet_ca`. IV Probit estimation results of the preferred model iteration are reported in Table 6.6, complete with the first stage F-statistic to evaluate the relevance of the `upto_month_avg_SI` instrumental variable.

Model 1 shows improved instrument relevance with an F-statistic of 18.7, up from the previousle observed 15.39. This score surpasses the Stock and Yogo benchmark for 5% confidence and 10% maximal IV size, indicating a robust model. Furthermore, the key coefficient `mh_ca` rises to 0.530 and is highly significant, confirming earlier findings. As for Model 2, it also exhibits an F-statistic of 18.7, meeting the Stock and Yogo criteria for 10% maximal IV size. However, the results diverge from those of the full controls model. While the earlier model in Column 2 of Table 6.4 showed a non-significant coefficient of 0.332 for `mh_ca`, the updated results in Table 6.6 reveal a coefficient of 0.408, which is significant at the 5% level.

The change in the significance of the regressor of interest in Model 2 warrants further discussion. The omission of social network indicators is motivated by previous literature describing a relation between mental health and network characteristics which is fraught with reverse causality concerns. For this reason, the exclusion of this set of covariates may have improved the model's ability to isolate the effect of mental conditions on labor market participation.

Conversely, the exclusion of financial indicators is more problematic. Financial stability is a major factor affecting mental health, and research would suggest that the effect of financial status on mental conditions is stronger than the reverse (Hajek and König (2022), Niedzwiedz et al. (2016)). By excluding these variables, the model might be missing out on important controls, which could bias the coefficients of the remaining variables. Reintroducing only the financial covariates (`log_inc_pre_ca`, `job_flex_ca` and `ends_meet_ca`) into the model seems to accredit this suspicion: `mh_ca` drops back to 0.38, not significant at any level.

6.7 Conclusion

This chapter has provided a comprehensive analysis of two models to understand the impact of mental health on labor market participation since the onset of the COVID-19 pandemic. I began by outlining the tests for instrument validity, focusing on relevance and exogeneity, to

VARIABLES	(1) IV Probit reduced_hours	(1) IV Probit increased_hours
mh_ca	0.530***	0.408**
	(0.140)	(0.194)
age	0.0129**	-0.00796
	(0.00523)	(0.00677)
female	-0.176**	-0.109
	(0.0726)	(0.0905)
rel_status	0.334***	0.184
	(0.0838)	(0.121)
isced97educ	-0.0273	0.129***
	(0.0254)	(0.0380)
diagnosed_ca	-0.109	-0.267*
	(0.158)	(0.155)
ca_symptoms	0.167	-0.400**
	(0.182)	(0.201)
longterm_condition	-0.160**	-0.0160
	(0.0709)	(0.0687)
health	-0.0707	-0.226***
	(0.0458)	(0.0395)
pain	-0.125*	0.0776
	(0.0740)	(0.0999)
bmi_cat	-0.0666	0.0392
	(0.0468)	(0.0430)
flu_vax	-0.155**	0.0510
	(0.0708)	(0.0828)
iadl_score	0.0232	0.00123
	(0.0597)	(0.0503)
smoker	-0.0348	-0.0700
	(0.0753)	(0.0814)
alcohol	-0.0369	-0.164
	(0.103)	(0.129)
sport	-0.0437	-0.133
	(0.154)	(0.161)
Constant	-1.437***	-0.721
	(0.420)	(0.470)
Observations	2,297	2,296
F(m, n-(k+1))	18.79	18.78
Prob >F	0.0000	0.0000

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

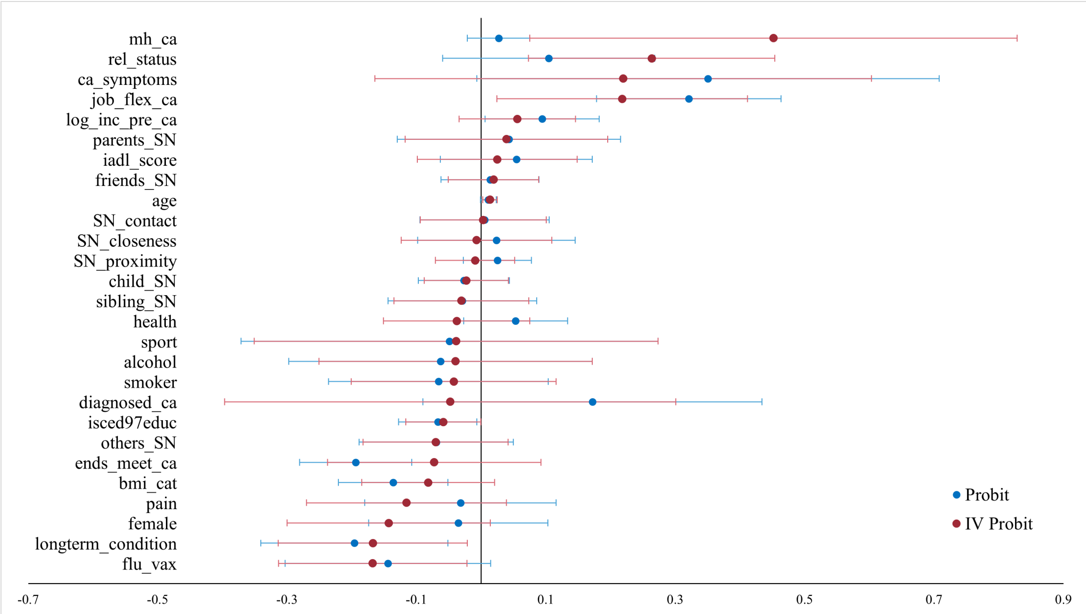
Table 6.6: Robustness Check for Model 1 and Model 2 using a reduced set of variables.

