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Introduction

1 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.

1.1 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, environmen-

tal 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 individuals' 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 though 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.

1.2 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 men-

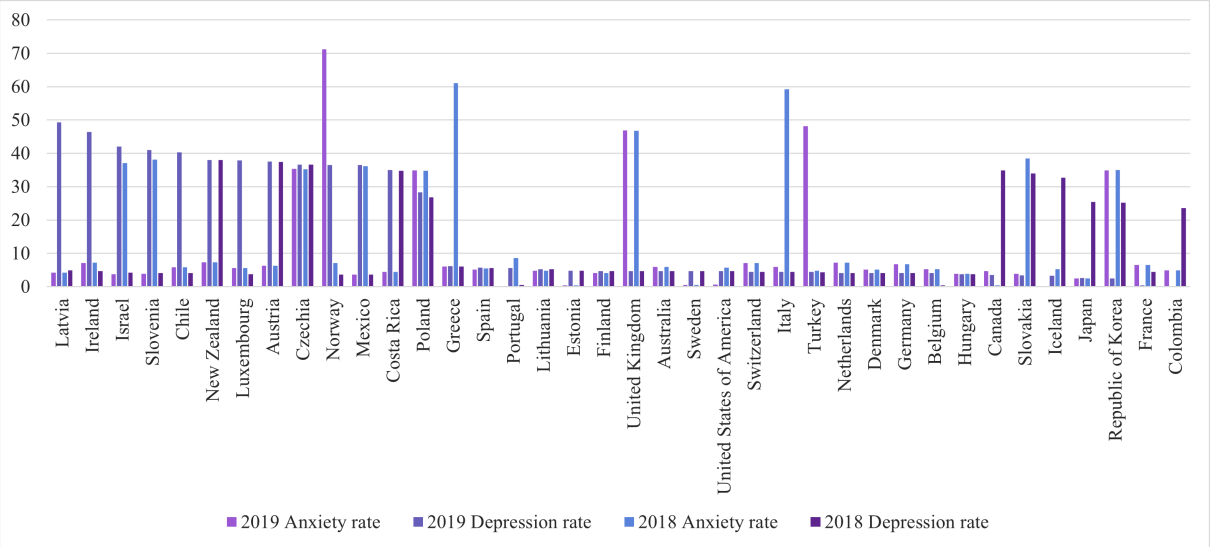

Figure 1.1: *Prevalence of anxiety and depression disorders per* 100 *inhabitants, 2018-2019.*
Source: Global Burden of Disease Study 2019 (GBD 2019), available from https://vizhub.healthdata.org/gbd-results/.

tal 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.

1.2.1 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 Di-

agnostic 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.

1.2.2 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.

1.2.3 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 increase prevalence of symptoms in women from low and middle income countries in the perinatal period. Alexandrino-Silva et al. (2012) analyze symptomatics 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 ipairment, 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.

1.3 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.

2 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 outcomes related to mental health are:

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

2. **Physical Well-being.** Such as likelihood of hospitalization, quality of life, healthcare utilization, physical mobility, and dependence on external assistance.

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

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

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.

2.1 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. A systematic review by Rönnblad et al. (2019) 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.

As an example of the many correlational studies, 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.

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 bil-

lion. 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 to control for endogeneity concerns. 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.

2.2 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) investigates 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 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. Starting with a paper by Santini et al. (2021-A) The

second 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 multilevel 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 third 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 were 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.

2.3 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 di-

minished 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 statust 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) investigates 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 indicaotr 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 directions 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.

2.3.1 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 enxiety. 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 authord fit 60 models using ordinary least squares (OLS) regression for 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.

2.4 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.

3 data

The overarching question guiding this study is: ”How does mental health, as measured by various indicators, affect individual outcomes such as labor market participation, community activity, and social network strength?” To answer this question, we employ a dataset known as the Survey of Health, Ageing and Retirement in Europe (SHARE), which offers a rich array of variables pertinent to our study.

3.1 SHARE data

3.2 OxGRT data

3.3 Variables manipulation

4 strategy

5 estimation

6 discussion

7 conclusion

8 References

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21. Adams-Prassl, Abi, et al. "The impact of the coronavirus lockdown on mental health: evidence from the United States." Economic Policy 37.109 (2022): 139-155.

22. Alexandrino-Silva, Clóvis, et al. "Gender differences in symptomatic profiles of depression: results from the Sao Paulo Megacity Mental Health Survey." Journal of affective disorders 147.1-3 (2013): 355-364.

