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Economics of Mental Health

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Economics of Mental Health*

Abstract

This chapter provides an overview of the rapidly evolving economics literature on mental health, focusing on research published since 2015. This literature has grown substantially, reflecting the increased recognition of the prevalence and economic costs of mental illness, declining stigma, and the growing availability of data on mental health. In addition to the economic costs of mental illness, the review focuses on four broad classes of determinants of mental health: endowments, economic resources, education, and trauma. We also examine the determinants and effects of mental health treatment. Finally, we discuss how certain features of mental illness, including its episodic and recurrent nature, pose challenges for the canonical health capital model.

JEL classification

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mental health, health economics, economic costs, health capital

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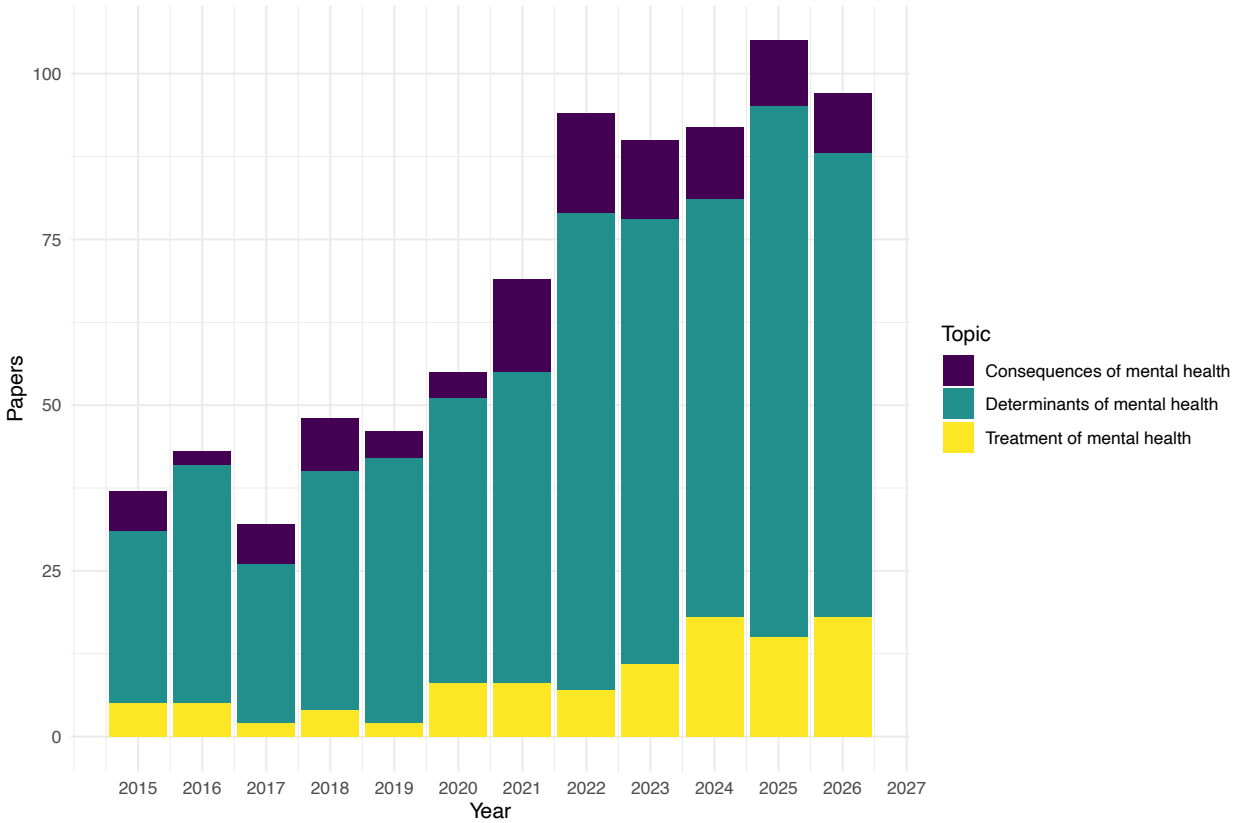
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0. Introduction

This chapter provides an overview of the rapidly evolving economics literature about mental health. In rich countries, about 20 percent of the population has a mental health condition at any point in time, with about 5 to 6 percent being severely affected. Nor are low and middle-income countries spared: Worldwide, it is estimated that at least 1 in 8 people, nearly 970 million, have a mental health disorder, and this may be an undercount (IHME 2025). Mental health disorders are equally prevalent among adolescents 10 to 19 (WHO 2025a), setting teens on a difficult path going forward. These conditions cause a great deal of human suffering, directly lowering the utility of affected children, their families, and people who care about them in addition to imposing a wide variety of economic costs.

The review is focused on studies from 2015 or later, though some critical earlier studies are also cited. As Figure 1 suggests, it was unusual for economists to study mental health until quite recently, with the literature growing particularly rapidly post-COVID. This new emphasis on mental health likely reflects the confluence of three factors: 1) The widespread discussion of the mental health consequences of the pandemic and a resulting reduction in the stigma surrounding mental illness; 2) a dawning realization that mental illness is one of the most pervasive and costly of maladies (as discussed in Section 1); and 3) the growing availability of relatively well-measured data about mental health from administrative and survey sources as well as from experiments (as discussed in Section 2).

Figure 1: Economics Papers About Mental Health



Notes: Figure 1 is based on a 32-keyword title-and-abstract Web of Science search of papers published or forthcoming in the top 100 economics journals (Ham et al. 2026) from 01/01/2015 and 12/31/2026. Keywords were chosen by searching within a manually collected set of papers, adding search terms until 96% of the papers were included. After screening out non-mental health related papers (e.g. "Great Depression"), 874 remaining studies were categorized using title and abstract by DeepSeek API. A hand audit suggested a 98% accuracy rate.

Figure 1 breaks the literature into three broad categories. Some of the earliest literature (especially pre-2015) focused on documenting the often devastating consequences of mental illness. A second group of studies (discussed in Sections 3.2-3.6), delves into the determinants of mental health. This literature demonstrates that a broad list of shocks and stressors can cause mental illness and that while children are especially vulnerable, adults are not immune. A growing number of studies in the third category focus on the determinants and effectiveness of treatment (discussed in Sections 3.7 and 3.8). The main takeaways from this work are that access to mental health treatment is highly variable even in places with universal insurance, and that a significant amount of the treatment that is available is of uncertain quality and efficacy.

The standard model of health as human capital provides a general framework for this review and is outlined in Section 3.1. The review focuses on four broad classes of determinants of mental health: Endowments, economic resources, education, and trauma, as well as on the determinants and effects of treatment. We point out that some of the characteristics of mental illness, such as its tendency to ebb and flow, that pose special problems for the canonical model.

In addition to limiting the time period, difficult decisions had to be made about scope. Most of the research on mental health comes from outside of economics, but this survey focuses on the literature published in economics journals. The most controversial choice may be that we are not including a comprehensive treatment of the economic literature on substance use disorders, but including substance use only when it co-occurs or results from other mental illness. There is a large, interesting, and venerable literature about topics including youth smoking and drinking, effects of cigarette and alcohol taxes, whether risky behaviors including substance abuse are substitutes or complements, economic determinants of substance abuse, the effectiveness of substance use policies, and rising numbers of "deaths of despair" resulting from obesity, smoking, and alcohol consumption. This literature deserves its own survey.

1. Economic Consequences of Poor Mental Health

Poor mental health is extremely costly to individuals, families, and society. Much of the work summarized in Table 1 focuses on the effects of mental illness on labor market outcomes, following a long tradition in labor economics. In a review of the relationship between health and labor supply, Currie and Madrian (1999) found that poor mental health was the leading cause of lost workdays among adult workers, and a primary reason for adult non-participation in the labor market. More recently, in 2024–2025, 55 percent of workdays lost in the United Kingdom were due to stress, depression, and anxiety, compared to only 17 percent for musculoskeletal conditions including back pain, the second largest category (Health and Safety Executive 2025). And when people lost workdays because of mental illness, they lost 21.1 days per incident, compared to 14.3 days for a bought of sickness due to musculoskeletal conditions. Biasi et al. (2027) use Danish registry data to document that people with specific diagnoses of depression, bipolar disorder, or schizophrenia have earnings 31, 36, and 73 percent less than their siblings. Much of this earnings penalty comes from affected people being less likely to have any earnings at all. People with mental health diagnoses are also more likely to receive government disability payments.

In addition to the obvious costs posed by lost work time (absenteeism), many employed U.S. workers say that they have large numbers of bad mental health days, which may impair their productivity on the job (presenteeism) as well as promoting absenteeism (see Bubonya et al. 2017). The U.S. General Social Survey has asked employed workers about the number of days

that their mental health was "not good" in the past month, since 2002.[1] A remarkably high fraction, some 40 percent, report bad mental health days in the past month, with over 10 percent reporting 10 or more such days.

About half of adult mental health conditions are thought to have their origins in childhood (Kessler et al. 2005). These conditions impose significant burdens on families, though there has been little research quantifying the effects on parents and siblings. A large prior literature (see Currie (2025) for a brief review) has shown that child mental health problems predict a wide range of poor outcomes in adulthood including lower educational attainment, lower probability of employment, lower earnings, higher welfare use, and greater involvement in crime. For example, Cornaglia et al. (2015) use British survey data and find that a higher score on a 12-item mental health screener is highly predictive of both leaving school early and non-participation in the labor force. Anderson et al. (2015) find large effects of childhood mental health on future involvement in property crimes, though in view stereotypes about violence among the mentally ill, it is noteworthy that they find no effect on violent crime. Attanasio et al. (2020) compare cohorts of British children born in 1970 and 2000 and divide non-cognitive skills at age 5 into "internalizing" (e.g. depression) and "externalizing" (e.g. ADHD) behaviors. They find that these skills are important predictors of adult outcomes, and that inequalities stemming from these two kinds of skills increased between the two cohorts, especially among boys.[2]

At the other end of the lifespan, the aging of populations worldwide has focused attention on Alzheimer's disease and related dementias (ADRD). Cognitive impairment becomes increasingly common with age: Of people 65 and older, about 72 percent are estimated to have normal cognition, while 18.6 percent have mild deficits and 9 percent have dementia. The share with dementia varies widely within the elderly, rising from 3% for people 65-69 to 20% for people 80 and over. Of note however is that while the population is aging, rates of dementia have fallen 30 percent since 2000. Cutler and Peterson (2025) argue that increasing education and declining pollution levels can largely explain this surprising decline. The economic toll of dementia starts compounding well before diagnosis. Household net worth begins to decline roughly six years prior to onset, driven primarily by reduced financial assets. The decline is concentrated among wealthier households and those without a partner (Li et al., forthcoming). Over the last five years of life, total health care costs are 57 percent higher for people with dementia than for those who die of other causes. This gap is not driven by Medicare, which spends similarly across disease groups. It comes instead from uninsured costs: out-of-pocket spending is 81 percent higher, and informal caregiving costs more than double. This burden falls hardest on the least financially prepared. Out-of-pocket spending consumes 48 percent of wealth among dementia decedents without a high school education, and 58 percent among unmarried women (Kelley et al. 2015).

The high incidence of mental illness among those on disability, the homeless, and the incarcerated provide additional indicators of the heavy toll that mental illness takes. In the U.S., a third of people with Social Security Disability Insurance, and half of the people with Supplemental Security Income have mental health conditions (Center on Budget and Policy Priorities 2024; Social Security Administration 2025). Data from Canada, Germany, and the U.S. suggests that two-thirds of unhoused adults have a mental health condition (Barry et al. 2024),

[1] The specific question is: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

[2] They decompose the increase in inequality into the increase due to changes in the characteristics of mothers and the increase due to "returns" to those characteristics. About half of the increase in inequality in externalizing behaviors is explained by changes in maternal characteristics (such as maternal smoking and employment), but most of the increase in inequality in internalizing behaviors is due to changes in returns to maternal characteristics.

while over a third of the U.S. prison population has a mental illness (Substance Abuse and Mental Health Services Administration 2024).

Perhaps the most extreme outcomes of mental illness are self-harming behaviors, including suicide, which imposes heavy costs on survivors as well as on deceased person. In the U.S., suicide is the 11th leading cause of death overall, and the second ranked cause among people 10 to 34. While rates of mental illness are thought to be relatively similar across countries, suicide rates vary widely. For example, in 2021, the age-adjusted rate was per 20.6 100,000 in South Korea, 14.2 per 100,000 in the U.S., 9.9 per 100,000 in Switzerland (where it is legal), 4.6 per 100,000 in Italy, and 1.5 per 100,000 in Peru (WHO 2025b). Similarly, while male suicide rates are consistently higher than female suicide rates, women have higher rates of mental illness, including depression.

Within the U.S., there is considerable variation in suicide rates, which range from 6.7 in New Jersey to 29.7 in Alaska, even though, again, rates of mental illness are thought to be similar across areas (National Center for Health Statistics 2026). Currie (2025) shows that among young people, variation in these rates is strongly related to state regulations regarding firearms, demonstrating that the policy environment is an important mediator between rates of mental illness and suicide. Together these facts demonstrate that rising (or falling) suicide rates do not necessarily reflect changes in underlying rates of mental illness. Another reason for the disconnect is the huge difference in the prevalence of mental illness and suicide: If 15-20 percent of the population has a mental illness, while roughly 0.016 persons per 100 die by suicide, the two series have scope to move in quite different directions. Clearly, most people with mental illness do not die by suicide, though mental illness does place them at higher risk.

Moreover, Stone et al. (2018) show using data from the U.S. CDC National Violent Death Reporting System, that only half of people who die by suicide had a pre-existing mental illness. In the other half of deaths, people often had a relationship, employment, or financial problem at the time of the death that was thought to have contributed. While these statistics may reflect some under-diagnosis of mental illness, they also suggest that it may be a misconception that only people with mental health disorders die by suicide. For example, observations about strong links between suicide and financial distress are an important part of some economic theories of suicide discussed in Hamermesh and Soss (1974).

In terms of the direct monetary costs of mental health care, lost work time, and other costs, it seems fair to say that the total is very large, though well-grounded comprehensive estimates are hard to come by and exact amounts are sensitive to the costs that are included. Mark et al. (2026) provide new estimates of the growth in U.S. direct health care spending for mental health from 2000-2021.[3] They find an overall increase from $58.74 billion to $126.52 billion ($2021) with the two largest expenditure categories in 2021 being depression and anxiety.[4] The real rate of increase in spending was 3.27 percent per year, which exceeded the rate of increase for all medical services of 2.36 percent per year. These costs can be compared to the $900.8 billion that the U.S. spent on Medicare, one of the most expensive social programs. And while spending on other forms of health care grew mainly because of increases in costs per case, increases in mental health spending were driven by a roughly 250 percent increase in the number of people being treated.

[3] These estimates come from the U.S. Bureau of Economic Analysis' Health Care Satellite Account which combines data from Medicare claims, Marketscan, and the Medical Expenditure Panel Survey (MEPS). The authors point out that they do not include nursing home care for dementia and related disorders, which might, if included, add another $40 billion dollars to the total.

[4] Claims are categorized using the primary diagnosis. Over the same period, expenditures on substance use disorders grew from $5.37 billion to $13.09 billion ($2021).

Abramson et al. (2025) have built a macroeconomic model of the costs imposed by mental illness which includes not only direct health care costs and lost work time, but the fact that the fact that people with mental illness consume less, invest less in a house, stocks, and other risky assets, and may choose less-demanding jobs. Their model implies costs of $282 billion annually, more than double the direct medical costs.

Although these numbers are high, they are far lower than the estimates of the burden of mental illness given in many other sources. For example, researchers from the Harvard Chan School of Public Health have estimated that the global burden of mental illness is about $5 trillion, which is about 4.5 percent of global GDP. Their estimate for North America is that the burden is closer to 8 percent of GDP (because wages are higher). Moreover, lobbying organizations such as the Alzheimer's Association claim that the direct medical costs of Alzheimer's and related dementias were over $350 billion in 2023, larger than Mark et al.'s estimate for the direct medical costs of all mental illness together. These wildly varying estimates underscore the difficulties involved in developing credible measures of the burden of mental illness, a topic that is explore further in the next section.

2. Measurement of mental health

The rising number of cases has focused attention on mental illness. However, sky-rocketing caseloads are disconcerting but do not necessarily represent a massive deterioration in people's mental health. For example, higher caseloads might represent a greater probability that low acuity cases will receive treatment. There has been a perfect storm of changes that have complicated the interpretation of trends in measured mental illness. These changes have affected attitudes towards mental illness, the availability of treatment, insurance coverage (in the U.S. in particular), mental health screening, and mental illness coding conventions as reflected in both the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD). Any one of these changes could have caused significant changes in trends. Together, they make trends very difficult to measure.

Attitudes towards mental health matter for measurement, because if a condition is highly stigmatized, then people may be unwilling to admit that they have it. Bharadwaj et al. (2017) demonstrate that there has been significant under-reporting of mental health conditions compared to other physical health conditions, such as diabetes. However, this stigma has been falling over time. Using data from three waves of the General Social Survey (1996, 2006, 2018), Pescosolido et al. (2021) find that respondents have become more likely to endorse a genetic basis for depression, and less likely to want to distance themselves from a depressed person at work or socially. Angermeyer et al. (2017) show that knowledge about mental health conditions and attitudes towards mental health care have improved worldwide.

Improvements in treatment also have the potential to cause more people to seek care. Several new drug classes have been approved for the treatment of depression, including zuranolone, the first drug approved specifically for post-partum depression. While the treatment of anxiety still relies largely on off-label use of anti-depressants, extended release versions have become available. And new non-stimulant treatments for Attention Deficit Hyperactivity Disorder (ADHD) have become more widely available. Mark et al. (2026) also argue that mental health treatment has moved away from psychotherapy to medications that are often prescribed by primary care providers, making it easier for patients to receive care.

Similarly, many countries have seen expansions in health insurance coverage of mental health treatment, and we know that people are more likely to seek care when they are more

generously insured. In the U.S., the Mental Health Parity Act of 2008 required insurers to cover mental illness like they covered physical health conditions in terms of limits on visits, copays, prior authorization, and other characteristics of coverage. The Affordable Care Act of 2010 included mental health care as one of the essential health benefits that all insurers were required to cover as of 2014. In the U.K., therapy was historically very difficult to access through the public system, but the Improving Access to Psychological Therapies (IAPT) program introduced in 2008 (NHS Talking Therapies) dramatically increased access to care, although demand continues to outstrip supply. In 2022-23, 1.24 million people were seen, 664,000 had a course of treatment, with 50 percent of those who completed treatment having their symptoms resolve (National Collaborating Centre for Mental Health 2024). In Denmark, landmark legislation in 2013 guaranteed the right to treatment and evaluation within 30 days for moderate to severe conditions, which reduced waiting times and increased the number of patients treated in the public system by 25 percent (Nordentoft et al. 2023). In 2022, a pilot program providing free public treatment for individuals 18 to 24 with mild or moderate anxiety and depression became permanent, eliminating a 40 percent copayment.[5] All of these policies were intended to increase the number of people being treated for mental illness, so it is ironic that increases in the numbers of people being treated are often interpreted as a sign of social calamity.

Along with growing acceptance of mental illness and expanded options for treatment, screening for mental illness has greatly increased. In general, where there is more screening, we would expect to find more cases. For example, Chorniy et al. (2018) show that provider mandates to screen under Medicaid in South Carolina increased child diagnoses of both Attention Deficit Hyperactiviy Disorder (ADHD) and asthma. As part of the U.S. Affordable Care Act, insurers were required to pay for screenings if they were recommended by the U.S. Preventive Services Task Force. This made USPST recommendations, such as screening women and girls over 12 for depression annually, legally binding for insurers. Choi et al. (2026) show that these screening mandates coincided with growing trends in the diagnoses of mental illness of teen girls compared to teen boys. However, the U.K. and most European countries have explicitly rejected universal screening mandates for mental illness, because of high rates of false positives, possible over-diagnosis of mild cases, and lack of clinical evidence that it helps to prevent either mortality or long-term illness.[6]

Changes in the definition of mental illness are among the most important factors that may be driving increases in caseloads, especially for the most rapidly growing categories, of anxiety, depression, and ADHD. Mental illness is usually diagnosed using the DSM, and in 2013, there was a transition from DSM-4 to DSM-5 which substantially redefined many mental disorders. For example, several disorders were added to the depression category, including disruptive mood dysregulation disorder, bereavement disorder, dysthymic disorder (persistent low mood), and premenstrual dysphoric disorder. Post-traumatic stress disorder, which had been a separate category, was classified as an anxiety disorder and a rule that only persons over 17 could be diagnosed with social anxiety disorder was dropped. Other changes with the introduction of the DSM-5 included the creation of a new Autism Spectrum Disorder diagnosis, which combined four previously separate diagnoses into one larger category, and changes in the criteria for ADHD which allowed people who first had symptoms after age seven to qualify for a diagnosis. These changes have been associated with a subsequent explosion in cases of autism (broadly defined) and ADHD (Vande Voort et al. 2014; Frances 2025).

In the U.S. a belated switch from ICD9 in ICD10 in 2015 (most European countries had switched by 1994), added additional difficulty to the problem of discerning time trends because

[5] This policy came as part of the agreement on the finance act for 2022 (Finansministeriet 2021).
[6] See for example, UK:Visintin (2026).

the ICD10 increased the number of available diagnostic codes 5-fold and added many new mental health codes, including a range of new codes for anxiety disorders that allowed greater specificity in diagnosis. Other changes that occurred with the transition to ICD10 included a greater emphasis on coding suicidal ideation and forcing practitioners to choose codes that indicated whether an injury was due to self-harm or not. Stewart et al. (2017) show that this change led to increases in the number of injuries and poisonings coded as due to self-harm (from about 10 to 15 per 100,000) and that these gains were offset by declines in injuries or poisonings with undetermined causes. Another U.S. specific change was that after 2007, providers were allowed to bill more for more complex cases, where listing specific mental health conditions (such as depression) as secondary diagnoses made a case more complex.

Choi et al. (2026) work through the consequences so many of these changes for the specific case of diagnoses associated with Emergency Department visits of teens 10-19. They show for example, that after 2013, overall diagnoses of mental illness was roughly constant. Although there was a large increase in diagnoses of depression and anxiety, these diagnoses were offset by reductions in all other mental health diagnoses. Looking specifically at suicidal behaviors, they conclude that although reported suicidal behaviors rose 228 percent between 2006 and 2021, the true rise was likely closer to 66 percent (which is also the increase in youth suicide observed over the same period.)

Many countries are now in the process of transitioning from ICD10 to ICD11, which was introduced in 2018 and adopted by the World Health Organization for reporting purposes in 2022. ICD11 continues the trend toward revising mental health disorders, moving dementia out of the chapter on mental disorders and into the section on diseases of the nervous system; eliminating subtypes of personality disorders; moving obsessive-compulsive disorders out of anxiety disorders into a stand-alone category; and introducing new disorders such as complex PTSD, body dysmorphic disorder, and gaming disorder. This state of change reflects real uncertainty about the definition and diagnoses of mental health disorders (Seemüller 2023).

These examples show that one must be careful about drawing inferences about changes in mental health disorders from diagnosis, claims, or utilization data. What about survey data? As Choi et al. (2026) point out, the problem is that there are few sources of data that have asked the same questions about mental health in a similar way over long periods of time.[7] Moreover, questions about diagnoses or treatment suffer from all the potential biases discussed above. What is needed is a long time series of more neutral questions about signs and symptoms of mental illness. The few existing sources tend to show trends that are quite different from trends in diagnoses or treatment. For example, the U.S. General Social Survey questions about bad mental health days show relatively constant numbers over time. Currie (2025) points out that questions from the Youth Risk Behavioral Surveillance Survey of U.S. highschoolers show that in 2021 almost 40 percent of youth report feeling sad or hopeless, but that this level was flat at about 30 until 2017. The U.K. Household Longitudinal Study reports scores on the 12-item General Health Questionnaire, a general screener for mental distress, over a long period of time. This measure shows increases in mental distress from 2008 to 2024, but they are relatively small. For example, an increase from 9 to 11 out of 36 among boys 16-19 and a corresponding increase from 10.5 to 13 among girls the same age.

Data on suicides is perhaps most accurately collected, though even these data may be subject to changes in reporting conventions over time. For example, it is possible that reductions

[7] In their appendix, they show that many U.S. surveys that ask about mental health have changed their measures significantly over time.

in stigma could increase doctor's willingness to code suicide as a cause of death.[8] It is also possible that greater openness about mental illness combined with a higher probability of being in treatment at the time of a death could increase counts of suicides by making the intentions of the deceased clearer.[9] And as discussed above, suicides do not move in lockstep with other measures of mental health.

The bottom line is that changes in the measurement of mental health over time have been non-trivial and have likely contributed to the impression of an exploding epidemic of mental illness. Any one of these changes had the potential to increase diagnoses of mental health conditions, but most research and reporting on trends in mental health diagnoses have completely ignored their possible impacts. What is undeniable is that many more people are being diagnosed and treated for mental health issues. This may be a positive development given a history of stigma and limited access to mental health care.

3. The Determinants of Mental Health

3.1 The Health Capital Model

The standard model of health capital has become a theoretical foundation for research in health economics (Grossman, 1972; Grossman 2000) and we argue in this section that despite stereotypes about people with mental illness being irrational, the model provides a useful framework for thinking about mental health. The model treats health as a durable capital stock. People receive an initial endowment but actively work to produce and maintain their stock of health capital over their lives. Individuals are assumed to maximize lifetime utility, which depends on consumption and health, by choosing how much to invest in health and other goods in each period. Utility is maximized subject to three constraints: (i) a health accumulation equation that depends on how the stock evolves with investment (the production function) and depreciation; (ii) a time constraint that allocates a fixed time endowment across sick time, market work, leisure, and time devoted to health investments; and (iii) a budget constraint that equates wage earnings and non-labor income to expenditure on consumption and purchased health inputs.

Health capital increases utility directly and indirectly by reducing sick time and thereby expanding the time available for productive and enjoyable activities. Hence people treat health as both a consumption and an investment good. Health cannot be directly purchased but is produced by combining time and material inputs such as medical care. Education is assumed to raise the marginal product of both inputs. In the canonical exposition, depreciation is treated as an exogenous function that increases with age.

This framework can be applied to mental health as follows: Consider an individual whose lifetime utility depends on consumption and mental health:

$$\sum_{t=0}^{T} \beta^t U(C_t, M_t)$$

where C_t represents consumption and M_t represents the stock of mental health. In what follows, we abstract from the fact that the individual also cares about their physical health. $M_t$captures

[8] Inconsistent coding of suicide as a cause of death is a recognized problem, though in the U.S. the situation improved after a working group published new guidelines in 1988 (Rosenberg et al., 1988). Using law changes over time, Fernandez (2018) finds that states that have medical examiners rather than relying only on county coroners, have higher suicide rates and lower rates of accidental death recorded. As of the end of his sample period 11 states had only county coroners.

[9] O'Carroll (1989) and Breiding and Wiersema (2006) point out that the deceased intentions are often unclear, especially in the case of drug overdoses.

symptom burden and functioning, including emotional regulation, cognitive performance, stress resilience, and the capacity to engage in daily activities.

The mental health stock evolves according to a discrete-time accumulation equation:

$$M_{t+1} = (1 - \delta_t)M_t + I_t$$

where δ_t is the period depreciation rate and I_t is gross investment in mental health. In a departure from the canonical model, depreciation can be modeled as something that depends on circumstances and choices (e.g., Fu 2016). This extension is especially useful when considering mental health: the idea that depreciation of the mental health stock may vary non-monotonically over time may be one of the key differences between models of physical health capital and models of mental health capital, though many physical ailments also have the feature that they come and go. Because mental health and treatment-seeking can propagate through contagion in symptoms, coping behavior, and help-seeking itself, the depreciation rate can also depend on the mental health or treatment status of others in an individual's family, peer group, or community, and not only on her own circumstances. Hence, modelling the way that network effects affect depreciation may also be important.

Depreciation is assumed to be increased by trauma, job loss, family conflict, and other stressful events, or by chronic stressors. Depreciation can also be state-dependent: δ_t may increase when M_t is low. Evidence about relapse and recurrence and "scaring versus vulnerability" patterns in depression suggest that depressive episodes leave lasting damage that increases future vulnerability beyond what would be predicted from pre-existing risk alone (Burcusa and Iacono 2007; Bos et al. 2018). With state-dependent depreciation, a sufficiently severe shock can push an individual below a threshold from which recovery is slow or incomplete even after the original stressor has passed, generating high persistence in mental health capital. This persistence is consistent with models that include adjustment costs or non-linearities that can generate threshold dynamics (Galama 2011).[10]

The depreciation rate may also depend on economic conditions. Financial strain, job insecurity, workplace stress, and the evils associated with poverty (poor housing conditions, eviction, exposure to violence) can be modeled as factors that increase the depreciation of mental health capital. Hence, income can operate not only as a resource for investment through the budget constraint, but also as a direct determinant of depreciation rates. This dual role can generate a steeper socioeconomic gradient in mental health than would arise if income operated only through the budget constraint.