ensure the robustness of our IV Probit estimators. Through a series of tests, I identified the most reliable specifications for both Model 1 and Model 2.

For Model 1, the preferred specification revealed that a one-unit increase in the mental health index (`mh_ca`) is associated with a 12.8% increase in the probability of having reduced work hours, significant at the 5% level. This model also highlighted the role of various covariates such as age, education, and job flexibility in influencing work hours. In contrast, Model 2 showed that mental health (`mh_ca`) did not significantly affect the likelihood of increasing work hours. However, it did reveal that higher pre-pandemic income and education levels were positively associated with an increase in work hours, while age had a negative association.

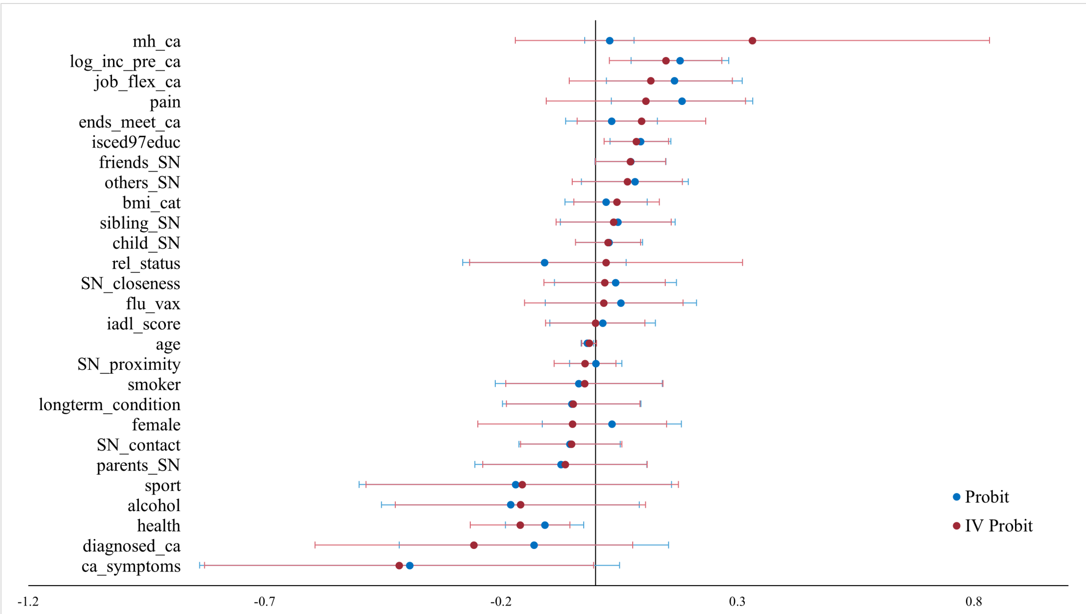
Notably, of the three proposed instruments, `upto_month_avg_newcasesperm` lacked the necessary relevance to explain `mh_ca`. Instead, `covid_death` and `upto_month_avg_SI` proved to be particularly strong predictors of mental well-being. Unfortunately, the distribution of `covid_death` is extremely skewed towards zero, thus its inclusion generated noise in the estimation process, confounding second stage standard error estimates of the endogenous. A reason for this sparsity is possibly due to the timing of data collection being more concentrated toward the first waves of the pandemic. However, as SHARE Wave 9 is released, this same model can be replicated in combination with the second iteration of the SHARE Corona Survey and updated data.

Figure 6.1: Point Estimates and Confidence Intervals for Preferred Model Versions.



(a) From Table 6.2, Column 2. Dependent Variable: `reduced_hours`.

Instrumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.



(b) From Table 6.4, Column 2. Dependent Variable: `increased_hours`.

Instrumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.

7 Conclusion

The overarching research objective of this study has been the exploration of how mental health, as measured by an ad-hoc index constructed from SHARE data, affects individual outcomes, specifically labor market participation during the COVID-19 pandemic. The demographic of reference are working older European adults with an average age of roughly 61 years.

In Chapter 2, I set the stage by outlining the importance of mental well-being, defining what constitutes mental health, discussing the epidemiology of common disorders, and exploring the impact of COVID-19 on mental health. In Chapter 3, I framed the research question through a detailed literature review. I emphasized publications that focus on correlational analyses and pointed out those that fall short in tackling the methodological challenges of establishing a causal link between mental health conditions and individual outcomes. I categorized the literature into three main areas related to mental health: labor market outcomes, individual conditions like loneliness, and social capital, specifically focusing on social networks. A deep understanding of the interactions between multiple factors and mental health is essential for a comprehensive view of the subject, and motivates the selection on observables.