23. Arpino, Bruno, et al. "Loneliness before and during the COVID-19 pandemic—are unpartnered and childless older adults at higher risk?." European journal of ageing 19.4 (2022): 1327-1338.

24. Atzendorf, Josefine, and Stefan Gruber. "Depression and loneliness of older adults in Europe and Israel after the first wave of covid-19." European journal of ageing 19.4 (2022): 849-861.

25. Banerjee, Souvik, Pinka Chatterji, and Kajal Lahiri. "Effects of psychiatric disorders on labor market outcomes: a latent variable approach using multiple clinical indicators." Health economics 26.2 (2017): 184-205.

26. Chesney, Edward, Guy M. Goodwin, and Seena Fazel. "Risks of all-cause and suicide mortality in mental disorders: a meta-review." World psychiatry 13.2 (2014): 153-160.

27. Cohen-Cline, Hannah, et al. "Associations between social capital and depression: A study of adult twins." Health and place 50 (2018): 162-167.

28. Coleman, Max E., et al. "What kinds of social networks protect older adults' health during a pandemic? The tradeoff between preventing infection and promoting mental health." Social Networks 70 (2022): 393-402.

29. Deng, Jiawen, et al. "The prevalence of depression, anxiety, and sleep disturbances in COVID-19 patients: a meta-analysis." Annals of the New York Academy of Sciences 1486.1 (2021): 90-111.

30. Ehsan, Annahita M., and Mary J. De Silva. "Social capital and common mental disorder: a systematic review." J Epidemiol Community Health 69.10 (2015): 1021-1028.

31. Ferreira-Alves, José, et al. "Loneliness in middle and old age: Demographics, perceived health, and social satisfaction as predictors." Archives of gerontology and geriatrics 59.3 (2014): 613-623.

32. Fokkema, Tineke, Jenny De Jong Gierveld, and Pearl A. Dykstra. “Cross-national differences in older adult loneliness.” The Journal of psychology 146.1-2 (2012): 201-228.

33. Frijters, Paul, David W. Johnston, and Michael A. Shields. “Mental health and labour market participation: Evidence from IV panel data models.” (2010).

34. Global Burden of Disease Collaborative Network. “Global Burden of Disease Study 2019 (GBD 2019) Results”. Seattle, United States: Institute for Health Metrics and Evaluation (IHME), (2020). Available from `https://vizhub.healthdata.org/gbd-results/`.

35. Gu, Naeun. “The effects of neighborhood social ties and networks on mental health and well-being: A qualitative case study of women residents in a middle-class Korean urban neighborhood.” Social Science and Medicine 265 (2020): 113336.

36. Hajek, André, and Hans-Helmut König. “Which factors contribute to loneliness among older Europeans? Findings from the survey of health, ageing and retirement in Europe: determinants of loneliness.” Archives of gerontology and geriatrics 89 (2020): 104080.

37. Hale, Thomas, et al. “Variation in government responses to COVID-19.” (2023).

38. Jarach, Carlotta Micaela, et al. “Social isolation and loneliness as related to progression and reversion of frailty in the Survey of Health Aging Retirement in Europe (SHARE).” Age and ageing 50.1 (2021): 258-262.

39. Kessler, Ronald C., et al. “Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication.” Archives of general psychiatry 62.6 (2005): 593-602.

40. Lakhan, Ram, Amit Agrawal, and Manoj Sharma. “Prevalence of depression, anxiety, and stress during COVID-19 pandemic.” Journal of neurosciences in rural practice 11.04 (2020): 519-525.

41. Lakner, Christoph, et al. “How much does reducing inequality matter for global poverty?.” The Journal of Economic Inequality 20.3 (2022): 559-585.

42. Landstedt, Evelina, et al. “Disentangling the directions of associations between structural social capital and mental health: Longitudinal analyses of gender, civic engagement and depressive symptoms.” Social Science and Medicine 163 (2016): 135-143.

43. Luchetti, Martina, et al. “Loneliness is associated with risk of cognitive impairment in the Survey of Health, Ageing and Retirement in Europe.” International journal of geriatric psychiatry 35.7 (2020): 794-801.

44. Luo, Ye, et al. “Loneliness, health, and mortality in old age: A national longitudinal study.” Social science and medicine 74.6 (2012): 907-914.

45. Morrow-Howell, Nancy, et al. “Depression in public community long-term care: implications for intervention development.” The Journal of Behavioral Health Services and Research 35 (2008): 37-51.