Gross investment in mental health capital is produced according to a household production function:

$$I_t = f(X_t, t_M; E_t, \Gamma_t)$$

where X_t are purchased inputs (e.g. psychotherapy visits, psychiatric consultations, medications and goods that contribute to wellness), t_M is time devoted to mental health production (e.g., sleep, exercise, mindfulness practice, time in treatment), and E_t is a productive efficiency parameter capturing education and mental health literacy. Γ_t captures other investment-productivity shifters, i.e., factors that affect how effectively purchased inputs and time translate into improvements in mental health, holding depreciation fixed. It primarily reflects access to and quality of care because these factors affect the effectiveness of a given X_t (e.g., via delays in

[10] Panel data evidence in economics documents substantial persistence and state dependence in mental health outcomes over time (e.g., Roy and Schurer 2013; Ohrnberger et al. 2017). This reduced-form persistence is consistent with state-dependent dynamics in the law of motion, but it does not, by itself, distinguish whether persistence operates through state-dependent depreciation versus state-dependent investment or investment productivity.

treatment, discontinuities in care, and provider-patient match quality). To the extent that mental health investment is supported or impeded by the household, Γ_t can also reflect within-family features that affect adherence and the ability to convert treatment time into recovery, consistent with extensions that treat the family as a producer of health (Jacobson 2000).

As discussed further below, access to care and quality of care are important determinants of the productivity of investments in mental health. This logic extends naturally from the household to a wider peer or community network: because individuals who observe others seeking and completing treatment may face lower effective barriers to care, the productivity shifter can also depend on the mental health and treatment status of an individual's broader network, so that network exposure operates both as a risk factor through depreciation and as a moderator of treatment returns through investment productivity.

The time constraint is given by:

$$\Omega = s(M_t) + t_w + t_l + t_M$$

where Ω is the time endowment, $s(M_t)$ is the time lost to illness, which is decreasing in the mental health stock, t_w is the time spent on market work, t_l is leisure time, and t_M is the time spent investing in health.

Finally, the budget constraint is given by:

$$w\,\psi(M_t)t_w + V = p_x(S_t)X_t + p_c C_t$$

where w is the market wage, $p_x(S_t)$ is the price of purchased health inputs with S_t summarizing stigma and beliefs, p_c is the price of the consumption good, and V is non-labor income. There are two key departures from the standard model.

First, the price of purchased health inputs includes stigma. Stigma can raise the effective (shadow) price of treatment through psychic costs, disclosure concerns, and other frictions, thereby reducing and delaying utilization even when monetary prices are low. Because stigma and the returns to treatment are imperfectly observed, individuals may act on perceived rather than actual values of these parameters: biased beliefs about the efficacy of available treatments, about the prevalence of stigma among their peers, or about their own symptom severity can suppress investment independent of the parameters' realized values.

Second, earned income includes the term $\psi(M_t) \in (0,1]$ which is a productivity scaling factor that is increasing in M_t. This is a reduced-form way to capture the idea that mental health affects productivity in the workplace and allows a connection between mental health capital and labor-market outcomes. While physical health may also lead to reduced productivity at work, it may be more likely to lead to absenteeism then *presenteeism*, defined as reduced productivity while physically present at work due to mental health issues (such as depression, anxiety, or burnout).

Consistent with the standard model, higher wages raise the return to mental health capital through the value of effective work time as well as through the budget constraint, while education increases investment efficiency. Relative to the canonical model, our description places greater emphasis on several features of mental health: depreciation that may be non-monotonic and dependent on circumstances; access to and quality of care that affects the productivity of investment; the fact that mental health can affect performance at school and work through presenteeism as well as absence; the role of stigma and imperfect information in alter treatment decisions; and the idea that mental health and treatment-seeking may propagate through family, peer, and community networks.

3.1.1 Mental Illness and the Assumption of Rational Choice

A potential objection to applying a utility-maximization model to mental health is that the capacity for forward-looking, rational choice is impaired by mental illness, so that a framework built on fully informed optimizing agents seems poorly suited to conditions that distort beliefs, sap motivation, and shorten time horizons. Recent work illustrates how some of these concerns can be accommodated within a standard optimizing framework. Abramson et al. (2025) embed mental illness in an otherwise standard dynamic life-cycle model by allowing key parameters to vary with illness severity: individuals with more severe illness evaluate choices under more pessimistic worst-case beliefs about both asset returns and their own future mental health, lose a larger share of their time endowment to rumination, and face a higher utility cost of seeking treatment due to stigma. However, they remain forward-looking, expected-utility maximizers with an unchanged discount factor. In their model, behaviors including undertreatment, reduced risk-taking, and the choice of less demanding jobs arise as optimal responses to mental illness induced parameter shifts rather than from a breakdown of optimization itself.

The approach in Abramson et al. (2025) illustrates that some features of mental illness can be incorporated into a standard optimizing framework without abandoning its basic structure. This approach is like the one taken by behavioral economists and recognizes that people can still make optimizing choices and respond to incentives even when their perceptions are distorted by mental illness. The important thing from a modelling perspective is to capture the way that the basic parameters of the model can be affected by mental health.

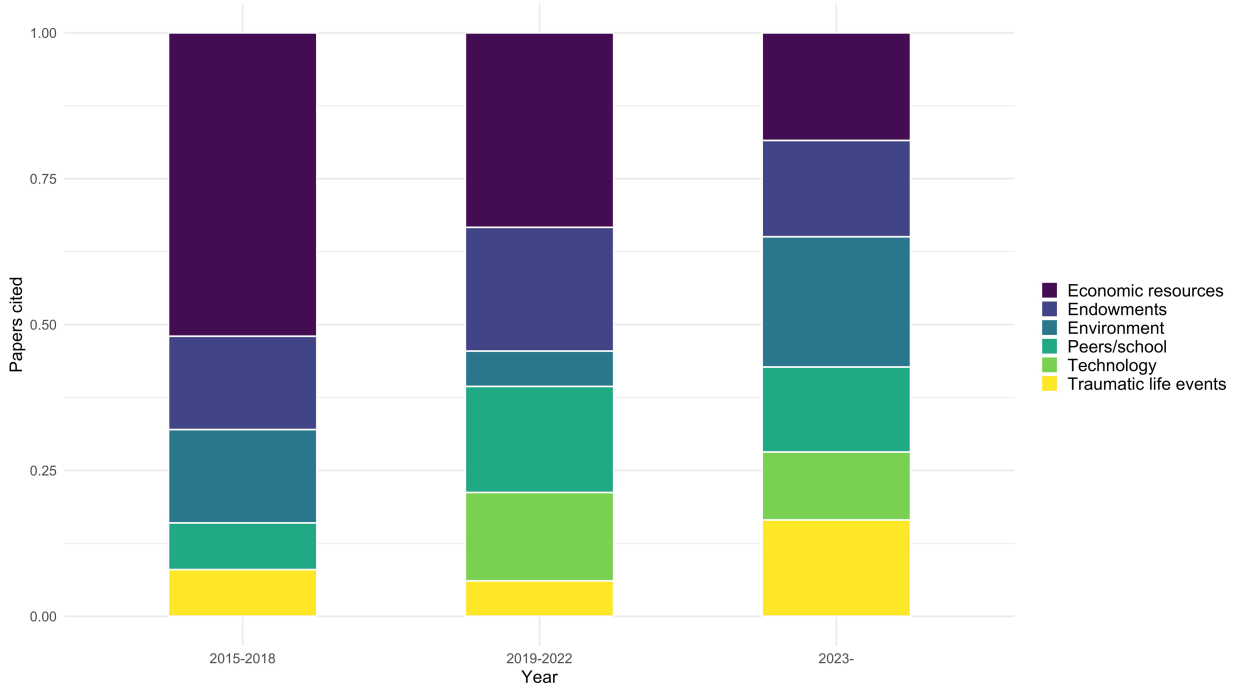
More generally, we use the health capital model as an organizing framework for thinking about the channels through which individual circumstances and choices shape mental health, without requiring that all the assumptions of the canonical model apply directly to mental health. In the sections that follow, this framework is used to organize the evidence on how endowments, economic resources, education, environmental conditions, traumatic events, and access to and quality of treatment shape mental health.

Figure 2 shows that the share of papers examining the impact of economic resources on mental health has declined over time, while there have been large increases in the share examining the effects of pollution, peers and schooling, technology (social media), and traumatic life events.

3.2 Endowments: Fetal and Family Origins

Each individual inherits an initial mental health capital stock H_0 and a baseline depreciation rate δ. This section reviews evidence from two distinct lines of research that bear on these starting conditions: the intergenerational transmission of mental health from parents to children, and the fetal and early-childhood origins of mental health.

Figure 2: Research on Causes of Mental Illness by Category



Notes: This figure breaks down the papers cited in Tables 2 to 6 by publication year and category of cause. Endowments = Table 2; Peers/school = Table 3, Panels A and B; Technology = Table 3, Panel C; Economic resources = Table 4; Environment = Table 5; Traumatic life events = Table 6.

3.2.1 Intergenerational transmission of mental health

A natural starting point for understanding the determinants of a child's initial mental health stock, H_0, and baseline depreciation rate, δ, is parental mental health. Parental mental health may shape these initial conditions through several overlapping channels, including genetic transmission of risk and the quality of the early family environment, including parenting behaviors. Panel A of Table 2 summarizes the economic literature on the intergenerational transmission of mental health. Recent survey-based evidence suggests substantial persistence in mental health across generations, with parent-child associations of about 0.2 (Bencsik et al. 2023; Vera-Toscano and Brown 2022). These estimates are larger than intergenerational persistence in longevity (Black et al. 2023) but comparable to persistence in birth weight (Currie and Moretti 2007; Black et al. 2007). Population-wide administrative data likewise indicate substantial transmission on the extensive margin. Using register-based measures of mental health derived from diagnoses and treatment, two recent studies find that parental mental health conditions raise children's probability of a mental health event by about 9 percentage points in both Norway and Denmark, with relative increases ranging from 40 to 83 percent depending on baseline prevalence (Bütikofer et al. 2024; Bhalotra et al. 2026c).

Overall, the literature points to substantial intergenerational persistence in mental health. At the same time, intergenerational persistence in mental health appears lower than the benchmark estimates of 0.4–0.5 typically reported for income (Black and Devereux 2011; Mogstad and Torsvik 2023), suggesting greater mobility across generations. This may reflect the fact that mental health is more exposed to idiosyncratic shocks over the life cycle, but it may also be consistent with the role of public health systems and social insurance in high-income settings in weakening the transmission of health disadvantage across generations. A further complication is that estimated transmission coefficients may depend on the ages at which parents and children are observed. This matters because the age profile of mental health remains unsettled: some studies report a U-shape, with mental health worst in midlife (Blanchflower and Oswald 2008, 2016; Lang et al. 2011), while others find no U-shape or even an inverse U-shape (Bell 2014; Dijk and Mierau

2023). If mental health changes systematically with age, measuring parents and children at different points in the life cycle may mechanically raise or lower estimated transmission coefficients.

What drives the associations?

The strong parent–child association in mental health is consistent with multiple mechanisms: genetic inheritance of risk alleles, epigenetic transmission through prenatal exposures, shared family environments including parenting behaviors and household stress, gene–environment interactions, and family propensities to seek care and/or access to care. Disentangling these pathways is both scientifically important and relevant for policy since environmental channels are more readily amenable to intervention than genetic ones. Purely observational designs cannot separate biology from environmental factors because biological parents transmit both.

Bhalotra et al. (2026c) address this identification problem using an adoptee design, comparing parent-child associations in biological families with those in families with internationally adopted children, who are genetically unrelated to their adoptive parents. They find that roughly half of the overall association in mental health reflects biological pathways, with the remainder attributable to family environment. Importantly, this decomposition differs sharply by parent gender: mother-child transmission is approximately three-quarters environmental, whereas father-child transmission is predominantly biological. An important caveat of adoptee designs is their limited external validity since adoptive parents are typically screened for health and economic stability. To the extent that this reduces variation in children's rearing environments, it may inflate the estimated role of biological factors. This implies that the estimated contribution of environmental factors to the intergenerational transmission of mental health may be a lower bound. At the same time, the results do not identify which specific dimensions of the family environment drive this transmission.

There is little evidence on which interventions can weaken the intergenerational transmission of mental health. A notable exception is Bütikofer et al. (2024), who evaluate a 2007 Norwegian pilot program in 26 municipalities that allocated additional resources toward young children (birth to age six) of parents with mental health diagnoses. The program implemented a variety of light-touch changes including new screening tools for psychological distress, specialist team training, and coordination with childcare centers. Using a triple-difference design that compares children across treated and matched control municipalities, birth cohorts, and parental mental health status, the authors find that the pilot reduced the parent–child mental health association by approximately 39 percent. Effects are stronger for children exposed at younger ages and for children of college-educated parents, consistent with a model in which early investment and parental capacity to engage with services amplify the returns to intervention.

Key Takeaways and Emerging Themes

Four broad conclusions emerge from this literature. First, evidence from both survey and administrative data point to substantial persistence in mental health and an important role for family environment alongside biology. Second, while there is a large literature outside economics linking maternal mental health to short-run infant outcomes such as secure attachment, there is very little causal evidence on how parents' mental health shapes children's longer-run outcomes. Similarly, there is scarce evidence on which targeted policies can durably weaken the intergenerational transmission of mental health. Finally, no existing study provides credible causal evidence on inheritance-environment interactions, that is, whether children with high risk of mental illness are differentially protected by high-quality family environments.

A large developmental psychology literature argues that some children are especially sensitive to environmental conditions (so-called "orchids") while others are more resilient

("dandelions") with "tulips" lying in between. If, for example, genetic risk is expressed primarily in adverse environments, then environmental interventions may effectively mute biological risk even in the absence of any literal epigenetic change. If, instead, positive environmental factors operate additively, the policy implications are quite different. In the language of the model, the effect of environmental inputs on depreciation rates may depend on the child's initial endowment, H_0, but existing evidence does not yet show whether sensitivity is driven mainly by innate risk, environment, or their interaction.

3.2.2 Effects of in-utero shocks

A large literature establishes that prenatal and early-childhood conditions have persistent consequences for a wide range of adult outcomes, including educational attainment, earnings, and physical health. (Almond and Currie 2011, Almond et al. 2018). Earlier studies in this 'fetal origins' literature focus on the mental health consequences of extreme nutritional shocks (e.g., the Dutch Hunger Winter and the Chinese Great Leap Forward famine) and disease environments (e.g. influenza). A more recent literature documents the effects of relatively mild nutritional deprivation (e.g., Ramadan fasting). Panel B of Table 2 summarizes advances in the economics literature on the fetal and early-childhood origins of mental health during the past decade, including studies of armed conflict, milder nutritional and economic shocks, maternal stress, and ambient environmental conditions.

Fetal and early-life origins of long-run mental health

More than 473 million children, or over one in six worldwide, now live in conflict-affected areas. This share has risen sharply over time, from about 10 percent in the 1990s to nearly 19 percent today, and by the end of 2023 an estimated 47.2 million children had been displaced by conflict and violence (UNICEF 2024). While a large economics literature links exposure to armed conflict to worse physical health (e.g., Akbulut-Yuksel 2014, 2017; Akresh et al. 2012, 2023; Mansour and Rees 2012; Kesternich et al. 2014), its effects on mental health have received much less attention. Two recent studies help fill this gap. Singhal (2019) examines the impact of the American bombing campaign in Vietnam, using distance from the border between North and South Vietnam as an instrument for bombing intensity. Among individuals who were age five or younger during the war, a 1 percent increase in bombing intensity raises the probability of severe mental distress in adulthood by 16 percentage points, or roughly 50 percent relative to the mean prevalence.

Akbulut-Yuksel et al. (forthcoming) study the long-run mental health consequences of Allied bombing of German cities during World War II. They identify these effects by exploiting plausibly exogenous variation across cities in bombs dropped per square kilometer, interacted with an indicator for being ages 0 to 5 during the war, and comparing cohorts born in 1934-1945 with older pre-war cohorts and post-war cohorts. They find that a one-standard-deviation increase in bombing intensity during childhood is associated with about a 10 percent decline in a standardized mental health score later in life, equivalent to a 16.2 percent increase in the probability of clinical depression.

Emerging evidence also shows that the relationship between early-life conditions and later-life mental health extends beyond catastrophic shocks such as famine and armed conflict to more moderate fluctuations in household resources that are highly relevant for current policy. Evidence from Sub-Saharan Africa indicates that adverse shocks around birth, including drought and declines in agricultural income, have persistent effects on later-life mental health, increasing both mental health-related disability and the risk of severe mental distress (Dinkelman 2017; Adhvaryu et al. 2019).

Recent studies also identify a stress as a distinct mechanism that affects subsequent mental health. Elevated maternal cortisol during gestation is one pathway for this mechanism. Cortisol crosses the placental barrier and can permanently alter the hypothalamic-pituitary-adrenal axis and other stress-response systems during critical periods of fetal brain development. These alterations in turn can increase vulnerability to anxiety, depression, and attention disorders decades later.

Persson and Rossin-Slater (2018) provide some of the cleanest causal evidence on this channel using Swedish administrative data linking the full population of births to four-generation family trees. The identification strategy compares outcomes for children whose mothers experienced the death of a close relative while the child was in utero against outcomes for children whose mothers experienced a comparable bereavement in the year after birth, a design that holds constant family propensity for bereavement while isolating the specific effect of prenatal versus postnatal exposure. In-utero exposure to maternal bereavement increases consumption of ADHD medication in childhood by 24 percent and raises the probability of receiving anti-anxiety drugs and antidepressants at age 35 by 19 and 12 percent respectively.

Finally, an emerging literature considers whether chronic ambient conditions in utero affect later mental health. The evidence here is more limited and mixed. Recent work links higher birth-year temperatures to worse adult mental health in Africa, while evidence from China finds no effect of cleaner household air in utero on depressive symptoms through age 15, despite improvements in birth outcomes and physical health (Adhvaryu et al. 2024; Ai and Tan 2025). One important caveat is that many cases of depression are diagnosed only later in life, so studies that follow children only into adolescence may miss important longer-run effects.

Key Takeaways and Emerging Themes

Overall, the evidence suggests that fetal and early-childhood conditions have persistent effects on later-life mental health and that mental health endowments are not only sensitive to rare catastrophic events but also to moderate fluctuations in household resources, maternal psychological stress, and ambient environmental conditions.

In contrast to the increasingly well-documented reduced-form effects, the mechanisms underlying them remain much less clearly identified. Most studies rely on heterogeneity analyses and secondary outcomes rather than designs that can credibly isolate individual channels, and the relevant mechanisms are likely to differ across shocks. Understanding this heterogeneity is important for policy, since the appropriate intervention depends on whether early-life insults operate primarily through nutrition, stress, parental investments, institutional disruption, or some combination of these pathways. Conflict, for example, likely affects later mental health through multiple channels at once, including nutritional deprivation, direct exposure to violence, bereavement, forced displacement, losses in household wealth and employment, and the destruction of health and public-health infrastructure. Consistent with an important institutional channel, evidence from Germany suggests that the long-run mental health effects of wartime bombing were especially pronounced in cities where bombing caused greater damage to hospitals and where post-war health-care systems were more severely strained (Akbulut-Yuksel et al. forthcoming). In contrast, household resource shocks, may operate through maternal nutrition, liquidity constraints, and parental investments in children. Evidence from Ghana, for example, shows that adverse cocoa-price shocks around birth affect cash savings, maternal nutritional status, breastfeeding, and vaccination take-up, though the separate contribution of each channel is difficult to identify (Adhvaryu et al. 2019).

Among the early-life insults studied so far, maternal stress has perhaps the clearest proposed mechanism, operating through cortisol and other stress-response systems during fetal

development. Here, the contrast with other outcomes is especially revealing. In Sweden, prenatal exposure to bereavement increases later use of ADHD medication and adult psychotropic drugs, but does not appear to generate lasting effects on physical health, a pattern more consistent with stress-specific fetal programming than with general developmental deprivation (Persson and Rossin-Slater 2018). Similarly, Black et al. (2016), using a related design in Norway based on grandparent deaths, find small negative effects on birth outcomes but no lasting consequences for education or earnings. Taken together, these findings suggest that the mental health consequences of early-life shocks need not mirror their effects on physical health or socioeconomic outcomes, underscoring that mental health may follow partly distinct developmental pathways.

Finally, these findings have important implications for the origins of inequality. A recurring pattern is that the socioeconomic gradient in mental health begins very early in life and may partly reflect unequal exposure to adverse prenatal and early-childhood environments. The same shocks that shape mental health endowments are not randomly distributed across populations. Armed conflict is disproportionately concentrated in low- and middle-income countries and in settings with weaker institutional infrastructure. Likewise, high ambient temperatures and other environmental stressors are more prevalent in poorer regions and are expected to intensify with climate change. If such exposures worsen mental health from birth onward, then they may contribute to widening inequalities in mental health both within and across countries.

3.3 Education, school, and community resources

In the standard model, education raises the efficiency with which individuals transform health investments into health capital. Under this formulation, education is unambiguously protective: more schooling lowers the effective cost of health production and monotonically improves health outcomes.

The schooling environment, however, is not a neutral backdrop to the investment process. Academic advancement brings competitive pressure, performance anxiety, and exposure to social hierarchies that can directly raise the rate at which mental health capital depreciates, so that the psychosocial costs of schooling may partially offset its efficiency gains. The model also abstracts entirely from peer dynamics, yet schools are among the most densely peer-structured environments individuals encounter over the life course. Peer mental health, peer composition, and peer norms are not inputs in the original framework, but there is strong reason to expect that the mental health of those around a student shape their own through social contagion, relative positioning, and norm transmission.

The economic literature of the past decade has focused primarily on the school environment and peer dynamics within schools rather than on the relationship between years of schooling and mental health that is the focus of the original framework. More recently, the rapid diffusion of social media has extended peer dynamics beyond the school day, adding a new set of channels through which the social environment of schooling shapes mental health. Panel A of Table 3 summarizes the research on schooling and mental health, which is discussed below.

3.3.1 School structure, academic achievement, and transitions

One strand of the literature points to the potential mental health benefits of access to better or better matched educational environments. Bütikofer et al. (2023) exploit GPA-based admission cutoffs for oversubscribed higher-achievement high schools in Oslo and Bergen in a regression discontinuity design. Eligibility to attend a higher-achievement school increases high school completion and higher education enrollment. They find no detectable effects on mental health during high school itself, but eligibility reduces the probability of diagnosis or treatment for

psychological conditions in the three years after secondary school by about 7.5 percent. The gains are largest for students whose educational attainment also improves. Together with the delayed timing of the effect, this finding suggests that the mental health benefits operate mainly through the opportunities opened by a stronger educational trajectory, as the framework suggests, rather than through an immediate reduction in in-school stress.

Stenberg and Tudor's (forthcoming) work points in a similar direction. Using a regression discontinuity design based on GPA cutoffs for oversubscribed upper-secondary programs, they examine how assignment to field of study at age 16 affects antidepressant use at ages 40 to 45 and mental-health-related hospitalizations in adulthood. They find that admission to one's preferred field reduces later mental health problems. The average effect is driven primarily by Engineering, with some contribution from Business. They also examine heterogeneity by the nature of the second-choice option and find only weak evidence that the effects are stronger when the fallback option is another academic field rather than a non-academic program. Finally, they show that earnings differences account for roughly 40 percent of the estimated mental health gap. This suggests that educational assignment can affect mental health through a longer-run opportunity channel, consistent with the findings in Bütikofer et al. (2023).

At the same time, school transitions and academic milestones can impose substantial psychological costs. Chen et al. (2024) provide direct evidence about this using Taiwan's administrative health insurance records. Because Taiwan has a September school-entry cutoff, children born in August reach each major school milestone, including entry into primary school, entry into middle school, and high-stakes examinations for high school and college entry, one year earlier than children born in September of the same calendar year. The authors combine a regression discontinuity design around this birth-date cutoff with a difference-in-differences strategy that compares the two groups over the months surrounding each milestone. This strategy allows them to identify the effect of each transition separately, rather than recovering only a single composite effect of school starting age. The results show that both primary and middle school entry are associated with sharp increases in psychiatric prescriptions, including not only ADHD medication but also antidepressants and, at middle school entry, anti-anxiety and antipsychotic drugs. In contrast, there is no increase in prescribing in the period leading up to high-stakes examinations, but prescriptions fall sharply once the examinations are over. The effects are stronger in counties where parents and children report especially high educational aspirations. Taken together, these patterns are more consistent with genuine stress responses to academic pressure than with diagnostic labeling or relative-maturity effects.

Evidence from Covid-related school closures further reinforces the idea that exposure to the school environment is not unambiguously protective for mental health. Papers exploiting the temporary shift away from in-person schooling suggest that, for some adolescents, reduced school exposure led to improvements in mental health or lower mental health care use (Björkegren et al. 2024; Hansen et al. (2024) find that exploit staggered reopenings of schools across the U.S. and find that school closures reduced adolescent suicides, while openings increased them. Chandler et al. (2022) show similar respects with respect to school holidays in Germany, which occur at different times in different jurisdictions. These findings indicate that the daily school environment can itself be a source of strain, whether through academic pressure, social comparison, bullying, or the general demands of in-person attendance. When read together with the evidence on school transitions, the Covid closure studies make clear that schools are not only sites of skill formation and social support but can also be settings in which stress accumulates.

3.3.2 Peer effects, bullying and victimization

Peers are a central feature of the school environment, and one line of research examines how peer groups shape adolescent mental health. Studies in this literature typically exploit quasi-random variation in peer group composition generated by the assignment of students to classrooms within a school and grade, using school-by-grade fixed effects to isolate the variation in peer characteristics that is plausibly independent of individual selection. Existing work has examined a range of peer attributes such as peers' depressive symptoms, genetic predisposition to depression, religiosity, and gender composition (see Panel B of Table 3). Across these settings, the evidence points to meaningful and often persistent effects.

A complementary strand of the literature focuses on peer victimization as a specific mechanism through which the school social environment harms mental health. Several papers exploit the staggered passage of state-level anti-bullying laws across the United States to study effects on suicidal behaviors and depression among adolescents (Churchill et al. 2025; Rees et al. 2022). These studies find that the passage of anti-bullying legislation is associated with reductions in suicidal ideation, suicide attempts, and depression of between 5 and 6 percent on average, though the protective effects are concentrated among groups at elevated risk (e.g., non-white females, LGBTQ students, and overweight adolescents) rather than distributed uniformly across the student population. These results suggest that targeted interventions for high-risk groups may generate substantially larger returns than broad-based legislative interventions.

The evidence also suggests that it is not only peer characteristics that matter, but also an adolescent's own position within the peer group. Using data from the National Longitudinal Study of Adolescent to Adult Health, Kiessling and Norris (2023) ask whether students' rank in the local achievement distribution affects mental health, holding their own cognitive ability constant. They exploit variation in the ability composition of peers within the same school and grade, so that two students with similar own ability may nonetheless occupy different positions in the local ranking.

The results show that students who rank higher in their cohort experience better mental health. The average effects are modest: a one standard deviation increase in relative rank, corresponding to roughly a 28-percentile improvement in position, raises mental health by about 0.06 standard deviations. However, the effects are substantially larger for students at the lower end of the ability distribution. Examining components of the mental health index, shows that rank mainly affects items related to low motivation and the absence of positive affect, rather than loneliness or more outwardly social dimensions. These findings suggest that peer environments shape mental health not only through exposure to peers' traits or distress, but also through rank, social comparison, and academic self-perception.

3.3.3 Digital technology, social media and school phone policies

Digital apps have become an increasingly important part of the social environment in which adolescents and young adults interact, form identities, and assess their social standing. Relative to offline interactions, these platforms increase the scope for repeated comparison with peers and make social feedback more immediate and more measurable. They may therefore affect mental health not only through changes in time use or exposure to online harassment, but also through self-evaluation, status anxiety, and persistent comparison with others.

Several economics papers use variation in platform access or use that is plausibly unrelated to individuals' underlying mental health. Braghieri et al. (2022) exploit Facebook's staggered rollout across U.S. colleges and estimate a generalized difference-in-differences model that compares student outcomes at a given campus before and after Facebook became available there, relative to campuses that had not yet gained access. They find that Facebook's arrival increased an index of poor mental health by 0.085 standard deviations, with somewhat larger effects for

students predicted to be more susceptible to mental illness. Allcott et al. (2020) use a randomized experiment in which participants were paid to deactivate Facebook for the four weeks before the 2018 U.S. midterm election. They find that temporary deactivation improved subjective well-being by about 0.090 standard deviations. In contrast, Büyükeren et al. (2026) exploit Tinder's early campus diffusion, which disproportionately targeted Greek organizations, and find that while the app substantially altered relationship behavior, it did not worsen mental health on average and may even have improved it for women.

A complementary strand of the literature examines the effects of restricting phone access during the school day. Abrahamsson (2026) exploits staggered variation in the timing of voluntary smartphone bans across Norwegian middle schools, using an event-study design that compares cohorts differentially exposed to a ban within the same school. It finds that banning smartphones reduces specialist consultations for psychological symptoms by approximately 60 percent and GP consultations by 29 percent for fully exposed girls. Mental health gains are mainly observed among girls from low-SES backgrounds. There is however evidence of reduced bullying for both girls and boys.