In Chapter 4, I introduced the data sources for this study, specifically the SHARE and OxGRT datasets. I elaborated on the rationale behind using the `mh_ca` indicator to measure mental health conditions and detailed the dependent and independent variables used in the models. In Chapter 5, I tackled the identification challenges arising from the endogeneity of `mh_ca` and proposed methodological solutions. Specifically, I addressed issues of reverse causality, measurement error, and simultaneity through the use of IV-Probit models, employing a combination of three candidate instrumental variables. Such variables are represented by: a Stringency Index provided by the OxGRT dataset, the number of COVID-19 cases per million inhabitants in the state of residence of the respondent and, finally, an indicator capturing the number of COVID-19 related deaths experienced by the individual and the strenght of their relationship with the respondent.

In Chapter 6, I began by discussing the tools used to test the validity of the instrumental variables, a critical aspect of the IV-Probit methodology. Then, I presented various modeling alternatives for two models: Model 1, which uses `reduced_hours` as the dependent variable, and Model 2, based on the `increased_hours` dependent variable. Between the three instrumental variables candidates, the Stringency Index `upto_month_avg_SI` proved to be the most valid. Conversely, the more appealing candidate `covid_death` was fatally affected by distribution sparsity, motivating its exclusion to preserve second stage estimate accuracy. Finally, `upto_month_avg_newcasesperm` failed relevance testing.

Results from the most reliable model iterations revealed a significant positive impact of worse mental health on the probability of having reduced working hours since the start of the pandemic. On the other hand, neither better nor worse mental conditions are significantly associated with increased working hours.

These results align with existing literature and underscore the importance of maintaining good mental health to prevent negative individual outcomes. The findings also support the need for systemic interventions to increase awareness, reduce stigma, and improve access to mental health services. I argue that the reduction in work hours due to poor mental health has had a negative impact on value creation during the pandemic. Similar systemic shocks could reasonably produce comparable effects in this demographic. Furthermore, according to previous literature, this specific cohort of older working adults has been less affected by the mental health impact of COVID-19 relative to the younger demographics or other at-risk groups, for which effects on individual outcomes could be comparatively stronger. Therefore, affordable care and widespread information are crucial for mitigating adverse impacts and promoting a swift return to healthier conditions.

This dissertation has several limitations that warrant discussion. First, the composition of the sample is influenced by data availability in the SHARE Wave 8 and Corona Survey datasets. Some countries are disproportionately represented, while others with large populations are notably underrepresented. Furthermore, the cross-section nature of the dataset restricts modeling choices. Second, the use of IV-Probit methodology restricts the interpretation of results to Local Average Treatment Effects (LATE), limiting the generalizability of the findings.

A further limitation arises from the use of IV-Probit with this specific dataset. The candidate instrument `covid_death` is arguably the most relevant and exogenous, but its distribution is heavily skewed toward zero. This skewness adversely affects the second-stage standard error estimates of the endogenous variable, forcing us to exclude it from the instrument pool. For future research, the model and dataset could be expanded to panel data methods from the forthcoming SHARE Wave 9 and the second version of the Corona Survey. This would potentially address a number of the aforementioned limitations. Nonetheless, the results are consistent in both magnitude and interpretation with prior studies, such as Frijters et al. (2010), thereby enhancing credibility.

In conclusion, policymakers should target older working adults with interventions aimed at prioritizing mental health in order to improve labor market participation during adverse systemic events, such as-but not limited to-a pandemic. Specific interventions could include mental health screenings, subsidized counseling services, or workplace mental health programs to provide easily available and effective means of intervention and care.

This dissertations contributes to the existing literature by providing empirical evidence of the impact of mental health on labor market outcomes during a global adverse event. The study's novelty lies in its methodological approach, combining Probit methods—commonly used in this field—with innovative Instrumental Variables to tackle endogeneity issues. Specifically, the stringency of government responses to the virus serves as a relevant and, based on tests on overidentified model iterations, reasonably exogenous instrument in relation to the working time choices of the target demographic.

In summary, this dissertation not only sheds light on the complex interplay between mental health and labor market outcomes but also offers a methodologically rigorous approach to addressing endogeneity issues. While the findings suggest the urgent need for targeted mental health interventions among older working adults in the wake of shocks such as the COVID-19 pandemic, further research is needed to generalize these results and inform policy.