46. Murayama, Hiroshi, et al. “Do bonding and bridging social capital affect self-rated health, depressive mood and cognitive decline in older Japanese? A prospective cohort study.” Social Science and Medicine 98 (2013): 247-252.

47. Nadinloyi, Karim Babayi, Hasan Sadeghi, and Nader Hajloo. “Relationship between job satisfaction and employees mental health.” Procedia-Social and Behavioral Sciences 84 (2013): 293-297.

48. Niedzwiedz, Claire L., et al. “The relationship between wealth and loneliness among older people across Europe: Is social participation protective?.” Preventive medicine 91 (2016): 24-31.

49. OECD/EU, “Health at a Glance: Europe 2018: State of Health in the EU Cycle”, OECD Publishing, Paris, (2018). https://doi.org/10.1787/health_glance_eur-2018-en.

50. OECD/EU, “Health at a Glance: Europe 2022: State of Health in the EU Cycle”, OECD Publishing, Paris, (2022). https://doi.org/10.1787/507433b0-en.

51. Pieh, Christoph, et al. “Mental health during COVID-19 lockdown in the United Kingdom.” Psychosomatic medicine 83.4 (2021): 328-337.

52. Riumallo-Herl, Carlos Javier, Ichiro Kawachi, and Mauricio Avendano. “Social capital, mental health and biomarkers in Chile: Assessing the effects of social capital in a middle-income country.” Social science and medicine 105 (2014): 47-58.

53. Rönnblad, Torkel, et al. “Precarious employment and mental health.” Scandinavian journal of work, environment and health 45.5 (2019): 429-443.

54. Santini, Ziggi Ivan, and Ai Koyanagi. “Loneliness and its association with depressed mood, anxiety symptoms, and sleep problems in Europe during the COVID-19 pandemic.” Acta neuropsychiatrica 33.3 (2021-A): 160-163.

55. Santini, Ziggi Ivan, et al. “Social disconnectedness, perceived isolation, and symptoms of depression and anxiety among older Americans (NSHAP): a longitudinal mediation analysis.” The Lancet Public Health 5.1 (2020): e62-e70.

56. Santini, Ziggi Ivan, et al. “The moderating role of social network size in the temporal association between formal social participation and mental health: a longitudinal analysis using two consecutive waves of the Survey of Health, Ageing and Retirement in Europe (SHARE).” Social Psychiatry and Psychiatric Epidemiology 56 (2021-B): 417-428.

57. Schaub, Rainer T., and Michael Linden. “Anxiety and anxiety disorders in the old and very old—results from the Berlin Aging Study (BASE).” Comprehensive psychiatry 41.2 (2000): 48-54.

58. Shiovitz-Ezra, Sharon, and Sara A. Leitsch. “The role of social relationships in predicting loneliness: The national social life, health, and aging project.” Social Work Research 34.3 (2010): 157-167.

59. Sirven, Nicolas, and Thierry Debrand. “Social capital and health of older Europeans: Causal pathways and health inequalities.” Social Science and Medicine 75.7 (2012): 1288-1295.

60. Sunwoo, Lee. “Loneliness among older adults in the Czech Republic: A socio-demographic, health, and psychosocial profile.” Archives of Gerontology and Geriatrics 90 (2020): 104068.

61. Vieira, Edgar Ramos, Ellen Brown, and Patrick Raue. “Depression in older adults: screening and referral.” Journal of geriatric physical therapy 37.1 (2014): 24-30.

62. Wang, Cuiyan, et al. “A longitudinal study on the mental health of general population during the COVID-19 epidemic in China.” Brain, behavior, and immunity 87 (2020): 40-48.

63. Wolitzky-Taylor, Kate B., et al. “Anxiety disorders in older adults: a comprehensive review.” Depression and anxiety 27.2 (2010): 190-211.

64. Woody, C. A., et al. “A systematic review and meta-regression of the prevalence and incidence of perinatal depression.” Journal of affective disorders 219 (2017): 86-92.

65. World Health Organization, “World mental health report: transforming mental health for all”, Geneva, 2022. Licence: CC BY-NC-SA 3.0 IGO.

66. Zenebe, Yosef, Baye Akele, and Mogesie Necho. “Prevalence and determinants of depression among old age: a systematic review and meta-analysis.” Annals of general psychiatry 20.1 (2021): 1-19.

9 appendix