These findings are at odds with Allcott et al. (2026), who study the adoption of Yondr lockable phone pouches across nearly 5,000 U.S. schools in a staggered difference-in-differences design. They find that pouch adoption substantially reduces in-school phone use.[11] In the first post-adoption year, disciplinary incidents rise by 16 percent and student well-being falls by approximately 0.2 standard deviations. Both of these effects dissipate subsequently. These two studies also consider effects on educational achievement. Abrahamsson (2026) finds that smartphone bans improve low-SES girls' GPA and test scores, with larger test score gains at schools with strict bans (where phones are confiscated before class) than at schools with lenient policies that merely require silent mode. Allcott et al. (2026), on the other hand, find zero average effects on test scores, though there is heterogeneity by school level: high schools see modest positive effects in mathematics, while middle schools see small negative effects. The authors also find no detectable effects on attendance, self-reported classroom attention, or perceived online bullying.

These conflicting do not point to a single "average" effect of digital technology on youth mental health. This conclusion is consistent with the broader scholarly literature outside economics. For example, Hancock et al. (2022) review 226 studies on social media use and child mental health and find that greater use is linked to increases in anxiety and depression, but also to small gains in connectedness and social well-being, with relatively neutral effects on overall wellbeing. As Currie (2025) argues, given that large numbers of youth had mental health problems as far back as 1970, before there was any social media, it cannot be the case that social media is the sole, or even the most important driver of the youth mental health crisis.

Key Takeaways and Emerging Themes

Three broad conclusions emerge from this literature. First, when it comes to education and mental health, it is not only the quantity of schooling that matters, but also the environment in which schooling takes place. While standard human-capital models emphasize the efficiency gains associated with education, the evidence reviewed here shows that school quality, educational match, academic pressure, peer dynamics, bullying, and digital technologies can each independently shape mental health. Second, an important emerging theme is heterogeneity. The effects of school environments are not uniform, but vary across students depending on their ability, aspirations, social position, gender, vulnerability, and underlying susceptibility to mental health

[11] Yondr pouches are fabric cases with magnetic locking mechanisms that physically prevent students from accessing their devices throughout the school day.

problems. Third, the literature on digital technologies remains comparatively underdeveloped and points to a clear need for further research that separates distinct margins of exposure. Platform access and social media use primarily reshape social comparison and interaction outside school, whereas school-day restrictions target attention, peer dynamics, and cyberbullying during school hours. Two important topics for future research include how digital platforms affect minority and socially isolated groups, for whom there is some evidence that online interaction may be protective,[12] and whether and how digital environments and school policies interact with mental health diagnosis, treatment, and suicide and self-harm contagion.

3.4 Economic Resources

Income and employment can affect mental health through two routes. First, they affect time and money budget constraints and therefore determine the resources available for mental health investment, including both underlying determinants of mental health like adequate nutrition and stable housing, and treatment. Second, they may influence the depreciation rate of mental health capital, δ, through the psychological consequences of economic insecurity, loss of social identity, and uncertainty about the future. A large literature examines the relationship between income and life satisfaction (see for example, Kahneman and Deaton 2010) or life satisfaction over the life-course (see Galambos et al. 2021). Here we focus on research that explicitly examines measures of mental health.

3.4.1 Income effects: evidence from lotteries and policy-induced transfers

The cleanest evidence on whether income protects mental health comes from settings that generate exogenous variation in economic resources. Examples include windfalls from lotteries, and policy-induced cash transfers (see Panel A of Table 4).

Cesarini et al. (2016) link Swedish lottery records to administrative population registers and estimate the effects of variations in randomly assigned lottery prizes among lottery participants. They find that substantial gains in wealth have little effect on most adult health outcomes over a ten-year horizon, though there is suggestive evidence of a small decline in psychiatric drug consumption. Lindqvist et al. (2020) follow this sample for twenty-two years and find persistent gains in overall life satisfaction with satisfaction about finances making an important contribution. Effects on happiness and mental health are much smaller and weaker statistically. These results do not imply that income is irrelevant for mental health. Instead, they suggest that the marginal mental health return to additional income may be small in high-income settings with broad social insurance and public provision of health care. The relationship between income and mental health may be highly nonlinear: additional income may have limited benefits at higher resource levels, while negative income shocks may be harmful if they tighten constraints or increase insecurity.

Consistent with this interpretation, evidence from policy-induced income variation in lower-income settings generally points to larger mental health effects. For example, Haushofer and Shapiro (2016) evaluate a randomized unconditional cash transfer program in Kenya that provided poor rural households with large one-time transfers delivered through mobile money. The transfers increased consumption and asset ownership and improved psychological well-being in the year of receipt. Recipients had higher happiness and life satisfaction and lower levels of stress and depression. Christian et al. (2019) study Indonesia's Program Keluarga Harapan, a large conditional cash transfer program targeted at poor households and tied to investments in children's health and education. Exploiting both the program's staggered nationwide rollout across districts

[12] Berger et al. (2022), reviewing 26 studies, likewise show that the effects are not uniformly negative and may be beneficial for some groups, particularly LGBTQ youth, for whom social media can reduce isolation and provide access to affirming peers.

and an embedded randomized experiment over early treatment areas, they find that access to the program reduced annual suicide rates by about 0.36 per 100,000 people, or 18 percent.

3.4.2 Employment transitions and housing stability

A second line of research asks how transitions into and out of work impact mental health. These studies not only capture income changes but also the non-monetary dimensions of employment, such as social integration, daily structure, and occupational identity. In countries with high levels of income-protection, the impact of job loss reflects mostly these latter channels.

Existing studies of job loss and retirement typically rely on survey data and fixed-effects models, matched comparisons, or variation arising from plant closures, sectoral downturns, and pension-age thresholds to address the endogeneity of employment status. The resulting evidence is mixed: unemployment and job loss are often associated with worse mental health, while retirement studies range from short-run improvements or null effects to adverse longer-run effects (see Panel B of Table 4).[13] The lack of uniform findings likely reflects differences in identification, as alternative empirical strategies recover distinct treatment effects across populations and margins of employment transitions. Schiele and Schmitz (2016), for example, exploit plant closures in Germany as a plausibly exogenous shock to employment and use quantile treatment methods to examine heterogeneity across the health distribution. They find that the adverse effects of job loss are concentrated among individuals with poor baseline mental health, indicating that job loss has the largest effects on those with existing vulnerabilities rather than generating uniform harm.

In contrast to the mixed evidence on effects on adult mental health, parental job loss consistently worsens child mental health. Jones et al. (2024) use linked administrative school and tax records for the population of children enrolled in public and independent schools in British Columbia, Canada to study how recession-related household earnings losses affect new in-school mental health special-needs classifications. Combining propensity score matching with an event-study design, they find that children in households with earnings losses experienced a 0.5 percentage point increase in new mental-health designations during the recession, an increase of about 20 percent relative to the pre-recession mean. These effects persist and grow over time, especially among children who were 10 or younger when the recession hit. Fontes et al. (2024) use the Brazilian High-Risk Cohort Study, a rich longitudinal dataset following 2,510 children in São Paulo and Porto Alegre. These data include psychiatrist-confirmed mental health diagnoses and detailed Development and Well-Being Assessment (DAWBA) measures of child psychopathology.[14] Exploiting parental job-losses using a staggered difference-in-differences framework, they find a 6 percentage point increase in the probability that a child is diagnosed with a mental disorder, a 24 percent increase relative to baseline. The DAWBA index rises by 0.186 standard deviations with parental job loss. They further show that parental job loss increases child maltreatment and exposure to family conflict, suggesting that job loss may affect not only economic resources but also the environment in which children grow up.

Housing stability may be a particularly important aspect of a child's environment. In the United States, an average of 2.9 million children faced an eviction filing each year between 2007 and 2016, and families with children faced eviction filing rates roughly twice as high as families

[13] Retirement's effects may also extend to cognition specifically, and not only to diagnosable mental illness. Using a German pension-eligibility reform as an instrument, Bergschneider et al. (2026) find that an additional year of retirement lowers a Stroop-test measure of cognitive function by 0.13 standard deviations.

[14] Development and Well-Being Assessment is a structured package of interviews, questionnaires, and rating techniques used to assess child and adolescent psychiatric disorders, combining algorithm-based predictions with review by trained clinicians or psychiatrists.

without children (Graetz et al. 2023). Cassidy et al. (2025) investigate the relationship between housing instability and child mental health by exploiting the staggered rollout of a universal access to counsel program in New York housing courts which gave families access to legal representation. Gaining representation reduced the probability that the eviction process would be initiated, so the rollout serves as an instrument for housing instability. They find that in children with no prior mental health history, access to counsel reduces new mental health diagnoses by 7.2 percent and depression, anxiety, and adjustment disorder claims by 11.2 percent within two years. That a procedural intervention of this kind affects mental health is notable, since it suggests that the instability surrounding eviction proceedings, and not only the realized displacement, may matter for children's mental health.

3.4.3 Financial uncertainty, job insecurity, and aggregate economic conditions

Research suggests that mental health deteriorates not only in response to realized losses in employment or income, but also in response to perceived job insecurity, broader economic risk, and community-level shocks.

One implication is that the mental-health costs of labor-market disruption are not confined to the workers who lose their jobs. Using Swedish administrative data, Bach et al. (2026) exploit the quasi-random timing of job losses resulting from corporate mergers to show that workers who were retained experienced an 8 percent increase in depression diagnoses and a 2 percent increase in antidepressant use, highlighting the importance of job insecurity and organizational disruption. Ahammer et al. (2025) document analogous effects among surviving workers in Austrian firms experiencing mass layoffs. The remaining employees receive 20 percent more psychotherapy and are more likely to have an anti-depressant prescription in the six quarters following the event.

Studies have reached similar conclusions at the community level. Evidence from the Great Recession and from trade-induced labor-market shocks shows that mental health worsens in areas exposed to rising unemployment, foreclosure activity, and import competition. Currie et al. (2015) examine the effects of the Great Recession on maternal depression using data from the Future of Families Survey. They find mixed effects, with an 18.2 percent increase in depression among Hispanic mothers but an 11 percent decrease in depression among non-Hispanic White mothers. These disparate findings may reflect the differential impact of area-level unemployment rates. Currie and Tekin (2015) find that higher zip-code level foreclosure rates predicted increases in mental-health hospitalizations. Adda and Fawaz (2020) focus on the China shock and find that a one standard deviation increase in import penetration in a commuting zone raises mental health hospitalizations by 1.2 percent and also increased the risk of suicide. These studies may reflect an increase in the number of individuals who are directly affected in these areas or the effects of heightened uncertainty and neighborhood instability. In some cases, institutional factors may also be at work if adverse local shocks weaken local health infrastructure as well.

Key Takeaways and Emerging Themes

Overall, the evidence suggests that the relationship between economic resources and mental health is both nonlinear and asymmetric. Positive income shocks appear to have modest effects in high-income settings with strong safety nets, whereas policy-induced transfers in poorer settings can produce large improvements, consistent with the view that additional resources matter most when basic needs are unmet. Negative shocks such as job loss, earnings declines, housing instability, and broader economic deterioration worsen mental health more consistently, possibly because they affect not only the resources available for investment but also the depreciation of mental health capital through stress, insecurity, and instability. A recurring theme is that these mechanisms may be especially important for children, since family conflict,

housing instability, and local economic distress shape the environment in which mental health capital develops.

These findings suggest that income protection during downturns, while necessary, may not be sufficient: even when household resources are partly insured, mental health may still deteriorate if families remain exposed to community-level instability, persistent uncertainty, and the psychosocial costs of living in economically precarious environments.

3.5 Environmental Determinants of Mental Health

A growing strand of literature, summarized in Table 5, examines the relationship between climate, pollution, and mental health. The effects can be immediate, corresponding to a discrete decline in mental health, or cumulative over time. Most of the literature focuses on air pollution, measured using exposure to particulates, and the effects of high temperature. Research also focuses on several critical periods, including time in utero, adolescence, and old age.

3.5.1 Fetal Exposures and Mental Health

There are a number of ways that pollution exposure during pregnancy can affect the developing fetus. Exposure to carbon monoxide (from vehicle exhaust or combustion) can restrict fetal blood supply, delivering fewer nutrients and less oxygen to the developing fetus. Some pollutants can cross the placenta and directly affect the fetus. And many pollutants are thought to cause general inflammation in the mother's body, which can lead to restricted growth in utero and preterm delivery. All these mechanisms mean that infants exposed to pollution in utero are frequently low birth weight and delivered pre-term (Almond et al. 2018). In turn, children who are low birthweight or preterm have a higher probability of being diagnosed with ADHD and other mental health disorders (Currie 2025).

Hence, it is not surprising that fetal exposure to air pollution during pregnancy is linked to deteriorations in mental health. For example, Ai and Tan (2025) study the switch from coal burning for home heating to piped gas, exploiting the staggered rollout of gas across communities. They show using Chinese data that gaining piped gas is associated with better birth outcomes and reductions in depressive symptoms through age 15. Thies (forthcoming) finds that in Germany, higher exposure to nighttime thermal inversions during pregnancy increases exposure to particulates, which in turn leads to greater neuroticism and internalizing behaviors at ages 5 to 10.

High temperature during pregnancy has also been shown to have negative effects on fetal development (Kim et al. 2021). It has been linked to increases in depressive symptoms in both adolescents (Ai and Tan 2023) and adults (Adhvaryu et al. 2024), though not to increases in clinical diagnoses.

3.5.2 Contemporaneous Effects on Mental Health and Suicide

Following Graff-Zivin and Neidell (2012), a large literature has linked pollution exposure to reductions in worker productivity. Emerging research suggests that much of this effect could be operating through deteriorations in mental health. Inflammation caused by pollution is thought to directly cause depression and anxiety and can also exacerbate physical health conditions like heart disease, leading to indirect effects on mental health.

Fan et al. (2025) examine the effects of increases in particulates caused by thermal inversions on antidepressant usage in the U.S. They find a large positive effect that is concentrated

among adults 40 to 64 in high pollution areas. Chen et al. (2024) use data from the China Family Panel Studies to show that thermal inversions, which trap pollution at ground level, increases particulates, reduces a mental health index, and increases the probability of severe mental illness. They point to reductions in exercise as one possible mechanism. Hou et al. (2023) uses the same data to examine the impact of high temperature, finding that a one standard deviation increase in temperature is associated with a 0.08 increase in the probability of severe mental illness. They point to deteriorating sleep quality as a mechanism. Janzen (2025) examines calls to Germany's largest tele-counseling service, finding that they rise on both cold days and hot days.

Several studies link spikes in pollution and temperature to increases in suicide, which suggests that people at risk can be pushed over the edge by changes in environmental conditions. Persico and Marcotte (2026) use wind direction as an instrumental variable for changes in particulates and find that suicides go up half a percentage point for each 1 unit change in PM2.5. The effects are larger in poorer and more rural places, places with higher baseline pollution levels, and in places with weaker gun laws. Effects are also largest for those over 55. Molitor et al. (2023) find similar effects of wildfire smoke in rural counties, but no effect in urban counties. Currie and Saberian (2025) find that wildfire smoke increases mental health hospitalizations, which larger effects on the elderly. They point out that fires also have more direct impacts on mental health through mechanisms such as evacuations and economic disruption.

Burke et al. (2018) show that there is a relationship between monthly temperatures and suicide rates in both the U.S. and Mexico. Mullins and White (2019) find that both suicide and emergency department visits for mental health rise with temperatures about 80 degrees Fahrenheit. Carleton (2017) reports that crop damaging heat during the growing season increases suicide in India, while there is no effect of similar heat levels outside the growing season.

3.5.3 Pollution, Temperature and Dementia Risk

Several of the studies discussed above suggest that older people are especially at risk from pollution. This might reflect both the cumulative impacts of a lifetime of exposure, and a generally lower health stock that leaves them especially vulnerable. An emerging literature suggests that pollution and high temperature also increase dementia risk.

Bishop et al. (2023) find that a 1 unit increase in PM2.5 over the past decade increases the probability of a dementia diagnosis by 11 percent. Using data on power plant emissions, Cutler and Peterson (2025) conclude that much of the decline in dementia from 2000 to 2020 may be due to reductions in pollution.

Key Takeaways and Emerging Themes

The studies reviewed in this section show that there is a strong relationship between air pollution, high temperatures and mental health over the life course. Air pollution and high temperature affect fetal development which has long-term impacts on brain development and mental health. But environmental factors also have contemporaneous effects, which are dramatically illustrated by spikes in suicide accompanying high pollution and high temperature days. At older ages, pollution has been associated with increasing dementia risk, which may reflect cumulative pollution exposure. Tracking exposure to environmental influences over the life course from the fetal period through old age would be an extremely ambitious but increasingly feasible undertaking.

A second takeaway from Table 5 is that few studies have examined factors other than air pollution (especially particulates) and high temperature. One might think that water pollution, exposure to toxic releases, or climate disasters might also have effects on mental health, suggesting that these are fruitful avenues for further research.

3.6 Traumatic Life Events and Mental Health

This section examines how traumatic events affect mental health capital. We focus on two broad categories of traumatic events: family health shocks and exposure to violence. Trauma can be understood to raise the rate of depreciation δ of the mental health stock and weaken the resources available for repair. But these events may also generate an immediate, discrete decline in the stock of mental health capital, while others may surface only later if distress is initially suppressed or if coping mechanisms erode over time. Traumatic events therefore affect mental health both directly and through losses of time, income, or social resources, creating a compounding dynamic in which the ability to restore the stock is impaired.

3.6.1 Family health shocks

A growing literature asks how serious health shocks and deaths of family members affect the well-being of other relatives (see Panel A of Table 6). Much of this work focuses on labor-market adjustments, but several papers also study mental health directly and asks whether it helps explain economic responses. Adhvaryu et al. (2026) analyze childhood cancer diagnoses in Denmark, matching affected families to observationally similar unaffected families and tracing outcomes in an event-study framework. Breivik and Costa-Ramón (forthcoming) study child hospitalizations in Finland and Norway, comparing families whose child is hospitalized earlier with otherwise similar families whose child is hospitalized later. Jensen and Zhang (2026) turn to parental death in adulthood, exploiting the timing of sudden first parental deaths in Denmark within a matched-control difference-in-differences design. Across these settings, a common finding is that family shocks generate persistent labor-market costs for exposed relatives, with especially large effects for women. Child health shocks reduce maternal earnings substantially and persistently, with much smaller or undetectable effects on fathers. Likewise, parental death lowers adult children's earnings, but daughters experience larger declines five years after the loss, with particularly large declines for women with young children.

Mental health also deteriorates after these shocks, though the patterns differ across contexts. Adhvaryu et al. (2026) show that both mothers and fathers roughly double use of psychotherapy in the two years following a child's cancer diagnosis, with effects remaining elevated for up to ten years and becoming much larger when the shock culminates in the child's death. Breivik and Costa-Ramón (forthcoming) measure mental health through specialist and inpatient psychiatric contacts in Finland and through primary care diagnoses in Norway. They find that maternal mental health contacts rise by 55 percent in Finland and 6 percent in Norway in the year after a child's hospitalization, while paternal effects are small and largely insignificant in both countries. Fatal child health shocks generate substantially larger and more persistent maternal mental health effects than non-fatal hospitalizations, whereas fathers appear to respond mainly in the year of the fatality. Jensen and Zhang similarly show that parental death worsens mental health for both men and women: psychologist visits rise by about 78 to 147 percent depending on the deceased parent and the child's gender, and mental-health-related prescription use also increases.[15] Notably, all three papers find limited support for the view that mental health deterioration alone explains the observed earnings losses.

The consequences of child health shocks also extend beyond parents to unaffected siblings. Currie et al. (2024a) study how having a physically disabled younger sibling affects children's

[15] Altındağ et al. (2026) examine parental deaths due to dementia (ADRD) in Denmark, using a similar event-study design and compare them with parental deaths from other causes. They find large and persistent effects on mental health: daughters' mental health care visits increase by 10 to 28 percent around the time of the parent's death and remain elevated for up to seven years. Because dementia typically involves a prolonged and observable decline before death, these estimates likely capture the effects of anticipatory grief and caregiving burden in addition to bereavement.

mental health. They use Danish administrative data and measure mental health between ages 9 and 20 based on specialist contacts, including psychologists and psychiatrists, as well as prescription drug use. Their identification relies on a family fixed-effects difference-in-differences design that compares the birth-order gap in mental health between the first- and second-born child in families with a disabled third-born child to the corresponding gap in families without one. Because the second-born child is younger at the time of diagnosis and outcomes are measured at fixed ages, the second-born is exposed to the household strain of the sibling's disability for a larger portion of their early childhood. Second-born children in affected families are 13 percent more likely to use any mental health service, with particularly large increases in psychiatric contacts and prescription drug use. The effects are more than twice as large for highly demanding disabilities than for milder and more manageable conditions. They are also concentrated among children of less educated mothers.

The paper also asks how the birth of a disabled child affects parental outcomes, and the resulting patterns help illuminate the mechanisms through which household disruption operates. Employment effects fall mostly on mothers: maternal employment declines by 6.4% in the full sample, with the burden concentrated among low-education mothers and among mothers of children with episodic and unpredictable disabilities such as epilepsy. Despite these employment losses, total household income shows little change, indicating that the social safety net successfully replaces lost earnings through transfers. At the same time, household wealth falls, indicating that families draw down assets to meet costs that transfers do not fully offset. The paper further exploits a 1998 reform that replaced capped benefits for disabled children with full wage replacement and extended the duration of eligibility. Families whose disabled child was born before the reform, and who therefore faced the less generous regime, experience substantially larger maternal employment losses and larger declines in household wealth. These differences are especially pronounced among low-educated families, who have limited asset buffers prior to the birth of the disabled third child. The paper shows that the reform attenuated the employment and wealth consequences of the shock but did not eliminate them.

The cleanest study on the role of income insurance in mitigating the mental health consequences of family trauma comes from Fadlon et al. (2026), who study spousal death in Denmark. Using administrative data on the universe of Danish households, they compare survivors whose spouse dies following a sudden fatal health event to otherwise similar households that experience the same type of shock a few years later, in a dynamic difference-in-differences design that treats the exact timing of sudden death as quasi-random. They show that spousal death has large, immediate, and persistent effects on mental health: take-up of psychotropic medication doubles in the first month after the death and remains about 10 percent above the counterfactual even four years later.

The paper's central contribution is to show that a substantial share of this immediate mental health deterioration is tied to the income loss generated by the spouse's death. The authors measure the drop in household income from the year before to the year after the shock and instrument it with the deceased spouse's baseline share of household earnings. Survivors who lose an earning spouse experience both larger income losses and larger immediate increases in mental health medication. Quantitatively, a one-standard-deviation reduction in income loss, equal to 14.4 percentage points, is associated with about a 10-percentage point smaller increase in mental health medication take-up, relative to an average treatment effect of 17.6 percentage points. The fact that these differences are concentrated in the immediate aftermath, rather than persisting over many years, points to liquidity and short-run financial instability rather than permanent income effects as the key mechanism.

3.6.2 Exposure to violence

Violence is a pervasive feature of many people's lives. Globally, one in four women has experienced physical or sexual intimate partner violence at least once (García-Moreno et al. 2021), and one in five children are in a conflict zone, or are affected by violent conflict (UNICEF 2024). In the United States alone more than 240,000 students were on school grounds during a shooting in the two decades prior to 2020 (Rossin-Slater et al. 2020). Despite this scale, the mental health consequences of violence exposure have been difficult to establish causally, as selection into violent environments and the absence of longitudinal administrative data on victims have long constrained the empirical literature. A growing body of work using quasi-experimental designs and administrative health records has begun to fill this gap, moving beyond the self-reported, cross-sectional evidence that characterizes much of the earlier research. Existing studies, presented in Panel B of Table 6, focus on different forms of acute traumatic violence in different settings but converge on a common finding: violence generates large and persistent mental health deterioration, and the costs extend well beyond direct victims to family members living in the same household.

The direct mental health effects of acute violence are large and concentrated at the severe end of the exposure distribution. Rossin-Slater et al. (2020) study 44 U.S. school shootings between 2008 and 2013 using large-scale prescription data and a difference-in-differences design that compares youth living near affected schools with otherwise similar youth in more distant areas. They find that fatal school shootings increase antidepressant use among nearby youth by about 21 percent over the following two years, with effects remaining visible into the third year, while non-fatal shootings generate no detectable response. A particularly interesting result is that the effects are smaller in areas with a greater local supply of non-prescribing mental health providers, such as psychologists and social workers, which is consistent with the idea that access to behavioral treatment can partly buffer the mental health consequences of these events. In related work on U.S. mass shootings as well as the "Beltway Sniper attack" in the Washington D.C. area in 2002, Currie et al. (forthcoming) show that the stress engendered by the attacks increased the incidence of very premature and very low birthweight births in the U.S., suggesting one mechanism for intergenerational effects of violence.

In a study of the 2011 Utøya mass shooting in Norway, Bharadwaj et al. (2021) compare survivors to matched youths from the same political youth organization who were not present on the island. Using a difference-in-differences framework, they show that survivors experienced a nearly 400 percent increase in mental health diagnoses in the short run, a large rise in overall health-care use, and a sharp deterioration in academic performance, with GPA falling by nearly 0.5 standard deviations. The effects are not limited to survivors themselves. Parents and siblings experience substantial increases in doctor visits and mental health diagnoses, and younger siblings also see meaningful declines in school performance, with exam scores falling by about 0.2 standard deviations. By contrast, the evidence for spillovers to school-aged peers is limited, suggesting that the consequences of extreme violence spread strongly within the family but may attenuate outside the household.

Bhuller et al. (2024) examine domestic violence in Norway, using a not-yet-treated difference-in-differences design in which future victims serve as the comparison group for current victims. A police-reported domestic violence incident increases victims' mental health diagnoses by 35 percent in the year of the event, primarily due to an increase in mood, depression, sleep, and anxiety disorders. Children are affected as well. Their mental health diagnoses increase by 19 percent in the year of the event. Notably, the effects on victims' mental health taper over time, whereas the effects on children are more persistent, with an average increase of 15 percent in the four years after the event. The long-run mental health deterioration is driven by mood, depression,

sleep, and anxiety disorders. These findings underscore that violence within the home can have durable consequences for other family members, not just the direct victim. Currie et al. (2022) show that mothers subject to domestic violence results bear lower birthweight infants, demonstrating once again how violence can lead to intergenerational effects.

Key Takeaways and Emerging Themes

Three broad conclusions emerge from this literature. First, traumatic events harm mental health through multiple simultaneous channels that compound one another and are difficult to disentangle. Across the studies reviewed here, shocks as varied as child illness, bereavement, mass shootings, and domestic violence generate substantial negative effects on mental health, often alongside changes in employment, family stability, and access to informal support. The challenge for both research and policy is that these channels operate jointly, and few studies are able to separately identify their relative importance.

Second, the costs of trauma extend well beyond the directly exposed individual. Child health shocks impair the mental health of parents and unaffected siblings, parental death affects adult children, and violence exposure spills over to family members living in the same household and infants in utero. Trauma is therefore best understood as a family-level shock, and possibly a community-level shock, rather than an individual event. Third, the effects are highly heterogeneous. They are consistently larger for severe or fatal shocks, for mothers relative to fathers, and in some cases for lower-resource families, suggesting that average effects may understate the burden borne by the most exposed groups.

An important caveat is that much of the literature comes from Scandinavian countries, where public insurance, income support, and access to health care are unusually generous. The large and persistent mental health effects that are observed in these settings may represent lower bounds on the costs of trauma in countries with weaker safety nets (though Northern countries also tend to have higher rates of mental illness than sunnier climes). A related emerging theme is that economic buffers and access to health care can mitigate these consequences in some contexts, though not always. Some mental health damage remains even after income support and health care access have softened the initial shock. Understanding what determines this remaining burden, and how treatment access and different public policies shape recovery, are important open questions for future research.

3.7 Access to and Quality of Mental Health Care

The standard economic theory of demand implies that a fall in the effective price of purchased mental health inputs increases the quantity demanded. Health insurance is a central determinant of this price and can therefore increase the use of mental health treatment. It is not, however, the only determinant of access. Provider availability, waiting times, and, for some populations, more acute institutional barriers also shape whether and how quickly people receive care. Whether greater utilization improves mental health depends, in turn, on the effectiveness of the marginal care induced by expanded access. Insurance may also affect mental health through channels other than treatment, for example by reducing financial risk and the stress associated with unexpected medical expenses. To the extent that expanded access improves mental health, these gains may translate into downstream outcomes such as employment, earnings, educational attainment, and crime, given the substantial effects of mental illness on these outcomes documented in Section X. Finally, access and treatment also depend on provider behavior. Insurance rules, including reimbursement arrangements and prior-authorization requirements, can alter providers' incentives, while differences in practice styles and prescribing patterns can shape the care patients receive and providers' willingness to treat them.