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This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8 and 9 (DOIs: 10.6103/SHARE.w1.800, 10.6103/SHARE.w2.800, 10.6103/SHARE.w3.800, 10.6103/SHARE.w4.800, 10.6103/SHARE.w5.800, 10.6103/SHARE.w6.800, 10.6103/SHARE.w7.800, 10.6103/SHARE.w8.800, 10.6103/SHARE.w8ca.800, 10.6103/SHARE.w9ca800) see Börsch-Supan et al. (2013) for methodological details.(1) The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782, SHARE-COVID19: GA N°101015924) and by DG Employment, Social Affairs and Inclusion through VS 2015/0195, VS 2016/0135, VS 2018/0285, VS 2019/0332, and VS 2020/0313. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C, RAG052527A) and from various national funding sources is gratefully acknowledged (see `www.share-project.org`*).*

9 Appendix

9.1 R-UCLA & EURO-D Scales

Statement	Never	Rarely	Sometimes	Often
I feel in tune with the people around me	1	2	3	4
I lack companionship	1	2	3	4
There is no one I can turn to	1	2	3	4
I do not feel alone	1	2	3	4
I feel part of a group of friends	1	2	3	4
I have a lot in common with the people around me	1	2	3	4
I am no longer close to anyone	1	2	3	4
My interests and ideas are not shared by those around me	1	2	3	4
I am an outgoing person	1	2	3	4
There are people I feel close to	1	2	3	4
I feel left out	1	2	3	4
My social relationships are superficial	1	2	3	4
No one really knows me well	1	2	3	4
I feel isolated from others	1	2	3	4
I can find companionship when I want it	1	2	3	4
There are people who really understand me	1	2	3	4
I am unhappy being so withdrawn	1	2	3	4
People are around me but not with me	1	2	3	4
There are people I can talk to	1	2	3	4
There are people I can turn to	1	2	3	4

Table 9.1: R-UCLA scale items and scoring.

Statement	**Symptom**	**Agree**	**Disagree**
In the last month, have you been sad or depressed?	Depression	1	0
What are your hopes for the future?	Pessimism	1	0
In the last month, have you felt that you would rather be dead?	Suicidality	1	0
Do you tend to blame yourself or feel guilty about anything?	Guilt	1	0
Have you had trouble sleeping recently?	Sleep	1	0
In the last month, what is your interest in things?	Interest	1	0
Have you been irritable recently?	Irritability	1	0
What has your appetite been like?	Appetite	1	0
In the last month, have you had too little energy to do the things you wanted to do?	Fatigue	1	0
How is your concentration? For example, can you concentrate on a television program, film or radio program? Can you concentrate on something you read?	Concentration	1	0
What have you enjoyed doing recently?	Enjoyment	1	0
In the last month, have you cried at all?	Tearfulness	1	1

Table 9.2: EURO-D scale items and scoring.

9.2 Models Summary Statistics

Model 1: `reduced_hours`

Country identifier	**0**	**1**	**Total**	**Percent**
Austria	36	7	43	1.87%
Belgium	108	19	127	5.53%
Bulgaria	65	11	76	3.31%
Croatia	49	5	54	2.35%
Cyprus	8	2	10	0.44%
Denmark	202	18	220	9.58%
Estonia	282	57	339	14.76%
Finland	108	14	122	5.31%
France	55	21	76	3.31%
Germany	205	44	249	10.84%
Greece	79	18	97	4.22%
Hungary	14	2	16	0.70%
Israel	22	4	26	1.13%
Italy	41	20	61	2.66%
Latvia	72	5	77	3.35%
Lithuania	143	19	162	7.05%
Luxembourg	11	3	14	0.61%
Malta	10	7	17	0.74%
Netherlands	27	11	38	1.65%
Poland	99	24	123	5.35%
Romania	54	9	63	2.74%
Slovenia	39	6	45	1.96%
Spain	9	5	14	0.61%
Sweden	94	16	110	4.79%
Switzerland	84	34	118	5.14%
Total	**1916**	**381**	**2297**	**100%**

Table 9.3: Country Composition of the Sample.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
reduced_hours	2297	0.1659	0.3720	0	1
mh_ca	2297	0.8296	1.3224	0	7
age	2297	60.7266	5.4547	37	90
female	2297	0.5908	0.4918	0	1
rel_status	2297	0.7222	0.4480	0	1
isced97educ	2297	3.8633	1.1494	1	6
SN_contact	2297	1.9304	0.9084	1	6
SN_proximity	2297	3.5358	1.6752	1	8
SN_closeness	2297	3.2523	0.5748	1	4
child_SN	2297	0.8542	0.9523	0	7
sibling_SN	2297	0.2773	0.5845	0	5
parents_SN	2297	0.1241	0.3588	0	2
friends_SN	2297	0.6670	1.0246	0	7
others_SN	2297	0.1959	0.5513	0	6
log_inc_pre_ca	2297	7.5702	0.9219	-2.009	14.627
job_flex_ca	2297	0.3875	0.4873	0	1
ends_meet_ca	2297	3.1367	0.8703	1	4
diagnosed_ca	2297	0.0588	0.2352	0	1
ca_symptoms	2297	0.0287	0.1671	0	1
longterm_condition	2297	0.4523	0.4978	0	1
health	2297	2.7902	0.9414	1	5
pain	2297	0.3274	0.4694	0	1
bmi_cat	2297	2.9203	0.7888	1	4
flu_vax	2297	0.2138	0.4100	0	1
iadl_score	2297	0.0805	0.5247	0	9
smoker	2297	0.1872	0.3902	0	1
alcohol	2297	0.0814	0.2735	0	1
sport	2297	0.9604	0.1951	0	1

Table 9.4: Summary Statistics of Dependent and Independent Variables.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
covid_death	2297	0.0674793	0.5808128	0	18
upto_month_avg_SI	2297	42.25638	5.149009	34.84262	58.863
upto_month_avg_newcasesperm	2297	14.25918	10.47381	1.535301	49.18575

Table 9.5: Summary Statistics of Instrumental Variables.