Table 7 reviews evidence about these channels. Panel A considers health insurance, examining its effects on mental health care utilization, mental health, downstream socioeconomic outcomes, and provider behavior. Panel B turns to the broader availability of mental health care, considering provider supply, waiting times, and provider practice styles, as well as barriers to care among at-risk populations such as incarcerated and veterans with mental illness.

3.7.1 The Role of Health Insurance

A growing literature shows that health insurance coverage affects the utilization of mental health care. Ayyagari and Shane (2015) use a regression-discontinuity/difference-in-differences design around the 2006 introduction of Medicare Part D, comparing adults ages 60–64 to those ages 65–70 before and after the reform. They find that Part D lowered out-of-pocket spending for prescriptions and raised antidepressant use, with the increase concentrated among individuals who had lacked prescription drug coverage before the reform. Serena (forthcoming) studies a Danish policy that introduced 60 percent public coverage of psychotherapy for depression and anxiety among people under age 38. Because coverage for physician and hospital care is already universal in Denmark, the reform varies only the price of psychotherapy itself. Using regression-discontinuity and difference-in-differences designs around the age cutoff, the paper finds that the subsidy raised psychotherapy use by about one percentage point of the population per year, a 65 percent increase relative to the pre-reform share of roughly one percent. These studies show that lowering the out-of-pocket cost of mental health treatment raises utilization of both pharmaceutical and non-pharmaceutical care.

A related literature asks whether health insurance affects mental health itself and suggests that it may do so through several channels. Solomon and Dasgupta (2022) exploit the staggered adoption of state mental health parity laws between 1998 and 2008, which required insurers to cover mental health care on terms comparable to physical health care. Comparing states that adopted full parity to those that did not, they find that parity laws reduced suicide rates among college-age individuals by 3 percent and the incidence of poor mental health days by 4.2 percent. Because these laws specifically expanded coverage for mental health care, the results are consistent with improved access to treatment as the underlying mechanism.

Other studies point to channels that do not operate primarily through mental health treatment. Guldi and Hamersma (2023) study changes in Medicaid income-eligibility thresholds for pregnant women. A 10 percent increase in the eligibility threshold reduced reported maternal depression by 1 to 3 percent three years after birth. The authors argue that reduced financial stress, rather than greater use of mental health treatment, is the more likely mechanism in their setting, since treatment options were limited for their 1988 birth cohort: SSRIs were not yet established as safe during pregnancy, and Medicaid coverage of outpatient psychotherapy was limited and uncertain.

Mann et al. (2024) study state mandates requiring Medicaid coverage of gender-affirming care. Using a triple-differences design comparing lower- and higher-income transgender adults across states with and without mandates, they find that mandates reduced the incidence of mental distress among low-income transgender adults by 13 percent and reduced poor mental health days by 14.6 percent after two years. The evidence suggests that these improvements operated through increased use of gender-affirming care rather than conventional mental health treatment. Taken together, these studies suggest that insurance can improve mental health not only by expanding access to mental health treatment but also through financial protection and improved access to other forms of health care.

Several recent studies ask whether health insurance coverage of mental health care also affects downstream socioeconomic outcomes. In contrast to the literature linking coverage to greater utilization and improved mental health, the evidence on socio-economic outcomes is mixed. Solomon and Dasgupta (2022) find that state mental health parity laws increased college GPA by 4.24 percent but had no effect on college dropout. Serena (forthcoming) finds no detectable effects of Denmark's expansion of psychotherapy coverage on employment, sickness benefits, or disability pension receipt. Andersen (2015) exploits the staggered adoption of state mental health parity mandates between 1997 and 2001 to examine heterogeneity in their labor market effects. Using a triple-differences design that interacts mandate adoption with individuals' levels of mental distress, he finds that parity mandates increased insurance coverage, wages, and hours worked among individuals with moderate mental distress. These results suggest that null average effects may mask economically meaningful gains for groups whose labor market outcomes are more responsive to expanded mental health coverage.

Previous studies on the impact of Medicaid coverage on criminal justice involvement also yield mixed results. Studies using aggregate crime data generally find that Medicaid coverage reduces crime, although they differ in which offenses respond. Using difference-in-differences designs that exploit variation in Medicaid policies, some studies find effects concentrated in violent crime, particularly aggravated assault (Vogler 2020), while others find effects on both violent and property crime (Wen et al. 2017; He and Barkowski 2020) or primarily on nonviolent crime (Deza et al. 2024). Reporting issues in the aggregate crime data are a potential limitation of these studies.

Studies using individual-level criminal justice records avoid these concerns but also yield mixed results (Aslim et al. 2022; Burns and Dague 2023; Packham and Slusky 2023). Finkelstein et al. (2025) provide experimental evidence by linking participants in the Oregon Health Insurance Experiment, in which low-income adults who had applied for Medicaid coverage were chosen to enroll by lottery, to individual-level administrative criminal justice records. They find no statistically significant effects of Medicaid coverage on criminal charges or convictions. The null results persist among subgroups at elevated risk of criminal justice involvement, including individuals with prior convictions and those with a recent mental health emergency department visit, although the authors note that confidence intervals widen substantially for these smaller subgroups.

Jácome (2024) examines the reverse experiment in a much higher-risk population, exploiting the loss of Medicaid eligibility at age 19 among low-income men in South Carolina. Using a triple-differences design, she finds that men with mental health histories who lose coverage are 19 percent more likely to be incarcerated in the following year. The effects are larger among those who had recently used mental health care or relied on Medicaid for access to mental health medications. Together, these studies illustrate that the effects of insurance coverage may extend beyond mental health and health care utilization, to education and employment, to crime.

Insurance can also affect mental health care by changing providers' incentives and behavior. Chorniy et al. (2018) study South Carolina's transition from fee-for-service Medicaid to managed care and find increases in diagnoses and treatment for ADHD and asthma, accounting for roughly one-third of the growth in caseloads for these conditions. The authors attribute these changes to the risk-adjustment and quality-control incentives embedded in managed-care contracts. Currie and Musen (2025) examine a different insurer intervention: state Medicaid prior-authorization requirements for antipsychotic prescribing to young children. These requirements reduced antipsychotic prescribing to children under six by 22–30 percent, with no corresponding effect among privately insured children or older children enrolled in Medicaid. The absence of spillovers to patients who were not subject to the requirements suggests that the policy operated

primarily through the hassle costs imposed on physicians, rather than by providing information that changed their prescribing behavior more broadly. These findings underscore that changes in observed diagnoses and treatment following insurance reforms may reflect provider responses to the rules of coverage as well as changes in patients' demand for care.

Key Takeaways and Emerging Themes

Several broad conclusions emerge from this literature. First, health insurance can affect mental health through multiple channels. Lowering the out-of-pocket price of mental health treatment increases utilization, but insurance may also improve mental health through financial protection and access to other forms of health care. At the same time, insurance coverage does not guarantee effective access to mental health care. This distinction is particularly important in high-income countries with universal health insurance, where some mental health services remain only partially covered and waiting times, provider shortages, and other non-price barriers can constrain access. Finally, the details of insurance design matter: reimbursement rules, prior-authorization requirements, and other features of coverage can alter providers' diagnosis and treatment decisions. Thus, the relevant policy question is not simply whether individuals are insured, but which services are covered, on what terms, and under what incentives for providers.

A second emerging theme is the heterogeneity in downstream socioeconomic effects. Expanded coverage does not uniformly translate into improvements in education, employment, or criminal justice outcomes, and average effects can mask important differences across populations. While the evidence clearly shows that prices and coverage affect utilization, tracing the full pathway from coverage to effective access, treatment, mental health, and socioeconomic outcomes is more difficult. How these links depend on the type of treatment and the organization of the health-care system, and which groups are most affected is an important question for future research.

3.7.2 The Role of Broader Care Availability

Health insurance is only one determinant of access to mental health care. Even when the monetary cost of care is covered, the availability of providers and the time patients must wait for treatment can affect whether and when care is received, with consequences for health and socioeconomic outcomes. Dias and Fontes (2024) study a large-scale Brazilian reform that expanded community-based mental health care through the rollout of Psychosocial Care Centers, intended as substitutes for psychiatric hospitalization. Exploiting the staggered introduction of these centers across municipalities, they find that greater availability of community-based care increased the local supply of mental health professionals by 46 percent and outpatient mental health procedures by 113 percent, while reducing psychiatric hospitalizations by 7 percent in the first year. The reductions were larger among schizophrenia admissions and in long-stay admissions. The reform had no significant effect on suicide, overdose, or other mental-disorder mortality. However, it increased homicides by 7.7 percent. This finding underscores that, for patients with the most severe conditions, the loss of inpatient specialist care can leave them without important clinical support, with potentially harmful consequences.

Costantini (2025) examines the consequences of delayed treatment among U.S. veterans experiencing mental health emergencies. She exploits variation in clinic congestion to isolate differences in the time between an emergency-department visit and a scheduled follow-up appointment. Longer waits increase the probability that patients miss their follow-up visit by 2 percentage points (5.6 percent) and increase the probability that they subsequently disengage from mental health care. The consequences persist beyond treatment engagement: an 11.7-day increase in waiting time raises mortality by about 1.5 percent after two years and 1.9 percent after five years.

Effects of delayed access to care also extend to labor market outcomes. Prudon (2025) uses administrative data from the Netherlands and exploits variation in waiting times for mental health treatment across municipalities. A one-month increase in waiting time reduces employment by two percentage points over the following eight years and raises the probability of receiving disability benefits by one percentage point, with larger employment effects among individuals with lower educational attainment.

For some high-risk populations, barriers to mental health care arise not only within the health-care system but also from the institutions and circumstances that shape their access to treatment. Bhuller et al. (2025) study the mental health consequences of correctional sentencing in Norway, combining administrative data on health-care use with quasi-experimental variation in sentencing. They find that rehabilitation-oriented correctional sentences improve defendants' mental health, with effects that persist five years after sentencing. Alsan and Yang (2025) provide experimental evidence from U.S. jails, randomly offering health-care accreditation to 44 facilities. Accreditation raised compliance with care-quality standards by 11 to 15 percent overall, with the largest gains in compliance with mental health screenings within 14 days of admission. Accreditation reduced in-custody mortality to about one-third of the control-group rate and produced a suggestive 44 to 45 percent reduction in six-month recidivism. These results suggest that prison can serve as a point of entry into the health-care system for individuals who might otherwise remain undiagnosed and untreated, with potential gains on downstream outcomes.

Costantini (2026) turns to another vulnerable population: nearly 300,000 unhoused veterans with mental illness. These veterans are potentially eligible for two VA programs. Housing First provides immediate subsidized housing without treatment requirements. Treatment First instead combines temporary housing with treatment for conditions such as substance use. Using an instrumental-variables design, she finds that Housing First reduces three-year mortality by 4.6 percentage points (70 percent) relative to receiving neither program, while Treatment First has an effect size close to zero. Housing First substantially increases long-term housing stability and veterans' engagement with VA social workers yet has no effect on mental health care utilization. In contrast, Treatment First raises use of mental health care in the short run, but this effect fades over time. The mortality gains from Housing First appear to operate not through more treatment, but through removing exposure to the causes of death most closely tied to homelessness itself, including exposure to the elements, violence, and bloodborne infection. Housing First reduces social costs, largely because it reduces lengthy inpatient mental health stays. The paper suggests that materially improving people’s quality of life may also improve their mental health.

Key Takeaways and Emerging Themes

A central lesson from this literature is that insurance coverage alone does not ensure effective access to mental health care. Provider availability, waiting times, and the organization of care determine whether patients receive treatment when they need it. The evidence also suggests that the consequences of these barriers extend beyond treatment utilization: delays in care can affect mortality and employment, while the shift from inpatient to community-based care illustrates that expanding one form of access while reducing another may have unintended consequences for patients with more severe conditions.

A second theme is that, for populations facing substantial social and institutional barriers, improving outcomes may require looking beyond access to mental health treatment itself. Correctional institutions can provide one opportunity to identify and address previously unmet mental health needs, while the evidence on unhoused veterans shows that addressing housing instability can substantially improve mental health even without increasing mental health care utilization. More broadly, these findings suggest that the effectiveness of mental health care

depends not only on whether treatment is available, but also on the circumstances in which patients access and receive it.

3.7.3 The Role of Providers

Even when patients can access care, the treatment they receive depend on which provider they see and where they receive care. Currie et al. (2026) provide an overview of the large literature on physician decision making that includes many examples drawn from mental health. Berndt et al. (2015) develop a learning-by-doing model in which physicians who write fewer prescriptions have less incentive to master the complementary skills (dosing, side-effect management) that different antipsychotics require, and so rationally concentrate their prescribing on a small number of drugs. Consistent with the model, they document that most prescribers have a favorite drug. Their prescribing deviates significantly from national market shares, and the concentration of prescribing falls with prescription volume.

Cuddy and Currie (2020) study children covered by Blue Cross Blue Shield, a large national U.S. insurer, who filed a first mental health claim between ages 10 and 17. They find that 29.4 percent receive no follow-up care within three months and, among those who receive medication, about 45 percent receive a drug that raises a red flag under treatment guidelines. Much of this variation occurs within ZIP codes, pointing to an important role for differences across providers rather than local provider supply alone.

Currie and MacLeod (2020) show that provider skill matters for the relationship between treatment choices and patient outcomes. Using Blue Cross Blue Shield claims for 450,802 patients prescribed an antidepressant, they exploit patients who switch doctors to estimate the effects of prescribing styles while controlling for patient fixed effects. Among psychiatrists, prescribing from a broader portfolio of antidepressants leads to fewer subsequent mental-health-related emergency department visits and hospitalizations. Their interpretation is that skilled clinicians with a broad portfolio can better match treatments to patients. Broader prescribing does not improve outcomes among general practitioners, who have less skill in treating mental health conditions. Deviations from prescribing guidelines predict worse outcomes in both groups of physicians.

Currie and Zhang (2025) similarly document substantial differences in primary-care-provider effectiveness in the Veterans Health Administration (VHA). Veterans are quasi-randomly assigned to providers at the VHA. Using administrative patient records for 802,777 veterans assigned to 7,548 primary-care physicians, they construct value-added measures of provider effectiveness for mental health, circulatory conditions, and ambulatory-care-sensitive conditions. A one-standard-deviation increase in mental health effectiveness is associated with 3.8 percent lower mortality and 4.4 percent lower health-care costs over the following three years. More effective providers achieve these outcomes with fewer visits, specialist referrals, laboratory tests, and imaging. Thus, quality depends not simply on the amount of care provided, but also on how effectively care is allocated across patients.

Other recent work quantifies how much of the observed variation in treatment can be attributed to providers and places. Using private insurance claims for more than eight million U.S. children, Swagel (forthcoming) exploits patients' moves across providers and providers' entry and exit to estimate provider and place fixed effects separately. He finds that provider-level variation in ADHD medication and antidepressant prescribing is far larger than geographic variation. The estimates imply that equalizing primary-care providers' prescribing intensities would reduce the variance of provider prescribing rates by about 50 percent for ADHD medications and 65 percent for antidepressants. Ding (2026) uses a related movers-design approach in an older population of

Medicare beneficiaries, using patients who relocate across U.S. hospital referral regions. She decomposes utilization into origin, destination, and mover-specific components. She finds that place-specific factors account for 45.8 percent of geographic variation in mental health service use but only 15.1 percent of variation in drug use, consistent with psychotherapy and other in-person services being more constrained by local provider availability than prescription drugs.

What generates provider-level variation? In addition to provider skill levels, the evidence points to several mechanisms. Shapiro (2018) links pharmaceutical sales representatives' detailing visits to physicians' Seroquel prescriptions and exploits within-physician variation in detailing over time. A detailing visit increases the probability of prescribing Seroquel by 29.1 percent and increases the probability of prescribing it "off-label" (i.e. for a different use than what it is approved for) by 20.2 percent. Thus, detailing increases both on- and off-label prescribing, but shifts prescribing toward approved indications on net.

Currie et al. (2024) examine children's first antidepressant or anti-anxiety prescription and use physicians' training cohorts to distinguish common training effects from local peer effects. A 20 percent increase in same-ZIP-code peers' "red-flag" prescribing, defined as prescribing that deviates from clinical guidelines, increases red-flag prescribing by 7.7 percent among non-psychiatrists but only by 4.0 percent among psychiatrists. The weaker peer effect among psychiatrists suggests that their prescribing is less responsive to local practice norms and more strongly reflects persistent physician-specific practice styles.

Patient and family characteristics also shape provider decisions. Persson et al. (2025) exploit the fact that children who are younger than their classmates are more likely to receive an ADHD diagnosis. Sweden's school-entry cutoff generates exogenous variation in whether children are among the youngest in their class. They show that having an older cousin who is diagnosed with ADHD because of being young-for-grade increases the probability that a younger cousin will be diagnosed with ADHD by 10.0 and increases the probability that they receive ADHD medication by 6.5 percent. These effects are about 31 and 20 percent as large as the younger cousin's own relative-age effect on the corresponding outcomes. The results show that diagnoses can propagate within families. Marquardt (2026) combines electronic health record text with a structural model of ADHD diagnosis to decompose the male-female diagnosis gap. Differences in underlying symptoms explain only about one-quarter of the gap. Gender differences in the thresholds physicians use to diagnose ADHD account for 67 to 71 percent of the remainder.

Finally, Currie et al. (2024b) show that differences in treatment quality can have a socioeconomic dimension. They exploit a temporary extension of universal drug coverage to people under 25 in Ontario, Canada. They show that even under universal health and drug coverage, low-income children receive systematically different medications. Conditional on diagnosis, medical history, and physician, they are more likely to receive antipsychotics and benzodiazepines, sedating drugs with potentially serious side effects, and less likely to receive SSRIs, the first-line treatment for depression and anxiety.

These findings make it difficult to interpret observed treatment as a simple function of clinical need and raise the question of whether provider variation has implications for the quality of care.

Key Takeaways and Emerging Themes

The evidence on providers shifts attention from how much mental health care patients receive to the care they receive conditional on access. Treatment choices vary substantially across providers, reflecting differences in experience, pharmaceutical marketing, local practice norms, and diagnostic thresholds. Patient and family characteristics also influence diagnosis and treatment in

ways that are not fully explained by clinical need. Therefore, observed differences in treatment do not necessarily map directly into differences in underlying mental health. While there may also be variations in patient demand for different types of care, research designs that control for the endogeneity of physician selection continue to find large differences in physician behavior.

Provider variation has consequences for the quality and equity of care. Greater provider skill can improve the matching of treatments to patients, and differences in provider effectiveness translate into meaningful differences in health outcomes and costs. At the same time, socioeconomic differences in treatment persist even under universal health and drug coverage and among patients seeing the same physicians. Expanding access is therefore only part of the challenge. Understanding how provider skill, incentives, and practice styles can be improved, and how patients can be better matched to providers, remains an important area for future research.

3.8 Efficacy of Mental Health Treatments

Mental health is produced using a combination of health-care inputs and other individual and environmental resources, with the effectiveness of these inputs depending in part on the access to and quality of care through which they are delivered. This section examines the effects of two important forms of mental health treatment: psychological and psychosocial interventions, reviewed in Section 3.8.1, and pharmacological treatments, reviewed in Section 3.8.2. Table 8 provides an overview of the literature we reviewed on these topics. We ask whether these treatments improve mental health, whether their effects persist, and whether they extend to broader health, behavioral, and socioeconomic outcomes.

3.8.1 Effects of Psychological and Psychosocial Interventions

A growing experimental literature evaluates the effects of psychological and psychosocial interventions on mental health and socioeconomic outcomes. Table 8 shows that much of this evidence comes from low- and middle-income countries, and there is considerable variation in both the populations targeted and the interventions studied. Target populations range from women experiencing depression during or around pregnancy in Pakistan and India (Baranov et al. 2020; Sevim et al. 2024; Bhat et al. 2022) to at-risk young men in urban Liberia (Blattman et al. 2017; Blattman et al. 2023) and hairdresser clients in Abidjan, Côte d'Ivoire (Nilsson and Pougué Biyong 2025). The interventions are equally heterogeneous, ranging from structured cognitive behavioral and other forms of psychotherapy (Baranov et al. 2020; Barker et al. 2022; Blattman et al. 2017; Baird et al. 2025) to considerably lighter-touch approaches, such as exercises designed to promote gratitude, self-affirmation, and aspirations (Baranov et al. 2020b) or informal active-listening training with no clinical content (Nilsson and Pougué Biyong 2025).

The experimental literature generally finds that psychological interventions improve mental health in the short run. Barker et al. (2022) evaluate a group-based cognitive behavioral therapy (CBT) program among 7,227 individuals drawn from poor households in rural Ghana. The program consisted of twelve weekly 90-minute group sessions led by trained facilitators, covering standard CBT techniques for identifying and restructuring negative thought patterns. Participants were not selected based on mental illness, allowing the authors to ask whether CBT can improve well-being even among individuals without high levels of baseline psychological distress. One to three months after the intervention, CBT improved a mental health index by 0.15 standard deviations and reduced the probability of moderate and severe psychological distress by 6 and 4 percentage points, respectively. The effects were similar across individuals with different levels of baseline mental distress, suggesting that the benefits of CBT in this setting extended beyond those with initially poor mental health.

Baranov et al. (2020), in contrast, study a clinically targeted intervention among 903 pregnant women diagnosed with depression in rural Pakistan. The Thinking Healthy Programme, adapted cognitive behavioral therapy for delivery by community health workers rather than clinical specialists. Sixteen home visits were spread over twelve months and integrated into routine maternal and child health care rather than delivered as a stand-alone program. The program substantially reduced depression during the year following childbirth: at the one-year follow-up, women offered treatment were about 60 percent less likely to be depressed and experienced a 0.66 standard deviation reduction in depression severity.

Evidence about whether improvements in mental health persist is more limited and yields mixed results. Baranov et al. (2020) follow participants in the Pakistan intervention for approximately seven years after treatment. Although the effects attenuate substantially relative to the one-year follow-up, treated women continue to have lower depression severity, by 0.18 standard deviations, and are 5 percentage points (17 percent) less likely to be clinically depressed than women in the control group. Bhat et al. (2022) provide further evidence of persistence by revisiting two randomized trials that offered brief psychotherapy to 775 adults with depression in primary-care settings in India. The interventions, delivered by lay counselors over six to eight sessions, used behavioral activation and related techniques to help patients identify and change behaviors contributing to depression. Four to five years later, individuals offered psychotherapy were 11 percentage points less likely to be depressed than those in the control groups, although the long-run effects were driven primarily by the more effective of the two interventions.

Other studies find less persistent effects. Baird et al. (2025) study adolescent girls in Uganda who were at risk of moderate to severe depression at baseline. Girls were randomly offered group-based interpersonal psychotherapy delivered by lay providers, with a separate treatment arm receiving a lump-sum cash transfer after therapy. Focusing on the therapy intervention alone, the share of girls without depression increased by 5.4 percentage points one year after treatment, relative to 18.4 percent in the control group, but the effect had dissipated by the 30-month follow-up. Thus, while some psychological interventions generate mental health improvements that remain detectable several years after treatment, persistence is far from universal and remains much less well documented than short-run efficacy.

A smaller literature asks whether the benefits of psychological interventions extend to socioeconomic outcomes. Here, the evidence is considerably more mixed than for mental health. Labor market outcomes have received particular attention, motivated in part by the possibility that improved mental health may increase individuals' capacity to work. A meta-analysis by Lund et al. (2024) finds that psychotherapy raises an aggregate labor-market outcomes index by 0.16 standard deviations on average across low- and middle-income countries.

Yet improvements in mental health do not necessarily translate into greater employment or consumption at the level of individual studies. Bhat et al. (2022), for example, find substantial and persistent reductions in depression four to five years after psychotherapy in India but no corresponding increases in employment or consumption. The authors suggest that other constraints on employment, particularly among the largely female study population, may limit the extent to which improvements in mental health translate into economic gains.

Some of the clearest non-health effects concern crime and antisocial behavior. Heller et al. (2017) study Becoming a Man (BAM), a school-based program for economically disadvantaged male adolescents attending public schools in high-crime areas of Chicago. The program uses principles from cognitive behavioral therapy to help participants recognize situations in which automatic responses may lead to poor decisions and to consider alternative ways of interpreting and responding to those situations. Students participated in regular group sessions during the

school day led by trained counselors. Across two randomized trials, participation in BAM reduced total arrests during the intervention period by 28–35 percent and violent-crime arrests by 45–50 percent, while also improving school engagement. In the first trial, for which longer-run educational outcomes were available, the program increased high-school graduation rates by 12–19 percent.

Blattman et al. (2017) provide related evidence from a very different population and institutional setting. The study recruited 999 criminally engaged men in Liberia, many of whom were involved in activities such as theft, drug dealing, and violence. Participants were randomized to an eight-week group-based cognitive behavioral therapy program, a $200 unconditional cash grant, both interventions, or to a control group. The therapy was delivered by nonspecialists and sought to develop self-control and patience and to encourage participants to adopt a noncriminal identity and lifestyle. Both therapy and cash initially reduced crime and violence, but these effects generally faded over time when the interventions were provided separately. In contrast, combining therapy with cash generated substantial reductions in crime and violence that remained evident one year later.

Blattman et al. (2023) returned to the same experimental sample approximately ten years after the intervention and found striking evidence of longer-run persistence. Antisocial behavior, including robbery, theft, drug selling, and fighting, was 0.20 standard deviations lower among men assigned to therapy alone and 0.25 standard deviations lower among those assigned to therapy and cash, with the largest effects among men who had the highest levels of antisocial behavior at baseline. Together, these studies suggest that interventions incorporating cognitive behavioral principles can affect consequential behaviors among high-risk populations, even when they are delivered outside conventional mental health care settings.

An additional question is whether the benefits of psychological interventions extend beyond the individuals receiving treatment to other members of their families. Such spillovers may be particularly important when treating parents, since improvements in parental mental health could affect children through changes in parenting, investments, and the home environment. Evidence on these effects remains limited. Baranov et al. (2020) provide one of the few long-run tests. Seven years after the intervention, treated mothers had greater control over household spending and invested more time and resources in their children, with effects on parental investments of roughly 0.2 to 0.3 standard deviations. Despite these changes, however, the authors find little evidence of corresponding improvements in children's cognitive or socioemotional development.

Sevim et al. (2024) examine child outcomes following a different intervention for perinatal depression in rural Pakistan. Pregnant women with depression were offered a peer-delivered version of the Thinking Healthy Programme that emphasized behavioral activation, problem solving, and social support. The intervention began during pregnancy and combined individual and group sessions delivered by women from the local community without prior health-care experience. The program improved maternal mental health and functioning by 0.17 to 0.29 standard deviations over the first three years after childbirth and generated modest, though imprecisely estimated, improvements in parenting. Effects on children were more limited. The intervention produced improvements in socioemotional development at some ages, but these effects were transitory, and there was little evidence of improvements in cognitive development or physical health. Thus, the limited existing evidence suggests that treating parental mental illness can affect parental behavior and investments, but whether these changes generate persistent improvements in child outcomes remains unclear.

An important question raised by this literature is whether interventions that are effective under experimental conditions scale. Interventions implemented in experimental settings generally show substantial attention to recruitment, provider training, supervision, and treatment fidelity. Scaling requires not only maintaining treatment quality but also inducing individuals who could benefit from treatment to take it up and remain engaged. This latter problem may be particularly challenging for mental health care, where stigma, limited information about the benefits of treatment, and the symptoms of mental illness themselves may discourage help-seeking.

Roth et al. (2026) provide direct experimental evidence on the difficulties involved in persuading people to seek help. In a sample of 1,844 U.S. adults with elevated depression symptoms and no prior therapy experience, they find that participants substantially overestimate how much stigma toward depression exists: respondents believe 37.5 percent of Americans hold stigmatizing views, when the true number is 16 percent. Correcting this misperception lowered incentivized willingness to pay for four weeks of online therapy by $9.13, or 5.5 percent of the control-group mean. However, it appears that this negative effect appeared because the experimenters made stigma salient. Simply drawing attention to stigma, without supplying any information about its magnitude, produced a nearly identical decline. This evidence underscores the gap between making an effective treatment available and ensuring that it is used.

Key Takeaways and Emerging Themes

Several broad conclusions emerge from the experimental literature on psychological interventions. These interventions can produce substantial improvements in mental health across a wide range of populations and settings, including when treatment is delivered by community health workers, lay counselors, or peers rather than mental health specialists. Evidence on the persistence of these gains is more mixed: some effects remain detectable several years after treatment, while others attenuate or disappear. Understanding which features of interventions, populations, and settings determine whether initial improvements persist is an important question for future research.

Improvements in mental health also do not necessarily translate into better socioeconomic outcomes. Effects on employment and consumption are inconsistent, although interventions targeting populations at high risk of crime and violence have generated substantial and sometimes remarkably persistent reductions in antisocial behavior. Identifying when improved mental health relaxes a binding constraint on socioeconomic outcomes, and when other constraints limit these downstream gains, is therefore another important area for future research.