Model 2: `increased_hours`

Country identifier	0	1	Total	Percent
Austria	34	9	43	1.87%
Belgium	95	32	127	5.53%
Bulgaria	70	6	76	3.31%
Croatia	46	8	54	2.35%
Cyprus	9	1	10	0.44%
Denmark	175	45	220	9.58%
Estonia	304	35	339	14.76%
Finland	101	20	121	5.27%
France	59	17	76	3.31%
Germany	213	36	249	10.84%
Greece	88	9	97	4.22%
Hungary	13	3	16	0.70%
Israel	24	2	26	1.13%
Italy	50	11	61	2.66%
Latvia	70	7	77	3.35%
Lithuania	134	28	162	7.06%
Luxembourg	11	3	14	0.61%
Malta	15	2	17	0.74%
Netherlands	30	8	38	1.66%
Poland	118	5	123	5.36%
Romania	61	2	63	2.74%
Slovenia	39	6	45	1.96%
Spain	9	5	14	0.61%
Sweden	99	11	110	4.79%
Switzerland	99	19	118	5.14%
Total	**1966**	**330**	**2296**	**100%**

Table 9.6: Country Composition of the Sample.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
increased_hours	2296	0.1437	0.3509	0	1
mh_ca	2296	0.8299	1.3226	0	7
age	2296	60.7265	5.4559	37	90
female	2296	0.5906	0.4918	0	1
rel_status	2296	0.7221	0.4480	0	1
isced97educ	2296	3.8628	1.1494	1	6
SN_contact	2296	1.9304	0.9086	1	6
SN_proximity	2296	3.5353	1.6754	1	8
SN_closeness	2296	3.2520	0.5748	1	4
child_SN	2296	0.8541	0.9525	0	7
sibling_SN	2296	0.2761	0.5818	0	5
parents_SN	2296	0.1241	0.3589	0	2
friends_SN	2296	0.6664	1.0244	0	7
others_SN	2296	0.1960	0.5514	0	6
log_inc_pre_ca	2296	7.5701	0.9221	-2.009	14.627
job_flex_ca	2296	0.3872	0.4872	0	1
ends_meet_ca	2296	3.1372	0.8702	1	4
diagnosed_ca	2296	0.0588	0.2353	0	1
ca_symptoms	2296	0.0287	0.1671	0	1
longterm_condition	2296	0.4521	0.4978	0	1
health	2296	2.7901	0.9416	1	5
pain	2296	0.3271	0.4693	0	1
bmi_cat	2296	2.9207	0.7887	1	4
flu_vax	2296	0.2134	0.4098	0	1
iadl_score	2296	0.0806	0.5248	0	9
smoker	2296	0.1873	0.3902	0	1
alcohol	2296	0.0814	0.2736	0	1
sport	2296	0.9604	0.1951	0	1

Table 9.7: Summary Statistics of Dependent and Independent Variables.

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
covid_death	2296	0.067509	0.580938	0	18
upto_month_avg_SI	2296	42.25802	5.149529	34.84262	58.863
upto_month_avg_newcasesperm	2296	14.26275	10.4747	1.535301	49.18575

Table 9.8: Summary Statistics of Instrumental Variables.