A further question concerns spillovers to family members. Treating maternal mental illness can change parenting and investments in children, but there is limited evidence that these changes translate into persistent improvements in the index child's outcomes. Given that it takes time for changes in parenting practices to influence child outcomes, it would be interesting to see if the documented changes affect the outcomes of subsequent children.

Scaling these interventions beyond the experimental setting raises further questions about implementation, beyond the take-up and engagement challenges discussed above. Many of the interventions reviewed above demonstrate that psychological treatment can be effectively delivered by community health workers, lay counselors, or peers rather than clinical specialists. However, these interventions typically rely on structured provider recruitment, training, and supervision. Whether these inputs can be sustained at scale, and whether treatment fidelity can be maintained as programs move from closely monitored trials to routine implementation, remains less well understood.

Beyond the challenges of scaling, a related question concerns generalizability. Much of the existing experimental evidence comes from low- and middle-income countries or from disadvantaged and high-risk populations. It remains unclear whether comparable effects would be found when interventions are delivered through routine health-care systems in higher-income settings, or to broader populations not selected for such elevated risk or baseline distress.

3.8.2 Effects of Pharmacological Treatments

A large clinical literature has established the short-run efficacy of medications for several common mental health conditions. For example, medication for attention-deficit/hyperactivity disorder (ADHD) has been found to improve attention and reduce disruptive behavior in the short run, although evidence on longer-run effects is less conclusive (Coghill 2019; Swanson 2019. The small but growing economics literature on pharmacological treatments for mental illness has focused less on short-run symptom reduction and more on longer-run health, behavioral, educational, and labor market outcomes. In contrast to the experimental literature on psychological and psychosocial interventions reviewed above, much of which comes from low- and middle-income countries and focuses on high-risk populations, studies of pharmacological treatments typically use administrative data from high-income countries. A substantial share of these studies focus on children and adolescents. To identify causal effects, existing studies commonly exploit differences in providers' propensities to prescribe a given medication or changes in the availability or regulation of specific drugs.

Several studies ask how pharmacological treatment impact health and behavioral outcomes. Chorniy and Kitashima (2016) and Chorniy (2025) study the effects of ADHD medication among children enrolled in Medicaid in South Carolina, exploiting differences in providers' prescribing propensities to identify causal effects. Chorniy and Kitashima (2016) find that treatment reduces sexually transmitted diseases by 3.6 percentage points and substance abuse disorders by 7.3 percentage points. Using linked Medicaid, education, and juvenile justice records for more than 52,000 children, Chorniy (2025) documents effects on a broader set of outcomes, including reductions in injuries by 5.7 percent, teenage pregnancy by 40.3 percent, arrests by 11.1 percent, and subsequent diagnoses of depression or anxiety by 24.5 percent. The effects are generally more pronounced among girls, with limited evidence of improvements in health and behavioral outcomes among boys.

In contrast, Masiero et al. (2026) find less favorable effects of increased antidepressant prescribing. Using regional data from Switzerland between 2003 and 2014, the authors exploit variation in pharmaceutical companies' national sales growth interacted with their regional market shares to instrument for antidepressant use. They find that an increase of one defined daily dose of antidepressants per 1,000 inhabitants is associated with a 2 percent increase in hospital admissions for mental disorders and a 6.5 percent increase in admissions for depression, with no detectable effect on suicides. The increase in depression-related hospitalizations is particularly pronounced among teenagers.

Beyond health and behavioral outcomes, several studies examine the effects of pharmacological treatment on education and labor market outcomes. Biasi et al. (forthcoming) study the economic benefits of pharmacological treatment for bipolar disorder. The authors exploit the introduction of lithium in Denmark, comparing cohorts with different access to lithium during early adulthood and using unaffected siblings to characterize the economic penalty associated with bipolar disorder. Individuals with bipolar disorder earn approximately 42 percent less than their siblings, but access to lithium in early adulthood closes approximately 64 percent of this earnings gap.

Bhalotra et al. (2026) study the long-run consequences of antidepressant treatment among children with mental health problems in Denmark. Using population-level administrative data, the authors examine children who first visited a psychiatrist between ages 8 and 15 and instrument antidepressant receipt with the assigned psychiatrist's propensity to prescribe these medications. They find that antidepressant treatment improves 9th grade math and Danish test scores and increases subsequent educational enrollment. Treatment also reduces emergency department visits for self-harm shortly after initiation. The benefits extend into adulthood, with treated children more likely to be employed, earning more, and less likely to receive welfare benefits. The gains in academic achievement are larger among children from lower socioeconomic backgrounds, while labor market improvements are particularly pronounced among men and individuals from disadvantaged families.

The effects of pharmacological treatment on socioeconomic outcomes are not uniformly positive, however. Currie and Zwiers (2023) examine antidepressant treatment following childbirth using Dutch administrative data covering approximately 420,000 first births. They instrument postpartum antidepressant receipt with local providers' propensities to prescribe for female patients above childbearing age. Receiving antidepressants substantially increases the probability of continued medication use over the following two years, indicating considerable persistence in treatment once initiated. However, antidepressant receipt reduces the probability of employment in the year following childbirth, with no detectable effects on employment thereafter or on earnings, fertility, and marital outcomes. The initial employment effects are concentrated among women with lower pre-pregnancy incomes.

Angelucci and Bennett (2024) provide experimental evidence from India, where 1,000 adults with depression were randomly assigned to receive pharmacotherapy, livelihoods assistance, both interventions, or neither. The livelihoods intervention provided individualized support related to employment opportunities, work-related challenges, and personal finances. Pharmacotherapy alone produced relatively weak improvements in depressive symptoms that dissipated over time, whereas combining medication with livelihoods assistance generated more persistent reductions in depression. Nevertheless, neither intervention significantly increased work time, earnings, or household consumption.

The mixed effects of pharmacological treatment raise the question of whether its consequences depend on the appropriateness of the treatment patients receive. Cuddy and Currie (2026) examine this question using insurance claims for more than 45,000 adolescents receiving initial treatment for anxiety or depression in the United States. The authors distinguish between drugs approved by the Food and Drug Administration (FDA) for the relevant condition and age group, "gray-area" prescriptions that are not FDA-approved but are consistent with professional treatment guidelines, and red-flag prescriptions that are neither FDA-approved nor consistent with professional guidelines. They exploit geographic variation in provider practice styles to identify the effects of these different prescribing decisions on subsequent health outcomes. Relative to adolescents receiving mental health care without medication, FDA-approved prescriptions reduce the probability of subsequent self-harm by 34 percent, while gray-area prescriptions reduce it by 13 percent. In contrast, red-flag prescriptions, do not significantly reduce self-harm and increase the probability of emergency department visits or hospitalization by approximately 19 percent.

Albertini et al. (2025) provide related evidence on benzodiazepine prescribing following bereavement in the Netherlands. Using administrative data on individuals who experienced the death of a relative, the authors exploit quasi-random assignment to primary care physicians with different propensities to prescribe. Moving from a physician at the 10th to the 90th percentile of prescribing propensity distribution increases the probability of receiving benzodiazepines following bereavement by 12 percent. The difference in medication use persists for several years

and is accompanied by greater exposure to potentially inappropriate prescriptions. Patients assigned to higher-prescribing physicians also experience subsequent declines in income, with earnings losses stabilizing at approximately 4 to 6 percent after five years. In a complementary analysis, the authors exploit the staggered introduction of mental health nurses into primary care practices. These nurses provide basic non-pharmacological mental health care, and their introduction approximately halves both the differences in benzodiazepine prescribing and the associated labor market effects.

Key Takeaways and Emerging Themes

The evidence on pharmacological treatment highlights the importance of distinguishing between access to medication and access to appropriate treatment. Several studies document substantial benefits from psychiatric medications, including reductions in risky behavior and self-harm and improvements in education and labor market outcomes. At the same time, greater prescribing can increase health care utilization or adversely affect economic outcomes. These findings suggest that neither increasing nor decreasing psychiatric medication use is necessarily an appropriate policy objective. Rather, the challenge is to ensure that patients who are likely to benefit receive appropriate medications while limiting unnecessary or potentially harmful prescribing. Understanding how treatment guidelines, provider incentives, and alternative forms of care can improve this matching is an important area for future research.

A second emerging theme concerns socioeconomic inequalities in treatment. Bhalotra et al. (2026) find that antidepressant treatment generates particularly large benefits for children from disadvantaged backgrounds on several outcomes, despite evidence that these children are less likely to receive treatment. This raises the possibility that inequalities in access to effective treatment contribute to socioeconomic disparities in mental health and its consequences. Understanding the sources of these differences, including the potential roles of provider behavior, information and communication, stigma, and other barriers to care, is an important direction for future research.

The findings on the role of livelihoods assistance in Angelucci and Bennett (2024) and access to non-pharmacological mental health care in Albertini et al. (2025) raise a related question about complementarities between pharmacological treatment and other resources. Understanding when pharmaceutical treatment and other health and social policies complement or substitute for one another, and whether these relationships differ across socioeconomic groups, is therefore another important avenue for future research.

4. Conclusions, Challenges, and Future Directions

This survey has summarized evidence that mental health conditions are extraordinarily costly, not only in terms of direct medical costs, but through their effects on individual's education, employment, and earnings, and through their spillovers onto families and communities. Given its important economic impact, mental health deserves more attention from policy makers. We have highlighted a broad range of factors that contribute to mental health over the life course, including, but not limited to negative shocks to individual and family incomes and employment, violence and trauma, pollution, and access to health care. Effective mental health policy would not only address mental health care but would also tackle the broader social roots of mental health. Policies addressing housing instability, gun violence, and poverty, may turn out to be among the most effective pro-mental health policies.

Because children are especially vulnerable and at least half of mental illnesses arise in childhood, measures to identify children who are at risk and provide preventive services can be

highly effective. As we have discussed, several interventions in the in utero or early childhood period have been shown to affect the incidence of later mental illness and reduce the intergenerational correlation in mental illness. The intergenerational correlation in mental health is already much lower than the correlation in income, suggesting that early interventions may already be bearing fruit. And because children spend much of their waking time at school, school environments may be an especially fruitful place to intervene.

Turning to health care, insurance coverage of mental health care is necessary though far from sufficient to ensure that people receive adequate care when they need it. Factors such as persistent stigma, long waiting times, and poor quality and/or inappropriate care also need to be addressed. While poor quality care is a problem throughout the health sector, it may be even more acute in the mental health space. Large numbers of people are prescribed drugs that are unhelpful or even harmful, while perhaps they could be helped through more appropriate treatments.

Therapy appears to be broadly beneficial, at least in the short-run, both for high acuity and lower acuity cases. It is less clear when and why therapy has long-term effects on other outcomes, including employment and earnings. A significant data problem is that in many health care settings, therapy is a black box. We may know that someone receive 30 or 45 minutes of it, but we do not know the content or orientation of the therapist, which makes it hard to draw conclusions about efficacy. The strong anti-crime effects of manualized therapies in high-risk populations are remarkable and deserve more attention. Given how costly crime is both for the perpetrators and the victims, significant reductions in violent crime may justify efforts to make therapy more broadly available.

There are many opportunities and challenges facing researchers in this area. Improvements in measurement are fundamental. Researchers need to pay more attention to how the mental health measures they use are derived, and whether they are measured in a consistent way across time and across places. Some evidence suggests that the deterioration in mental health over time has not been nearly as great as most people believe. For example, suicide rates in the European Union have been consistently declining, and those in the U.S. began falling in 2018, rose during the pandemic, and have resumed their downward trend since 2022. It may be a good thing that more people are being diagnosed and treated for mental illness, rather than a sign of growing malaise. There would be a high return to developing consistent measures of underlying mental health and applying them consistently.

Greater understanding of the mechanisms underlying the documented effects of shocks on mental health would be helpful in terms of designing effective interventions. At present we can observe, for example, that parental job loss can lead to child mental health problems, but we do not know what fraction of this effect is through changes in parenting behavior relative to other changes in circumstances and living arrangements that accompany job loss. We also know that the impact of shocks tends to be largest for the most economically disadvantaged people, but it is not clear why. Do disadvantaged people have a higher underlying propensity to suffer mental illness or are the cumulative effects of multiple life shocks more toxic? The answers to these questions can shed light on the extent to which mental illness is a contributor to economic inequality rather than a consequence of it.

As we have discussed, most studies focus on people at specific ages, from childhood, through adulthood, and into old age. However, beyond noting that children with mental illness are more likely to become adults with mental illness, we are not aware of any studies that consider the relationships between mental health at different stages of the life course. While the demands in terms of data are daunting, it would be extremely useful to know if the child with ADHD today is at risk of becoming an adult with depression and anxiety, and an older person with dementia or

other cognitive impairments. Putting these pieces together could reshape how we think about the effectiveness of mental health interventions.

In terms of treatment, the multibillion-dollar question is how to improve the matching of patients to treatments. What types of guidelines, training, or incentives can help providers choose appropriate treatments, and how can barriers that prevent patients from seeking and receiving effective care be reduced? Stigma may be particularly important in this regard, by discouraging help-seeking or delaying treatment even when care is available. An important question is whether stigma and other barriers to seeking care are more consequential for lower-SES individuals, and whether they therefore contribute to socioeconomic disparities in treatment and mental health. Given the substantial variation in the treatment patients receive and the importance of treatment choices for subsequent outcomes, research on how to improve the quality and allocation of mental health care, while reducing barriers to its use, could have substantial returns.

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Table 1: Consequences of Mental Illness				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A: Effects in the Labor Market				
Babiarz and Yilmazer (2017). Effects of MH shocks on consumption; mediating role of insurance, wealth, and transfers.	Panel Study of Income Dynamics: 8 waves, 1999-2013. N = 36,459 obs. from 9,272 households.	FE: Individual FE isolate within-household consumption changes after a member's health diagnosis.	MH diagnosis → consumption ↓ 6-7% (physical diagnoses no effect); household-head income ↓ 62%, partially offset by gov't, private transfers; severe physical conditions: half the effect. No ↑ OOP health costs (physical do ↑), net wealth, assets ↓, debt ↑.	Consumption declines are strongest for food/housing, especially trips/vacations, and are driven by the uninsured.
Banerjee et al. (2015) Effects of psychiatric disorders on labor market outcomes.	US Comorbidity Survey (2001-2003) and National Latino and Asian American Study (2003): cross-sectional adults 25+. N = 7,566.	IV: Instruments current MH status with number of psychiatric disorders diagnosed before age 18.	1 SD ↑ in a MH-disorder index → employment ↓ 19 p.p. (22.6%) for men and 10 p.p. (14.5%) for women. Poor MH → 4 (8%) ↓ weeks worked last year and 2 (185%) ↓ days last month (conditional on employment).	N/A
Bhalotra et al. (2026a). Effects of postpartum depression on the labor-market motherhood penalty.	Linked Danish admin. registers, 1993-2022; assessed postpartum depression from the Danish National Birth Cohort (1998-2002); Danish Nurse Home Visiting Program (2012-2017). N = 74,382 first-time mothers.	DiD: Treats the timing of first birth as idiosyncratic, using women with later first births as controls for earlier ones and letting childbirth effects differ for women with postpartum depression; controls weighted by propensity scores.	First-time mothers' earnings 14.0% ↓ vs. 16.5% ↓ for non-depressed vs depressed mothers (1998-2002 sample); larger in recent sample (21.3% vs. 24.8%). Employment ↓ 7.8% (14.8%) non-depressed, ↓ 10.8% (17.8%) depressed in earlier (later) sample. No change in hours worked. No difference in GP spending; depressed larger ↑ in MH-care use.	The postpartum-depression penalty appears only among lower-educated women, and is larger in less family-friendly fields (lower gender wage gaps, women a larger share of top earners). Husbands of depressed mothers also see earnings ↓.
Bubonya et al. (2017). Effects of mental health on productivity at work.	HILDA (Household, Income and Labour Dynamics in Australia): 13 waves, 2001-2013. N = 78,305 obs. from 16,513 individuals.	FE: Individual FE via conditional maximum likelihood.	Men (women) in poor MH: reported productivity decrease 6.2x (6.9x) likelier; absence 4.9% (5.3%) likelier. Job stress ↓ productivity. Control over work → ↑ productivity only for those in good MH.	Higher job control is associated with significantly lower absenteeism for women in good health but significantly higher absenteeism for the mentally ill.
Cuddy et al. (2026b). Labor market effects of anxiety, depression, and self-harm.	Linked Swedish health, labor market registers. Individuals hospitalized for depression, anxiety, or self harm at age 25+.	DiD: Leverage staggered timing of mental health crises, comparing changes in outcomes around hospitalization for those earlier vs. later admitted.	Employment ↓ 11 p.p. (14%) over three years. Earnings ↓ 22% (half labor market exit, half wage decrease). Employment ↓ 3-4x larger than for heart attack, car accident. No recovery after 10 years in a supplementary matched DiD. Social assistance ↑, total income still down.	Effects are larger for patients who spend longer in the hospital, for lower-wage and lower-tenure workers, and for workers at smaller firms.

Paper / Research question	Data	Methods	Results	Heterogeneity
Danesh et al. (2026). Early-career effects of anxiety and depression.	Linked Colombian administrative data on employment and healthcare use, 2009-2019. N = 110,172 individuals.	DiD: Compares changes in labor market outcomes for young adults (18-45) newly diagnosed with anxiety or depression to matched controls.	Earnings ↓ %7.4 two years after diagnosis. Driven by reduction in working days immediately, increase in employment later on. Some evidence wages also decrease.	Effects stronger for women and older workers and for workers with higher baseline earnings and baseline labor-market attachment.
Dang et al. (2023). Effects of refugee MH on labor-market assimilation.	Building a New Life in Australia survey: 5 waves from 2013-2014. N = 3,130 obs., 1,322 individuals.	IV-FE: Instruments refugee MH by interacting years-post-arrival with an indicator for pre-arrival trauma exposure; includes individual FE.	1 SD ↓ MH → employment ↓ 6.1 p.p. (11.9%), earnings ↓ 22.8%; ↓ in labor-force participation, permanent positions, hours, life satisfaction. ↑ in low-skilled occupation. Gov't refugee aid significantly moderates the effects.	Effects stronger for refugees with more tenuous legal status, more recent arrival, more time in camps, and no in-country contacts. Smaller effects for weekend admissions.
Germinario et al. (2022). Effects of mental health on labor market outcomes.	National Longitudinal Survey of Youth (individuals 14-22 in 1979, followed since): N = 7,665 individuals observed 1992-1993.	Bounding: Uses nonparametric partial identification to bound the causal effect of mental health on labor outcomes.	Strictest assumptions: depression max → 10% ↓ in employment odds, 27% ↓ in earnings. Employment ↓ guaranteed only for move from little to severe depression; smaller changes: effects bounded near zero.	Employment effects stronger for Black people and men; earnings effects stronger for White or Hispanic people and men.
Li et al. (forthcoming). Effects of dementia on household finances.	Health and Retirement Study 2000-2016. N = 57,042 person-waves.	Weighting: Compare individuals with likely dementia based on Hudomiet et al. (2022) methodology to IPW controls. FE: Leverage differential timing of dementia onset with individual and calendar year FE.	Net worth relative to control group begins to decline six years before onset. FE: net worth $17k lower 6-4 years pre; $51k lower 2-0 years. Income declines are small relative to wealth effects. No change in spending, transfers; little increase in medical spending.	Effects years 6-4 driven by financial wealth, especially stocks. Timely diagnosis offsets some wealth losses. Effects concentrated among those with more baseline wealth, and those without a partner.
Peng et al. (2016). Short-term effects of depressive symptoms on labor market outcomes.	Medical Expenditure Panel Survey: 2004-2009. N = 69,420 obs. from 34,710 individuals.	Correlated random-effects model.	Depressive symptoms → employment ↓ 2.4 p.p. (3.2%); frequency, length of sick leave ↑, increasing in severity. No significant effect on wages or hours conditional on employment.	Employment effects ~2x stronger for men.
Panel B: Effects on Children				
Cornaglia et al. (2015). Effects of poor MH on education decisions.	Longitudinal Study of Young People in England: 2004-2008, ages 13/14 to 16/17. N = 7,567.	FE: Regresses educational outcomes on MH with school FE to absorb time-invariant characteristics shared within schools.	Poor MH → exam performance ↓ 0.083 SD (boys) and 0.158 SD (girls). Girls 35.5% likelier to be not in education, employment, training; null for boys. Effects mediated by truancy, substance abuse, and risky behavior.	N/A
Le and Nguyen (2017). Effects of parental mental health on child human capital.	Longitudinal Survey of Australian Children (LSAC): 2004-2012. N = 4,983 children aged 4-5 at baseline.	FE: Child FE compare a child's outcomes in years when parents were more vs. less healthy.	Changes in mothers' and fathers' MH have insignificant effects on indices of child cognitive and non-cognitive development overall.	For single mothers, physical illness predicts worse child cognitive outcomes and mental illness predicts worse non-cognitive outcomes.

Paper / Research question	Data	Methods	Results	Heterogeneity
Noonan et al. (2016). Effects of maternal depression on food insecurity.	Early Childhood Longitudinal Study-Birth Cohort: children born 2001 followed to age 4. N = 24,700 obs. of 9,100 mothers.	FE: Mother FE isolate within-mother fluctuations in depression over time; also tests postpartum-year depression's effect on year-2 food insecurity.	Severe maternal dep. → child food insecurity ↑ 79%, household food insecurity ↑ 69%. Severe postpartum → food-insecure at age 2 ↑ 74%, household food insecurity ↑ 51%.	N/A
Panel C: Societal Effects				
Abramson et al. (2025). Quantifying the social burden of mental health.	RAND American Life Panel (2012); mental-health-status transition rates from the PSID (2000–2020); treatment-seeking by status from the NIMH; parameter estimates drawn from the labor and health economics literature.	Model: A heterogeneous-agent macro model in which the mentally ill hold pessimistic expectations and have less time (due to rumination), which lowers treatment-seeking and produces self-reinforcing mental health spells; calibrated to the data and literature sources above.	The model estimates the total welfare cost of mental illness at 1.7% of aggregate consumption. In counterfactual simulations, universal treatment availability would recover a welfare benefit of 1.1% of aggregate consumption, while cutting treatment costs alone has a much smaller effect; a 10% increase in treatment efficacy is worth a further 0.7% of consumption.	Policies that increase treatment access among the young generate the largest simulated welfare gains.
Anderson et al. (2015). Effects of youth depression on later-life criminal behavior	National Longitudinal Study of Adolescent Health: 132 school cohorts and siblings, followed grades 7-12 through ages 25-32. N = 15,584 respondent-years.	FE: Alternately includes school FE and family FE.	With school FE, depression is associated with property-, non-drug-crime ↑ 46% and 14.2%. With family FE, property crime ↑ 85% but no effect on non-drug crimes. Null effects on violent crime and drug dealing in both models.	With school FE, little gender difference in property-crime effects, though only women see ↑ non-drug crimes.
Bos et al. (2023). Effects of a marginal mental health diagnosis on long-term outcomes.	Administrative health, labor market, and family-formation data for Swedish men born 1971–1983, drafted into military conscription 1987–2001 and assessed by 104 doctors. N = 400,104.	IV: Exploits the quasi-random assignment of draftees to military doctors to isolate marginal diagnoses driven by variation in doctors' tendency to diagnose mental illness; doctors in this setting do not treat or prescribe, so the diagnosis is identified apart from any treatment.	Marginal diagnosis → death from internal causes before 30 ↑ 1.23 p.p. (875%), null effects external causes, suicide. Outpatient hospital stay ↑ 19.5 p.p. (84%); sick days ↑ 9.42 p.p. (216%). Long-, short-spell unemployment ↑ 8.9 p.p. (164%) and 6.0 p.p. (108%). Income at 30 ↓ 1.04 log points. Family formation and fertility ↓. Limited evidence of ↑ in treatment or prescriptions.	N/A
Jayawardana (2023). Excess healthcare costs generated by young women's mental distress.	Australian Longitudinal Study on Women's Health: the 1989-1995 birth cohort, 2013-2017. N = 53,449 obs. From 16,892 women 18-27.	FE: Individual FE isolate effects of within-individual changes in MH on the probability of any medical costs and on total costs.	Women with psychological distress: 0.5% higher chance of incurring positive costs; 15% ↑ total costs, plus ↑ out-of-pocket costs. Severe psychological distress drives up to $100 million in health-care expenditure per year.	Any-cost effects are driven by prescription costs; total-cost increases by service use.

Paper / Research question	Data	Methods	Results	Heterogeneity
Kelley et al. (2015). The burden of health care costs in the last 5 years of life.	Health and Retirement Study linked to Medicare claims and the National Death Index, Medicare fee-for-service beneficiaries 70+ who died 2005-2010. N = 1,702 decedents (555 with >50% probability of dementia; 1,147 without, by cause of death: cancer, heart disease, other).	Comparison of means: Total social costs (Medicare, Medicaid, private insurance, out-of-pocket, and imputed informal care) over the last 5 years of life are compared across dementia and non-dementia cohorts, with a gamma distribution regression model used to adjust for age, sex, race, education, marital status, and coexisting conditions.	Total care costs over the last 5 years of life → $287,038 (dementia) $183,001 (non-dementia): 57% higher (cancer $173,383, heart disease $175,136, other $197,286). Medicare spending similar across groups; gap driven by out-of-pocket spending (81% higher) and informal care (more than double). Out-of-pocket spending is 32% of household wealth 5 years before death (dementia), 11% (non-dementia): 242% vs. 81% of wealth excluding housing.	The out-of-pocket burden is largest for the most financially vulnerable: those with less than a high school education and unmarried women Black decedents with dementia have lower out-of-pocket spending than non-Black decedents but more than offsetting informal care costs, so total burden is similar across race despite the different composition.

Table 2: Endowments				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A. Intergenerational Transmission				
Abramson et al. (QJE R&R). A macroeconomic model of child MH.	Panel Study of Income Dynamics (PSID); Child Development and Transition into Adulthood supplements; National Longitudinal Survey of Youth (NLSY), 1979 cohort.	Model: Embeds a model of child mental health -- direct inheritance from parents and parental investments (which also depend on parental MH) -- in an overlapping generations economy.	Parent mental illness → hours spent with child ↓ 15%, child mental illness ↑ 25 p.p. Eliminating parental mental illness → aggregate output ↑ 8.3%. Free treatment for children (+parents) → 0.78% (1.04%) annual-consumption-equivalent welfare gain.	Providing treatment to parents only before/after birth → 0.13% annual-consumption-equivalent welfare gain
Bencsik et al. (JHE 2023). Intergenerational health mobility in the UK.	British Household Panel Survey (BHPS) and UK Household Longitudinal Study (UKHLS) 1991-2017. N=1,741 parent-child pairs with SF-12 health measures in both generations. Children measured as young adults (25+).	Rank-rank regressions of child health on parent health (HRQoL via SF-12 physical and mental component scores). Decomposition into mental and physical health channels. Comparison with income mobility. Welfare measure combines health and income.	Rank-rank slope=0.21 (0.17) for mental health index and 0.15 (0.2) for physical health. Parent mental health is a stronger predictor of child (mental + physical) health beginning at ages 13-15. Rank-rank slope in welfare (health + income combined)=0.27, vs. 0.43 in US. UK Health mobility higher than income mobility.	Parent physical health more important at 10-12; parent mental health becomes more important at ages 13-15, with no statistically significant role for physical health. There are no significant differences in across racial/education groups.
Bhalotra et al. (2026c). Intergenerational transmission of mental health.	Danish administrative data. N=251,538 biological children + 1,908 foreign-born adoptees). Parent MH events from psychiatric hospitalizations and prescriptions from 5-years pre-birth to 3. Child MH events by age 15.	OLS associations for biological children. Comparison of biological vs. adoptee estimates to decompose biology vs. environment. Mother vs. father comparisons to identify gendered transmission.	Parental MH event → increases child MH event by age 15 by 83%. Paternal effect 2/3 maternal effect. Effects ~55% for adopted children implies ~50% of transmission is biological, ~50% environmental. ~75% of maternal effect is environmental vs. primarily biological father effect.	Mother-son correlations are stronger than mother-daughter correlations, and father-daughter correlations stronger than father-son correlations. No correlation between adopted daughters' MH and that of either parent; Adopted sons MH associated with mother's mental health but not father's.
Bütikofer et al. (2024). Effects of early-childhood intervention on intergenerational transmission of mental health.	Norwegian registry data. N=370,498 parent-child pairs. Parents' MH diagnoses from primary care (KUHR) and specialist care (NPR) at ages 25-30. Children's MH diagnoses at ages 13-18. Linked to education, earnings, and demographic registers.	OLS of child MH diagnosis on parental MH diagnosis, include MH of aunts/uncles to decompose biological vs. non-bio family effects. DDD: 2007 school-based early intervention for children of parents with MH issues: compares children above/below age cutoff before/after rollout in treated/matched control municipalities.	Parental MH diagnosis → 9.3 p.p. (40%) increase in child MH diagnosis. Extended family accounts for 42% of intergenerational persistence. 2007 pilot program reduced parent-child MH association by 39% (3.8 p.p. reduction in the intergenerational gradient).	Little difference between male vs. female children or high vs. low SES families. The direct effect of paternal mental health is stronger, but the extended-family effect is stronger on the maternal side. No differences based on the level of medical expertise within families.