9.3 Model 1 Results: Marginal Effects

reduced_hours	**dy/dx**	**Robust Std. Err.**	**z**	**P>Z**	**[90% Conf. Int.]**	
mh_ca	0.127794	0.077242	1.65	0.098	0.000742	0.254846
age	0.003839	0.001714	2.24	0.025	0.001019	0.006659
female	-0.04036	0.027635	-1.46	0.144	-0.08582	0.005094
rel_status	0.074605	0.037219	2	0.045	0.013385	0.135826
isced97educ	-0.01648	0.00802	-2.05	0.04	-0.02967	-0.00328
SN_contact	0.000908	0.014057	0.06	0.949	-0.02221	0.02403
SN_proximity	-0.00263	0.009139	-0.29	0.774	-0.01766	0.012403
SN_closeness	-0.002	0.016893	-0.12	0.906	-0.02979	0.025788
child_SN	-0.00643	0.00933	-0.69	0.491	-0.02177	0.00892
sibling_SN	-0.0086	0.015068	-0.57	0.568	-0.03338	0.016187
parents_SN	0.011083	0.022488	0.49	0.622	-0.02591	0.048073
friends_SN	0.005461	0.01015	0.54	0.591	-0.01123	0.022157
others_SN	-0.01984	0.016509	-1.2	0.229	-0.047	0.007314
log_inc_pre_ca	0.015827	0.011794	1.34	0.18	-0.00357	0.035227
job_flex_ca	0.061725	0.021027	2.94	0.003	0.027138	0.096311
ends_meet_ca	-0.02049	0.020688	-0.99	0.322	-0.05452	0.013538
diagnosed_ca	-0.01349	0.051919	-0.26	0.795	-0.09889	0.071907
ca_symptoms	0.062165	0.051923	1.2	0.231	-0.02324	0.147572
longterm_condition	-0.04735	0.01917	-2.47	0.014	-0.07888	-0.01582
health	-0.01067	0.017845	-0.6	0.55	-0.04002	0.018682
pain	-0.03266	0.025558	-1.28	0.201	-0.0747	0.009379
bmi_cat	-0.0231	0.012399	-1.86	0.062	-0.0435	-0.00271
flu_vax	-0.04738	0.022393	-2.12	0.034	-0.08422	-0.01055
iadl_score	0.007085	0.017444	0.41	0.685	-0.02161	0.035777
smoker	-0.01194	0.022498	-0.53	0.595	-0.04895	0.025062
alcohol	-0.01114	0.030266	-0.37	0.713	-0.06093	0.038639
sport	-0.0109	0.045047	-0.24	0.809	-0.085	0.063192

Table 9.9: `reduced_hours` IV Probit Second Stage Marginal Effects. Instumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.

reduced_hours	**dy/dx**	**Robust Std. Err.**	**z**	**P>z**	**[90% Conf. Int.]**	
mh_ca	0.006497	0.005889	1.1	0.27	-0.00319	0.016183
age	0.002664	0.001489	1.79	0.074	0.000216	0.005113
female	-0.00848	0.016919	-0.5	0.616	-0.03631	0.019345
rel_status	0.024992	0.020021	1.25	0.212	-0.00794	0.057924
isced97educ	-0.01602	0.007376	-2.17	0.03	-0.02816	-0.00389
SN_contact	0.001292	0.012181	0.11	0.916	-0.01874	0.021329
SN_proximity	0.006099	0.006424	0.95	0.342	-0.00447	0.016666
SN_closeness	0.005661	0.014855	0.38	0.703	-0.01877	0.030095
child_SN	-0.00635	0.00859	-0.74	0.46	-0.02048	0.007777
sibling_SN	-0.00693	0.014052	-0.49	0.622	-0.03004	0.016188
parents_SN	0.010299	0.021064	0.49	0.625	-0.02435	0.044946
friends_SN	0.003319	0.009256	0.36	0.72	-0.01191	0.018544
others_SN	-0.01656	0.014575	-1.14	0.256	-0.04053	0.007414
log_inc_pre_ca	0.022613	0.010771	2.1	0.036	0.004895	0.04033
job_flex_ca	0.076844	0.017305	4.44	0	0.04838	0.105307
ends_meet_ca	-0.04639	0.010543	-4.4	0	-0.06374	-0.02905
diagnosed_ca	0.041172	0.032017	1.29	0.198	-0.01149	0.093835
ca_symptoms	0.083953	0.043605	1.93	0.054	0.01223	0.155677
longterm_condition	-0.04692	0.017638	-2.66	0.008	-0.07593	-0.0179
health	0.012756	0.009821	1.3	0.194	-0.0034	0.02891
pain	-0.00764	0.018069	-0.42	0.672	-0.03736	0.022079
bmi_cat	-0.03255	0.010313	-3.16	0.002	-0.04952	-0.01559
flu_vax	-0.03446	0.019385	-1.78	0.075	-0.06634	-0.00257
iadl_score	0.013066	0.014345	0.91	0.362	-0.01053	0.036662
smoker	-0.01578	0.020741	-0.76	0.447	-0.04989	0.01834
alcohol	-0.01502	0.028678	-0.52	0.6	-0.06219	0.032153
sport	-0.01168	0.03936	-0.3	0.767	-0.07642	0.053063

Table 9.10: `reduced_hours` Multiple Probit Marginal Effects.