Paper / Research question	Data	Methods	Results	Heterogeneity
Eyal and Burns (2019). Effects of cash transfers on the intergenerational transfer of mental illness in South Africa.	Longitudinal mental health data from the National Income Dynamics Survey, 2008-2017. N = 1,885 African or Coloured adolescents aged 15-19.	IV: Child's transfer is instrumented using expansions of age-based eligibility. IV is repeated for 4 samples where mothers/fathers do/do not have depression. FE: Uses consecutive waves of the survey and individual fixed effects to estimate effects of gaining/losing coverage.	In the subsample whose mothers have depression, payments ($6-$20/month) decrease the odds of suffering from depression by 46-58 p.p. (256-322%). No effect in other subsamples. Fixed effects estimates suggest that payments decrease intergenerational transmission of depression by 45% for mothers and 70% for fathers.	Transfers are more protective of mental health among daughters.
Le and Nguyen (2017). Effects of parental mental health on child human capital.	Longitudinal Survey of Australian Children (LSAC), 2004-2012. N = 4,983 children ages 4-5 at baseline. Includes child development, parent health, and family characteristics.	FE: Child fixed effects compare child outcomes in years when parents are more/less mentally healthy.	Mother and father's mental health have insignificant effects on indices of child's cognitive and non-cognitive development.	For single mothers, physical and mental illness are associated with worse cognitive and non-cognitive outcomes, respectively for children.
Menta et al. (2023). Do mothers' genetic risk scores for depression predict their children's human capital?	Avon Longitudinal Study of Parents and Children (ALSPAC), UK. ~9,000 mother-child pairs from 1991-1992 Bristol birth cohort, linked to National Pupil Database.	OLS regression of child cognitive/non-cognitive outcomes on maternal polygenic risk score (PGS) for depression, controlling for child PGS. Decompose genetic inheritance vs. maternal depression. Robustness: controls for pleiotropy, assortative mating, dynastic effects.	1 SD increase in maternal depression PGS → 4.5% SD reduction in child cognitive skills (Key Stage test scores at ages 11, 14, 16) and 6.5% SD reduction in non-cognitive skills (SDQ at ages 11, 13, 16). Maternal depression is the dominant factor vs. genetic inheritance. Effects are robust to controls for pleiotropy and dynastic effects.	Little evidence of heterogeneity by child gender or birth order; the effects of mother's PGS are driven by mothers diagnosed with depression.
Moya et al. (2024). Effects of caregiver MH treatment on child mental health and development.	1,376 caregivers (714 treatment, 662 control) across 18 public childcare centers in Tumaco, Colombia. 4 cohorts 2018-2019. Baseline, 1-, and 8-month follow-ups. 82% experienced conflict-related violence; 54% displaced; 40%+ MH symptoms. COVID-19 disrupted 8-month data collection for Cohorts 3-4.	Cluster RCT randomization at childcare center level (N_c=18), stratified by center size, child age distribution, and SES. Evaluates 'Semillas de Apego,' a 15-session weekly psychosocial program for caregivers based on Child-Parent Psychotherapy (CPP). ATT via 2SLS instrumenting session attendance with treatment assignment.	At 8-months: ITT of 0.17 SD on caregiver MH index; 0.31 and 0.15 SD on quality and style of child-caregiver interactions; 0.10 SD on child MH (marginal sig.); 0.23 SD on early childhood development (significant). ATT for 8+ sessions: 0.32 SD caregiver MH, 0.59 SD relationship quality, 0.46 SD child development. Effects larger at 8-month than 1-month, suggesting sustained impacts.	Stronger effects for displaced caregivers and caregivers with above-median baseline MH problems. Small/null effects for food-insecure caregivers and those with below-median wealth. Effects are strongest for children below 3.
Smith (2026). Effects of parental depression on child development among Syrian refugees.	Syria Refugee Life Study, longitudinal, 3 waves 2021-2024. N = 1,496 Syrian refugees living in Jordan.	FE: Household fixed-effects isolate effects of within-family change in presence/length of parental depression. LASSO: Selects covariates that best predict child development.	LASSO: Parental depression is the strongest predictor of child socio-emotional problems. FE: +1 year of parental depression → 15% increase in abnormal socio-emotional development, lower school attendance.	Socio-emotional effects larger for fathers' depression, school attendance larger for mothers'.

Paper / Research question	Data	Methods	Results	Heterogeneity
von Hinke et al. (2022). Effects of mother's mental health on child development.	ALSPAC longitudinal data for 7,773 mother-child pairs born in 1991-1992 and followed through 16. Matched to age 16 test scores from the National Pupil Database. Includes measures of child development, maternal mental health at 18 weeks gestation and 8 weeks postpartum.	IV maternal mental health with the illness of a friend or relative during pregnancy (recorded at 18 weeks gestation or the 8 weeks postpartum). Control for friend/family illness beginning in the 8 months after birth.	1 SD worse mother's MH during pregnancy increases child's depression score 0.86 SD at age 9.5 and 0.40 SD at age 11.75. Also associated with a 0.65 SD increase in socio-emotional problems at age 6.75, but not significant at age 13. No significant effects child cognitive outcomes or on parental investments.	The effects on socio-emotional outcomes at ages 6.75 and 9.5 are significantly larger for girls than for boys.
Zhang and Kim (2023). Intergenerational effects of parental early-life famine exposure on children's adult mental health.	Chinese Family Panel Studies (CFPS) 2018 and 2020, combined with Lin and Yang (2000) famine intensity data. N = 3,485 parent-child pairs across 25 provinces. Parents born around the Great Famine (1959-1961); children observed in adulthood.	Cohort DID: Exploits geographic variation in famine intensity interacted with parents' birth cohort. Uses Piaget's four cognitive development stages (ages 0-2, 3-7, 8-11, 12-15) to define exposure as proportion of years exposed.	Parental famine exposure at ages 0-2 or 3-7 increases children's adult depression and loneliness. Later exposure (8-11, 12-15) has insignificant effects. Mechanisms: negative effects on parents' own mental health and reduced parent-child interaction.	Exposure at age 3-7 exposure has stronger effects for mothers, daughters, and mother-daughter pairs. Being an only child is protective. Effects observed regardless of rural status.
Panel B. Fetal and Early-Life Origins of Mental Health				
Adhvaryu et al. (2019). Effects of early-life family income shocks on adult mental health.	Real cocoa prices received by Ghanaian farmers, 1943-1997, matched to a 2009-2010 cross-sectional survey. N = 7,815 respondents.	DiD: Compares cohorts born in cocoa-producing regions exposed to high birth-year cocoa prices against same-cohort children from non-cocoa regions.	One SD ↓ in birth-year cocoa prices → a 0.08 SD (1%) ↑ in adult MH index, ~50% ↓ in severe mental distress. Cash savings and self-employment mediate; literacy, adult health matter less. Parental investments, maternal health/nutrition, and children's economic/ educational outcomes improve.	Effects stronger among those whose fathers worked in agriculture and among an ethnic group tied to cocoa production. Little gender heterogeneity.
Aizer et al. (2016). Effects of in-utero maternal stress on educational attainment.	Children born 1959-1965 in Providence, RI and Boston to mothers in the National Collaborative Perinatal Project, with third-trimester cortisol and follow-ups through age 7 plus a 2002-2004 survey on education and labor outcomes. N = 1,093.	FE: Family fixed effects isolate across-sibling variation in mother's third-trimester cortisol, driven more by short-term shocks than family characteristics.	High (80th+ percentile) third-trimester cortisol is associated with 1.1 (0.58 SD) fewer years of schooling and a 6-point (0.43 SD) lower verbal IQ at 7, with suggestive evidence of more chronic conditions at 7. Not driven by parental investments (weight gain, smoking, prenatal visits, assessments, preschool).	Effects on educational attainment driven by children of mothers with less than a high school diploma.

Paper / Research question	Data	Methods	Results	Heterogeneity
Akbulut-Yuksel et al. (forthcoming). Effects of early-life exposure to WWII bombing on long-term mental health.	City-level Allied bombing intensity across West Germany from Davis (2006), merged with German Socio-Economic Panel (GSOEP) 2002-2010. Treatment: born 1934-1945; control: born 1923-1933 or 1950-1960. N ≈ 8,770 across 75 cities.	Generalized DiD: Exploits city-by-cohort variation in bombing intensity (bombs/sq km). Compares cohorts ≤5 at war onset or born during the war to older/younger cohorts, across cities.	One SD ↑ in bombing intensity (82.7 bombs/sq km) → ~10% ↓ in standardized MH score and a 16.2% (3.3 p.p.) ↑ in clinical depression at ages 57-76. Cities bombed more heavily see larger effects. Healthcare destruction and wealth losses worsen; relief transfers mitigate. Not mediated by adult income, suggesting a trauma channel.	Driven by those born after 1937, especially in utero/very young 1942-1945. Effects similar for males and females. No effects for rural residents; concentrated in medium/large cities. Indistinguishable across parental education/occupation. Children who lost fathers show far larger effects.
Black et al. (2016). Effects of maternal bereavement during pregnancy on child outcomes.	Medical Birth Registry of Norway, Norwegian Death Register, and linked registers. N = 750,697 births (mothers with ≥2 births), 1967-2009. Linked to military IQ and labor records.	Two strategies: (1) compare children in utero during a grandparent death to those with a death just before/after birth (IV window); (2) mother FE across siblings.	In-utero bereavement has small but significant adverse birth effects: ~21g lower birth weight, ~0.09 fewer gestation weeks, higher C-section probability. No significant long-run effects on education, earnings, cognition, height, or BMI at 18. Contrasts with Persson & Rossin-Slater (2018), who find persistent MH effects in Sweden.	Larger birth effects for boys and for sudden/unexpected (cardiovascular) deaths. No long-run heterogeneity by parental education.
Cheng et al. (2024). Effects of early-childhood exposure to the Great Chinese Famine on adult mental health.	China Health and Retirement Longitudinal Study of adults aged 45+, four waves since 2011. N = 2,650.	DiD: Compares famine-exposed vs. unexposed cohorts across prefectures with different famine exposure.	A one-SD rise in famine intensity raises a mental-distress index ~3.9% for those exposed at ages 0-2 and 6.4% at ages 3-5, with similar effects on severe depression. Not driven by directly-recalled experience of starvation.	Little gender heterogeneity (unlike Li and Sunder), except effects are much stronger for girls with a brother within 3 years of their age.
Chorniy et al. (2020). Affects of a supplemental nutrition program for pregnant women on children's mental health and other outcomes.	South Carolina administrative birth records, Medicaid claims, and school records for all children born 2004-2009. N = 59,530 matched across datasets.	FE: Mother fixed effects compare siblings where one participated in WIC (Special Supplemental Nutrition Program for Women, Infants, and Children) and another did not.	WIC participants are 5% less likely to be diagnosed with ADHD, 5.1% less likely with other childhood MH conditions, and 7.9% less likely to repeat a grade. Improves health at birth (birth weight, LBW). Little effect on childhood physical health or long-term care use, though more preventive care among the lowest-income children.	Mental health effects concentrated among African Americans and lower-income Medicaid recipients.
Conti et al. (2024). Effects of an early home visiting program's delivery model on maternal and child mental health at primary school age.	Pro Kind RCT in Germany, 2006-2012, 13 sites in 3 states. N = 755 mothers randomized. Age-7 diagnostic interviews, N = 279 children, 306 mothers.	RCT: Mothers randomized to two home-visit delivery models from pregnancy through child age 2: continuous midwife (CM) vs. tandem midwife + social worker (TM).	The continuous midwife (CM) model reduces any child MH diagnosis by 5.1 p.p. (27%) and maternal mood disorder by 10.3 p.p. (42%); no significant effects under tandem (TM). CM also breaks intergenerational transmission of neurotic/stress disorders.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Fu et al. (2026). Effects of nuclear accident stress on birth outcomes.	Japanese administrative birth records, 2010-2015, matched to census. N = 954,172 births. Google search trends for radiation-related terms.	Cohort: compares pregnancies pre/post Fukushima disaster; prev. year births as placebo; allowed to differ w/ search intensity. FE: Family FE; compare treated to non-treated siblings.	Cohorts: Preterm births ↑ 17%. Low birthweight ↑ 7%; extremely low ↑ 77%. Similar results with family FE. Increased searches account for ~70% preterm effects ~30% birthweight effects; other disaster-related stressors drove BW effect.	Effects of search volume strongest in first, third trimesters. University-educated women almost fully protected.
Huang et al. (2027b). Effects of prenatal typhoon exposure on MH.	A 5% population sample of Taiwanese health insurance claims, 1998-2002. N = 69,549 individuals born 1959-1970.	Cohort DiD: Compare adult MH outcomes for birth cohorts who were/were not in-utero during a landfall, across counties that were/were not located in counties with typhoon landfall.	In-utero exposure to typhoon landfall increases MH diagnoses in adulthood by 12% and psychiatric drug use by 11%, relative to those with no exposure. Psychiatric visits and spending also higher.	The effects are completely concentrated among women and strongest for depression diagnoses and antidepressants. The effects are significantly stronger for those in direct-landfall counties.
Li and Sunder (2021). Effects of exposure to the Great Chinese Famine in-utero/in infancy on mental health in middle age.	2012-2014 China Family Panel Studies. N = 5,509 individuals from 3,860 households, plus regional famine severity from the 1991 Statistical Yearbook of China.	DiD: Compares cohorts born during the famine to those born just before/after, second-differenced across provinces by famine intensity.	Mostly null effects on mental-health indices at age 55. For women, exposure worsens a mental-health index by 7% and raises the likelihood of severe stress by 17.2%.	Effects on women appear only for the (most severely affected) 1959 birth cohort, not 1960 or 1961.
Persson and Rossin-Slater (2018). Effects of deaths in the family during pregnancy on child mental health.	Swedish administrative health data on every child born 1973-2011, matched to four-generation family trees. N = 296,557 whose mother experienced the death of a close relative during gestation or the year after birth.	Compares children whose mothers experienced a family death in utero vs. in the year after birth.	In-utero exposure raises MH-drug use in early/middle childhood, driven by a 24% rise in ADHD medication. At age 35, exposed individuals are 19% and 12% more likely to receive anti-anxiety drugs and antidepressants. Also worse physical health at birth and in year one, but not after.	All MH effects strengthen when the deceased is closer to the mother (parent or sibling). ADHD effects driven by younger cohorts in school when ADHD drugs and screenings emerged.
Procópio et al. (2024). Effects of maternal stress during pregnancy on the gender-differentiated development of children in Chile.	Early Childhood Longitudinal Survey (ELPI) in Chile, tracking children born 2006-2017 with assessments at multiple ages. N = 774 (388 boys, 386 girls).	Quasi-experimental: Compares children in utero during the February 27, 2010 earthquake (magnitude 8.8) with children aged 0-9 months. IV uses hypothetical gestation period from conception date to address birth-date endogeneity.	Boys show larger birth weight/length reductions (up to 194g, 0.94 cm), especially when exposed in trimesters 1-2. At ages 2-3, prenatally-stressed girls (not boys) show more socio-emotional problems including anxiety/depression. At ages 8-9, ADHD probability rises for both sexes but more for girls; boys show more asthma.	Boys bear larger birth costs but fewer later MH effects; girls are less affected at birth but more vulnerable to later socio-emotional and MH problems. Effects generally stronger for later-trimester exposure.

Paper / Research question	Data	Methods	Results	Heterogeneity
Sardoschau (2024). Effects of in-utero exposure to violence (maternal stress) on child health in Iraq.	UNICEF Multiple Indicator Cluster Surveys, Iraq, 2011. N = 22,109 households with children under 5. Location and severity of 2003-2009 post-invasion violent attacks from the Iraq Body Count Project.	FE: Mother fixed effects compare siblings whose districts experienced different in-utero violence. Restricts to single-casualty events to exclude infrastructure/health damage and isolate the maternal-stress channel.	Violent incident during pregnancy → 0.135 SD and 0.143 SD ↓ in child weight- and height-for-age Z-scores; more-exposed children catch up to siblings by age 3. Robust to controlling for violence in three months pre-pregnancy → in-utero exposure rather than selection. Affected children: more coughs, lower cognitive scores.	Effects do not vary with mother's age (a proxy for resources) or child gender. Strongest when violence is sectarian, further supporting a stress channel.
Turner et al. (2021). Effects of in-utero influenza exposure on mental health and mortality risk throughout the life-course.	1958 National Child Development Study (NCDS), UK. ~17,000 individuals born March 2-9, 1958, mothers pregnant during the 1957 Asian Flu. Mother-reported in-utero exposure; MH at ages 7-50; linked death records.	Inverse probability of treatment weighting (IPTW) and doubly-robust IPWRA. Mother-reported influenza identifies individual exposure; the 1957 flu hit young adults, so exposure is plausibly uncorrelated with maternal health.	In-utero influenza yields small mid-childhood MH reductions: a 3% rise in the Rutter index at age 11, driven by internalizing symptoms. Males show a 15% rise in depressive symptoms at age 50. Mortality: 75% higher stillbirth probability. Mortality selection implies effects are a lower bound.	Childhood internalizing effects stronger for females; adult depressive effects significant only for males. Effects appear at ages 7-11, fade in adolescence/early adulthood, and re-emerge in mid-life for males.
Wang and Wang (2022). Effects of exposure to the Great Chinese Famine in utero/early childhood on long-term mental health.	China Health and Retirement Longitudinal Study (CHARLS) waves 2011-2015, nationally representative aged 45+, born 1954-1966. Rural sample: N = 6,039-6,308.	Cohort DiD: Exploits geographic and temporal variation in famine intensity (province-level abnormal weighted death rates). Birth-county FE; controls for a cubic in birth year, gender, and parental education.	Famine exposure increases specific CES-D symptoms: "being bothered," "trouble keeping mind," and "fearful."	Effects entirely driven by females; no significant male effects on any symptom or the total score. The gap is attributed to son-preference in resource allocation during famine.
Wu et al. (2023). Effects of rainfall shocks in early childhood on long-term outcomes.	China Family Panel Studies, 2010-2016. N = 8,005 children born 1993-2006. Rainfall data from the National Population Information Center.	FE: Isolates within-county variation in rainfall shocks across cohorts born in the same region, using other regions to control for time trends.	Children exposed to positive in-utero rainfall shocks are 0.4 p.p. (17.4%) less likely to have severe mental illness at ages 10-17. Positive shocks also raise educational attainment and year-1 health for girls, possibly via higher breastfeeding as mothers' agricultural work hours fall.	Mental-health effects hold for both sexes; the rest appear only for girls, suggesting they stem from the interaction of gender preferences and family budget constraints.
Yang (2025). Long-run effect of childhood exposure to the Gwangju Uprising in South Korea.	2015 Korea Population and Housing Census (10% sample). N = 309,663 respondents. Uses geographic distance from the uprising center for variation.	DiD: Compares educational outcomes of cohorts who were older/younger than college age during the May 1980 Gwangju Uprising for individuals who were/were not born in Gwangju.	Childhood exposure to the Gwangju Uprising reduced college completion by 6.1 p.p (~12%). Mechanism analysis points to erosion of social capital, rather than mental health/trauma, as the likelier driver.	Those exposed to the uprising in-utero see the largest decreases in college completion.

Table 3: Causes of Mental Illness — Education, Schooling, and Community Resources

Paper / Research question	Data	Methods	Results	Heterogeneity
Panel A. School structure, academic achievement, and transitions				
Avendano et al. (2020). Effects of longer compulsory schooling on mental health.	UK's Annual Population Survey, 2004-2016 (N = 230,882). Understanding Society, 2009-2018 (5,421), UK Biobank (N = 15,432). National Child Development Study (N = 5,913)	RD (fuzzy): Uses the 1972 Raising of the School Leaving Age Order, which required cohorts born on/after Sept 1, 1957 to stay in school until 16. The birthdate cutoff instruments for an extra year of schooling.	Odds in school until 16 ↑ 19.2 p.p. IV: any MH condition ↑ 3.9 p.p. (30%); depression/anxiety ↑ 3.3 p.p., null for other conditions. Understanding Society, Biobank: insignificant. NCDS: those who wished they could leave at 15 → worse middle age MH.	N/A
Björkegren et al. (2024). Effects of pandemic-era remote instruction on student mental health.	Swedish administrative data matching individuals across population-level education and health-care registers. All upper- and lower-secondary students, 2015/16-2019/20. N = 3,276,398 student-periods.	DiD: In Sweden, upper-secondary schools (ages 17-19) went remote during the pandemic while lower-secondary (14-16) stayed open. Compares MH-service use across the two, before and after shutdown.	April-June 2020, 4.4% ↓ in MH-care contacts for remote students, driven by depression/anxiety. No effects on ADHD, SU, self-destructive behaviors, or ED. Driven by unplanned visits, not changes in health-system access. Persists even after control group gains remote exposure.	Effects twice as large for males as females (mostly higher female baselines). Strongest for academic (vs. vocational) programs, most likely to go remote, and for students with higher GPAs, no prior 2019-20 MH care, and parents in remote-friendly jobs.
Bütikofer et al. (2023). Effects of higher-achievement schools on mental health.	Norwegian educational, tax, health, and family registers. N = 19,932 students completing 10th grade in Oslo and Bergen, 2006-2010.	RDD: Identifies GPA cutoffs determining admission to oversubscribed high-achievement high schools, comparing outcomes on each side of the cutoffs.	Acceptance ↑ high-school graduation college enrollment only at best schools. Above-cutoff students at the best schools → 1.7 p.p. (~8.5%) ↓ in MH conditions 6 years post MS graduation. Not driven by reduced health-system engagement.	Reductions driven by depression/anxiety. Strongest at schools that most improve students' educational outcomes.
Chen et al. (2026b). Effects of teacher quality on student MH.	China Education Panel 2013. N = 3,529 7th graders at 43 school that randomly assign classes.	Natural experiment: leverage the fact that some schools in the sample randomly assign students to classrooms. School FE compare students in different classes at same school.	1+ year of head teacher experience → student mental health improves 0.6%. Improvements in teacher-student and teacher-parent relationships; more experience teachers have higher job satisfaction.	The benefits of teacher experience begin to diminish at older ages. Effects do not differ by gender. Stronger for low-SES, rural students.Experience of subject teachers has no effect.
Chen et al. (forthcoming). Effects of school milestones on mental health in Taiwan.	Taiwanese administrative health-insurance claims, 2000-2020. N = 1,448 cohort-months.	DiD/RDD: September-born children start school a year later than August-born peers; compares MH outcomes for August/September-born children before/after August-born children's school milestones.	Primary entry: ADHD Rx ↑ >400%, antidepressants ↑ 28.7%; anti-anxiety/psychotics ↓; antipsychotic volume ↑. MS entry: ADHD, antidepressant, anti-anxiety, antipsychotic ↑ 22.5%, 39.7%, 8.5%, and 11.1%. After HS entrance exams: ↓ 29.7%, 28.1%, 10.1%, 8.7%; after college entrance exams: ↓ 42.8%, 39.9%, 13.4%, 8.7%.	Persists after controls treated: milestones hardest for young-for-grade kids. ADHD and antipsychotics stronger for boys; bigger post-college-exam drops in anti-anxiety, antidepressants for girls. Lower-income: more ADHD Rx at school entry; higher-income: more at middle-school start, cut after exams. Effects increase with parents' educational expectations.

Paper / Research question	Data	Methods	Results	Heterogeneity
Linder et al. (2023). Effects of grading bias on young adult mental health.	Swedish administrative data on family background, educational attainment/performance, and health outcomes for all secondary-school graduates, 2001-2004. N = 131,864 students.	FE: School fixed effects isolate within-school, across-cohort variation in grading bias (residual GPA not predicted by SweSAT scores); cohort FE difference out common time trends.	A 1 SD ↑ in grading bias (grades over expected) → mental ill-health ↓ 1.9-2.3 p.p. (11-14%) among women; null for men. MH prescriptions ↓ (driven by antidepressants); internalizing diagnoses ↓, null for substance abuse. Effects appear 3-6 years post-grad. One SD grading bias → +0.157 (women) and +0.176 (men) years of education.	Stronger among women with lower-SES fathers. Potential worsens MH among men from higher-SES families. Most protective for Swedish-background women; grading bias is linked to more substance abuse for foreign-background men. Internalizing protection is driven by women with above-median GPAs.
Qin et al. (2025). Effects of teachers' education on student mental health.	China Education Panel Survey 2013-2015, includes teacher/class assignment. N = 2,314 students, 73 classes, and 43 schools with random class assignment.	FE: School-grade FE isolate within-school, within-grade variation in teacher education, driven only by random assignment.	A 7th-grade teacher with one more year of education → 0.15 SD MH-index ↑ in 8th grade, consistent across subindices. Survey data suggest more-educated teachers improve teacher-student, teacher-parent, parent-student, and student-student interactions around MH.	Concentrated among males, those with less-educated mothers, and rural students.
Stenberg and Tudor (2024). Effects of field of study admissions on long-term mental health.	Swedish administrative data matched to all applicants to high schools, 1977-1991, with preferred programs and GPAs. N = 247,074 applicants.	RDD: Admission to oversubscribed high-school programs is set by GPA cutoffs. Compares long-term MH for same-first-choice applicants just above/below the threshold.	At 40-45, individuals admitted to (completing) their first-choice program at 16 are 4% (8.4%) less likely to be prescribed antidepressants. Odds of severe-MH hospitalization ↓ 40%. Earnings gains explain ~40% of the main effects.	Strongest when second choice was academic (vs vocational). Engineering, business drive effects; natural/social science null, humanities ↑ antidepressant use. Overall, driven by women; ↑ engineering, ↓ social-science, humanities effects offset for men.
Panel B: Peer effects, bullying and victimization				
Chandler et al. (2022). Patterns in youth suicides around school holidays in Germany.	German administrative data on all deaths, 2001-2015. N = 87,648 deaths.	FE: State, year, calendar-month, and day-of-week FE control for cross-state, time, and seasonal/weekday differences. Isolates cross-state variation in school-holiday timing, which often changes year to year.	During school holidays, a state's probability of a youth suicide ↓ 0.65 p.p. (17%). In the first two school days after a holiday, it ↑ 1.21 p.p. (32%). No holiday effects for ages 25-29 or over 65.	Strongest for summer, fall, and Pentecost (May) holidays near the school-year boundaries; none for Christmas or Easter. Driven by male students.
Chen et al. (2026c). Effects of peer personality traits on students' mental health.	China Education Panel Survey 2013-2014, includes classroom assignments. N = 5,958 students, 194 classes, 63 schools that randomly assign classrooms.	FE: School-grade FE isolate variation in peer personality traits, driven only by randomization.	A 1 SD ↑ in peer "openness" → MH index ↑ 0.03 SD, robust to controlling for own and peers' cognitive ability. Peers' persistence has no significant effect.	Effects driven by male peers' openness (female peers' openness is null), but female MH more affected. Stronger for students with low initial openness. No heterogeneity by parental education or signs of admissions corruption.
Churchill et al. (2025). Effects of anti-bullying laws on weight-based disparities in suicidality.	CDC Youth Risk Behavior Surveys: cross-sectional 1991-2017. N = 1,167,921 responses.	DiD: Compares pre/post MH outcomes in states that adopt anti-bullying laws to those in non-adopting states. Alternative specifications interact the adoption indicator with BMI.	Anti-bullying laws → 6.1% ↓ in attempted suicides for overweight/obese teens. No effect for healthy-weight teens. Healthy-vs.-overweight suicidality gap ↓ 38%. Also ↓ in reported suicide plans and attempts requiring medical attention.	Concentrated among overweight/obese girls, with null effects for overweight/obese boys. Stronger in states with stronger anti-bullying laws.

Paper / Research question	Data	Methods	Results	Heterogeneity
Cuddy et al. (2026a). Effects of teen suicide on surviving peers.	Linked South Carolina health, crime, and education data. N = 135,247 students covered by Medicaid.	DiD: Compare pre-post outcomes for students at schools where a peer committed suicide to those for students at matched control schools.	Peer suicide → self harm diagnoses ↑ 47%, MH visit ↑ 5%. No increased contact with primary care or other providers. Referrals for violent crimes, drug-related arrests ↑.	More significant increase in visits for SU compared to ADHD. Self-harm strongest for Black males, other outcomes largest for white males. Effects for both those with/without prior MH history. Generally stronger for peers in same sex/grade as deceased.
Fruehwirth et al. (2019). Effects of peer religiosity on adult mental health.	National Longitudinal Study of Adolescent to Adult Health (Add Health, HRS), a sample of 7th-12th graders in 1994-1995.	IV: Instruments an adolescent's religiosity with within-school variation in the religiosity of their school-grade-race-gender-denomination group.	A 1 SD ↑ in religiosity → 0.31 SD ↓ in a depression index and 11% lower probability of depression. Robust to controls for peer/friend depression, indicating direct effects of individual religiosity rather than peer social effects.	The effect of peer religiosity is higher for students with a higher propensity for depression. There is no heterogeneity by individual religiosity.
Getik and Meier (2022). Effects of school-peer gender on mental health.	Swedish classroom assignments, 2004-2012, linked to all outpatient/inpatient MH diagnoses for 2004 and 2012. N = 576,285 students.	Natural experiment: Quasi-random assignment of students (and gender ratios) to classrooms within Swedish schools. School-by-cohort FE isolate within-grade, within-school variation in classroom gender composition.	Adding one female classmate to an average-sized class → MH-diagnosis prevalence ↑ 1.1% in the last three years of primary school, persisting to age 22 (the maximum examined). Also ↑ self-harm among boys.	Entirely driven by males, via hyperactivity, substance-related, and learning/socialization disorders. Pooled across genders, depression/mood disorders also rise. Little variation by parental SES.
Giulietti et al. (2022). Effects of peer mental health on long-term depression.	National Longitudinal Survey of Adolescent Health (Add Health), following 7th-12th graders in 1994 through 2008-2009.	FE: School fixed effects isolate within-school, across-cohort variation in the share of school-grade peers who were depressed in adolescence; cohort FE control for general trends.	A 1 SD (11.7 p.p.) ↑ in the share of depressed female peers → women's depression odds (ages 27-32) ↑ 2.6 p.p. (11.5%), ↓ college attendance, and income ↓ 6.2%. Null effects for men.	Among women, effects are stronger for those with worse baseline MH.
Golberstein et al. (2016). Spillovers in mental health care use: evidence from college room assignments.	Online survey of first-year college students on MH status and housing assignments at two large U.S. universities, 2009-2010. N = 2,203 respondents.	Natural experiment: First-year rooms are randomly assigned, conditional on observable assignment factors (room preferences, gender). Dorm FE isolate within-building variation in roommate/neighbor propensities.	The share of roommates with MH-service in the last 6 months has no effect on own subsequent use. But a 1 SD ↑ in the share of hallmates with recent MH-service use → own MH utilization odds ↑ 72.8% at follow-up.	Concentrated among those already reporting utilization at baseline.
Hansen et al. (2024). Patterns in youth suicides around Covid-19 school closures.	U.S. CDC Vital Statistics mortality data; SafeGraph anonymized smartphone foot-traffic data identify school returns; county-level Covid death data from the New York Times. N = 37,704 county-months.	FE: Census-division and month FE isolate within-division, cross-county variation, control for time trends. Restaurant/bar foot traffic isolates school returns from broader reopenings; mid-semester reopenings separate school-return and seasonal effects.	Relative to January 2020, teen suicide was 25-38% lower in March-May 2020. In 2019, school openings (5th-to-95th-percentile foot traffic) → 17.5% ↑ in teen suicides; in 2020, 24-26%. No relationship between K-12 foot traffic and 19-25 y/o suicides in either year. Google Trends suggests rising bullying around reopenings as a mechanism.	Fully-reopening counties (>=80% of Jan-Feb 2020 foot traffic) see the largest increases. Little variation by gender or between Black and white students; insignificant for Hispanic youth. Stronger for younger students (12-15 vs. 16-18) and for non-firearm suicides.

Paper / Research question	Data	Methods	Results	Heterogeneity
Hansen et al. (forthcoming). Spillovers in mental health among new mothers.	Danish register data merged with municipal nurse records (2012-2017) on nurse visits, MH screenings, and peer-group assignment. N = 22,735 first-time mothers.	Natural experiment: Conditional on observables, new mothers are randomly assigned to post-natal support peer groups. Birth-date and nurse-district controls isolate variation in peer mothers' depression symptoms.	A depressed peer → maternal MH-care visits ↑ 1.7 p.p. (11%), across GPs (11%), psychologists (10%), and hospitals (30%). No spillovers onto husbands. Self-reports: maternal deterioration, father well-being ↓. Exposure ↓ economic self-sufficiency, ↑ sick leave and unemployment benefits.	Little variation by baseline MH (a proxy for prior MH-system exposure) or by first-time vs. higher-parity status. Significant only among mothers over 25.
Jeong (2025). Effects of peer's genetic predisposition to depression on own mental health.	Add Health: follows U.S. students in grades 7-12 in 1994 through ages 33-44. N = 4,017 individuals.	FE: School fixed effects isolate within-school, across-cohort variation in peers' genetic predisposition to depression; cohort FE difference out shared trends.	A 1 SD ↑ in same-gender peers' genetic risk → depression probability ↑ 1.9 p.p. (7.2%) for girls and 3.8 p.p. (25%) for boys, exceeding own genetic-risk effects. At 28-33, women with 1 SD more at-risk female peers are 2.8 p.p. (13.6%) more likely to be depressed; no effect for men.	Both girls and boys with more-exposed peers socialize less; the friendship effect persists longer for women. More-exposed women show short- and long-run rises in alcohol/marijuana use and lower labor-force participation. More-exposed men are less likely to attend college; no effect for women.
Kiessling and Norris (2023). Effects of peer ability rank on long-term mental health.	Add Health: follows 7th-12th graders from 1994 through 2008-2009.	FE: Ability and school fixed effects compare MH across students of the same cognitive ability, same school, different cohorts (hence different rank). Cohort FE remove birth-year trends; school-grade FE control for "typical peer effects."	A 1 SD (28-percentile) ↑ in ability rank → 0.06 SD baseline MH ↑ plus higher academic expectations. Higher rank is linked to better long-term economic, educational, and family outcomes.	Driven by negative rank shocks and those at the bottom of the ability distribution, whose effects persist for 12 years. Strongest effects on positive attitude and motivation. Little heterogeneity by SES or school/cohort characteristics.
Li et al. (2025). Effects of peer's kindergarten attendance on mental health.	China Education Panel Survey, 2013-2015. N = 4,421 students.	FE: Chinese middle-school students are randomly assigned to classrooms; school FE isolate differences across same-school students assigned to 7th-grade classes with different shares of kindergarten-attending peers.	The kindergarten-attendance share of classmates has no effect on grades or MH in 7th grade. By end of 8th grade, a 1 p.p. higher share → MH/non-cognitive index ↑ 0.0074 SD and test scores ↑ 0.0072 SD.	Little variation by gender, though own-gender peers' kindergarten share matters more. Stronger for students with lower baseline test scores, less-than-college-educated mothers, and rural residence.
Nikolaou (2017). Effects of cyberbullying on youth suicide.	CDC Youth Risk Behavioral Survey: cross-sectional, 1991-2015. N = 322,570 responses.	IV: Instruments cyberbullying exposure with state-level passage of anti-cyberbullying laws.	Cyberbullying ↑ suicidal thoughts by 14.5 p.p. (121%), suicide plans by 11.7 p.p. (117%), suicide attempts by 8.7 p.p. (145%), injuries in attempts by 4.8 p.p. (244%). Separate analysis: ↑ in deaths	Much stronger for women across all margins, though male effects remain significant.

Paper / Research question	Data	Methods	Results	Heterogeneity
Rees et al. (2022). Effects of anti-bullying laws on suicidal behaviors among teenagers.	CDC Youth Risk Behavioral Survey: cross-sectional, 2009-2017; suicide deaths National Vital Statistics System, 1993-2016. N = 839,594 respondents; 1,224 state-years of mortality data.	DiD: Compares pre/post outcomes in states that do/do not adopt anti-bullying laws. All states adopt by the sample's end; later adopters serve as controls.	Adoption → 1.6 p.p. (5%) ↓ in depression and 1.3 p.p. (11%) ↓ in suicidal ideation among female teens, no effect for male teens or suicide plans/attempts by either gender. 16% ↓ in suicide deaths among girls. Decrease in bullying, concentrated among female and LGBTQ students.	Effects stronger for non-white female and LGBTQ teens.
Panel C: Digital technology, social media and school phone polices				
Abrahamsson (JHR 2026). Effects of smartphone bans on student outcomes and mental health.	Norwegian administrative registers (population, education, tax, health); Norwegian Pupil Survey on bullying (2007-2019); a 2019 principal survey on smartphone policies across all middle schools. N = 161,371 students; 477 schools.	DiD: Uses staggered timing of voluntary smartphone bans across Norwegian middle schools, comparing pre/post outcomes in adopting schools to those in non-adopting schools.	Girls exposed throughout middle school: psychological consultations ↓ ~2-3 visits (~60%), GP consultations ↓ 0.22 visits (29%). Girls' GPA ↑ 0.08 SD, teacher-awarded grades ↑ 0.09 SD, externally graded math ↑ 0.22 SD; academic high school enrollment ↑ 4-7 p.p. (8-14%) for girls. Bullying ↓ 0.42 SD for girls and 0.39 SD for boys. No detectable effects on boys' MH, GPA, or track choice.	MH and academic effects concentrate among low-SES girls; girls with academically educated fathers show no gain and some increased specialist use. Grade/test effects are larger at strict-ban schools (confiscation) than lenient ones (silent mode). Bullying effects for girls are also larger in low-SES schools.
Allcott et al. (2020). The well-being effects of deactivating Facebook during an election.	Experiment paying individuals to deactivate Facebook for the four weeks before the 2018 election. N = 2,648 respondents.	RCT: Participants randomized into 4 weeks of Facebook abstinence; WTP for a fourth month of access elicited via a BDM mechanism.	Well-being index ↑ 0.09 SD: +0.12 SD life satisfaction, -0.09 SD depression, +0.08 SD happiness. More use of internet, non-Facebook social media. ↑ in solitary activities (especially TV) and social ones. ↓ news engagement and knowledge, ↓ political polarization. No effect on political engagement. More likely to be deactivated 3 months post-endline.	Larger polarization decreases for older people, white people, and men. Well-being effects smaller for those with more social interaction, higher baseline well-being. Those with more positive baseline views of Facebook cut use less afterward, less likely to view deactivation as good. No differences for heavy vs. light users.
Allcott et al. (2022). Modeling the appeal of social media.	Survey data on phone use and subjective well-being collected by the researchers over 4.5 months in 2020. N = 1,938 participants.	Model: Captures habit formation (today's use raises tomorrow's demand) and self-control problems (people consume more than they'd chosen ex-ante). RCT: A "pay-to-reduce" treatment and a "limit" treatment (screen-time tools) identify the model parameters.	Payments ↓ screen time, even after they stop. Participants predict reduction, don't respond before payment: awareness of habit formation without acting on it. Limits work, but participants underestimate self-control issues. Both ↓ phone-addiction; payment ↑ well-being. Prediction: eliminating self-control problems → screen time ↓ 48 min (31%).	Both treatments are more effective for those with greater baseline desire to cut screen time and higher baseline addiction.

Paper / Research question	Data	Methods	Results	Heterogeneity
Allcott et al. (2026). The effects of school phone bans: national evidence from lockable pouches in the U.S.	Yondr administrative records for the 4,607 schools that purchased lockable phone pouches through 2026; Advan Research GPS phone-activity (40,542 schools, 2019-2026); school-level outcomes; Panorama Education student surveys; original surveys of teachers, parents, and students, April 2025-Feb 2026.	Staggered DiD: Compares outcome changes at lockable-phone-pouch-adopting schools to observationally similar never-treated schools.	Adoption → pings ↓ ~30% by year three; teacher-reported use ↓ from 61% to 13% of students. Year one: disciplinary incidents ↑ ~0.03 SD (suspensions ↑ ~16%); student well-being ↓ ~0.2 SD; both dissipated. Year two: well-being ~0.16 SD above baseline. Test-score effects near zero. No effects on attendance, self-reported attention, or perceived online bullying.	Test-score effects vary by level: positive high-school math, small negative middle-school. Younger students may have weaker self-regulation and substitute toward other disruptive behavior. Phone-use reductions are smaller in middle schools, worsening the cost-benefit of enforcement.
Arenas-Arroyo et al. (2025). Effects of high-speed internet on the gender gap in adolescent mental health in Spain.	Administrative data on Spain's fiber-optic rollout; province-year hospital-discharge diagnoses from the Spanish Ministry of Health, 2007-2019; ETUDES cross-sectional survey data on internet use among 14-18-year-olds. N = 650 province-years.	IV: Instruments fiber-optic penetration in a province with the lagged number of lines installed (not necessarily used).	1 SD ↑ in fiber penetration → 4.2% ↑ in MH diagnoses for girls (null for boys) and 13.5% ↑ girls' self-harm and suicide attempts. Up to 8.5% ↑ in girls' suicide deaths. ETUDES: Girls' addictive social media use rises, offline activity falls. No effect on online bullying. Deterioration in girls' parental relationships.	Concentrated among girls 15-19, insignificant for girls 20-24, and null for boys of all ages.
Braghieri et al. (2022). The mental health effects of social media: evidence from the Facebook rollout.	Timing of Facebook's rollout across 775 colleges (2004-2006), via the Wayback Machine, combined with National College Health Assessment: cross-sectional, 2000-2008. N = 374,805 responses.	DiD: Compares before-after MH changes at Facebook-adopting colleges to changes over the same periods at not-yet-adopting colleges.	College-level Facebook access → 0.085 SD ↑ in a poor-MH index, increase in MH problems interfering with schoolwork. Grows in the two semesters after introduction and rises with semesters of exposure. Treated students perceive more peer alcohol use without reporting more own use → distorted social comparison.	Effects rise with predicted MH susceptibility, largest in the top quintile. Stronger for female and non-Hispanic white students; weaker for international and younger students. Stronger for those more prone to unfavorable comparisons (off-campus residents, students in credit-card debt).
Büyükeren et al. (2026). Effects of Tinder on college-student mental health.	National College Health Assessment: cross-sectional, 2008-2019; Tinder mentions in college newspapers (Lexis Nexis, 2013-2016); daily Tinder usage (Complementics, 2017-2018). N = ~1.1 million responses.	DiD: Tinder was initially marketed to students in Greek life; compares Greek/non-Greek students before/after Tinder's summer-2013 launch.	Tinder's rollout → MH-index ↑ 0.033 SD among Greek-involved students. Increases in sexual activity (persisting 4 years) and inequality in number of partners, with no effect on long-term relationship formation or quality. Greek-involved students also saw more sexual assault and STD testing.	More MH gainsfor female students. Number of partners doesn't mitigate → not driven by more sex. No variation by race, sexual orientation, or weight. Stronger for students younger at introduction and at large research universities. Weaker in the South, at smaller, more religious colleges.
Carpenter and Churchill (2023). Effects of beauty pageant coverage on teen/adolescent mental health.	Behavioral Risk Factor Surveillance System (1991-2010) and Youth Risk Behavior Surveys (1991-2009): cross sectional. Pregnancy weight-gain data from NCHS Natality (1990-2002).	DiD: Compares MH/weight-gain changes for young women after their state's resident wins a national pageant to changes in non-winning states.	Pageant-aged women are 4.9% more likely to want to lose weight (null for older women, men), likelier to misperceive BMI, and likelier to engage in weight management. Pregnant women 1% likelier to gain insufficient weight, with a short-run ↑ in bad-MH days.	Especially strong for non-white women when the winner is herself non-white.

Paper / Research question	Data	Methods	Results	Heterogeneity
Colombo et al. (2025). Effects of high speed internet on mental health in Uruguay.	Timing of Uruguay's fiber-optic rollout via the Internet Archive; National Adolescence and Youth Survey, cross-sectional 2013 and 2018. N = 4,536 respondents aged 15-24.	FE: Neighborhood fixed effects isolate within-neighborhood changes in fiber access; year FE difference out common trends.	Moving from 0% to 100% predicted fiber connection → 9 p.p. (169.8%) ↓ in always/very-often loneliness but a 10 p.p. (232.6%) ↑ in always/very-often worry; no significant effect on fear or sadness. Probability of a medical appointment ↑ by 11 p.p. (12.8%). No effect on seeing a psychiatrist.	Rising worry across all subgroups; falling loneliness concentrated among boys. Those outside the capital are more negatively affected. Negative effects are generally stronger for girls, with no age differences. No evidence access crowds out in-person socializing; access is linked to more alcohol and marijuana use.
Donati et al. (2025). Effects of broadband internet on youth mental health in Italy.	All Italian hospital discharges, 2001-2013; municipality-level broadband availability, 2005-2011; granular 3G coverage, 2007-2013, aggregated to N = 87,307 municipality-years.	IV: Broadband access was greater nearer pre-existing telecom nodes. Instruments using distance to a major telecom node, interacted with a post-rollout indicator, assuming distance-outcome correlations were otherwise stable over the period.	Moving from 0% to 100% broadband → 111% ↑ in MH disorders for the 1985-1995 birth cohort. No effect on older adults. Mobile internet has a smaller but still large effect. Rises in self-harm, compulsory hospitalization, and unplanned procedures suggest result not driven by increased MH awareness.	Little variation by gender, though possibly stronger for males. Rising with age at exposure, especially large for those exposed before 16. Anorexia hospitalizations rise, but only among women.
Fruehwirth et al. (2024). The mental health effects of social media during the Covid-19 pandemic.	Three-wave survey of North Carolina university students on MH and social-media use, October 2019-October 2021. N = 441 respondents.	IV: Uses pre-pandemic social-media use as an instrument for during-pandemic use, first-differencing to remove time-invariant unobservables.	Four months into the pandemic, social-media use has null effect on anxiety or depression. Eighteen months in, after in-person return, an extra hour → +0.1 SD depression symptoms and +0.09 SD anxiety symptoms. Explains ~16% and ~30% of the rise in moderate-severe anxiety and depression, respectively.	Little heterogeneity overall, though some evidence use at four months improved MH for LGBTQ students. At 18 months, negative effects are weaker for non-white, LGBTQ, and first-generation students, concentrate among the most socially isolated at baseline.
Gawai and Deller (2025). Effects of broadband access on mental health in the U.S.	County Health Rankings (based on BRFSS), health behaviors from the CDC, SES/demographics from the American Community Survey, clinical-care access from IMPLAN, and broadband access from the FCC.	Spatial model: Health outcomes as a function of health behaviors, SES, clinical-care access, and broadband access, using spatial error, spatial lag, and spatial Durbin models to handle spatial correlation across counties.	Across models and broadband measures, access → fewer bad-MH days (0.02%-0.37%). In the Durbin model, MH effects are mostly indirect, i.e. spillovers from broadband gains in nearby counties. A similar but weaker effect appears for physical health.	N/A
Golin (2022). Effects of broadband internet on the gender mental health gap in Germany.	German Socio-Economic Panel 2008-2012. N = 8,526 West German respondents aged 17-59.	IV: Early connections to Germany's network were near "main distribution frames" (quasi-randomly distributed). Residing within 4.2 km instruments for early broadband exposure.	Negative effects appear only among young (17-30) women, who see a 1.45 SD deterioration in a MH index.	Effects on young women driven by less socialization and more emotional problems, tied to negative self-assessments of workplace achievement.

Paper / Research question	Data	Methods	Results	Heterogeneity
Johnson and Persico (2024). Effects of broadband internet on suicides and mental health in the U.S.	County-year mortality from the NCHS; self-reported MH from the CDC's BRFSS; zip-code high-speed-internet access from the FCC, 2000-2019; controls from the American Community Survey and Census. N = 28,197 county-years.	FE: County fixed effects isolate within-county variation in broadband access; year FE difference out common trends.	A 10 p.p. ↑ in a county's high-speed-internet access → 0.105 (1%) fewer suicides, concentrated 2000-2008 (null 2009-2018). Lower depression and alcohol use in the BRFSS. Poverty ↓ 0.089 p.p. (1.67%) and unemployment ↓ 0.013 p.p. (0.24%). At the zip-code level, increases in business establishments, employees, and payroll.	Repeating Braghieri et al.'s (2022) analysis: no Facebook effect on suicides. Broadband effects concentrate among those with more than a HS education, adults 25-64, strongest for whites and Hispanics, men. Strongest in non-metro counties and those with above-median unemployment, density, income, education, and Black population share.
Lichand et al. (2026). The educational impacts of school phone bans: evidence from Brazil.	Data from Rio de Janeiro school district, 2022-2024. N = 196,757 middle-schoolers (grades 6-9); 325 schools; 1,116,689 student-quarters. 2025 principal survey on pre-ban policies.	DiD: Exploits Rio's Aug. 2023 classroom phone ban (school-wide in Feb. 2024), compares test-score changes at schools with already-strict pre-ban restrictions (control) and those without (treatment).	The ban → composite math/Portuguese index ↑ 0.06 SD. Effects are positive for both subjects, larger and more precise in math. Phone use fell in control schools after the citywide ban, so reduced-form estimates likely understate the total effect.	N/A
Mosquera et al. (2020). Effects of Facebook abstinence on short-term mental health.	Experiment paying college students to log out of Facebook for a week in 2017. N = 1,765 subjects.	RCT: Participants randomized into a monitored week of Facebook abstinence; WTP for a week of Facebook elicited via a BDM mechanism, with those in the restriction paid that amount on completion.	Facebook abstinence → depression index ↓ 17% (null for life satisfaction, happiness, worry), healthy-activity index ↑ 0.86 SD. No reduced awareness of headlines, reduced ability to rate accuracy of politically-bias headlines. WTP for Facebook ↑ 16% → addictive properties.	Depression effects concentrated among men (none for women); the rise in Facebook's value was driven by women.
Zhang et al. (2024). Effects of broadband access on mental health in China.	China Family Panel Studies, 2010-2018. N = 103,276 respondent-years.	DiD: Compares pre-post MH across cities that had/hadn't yet implemented Broadband China (2014-2016). Propensity-score-matched controls; IV based on difficulty of building broadband in hillier terrain.	Across all three analyses, Broadband China exposure consistently → MH index ↑, with effects of 0.032 SD (DiD), 0.025 SD (PSM), and 0.048 SD (IV).	Mediation suggests the result is driven partly by higher income and household consumption. Stronger for those with a HS education or less and those over 45.

Table 4: Income, Employment, and Mental Health				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A: Income effects: lotteries and policy-induced transfers				
Akee et al.(2024). Effects of cash transfers during childhood on long-term mental health and other outcomes.	Great Smoky Mountains Study of Youth: follows children who were 9-13 y/o in western North Carolina in 1993. N = 11,230 respondent-years.	DiD: In survey year four, members of a Native American tribe began receiving casino profit-sharing transfers. Compares native/non-native children across cohorts with more/less exposure.	Transfers → no effect on dep./anx. symptoms at 16 or 21. At 30, the most-exposed cohort has 97.8% fewer depression and 87.5% fewer anxiety symptoms, alongside some ↓ in MH-care use (so not simply an income-on-access effect) and ↑ in long-term economic well-being.	At 16, transfers are protective among those with the best baseline MH; at 30, protection does not vary with baseline MH.
Apouey and Clark (2015). Mental health and other effects of lottery winnings.	British Household Panel Survey, 1996-2008. N = 115,668 respondent-years.	FE: Individual FE identify within-respondent fluctuations around lottery wins. Some regressions compare winners of smaller vs. larger pots.	Lottery wins → null effect on overall health index, though a large win over the last 3 waves → significant improvement in a mental-distress index. Small short-term ↑ in diabetes, and large ↑ in smoking and social drinking.	N/A
Cesarini et al. (2016). Effects of lottery wins on the long-run outcomes of winners and their children, including MH.	Detailed data on Swedish lottery players and winnings, linked to pop.-level health, education, and labor-market registers.	FE: Compare winners of the same number of prizes who received different amounts. Matching: For other lotteries, match on wins and account balances; for another, match winners to non-winners with same ticket count; compare TV-lottery contestants who won different amounts.	Winners → small (0.03 SD for a ~$100k win) ↓ MH-drugs, driven by anti-anxiety, sleeping. Ten-year mortality: precise null. Very small ↓ hospitalizations, ↑ physical health. Children of winning mothers: null on MH drug use, health at birth, some ↑ in early-adulthood BMI, ↓ in 5-year-post-win hospitalization risk; little effect on educational attainment, cognitive skills.	Mortality effects mostly null across subsamples and causes of death. Little heterogeneity in child-development outcomes.
Christian et al. (2019). Effects of cash transfers on suicide rates in Indonesia.	Village-level Indonesian census, including population, health/educational institutions, and suicide, 2000-2014. N = 3,138 villages.	DiD: Staggered rollout of a cash-transfer program, comparing wave-1 and wave-2 (2007-2013), villages to never-treated. RCT: Treatment/control in small set of subdistricts randomized into the program.	RCT: villages randomized into transfers → 19% lower suicide rates; low power and insignificant, but confirmed by DiD, which shows ~25% ↓ for earliest-treated villages.	Transfers especially effective at ↓ suicide under negative rainfall (income) shocks. No heterogeneity by village share of farmers, fraction poor, social institutions, or health institutions.
de Bruijn et al. (2026). Effects of welfare debt relief on MH.	Linked Dutch registers, including Rotterdam's welfare rolls, 2018-2021. N = 15,416 individuals with welfare debt.	RDD/DDIV: Exploits date cutoff for retroactive debt relief, comparing outcomes for individuals with debts originating before/after cutoff before/after relief.	Debt relief decreased MH medication use by 13.9% over two years. Short-run increase in employment, but overall little impact on labor market outcomes and welfare receipt.	Larger employment/MH effect for those with larger debts. Larger MH effects for debtors who hadn't made payments, and for those with less time on welfare roles, in better health condition.

Paper / Research question	Data	Methods	Results	Heterogeneity
Eyal and Burns (2019). Effects of cash transfers on the intergenerational transfer of mental illness in South Africa.	South Africa's National Income Dynamics Survey, 2008-2017. N = 1,885 African or Coloured adolescents aged 15-19.	IV: Instruments child receipt of a government transfer with age-based eligibility (expanded in exogenous steps). FE: Individual FE across waves estimate within-individual effects of gaining/losing coverage.	Transfers ($6-$20/month) → depression odds ↓ 46-58 p.p. (256-322%) for children of depressed mothers. FE: receipt ↓ intergenerational transmission of depression by 45% (mothers) and 70% (fathers).	Effects almost entirely concentrated among children of depressed mothers. Some evidence transfers are more protective for daughters.
Haushofer and Shapiro (2016). Effects of unconditional cash transfers on mental health (and many other outcomes) in Kenya.	RCT among low-income households in Kenya. N = 503 households.	RCT: Randomized receipt of a $404 PPP transfer, with further randomization of payment method (lump sum vs. installments), recipient (woman vs. man), and amount (some given extra).	In the receipt year, treated households → ↑ consumption, food security, asset accumulation, and income. No effects on health, education, or female empowerment. Psychological well-being ↑ 0.26 SD, though no effect on cortisol.	Psychological-well-being ↑ driven by transfers to women (plus ↑ empowerment). Well-being ↑ with transfer size. Cortisol ↓ when women receive and for larger transfers.
Keskar and Mookerjee (2026). Effects of women's empowerment on mental health.	Longitudinal Aging Study in India, 2017-2018: adults 45+. N = 51,020 individuals married 1970-2005.	DiD: Staggered rollout of inheritance-rights reforms for Hindu, Buddhist, Sikh, and Jain women Compares women married before vs. after the reforms across reform/non-reform states; non-eligible-religion women extra control.	Exposure → depressive-symptom odds ↓ 18.3%, depression index ↑ 5.4%, MH index ↑ 0.08 SD, life satisfaction ↑ 0.25 SD. Null for non-eligible-religion women. Mostly null for men, life satisfaction ↑ 0.2 SD. Treated women 9% likelier to live in landowning households, see a 0.1 SD ↑ in an autonomy index.	Robust to defining exposure by state of birth or residence. MH effects stronger among women from non-rich families, while (unsurprisingly) landownership effects are stronger for richer women.
Khumalo et al. (2026). MH effects of ageing out of gov't transfers	South Africa's National Income Dynamics Study (NIDS), longitudinal, 5 waves 2008-2017. N = 27,122 person-waves.	RDD: Exploits age cap for government transfer receipt, comparing outcomes for individuals just on either side of the cutoff (age 16-18).	Ageing out of transfers increases an index of depression symptoms by 0.42 SD.	Effects are concentrated among women, urban residents, the poorest households, and those without other sources of income.
Lindqvist et al. (2020). Long-run effects of lottery wins on mental health.	Follow-up to Cesarini et al. (QJE 2016). Survey of Swedish lottery players drawn from admin. data. N = 3,251 respondents.	Matching: Winners matched to non-winners with the same winning odds (same ticket count, same drawing).	5-22 years later, per $100,000 won → overall, financial satisfaction ↑ 0.037 SD and 0.067 SD. Null on happiness or MH. Happiness, overall satisfaction, MH effects grow with years since win, financial satisfaction fades; all four significant, positive >14 years post-win.	Little heterogeneity by gender, age at receipt, or income. Significant ↑ in MH among those surveyed longer after their win. Overall-life-satisfaction seems driven by lump-sum (not monthly) winners.
Pignatti and Parolin (2024). Effects of the 2021 child tax credit on parent's mental health.	Behavioral Risk Factor Surveillance System (BRFSS), 2021: cross-sectional MH and family structure. N = 438,693.	DiD: Uses the large 2021 child-tax-credit jump for children 5 and under, with interviews both before and after rollout. Compares families with vs. without children <=5, before vs. after.	Access to a more generous benefit → bad-MH days ↓ 0.09 SD. Effects appear after announcement but before rollout and dissipate when benefits stop. No strong evidence for the authors' proposed channels: labor-market status, health insurance, or care use.	Driven by individuals with high baseline bad-MH days; stronger for women, age <40, less-educated, and lowest-income families. Little difference by white/non-white or rural/non-rural. Stronger for single parents.