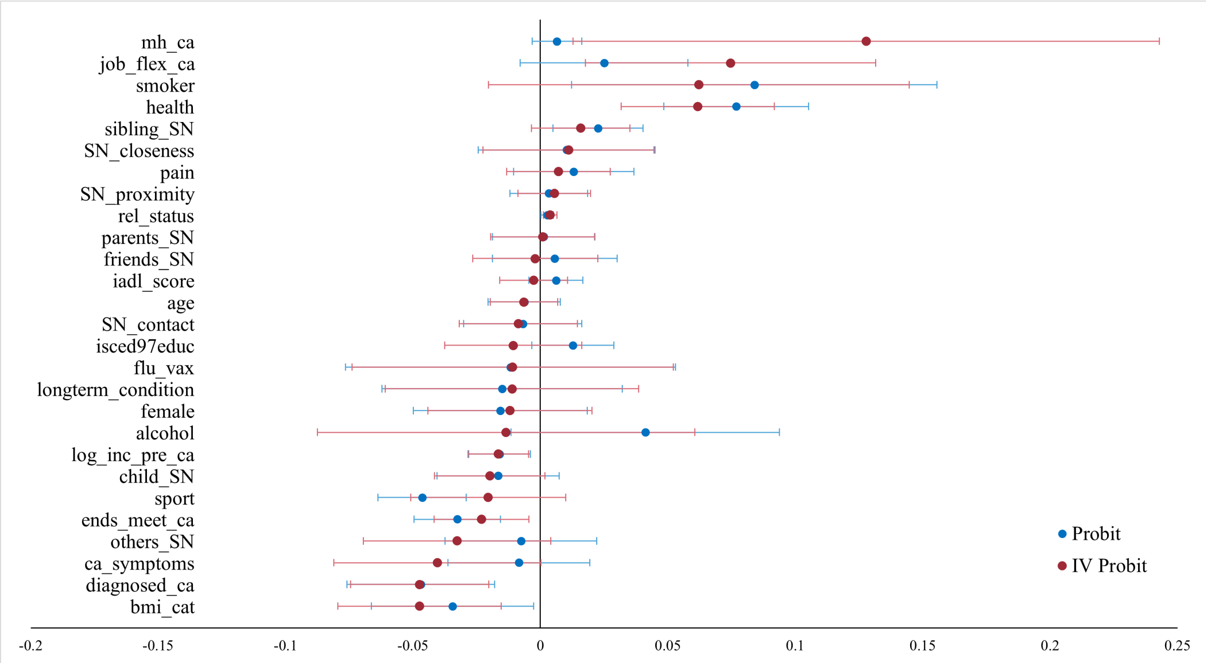

Figure 9.1: Model 1 Marginal Effects Point Estimates and Confidence Intervals. Dependent Variable: `reduced_hours`. Instrumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.

9.4 Model 2 Results: Marginal Effects

increased_hours	**dy/dx**	**Robust Std. Err.**	**z**	**P>z**	**[90% Conf. Int.]**	
mh_ca	0.076532	0.069942	1.09	0.274	-0.03851	0.191575
age	-0.00312	0.001607	-1.94	0.052	-0.00576	-0.00047
female	-0.01138	0.02471	-0.46	0.645	-0.05203	0.029262
rel_status	0.005114	0.034592	0.15	0.882	-0.05179	0.062013
isced97educ	0.019837	0.007208	2.75	0.006	0.007981	0.031692
SN_contact	-0.01187	0.012424	-0.96	0.339	-0.03231	0.008561
SN_proximity	-0.00517	0.008116	-0.64	0.524	-0.01852	0.008183
SN_closeness	0.004348	0.014936	0.29	0.771	-0.02022	0.028915
child_SN	0.006023	0.008045	0.75	0.454	-0.00721	0.019256
sibling_SN	0.00878	0.014099	0.62	0.533	-0.01441	0.031971
parents_SN	-0.0149	0.020399	-0.73	0.465	-0.04845	0.018654
friends_SN	0.01698	0.008632	1.97	0.049	0.002782	0.031178
others_SN	0.015504	0.013198	1.17	0.24	-0.0062	0.037213
log_inc_pre_ca	0.034169	0.011779	2.9	0.004	0.014795	0.053544
job_flex_ca	0.026912	0.018257	1.47	0.14	-0.00312	0.056942
ends_meet_ca	0.022396	0.018473	1.21	0.225	-0.00799	0.052781
diagnosed_ca	-0.05944	0.045012	-1.32	0.187	-0.13347	0.014602
ca_symptoms	-0.09593	0.050176	-1.91	0.056	-0.17846	-0.0134
longterm_condition	-0.01098	0.016508	-0.67	0.506	-0.03813	0.016174
health	-0.03682	0.016369	-2.25	0.024	-0.06375	-0.0099
pain	0.024512	0.022357	1.1	0.273	-0.01226	0.061286
bmi_cat	0.010324	0.011317	0.91	0.362	-0.00829	0.028939
flu_vax	0.003966	0.019494	0.2	0.839	-0.0281	0.036031
iadl_score	-0.00016	0.012373	-0.01	0.99	-0.02051	0.020193
smoker	-0.00546	0.019548	-0.28	0.78	-0.03761	0.026693
alcohol	-0.03673	0.030251	-1.21	0.225	-0.08649	0.013031
sport	-0.03584	0.038325	-0.94	0.35	-0.09888	0.027199

Table 9.11: `increased_hours` IV Probit Second Stage Marginal Effects. Instumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.

increased_hours	**dy/dx**	**Robust Std. Err.**	**z**	**P>z**	**[90% Conf. Int.]**	
mh_ca	0.006278	0.005694	1.1	0.27	-0.00309	0.015644
age	-0.00376	0.001452	-2.59	0.01	-0.00615	-0.00137
female	0.007323	0.016057	0.46	0.648	-0.01909	0.033735
rel_status	-0.02308	0.018827	-1.23	0.22	-0.05405	0.007886
isced97educ	0.020218	0.006985	2.89	0.004	0.008728	0.031707
SN_contact	-0.0117	0.011682	-1	0.316	-0.03092	0.007512
SN_proximity	8.43E-05	0.006011	0.01	0.989	-0.0098	0.009972
SN_closeness	0.008912	0.014053	0.63	0.526	-0.0142	0.032028
child_SN	0.006048	0.007716	0.78	0.433	-0.00664	0.01874
sibling_SN	0.01006	0.01323	0.76	0.447	-0.0117	0.031822
parents_SN	-0.0157	0.019796	-0.79	0.428	-0.04826	0.016863
friends_SN	0.015793	0.008172	1.93	0.053	0.002352	0.029233
others_SN	0.017701	0.012299	1.44	0.15	-0.00253	0.03793
log_inc_pre_ca	0.038082	0.011251	3.38	0.001	0.019576	0.056589
job_flex_ca	0.035563	0.015688	2.27	0.023	0.009758	0.061367
ends_meet_ca	0.007207	0.010577	0.68	0.496	-0.01019	0.024604
diagnosed_ca	-0.02786	0.031081	-0.9	0.37	-0.07898	0.023263
ca_symptoms	-0.08401	0.04833	-1.74	0.082	-0.1635	-0.00451
longterm_condition	-0.01075	0.015975	-0.67	0.501	-0.03703	0.015525
health	-0.02305	0.009044	-2.55	0.011	-0.03792	-0.00817
pain	0.039045	0.016271	2.4	0.016	0.012282	0.065808
bmi_cat	0.004731	0.009453	0.5	0.617	-0.01082	0.020279
flu_vax	0.011405	0.017423	0.65	0.513	-0.01725	0.040063
iadl_score	0.003207	0.012176	0.26	0.792	-0.01682	0.023235
smoker	-0.00763	0.019236	-0.4	0.692	-0.03927	0.024014
alcohol	-0.03847	0.029668	-1.3	0.195	-0.08727	0.010325
sport	-0.03628	0.035985	-1.01	0.313	-0.09547	0.022914

Table 9.12: `increased_hours` Multiple Probit Marginal Effects.

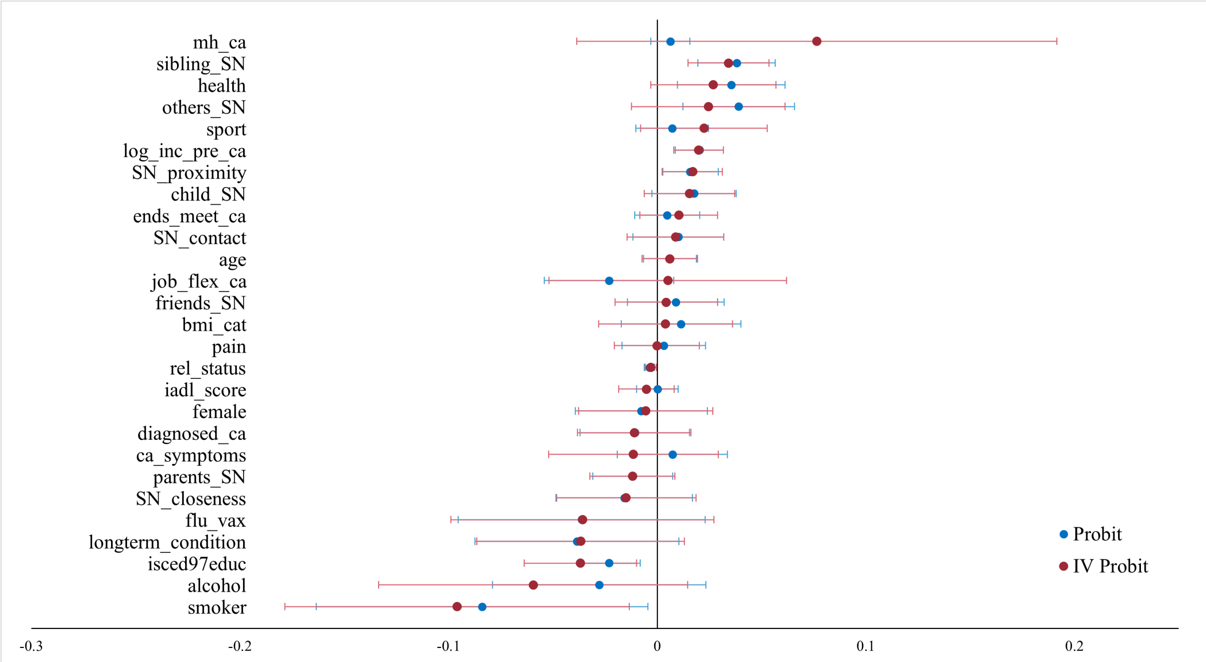

Figure 9.2: Model 2 Marginal Effects Point Estimates and Confidence Intervals.

Dependent Variable: `increased_hours`. Instrumental Variable: `upto_month_avg_SI`. Endogenous: `mh_ca`.