Paper / Research question	Data	Methods	Results	Heterogeneity
Silver and Zhang (2026). Effects of mental health disability transfers on health and well-being.	U.S. Veterans Health Administration admin. microdata on disability claims and exam outcomes. N = 867,016 veterans examined for mental disabilities, 2004-2019.	IV: Instruments disability-transfer receipt using quasi-random assignment of veterans to MH examiners. Facility-year FE keep comparisons within veterans facing the same examiner set.	An extra $1,000 → null on major depression and substance use, physical health, mortality. Food insecurity ↓ 2.2% (1yr); homelessness ↓ 1% (1yr) and 1.3% (5yr); VA debt ↓ 6.4% over 5 years. Health-care use ↑ 2.5% over 1 year, driven by outpatient; more adherence to preventive care; some evidence ↑ trust in VA.	Care-use effects larger for veterans living further from VA facilities. Effects weaker for veterans with baseline incomes over $30,000.
Panel B: Employment transitions and housing				
Baranov et al. (2022). Effects of Covid-19 economic shocks on mental health.	Survey before and after Covid-19 onset in peri-urban Punjab, Pakistan, Nov 2019-July 2020. N = 833 parents and 833 children across 29 villages.	DiD: Compares pre- vs. mid-pandemic MH across families with different pandemic shocks (job/income loss), with individual FE isolating within-individual change after a job loss.	Covid job loss → parental MH ↓ 0.88 SD and mental-distress ↑ 10%. Captured in child ratings of parents' stress/anger. ↑ reported domestic violence ↓ personal safety, family contentedness. No changes to child life satisfaction; aspirations/agency ↓ 0.43 SD, parent-reported child depression ↑ 0.39 SD.	N/A
Belloni et al. (2016). Effects of retiring during a recession on mental health.	Survey of Health, Ageing, and Retirement in Europe (SHARE), 2004-2013: Europeans 50+. Retirement-age laws from MISSOC.N = 21,960.	FE: Individual FE isolate within-respondent MH change after retirement. IV: Instruments retirement with legal eligibility. Retirement interacted with a recession-exposure variable.	FE: retirement → depression index ↓ 13%. IV insignificant overall, but in regions hit hard by the crisis → depression index ↓ 27% among men in a strongly-affected region-year. No effects for women.	The male effect in more-depressed regions is driven by blue-collar workers.
Bergschneider et al. (2026). Effect of retirement on cognitive ability in Germany.	German National Cohort (NAKO) 2014, N = 4,788 women 63-67 y/o. Administrative health insurance claims from one of Germany's largest insurers N = 1,122,061 women 63-67 y/os.	IV: Instrument for retirement pension receipt using increase in the retirement age for women beginning with the 1952 birth cohort.	1 year of retirement → Stroop cognitive health measure ↓ 0.13 SD. Null effect on cognitive disorder diagnosis or semantic fluency. Depression, hypertension, diabetes, sleep problems ↓.	N/A
Cassidy et al. (2025). Effects of housing instability on child mental health.	NYU Health Evaluation and Analytics Lab claims for a 10% sample of Medicaid children (4-17) in New York State, merged to housing-court records by address. N = 15,022 children in housing-court cases, 2016-2019; 128,000 child-half-years.	DiD: Exploit the staggered zip-code rollout of universal access to housing court counsel, comparing children with/without access before vs. after filings. IV: Instruments a possessionary judgment (step toward eviction) with counsel exposure.	Event study: at 2 years, universal-counsel → MH-claim and dep./anx./adjustment-disorder claims ↓ 2.5 p.p. (7.2%) and 1.8 p.p. (11.2%).IV: possessionary judgments → MH claim ↑ 53%, therapy ↑ 53%, and medication claims ↑ 83%. All driven by children without prior MH claim. Little ↑ in physical health use, so not about more health-system contact.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Cygan-Rehm et al. (2017). Bounding the effects of unemployment on mental health.	Surveys from four countries: Australia (HILDA, 2001-2012), U.K. (BHPS, 1991-2013), U.S. (PSID, 2001-2013), and Germany (SOEP, 2002-2012). N = 219,987 responses.	Bounding: Follows Manski-Pepper (2000) to bound the ATE of unemployment on MH under weak assumptions: unemployed are negatively MH-selected, treatment effects are strictly negative, and an IV (mother's education) is weakly, positively, monotonically related to MH.	Unemployment ↓ MH by at most 0.40 SD, 0.48 SD, and 0.46 SD in Australia, the U.K., and the U.S., at most 0.188 SD in Germany. Null effects ruled out in all four. Even short (3-month) spells have effects bounded below zero everywhere. Longer spells bite more in Germany, shorter spells in the U.K.; effects are negative regardless of duration.	Little gender heterogeneity in the effects of unemployment.
Farré et al. (2018). Effects of Great Recession job loss on mental health.	Spanish National Health Surveys, 2006 and 2011: cross-sectional. N = 24,856 responses.	IV: Instruments individual job loss with the construction-employment share in one's age-gender-province cell multiplied by annual construction employment growth, the sector hardest (and plausibly exogenously) hit by the Great Recession.	A 10 p.p. ↑ in construction-driven unemployment → good/very-good health ↓ 15% and mental-disorder prevalence ↑ 33%, with a 15% ↑ in a mental-distress index (especially mental strain). Physical-health effects small/inconsistent; some ↑ in suicides.	MH effects driven by ↑ in moderate, rather than severe, mental distress.
Fontes et al. (2024). Effects of parental job loss on child mental health.	Longitudinal survey following children initially 6-12 y/o in São Paulo and Porto Alegre, Brazil, 2010-2019. N = 2,510 children.	DiD: Compares outcome evolution across waves for children who experienced a parental job loss vs. propensity-score-balanced controls.	Wave after a parental job loss → probability of an MH diagnosis ↑ 6 p.p. (24%) and MH index ↓ 0.19 SD. Null by the next wave (~4 years later). Mechanisms: ↑ abuse/neglect (0.16 SD) and ↓ income (0.16 SD).	No family structure (including income) heterogeneity. Concentrated among families with a MH history. No variation by child/parent genetic risk.
Heller-Sahlgren (2017). Effects of retirement on mental health	SHARE, 2004-2012: longitudinal, follows adults 50+ in 10 European countries. N = 25,698 respondent-years.	IV/FE: Instruments retirement with having passed state pension age; individual FE isolate deviations from individual means.	Retirement → no immediate effect. By the next two waves (~5 years) → depression index ↑ 0.81-1.3 SD and severe-depression likelihood ↑ 0.72-1.16 SD.	Long-term effects do not vary with gender or educational/occupational background.
Jones et al. (2024). Effects of Great Recession job losses on child mental health.	British Columbia school admin. records 2002/03-2015/16, matched to parental tax records (Statistics Canada). N = 1,859,630 child-years.	DiD: Compares pre- vs. post-recession outcomes for children whose families did/didn't experience earnings losses; treated children propensity-score-matched to controls.	By 2010 (2 years later), new MH designations among children of earnings-loss families → ↑ 0.2 p.p. (8%); by 2013 → ↑ 0.5 p.p. (20%).	Larger for severe designations. Concentrated among the non-indigenous, English-speaking population. Some evidence effects are stronger for those younger during the recession.
Li and Liu (2026). Effects of housing wealth shocks on mental health.	China Family Panel Studies, 2010-2018. N = 23,312 individuals.	RDD: China's 2006 National Six Policy gave owners of properties <90 m^2 preferential down-payment ratios and deed taxes. Restricting to pre-2006 purchases, compares households around cutoff.	There is a sharp jump in property-value growth for houses just below the threshold. The discontinuity-induced housing-wealth shock → depression ↓ 3%, life satisfaction ↑ 8%, and confidence in the future ↑ 6%.	Depression effects stronger for those under 60; life-satisfaction effects concentrated among those over 60. Stronger among less-educated and lower-income households.

Paper / Research question	Data	Methods	Results	Heterogeneity
Mazzonna and Peracchi (2017). Effects of retirement on mental health.	SHARE, 2004-2006: longitudinal, follows adults 50+ in 10 European countries. N = 8,163 respondents.	IV: Instruments retirement status and length with a country's early- and normal-retirement eligibility ages; respondent FE isolate within-individual change after instrument-induced retirement.	Retiring has null effect, but additional retirement year → good health probability (including depression) ↓ 1%, cognitive ability ↓ 0.06 SD. Physical job retirement → good-health ↑ 11%, cognitive ability ↑ 0.5 SD, years still worsen, though net positive for 10 years.	The positive retirement effects among physically-demanding jobs appear only for men, though the effects of additional retirement years are consistent across men and women.
Picchio and van Ours (2020). Effects of retirement on mental health.	Dutch Longitudinal Internet Studies for the Social Sciences (LISS) panel, 2007-2018. N = 2,124.	RDD: Compares MH on either side of Dutch state-pension eligibility age(s).	Married man retires → own good-MH probability ↑ 21.5 p.p. (23%) wife's ↑ 13.8 p.p. (16%). Married woman retires → no effects on self or partner. Null for single men and women. Larger work-hour ↓ among retired men than women (higher pre-retirement hours).	Husband's eligibility predicts wife's retirement, but not vice-versa. Effects for retired men, spouses consistent across components (happiness, depression, anxiety, feeling down). Some evidence single women ↓ happiness but ↓ anxiety.
Salm et al. (Forthcoming). The role of grandchild childcare in mediating the effects of retirement on mental health.	SHARE, 2004-2019: longitudinal, follows adults 50+ in 10 European countries. N = 11,386 individuals.	IV: Causal-mediation model separates effect of retirement from mediating effect of childcare: retirement ages instrument for retirement and share of female children instruments for childcare intensity.	The overall retirement effect on MH is insignificant. The direct effect (childcare fixed) → MH-problems index ↑ 0.26 SD, but retirement-induced ↑ childcare → 0.3 SD ↓ in MH problems, overwhelming the direct effect.	Childcare is more protective in countries with more developed public childcare, so retirement is on net more conducive to good MH there.
Schaller and Zerpa (2019). Effects of parental job loss on child health.	Medical Expenditure Panel Survey, 1999-2012. N = 22,239 U.S. households with father employed at baseline; 19,336 with mother employed.	FE: Child FE isolate within-child outcome changes among families experiencing a job loss between surveys.	Father's job loss → fair/poor mental and physical health ↑ 85% and 52%, mental-distress ↑ 0.083 SD. Mother's job loss → no mental or physical health effect. Both maternal and paternal job loss ↓ private and ↑ public insurance coverage. No effect on care use, except ↑ MH visits after a paternal job loss.	Paternal-job-loss effects stronger in low-SES families. Positive effects of maternal job loss on MH among low-SES families. No significant differences by child age or gender.
Schiele and Schmitz (2016). Effects of job loss on (mental) health across the distribution of underlying health.	German Socio-Economic Panel (SOEP), 2000-2014: cross-sectional. N = 33,885 responses.	QTE: Quantile treatment effects, identified assuming individuals' health rankings are unchanged between all-job-loss and all-employed states. Treatment is job loss from plant closure; other job-loss sources excluded.	The overall ATT is null. For the bottom decile of baseline MH → MH index ↓ ~0.17 SD; second and third deciles similar but insignificant; no effects in the upper deciles. Negative physical-health effects for the bottom two-thirds; job loss ↑ BMI at the top of the distribution, with no effects lower down.	N/A
Watson and Osberg (2018). Effects of job insecurity on mental health in Canada.	Canada's National Population Health Survey, 1994-2011. N = 22,500 respondent-years.	FE: Respondent FE isolate within-individual fluctuations in real (predicted) and self-assessed job insecurity, removing bias from time-invariant determinants.	Among employed individuals, perceived job insecurity → psychological distress ↑ 0.12 SD (men) and 0.11 SD (women). A 1% ↑ in predicted job insecurity → distress ↑ 0.0075 SD (men) and 0.0048 SD (women).	Results are similar but smaller for the full working-age sample.

Paper / Research question	Data	Methods	Results	Heterogeneity
Panel C: Job security, macro-uncertainty and aggregate economic conditions				
Abrahams and Unel (2026). Effects of debt on suicide during the Great Recession.	CDC Vital Stats 2003-2015. Indebtedness data from Ahn et al. (2018). N = 3,098 counties.	DiD: Compare suicide rates in high/low 2006 indebtedness counties before/after the 2008 Recession.	IQR ↑ in 2006 debt-income ratio → 2006-2009 male suicide rate ↑ 4%, 40-64 y/o suicide rate ↑ 7%. Effects peak in 2009, dissipate by 2012.	Effects only appear for men and 40-64 y/os. Indistinguishable from zero for other groups, population as a whole.
Adda and Fawaz (2020). Effects of import competition on mental health.	BRFSS, 1997-2011; National Inpatient Sample hospital discharges for 20% of U.S. hospitals, 1993-2011; NHIS mortality, 1998-2009; industry-level U.S. imports from China. N = 10,830 commuting-zone-years.	IV: Instruments a commuting zone's Chinese import-shock exposure with other countries' change in Chinese-import exposure, isolating exogenous Chinese supply fluctuations.	One SD ↑ import competition → physical-health index ↓ 0.01 SD same-year, growing over 6 years, only in high routine-task-intensity areas (also see care-use ↓ emerging in years 2-6). Null effect on the MH components but hospital discharges show a 1 SD shock → MH hospitalizations ↑ 1.2%, persisting up to 5 years, with ↑ in suicides and overall mortality.	MH-hospitalization effects much stronger in higher routine-task-intensity areas.
Ahammer et al. (2025). Effects of company downsizing on the mental health of remaining workers.	Austrian Social Security Database employment records for all workers, linked to health-care claims for 75% of Upper Austria residents. Mass-layoff events from Statistik Austria, 1999-2014. N = 169,478 worker-layoffs across 1,131 events and 1,021 firms.	DiD: Compares changes in outcomes for workers staying on at a downsizing firm to contemporaneous changes among later-exposed workers.	Six quarters later, → no ↑ in physician visits, drug prescriptions ↑ 2.5%, inpatient days ↑ 13%, building over time. Psychotherapy ↑ 20%; six quarters later, antidepressants ↑ 0.7%. No change in MH diagnoses. No effects on heart attacks/strokes; cardiovascular-drug use ↑; late-emerging musculoskeletal diagnoses and drug-spending effects. Not driven by wage ↓.	Mostly driven by older, blue-collar, and especially low-wage workers. Younger, high-wage, white-collar workers barely affected.
Bach et al. (2026). Effects of mergers on employee mental health.	Swedish admin. data (medical records and socio-economic outcomes) matched to firm-level merger data from Serrano, 2007-2015. N = 562,741 individuals at firms that experience a merger.	FE: Worker FE isolate within-individual MH change after a merger.	FE: a merger → depression diagnoses ↑ 8% (null on anxiety), with ↑ outpatient care and hospitalization. Affected workers → antidepressant and other-MH-drug use ↑ 2% each. Death probability ↑ 30%, with suicide-death probability ↑ 40%. Event studies: effects strongest in the years immediately after mergers.	Effects for workers who lose jobs and those who stay, but significantly worse for those with post-merger wage ↓. No variation with firm size, job tenure, country of origin, or age. Horizontal mergers worse than vertical. Worse for workers with, lower cognitive ability or less education, and for women. No variation by country of origin or age.
Bingley et al. (2026). Mental and physical health gradients among Danish retirees.	Survey of Health, Aging and Retirement in Europe (SHARE), cross-sectional Danish subsample 2004-2022. N = 40,353 observations.	Descriptive: Compare health measures across income deciles.	Chronic disease gradient is small; larger for functional health, comprehensive health index, and MH. No consistent gradient for cognitive function. Functional and comprehensive health gradients narrow over 2004–2022 as lowest-income deciles catch up; MH gradient doesn't narrow.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Colantone et al. (2019). Effects of exposure to import competition on mental health on mental health.	British Household Panel Survey, 1991-2009. N = 29,405 respondent-years.	IV: Shift-share instrument for an industry's import-competition exposure (shifts = other countries' export changes in those goods; shares = baseline U.K. import distribution). Individual FE isolate within-individual MH change.	A 1 SD ↑ in import shock → mental-distress index ↑ 0.08 SD. Women suffer when husbands are shocked, but not vice-versa; likewise a father's shock → ↓ investments in children and in their self-esteem/life satisfaction, with no effect from shocks to mothers.	Effects consistent across the MH-index components. Generally stronger for individuals with worse baseline MH, and for younger workers, blue-collar workers, males, large-household members, and those in greater baseline financial distress.
Currie and Tekin (2015). Effects of Great Recession foreclosures on mental health hospitalizations.	ZIP-code-level foreclosures (RealtyTrac), ER visits, and hospitalizations (state admin. databases) in Arizona, California, Florida, and New Jersey, 2005-2009. N = 64,030 zip-quarters.	FE: ZIP-code FE and ZIP-specific linear time trends relate deviations of hospitalization outcomes from long-term trends to within-zip changes in foreclosure rates.	10 additional foreclosures per 100,000 → MH-related hospital visits ↑ 0.15%, with ↑ visits for cancer, heart conditions, and respiratory infections. Similar with house prices in the model, so effects not merely driven by price ↓.	Especially strong for older Americans (more vulnerable, though less likely to be foreclosed on). Stronger for people on public insurance (may reflect switching from private. Consistent across race,but higher in top-income-quartile zips, where foreclosure losses may be largest.
Currie et al. (2015). Effects of the Great Recession on maternal mental health.	Fragile Families and Child Wellbeing Study: longitudinal maternal MH before and during the Great Recession. N = 3,500.	FE: Compare before-vs.-during MH across states with different unemployment rates during 2008 recession; mother FE control for time-invariant mother characteristics.	Recession-induced ↑ in unemployment → no significant effect on maternal depression probability. Unemployment does → ↓ maternal physical health and ↑ health-compromising behaviors.	Negative effects concentrated among less-advantaged mothers; more-advantaged even improved on some dimensions: as unemployment ↑, white women were 11.1% less likely to be depressed while Hispanic women saw an 18.2% ↑ in depression.
Cutler and Sportiche (2022). Effects of the great recession on elderly mental health.	Health and Retirement Study, 2000-2016: panel of U.S. adults 51+. Housing prices from the FHFA. N = 9,425 respondents in the 51-61	FE: The recession shock is assigned by pre-recession location (to address endogenous migration), and individual FE isolate within-individual (and within-area) responses to recession shocks.	Changes in housing prices → no significant effect on depression, MH- or sleeping-med prescriptions, or physical health, for homeowners or non-homeowners.	Little socio-economic heterogeneity. Some finer subgroups (e.g. Black individuals with <$75,000 in assets or less than college) see large, significant ↑ in depression when prices fall; also ↑ medication use for poorer whites.
Erten et al. (2026). Effects of trade liberalization on adolescent mental health.	China Family Panel Studies, 2016, 2018. China Health and Nutrition Survey, 2000-2015. N = 4,749 11-20 year-olds.	Cohort; Compares pre/post outcomes in prefectures with higher/lower employment-weighted tariff gains from China's WTO accession in 2001.	IQR ↑ in exposure to liberalization → MH index improves by 0.19 SD. Driven by decrease in severe depression. Income and manufacturing employment ↑ for parents. Parental investments ↑.	N/A
Golberstein et al. (2019). Effects of economic downturns on the mental health of children.	National Health Interview Survey, 2001-2013: cross-sectional. N = 80,669 responses.	FE: State FE isolate within-state fluctuations in economic conditions (unemployment rates or housing prices).	A 1 SD ↓ in the state unemployment rate → child (4-17) MH index ↑ 2.3%; a 1 SD ↓ in housing-price index → MH ↑ 2.0%. 1 SD improvement in unemployment and housing prices → psychological problems ↓ 11%, 6.4%.	No consistent heterogeneity across gender and age groups. Not fully explained by parental job loss, since MH effects appear across the predicted-employment spectrum.
Joshi (2016). Effects of local house prices on mental health.	BRFSS, 2005-2011. County-level housing values from Zillow. N = 1,210,931 responses.	FE: County FE plus county-level unemployment rate as a control isolate within-county housing-price variation independent of labor-market changes.	A 1% ↓ in local housing prices → poor-MH days ↑ 0.18% among unlikely homeowners and 0.14% among likely homeowners; the difference is significant.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Kang et al. (2023). Effects of housing price inequality on mental health in South Korea.	National Health Insurance Service, 2006-2015: complete medical histories for a sample of South Koreans. Housing prices from Korea's Ministry of Land, Infrastructure, and Transport. N = 4,703,501 individual-years.	FE: County and individual FE isolate within-individual outcome changes around fluctuations in county-level housing-price inequality about county means.	A unit (5x mean) ↑ in the housing-price Gini (holding prices constant) → odds of MH treatment ↑ 21% and medical costs ↑ 18.5%. No effect on number of treatments or medication use. Effects concentrate among county non-movers. Some ↑ in physical-health treatment too.	Treatment-use effects higher for men than women. Main effects driven by older (45-64) adults and those with higher baseline income.
Page et al. (2019). Effects of aggregate and gender-specific labor demand shocks on child health, including severe emotional difficulties.	Restricted-use NHIS data on U.S. children 0-17, 1997-2012, linked to state monthly unemployment rates. N = ~105,681 children (severe emotional difficulties); up to ~410,000 for general health.	IV (Bartik shift-share): Builds predicted employment growth from state base-period industry shares times national industry growth, isolating demand-driven labor-market changes. Separate male and female indices exploit gender differences in industry composition.	Employment growth → no association with child health. But: a 1 p.p. ↑ female labor demand → costly-conditions index ↑ 0.015 SD, excellent-health ↓ 0.74-0.81 p.p., sick days ↑ 0.13, and severe emotional difficulties ↑ 14.5% (weakly significant); for men → costly-conditions index ↓ 0.009 SD, asthma ↓ ~5%. No effects on parents' MH, so not driven by reporting.	Male-labor-demand effects on child health substantially attenuated in single-mother households, consistent with an income channel operating through resident fathers. Somewhat stronger for school-aged children (6-17). Subgroup analyses by maternal education and child age are imprecise with few clear patterns.
Singhal and Tarp (2025). Effects of commodity price volatility on the mental health of farmers.	Vietnam Access to Resources Household Survey, 2016-2020: longitudinal. N = 7,743 household-years.	FE: Household FE isolate within-household MH fluctuations around changes in coffee prices and their variability. Households outside the coffee-producing Central Highlands are controls, differencing out unrelated time trends.	A 1 SD ↑ in coffee-price volatility → depressive-symptom index ↑ 12.3%; mean coffee-price level has no significant additional effect. No effect on severe-depression incidence. Volatility also worsens MH and memory, with no effect on sleep.	Women's MH is less sensitive to coffee prices, as is that of ethnic minorities.

Table 5: Pollution and Climate

Paper / Research question	Data	Methods	Results	Heterogeneity
Adhvaryu et al. (2024). Effects of temperature during pregnancy on child mental health in Africa.	World Health Survey (cross-sectional, 2002-2004); University of Delaware temperature data (1900-2010). N = 61,885 aged 18-65 in 19 African countries.	FE: Location and year-of-birth FE isolate within-location temperature fluctuations and difference out seasonal/cohort effects.	A 1 degree C ↑ in birth-year temperature → adult depression-symptom index ↑ 0.3 SD. No effects on formal depression diagnosis or MH-service use.	Effects stronger for younger cohorts and mild-to-moderate depression, with no ↑ in severe/extreme depression. No effect on a psychosis-symptom index.
Ai and Tan (2023). Effects of high temperature during pregnancy on adolescent mental health.	China Family Panel Studies, 2010, adolescents 10-15. Weather from China Meteorological Data Sharing Service System.	FE: City of birth by quarter of birth FE control for city-specific season confounders, year-month of birth control for shared time trends.	Relative to 20-25°C, 1+ day > 30°C while in utero → mental health index in adolescence 1.75% worse. 1+ day 25-30°C → 1.32% worse.	Effects driven by first- and second-trimester exposures, months 3-7. 25-30°C days most damaging in winter; 30°C+ days most damaging in spring. No difference by gender or rural status. Stronger effects in northern China, for mothers in agriculture.
Ai and Tan (2025). Effects of household air quality during pregnancy on long-term outcomes.	China Family Panel Studies: 2010, children 0-15 born 1995-2010. N = 3045.	DiD: Compares same-county cohorts exposed/unexposed in utero to pipeline gas (cleaner home heating), exploiting staggered rollout across communities.	In-utero piped gas → null on depressive symptoms through age 15. Improves height-age Z-scores, stunting, but not weight. Improves birth outcomes, medical costs, respiratory morbidity, and verbal test scores.	Girls, poor children, and rural children see larger health improvements.
Ai et al. (2023). Effects of fetal PM2.5 exposure on adolescent mental health in China.	China Family Panel Studies (2010-2018), merged with NASA SEDAC city-by-year PM2.5 (1998-2016) and NMIC wind-speed data. N = 5,017-6,143 adolescents 10-15, 125 cities, 25 provinces.	IV: Instruments pre-birth-year PM2.5 using mean 2-minute wind speed at 10m. City, birth-year, survey-year FE.	A 1 μg/m3 ↑ in in-utero PM2.5 → severe mental illness ↑ 0.6%; exposure above 50 μg/m3 → ↑ 3%. Also ↑ school absenteeism, parent conflict. Biological channel (lower birth weight, preterm birth, shorter breastfeeding) drives. Back-of-envelope: 2002-2007 PM2.5 rise induced ~950k severe cases by 2018 (~23.9 billion yuan in losses).	No significant heterogeneity by gender, maternal education, or household income.
Andersen and Morthorst (2025). Effects of in-utero PM2.5 on child and adolescent mental health in Denmark.	Satellite PM2.5 (1x1 km, Van Donkelaar 2021) linked to Danish admin. registers. N = 812,504 singleton births with a sibling (1999-2017); 478,280 for MH.	FE: Sibling (mother FE) comparison addresses residential sorting and pregnancy-timing selection.	A 10 μg/m3 ↑ in third-trimester PM2.5 → ADHD diagnosis by age 8 ↑ 0.4 p.p. (40%). Modest 13-gram (0.4%) birth-weight ↓; no effects on LBW, APGAR, or preterm birth. Pregnancy hypertension ↑ 0.8 p.p. (54%), suggesting an inflammation mechanism.	Effects concentrated in the trimester; ADHD effects larger for girls. Driven by higher-SES families (maternal education), likely differential diagnostic access. Much larger for children whose parents have an ADHD diagnosis, suggesting genetic amplification.
Ao et al. (2021). Combined effects of indoor and ambient air quality on elderly mental health.	China Health and Retirement Longitudinal Study of 45+-year-olds, 2011-2015, particulate matter concentrations from NASA. N = 28,962 respondent-years.	FE: Individual fixed effects identify within-individual changes in indoor heating sources and ambient pollution.	1 μg/m3 ↑ in PM2.5 → index of mental health ↓ 0.3% and depressive symptoms ↑ 0.24 p.p. (0.7%). Solid fuels inside the home → MH index ↓ 4%, depression ↑ 2.29 p.p. (6.4%).	Stronger for less educated individuals and for women, perhaps because they are more likely to cook. The effects don't seem to vary much by age (within an over-45 age group).

Paper / Research question	Data	Methods	Results	Heterogeneity
Balakrishnan and Tsaneva (2023). Effects of air pollution on mental health in India.	WHO's World Health Survey (2003) Study of Global Ageing and Adult Health (2007). N = 21,203. Pollution data from Van Donkelaar (2016).	IV: Nighttime thermal inversions as instrument for pollution exposure. Nighttime pollution may be less subject to differential avoidance behaviors.	1 μg/m3 ↑ in PM2.5 over last year → feeling low, sad, depressed ↑ 2.47 p.p. (10.3%), cognitive difficulties ↑ 2.31 p.p. (13%). Ability to control or cope with "important things in life", physical health ↓.	Effects do not seem to vary with worker industry or urbanity/rurality.
Barnor (2025). The impact of air pollution on mental health.	Administrative hospital admissions from Texas, 2010-2017. Census-tract level PM2.5 from CDC. Wind speed and direction from National Center for Environmental Prediction. N = 8,127 county-quarters.	IV: Uses the average prevailing wind direction in a county as an instrument for PM2.5 exposure, isolating out-of-county pollution sources that may be less correlated with local economic activity or other factors.	1 μg/m3 ↑ in quarterly PM2.5 → mental health diagnoses in hospitals ↑ 17%. Effects are strongest for depression and stress diagnoses, and insignificant for anxiety.	The effects are concentrated among the 18-65 age group, with null effects for the elderly and effects only on stress diagnoses for minors. There is little heterogeneity by gender.
Bishop et al. (2023). Effects of air pollution on dementia.	20% sample of all Medicare beneficiaries 65+ in 2004, followed 1999-2013. N = 1,171,094 individuals. 485 U.S. PM2.5 monitors, 2001-2013.	IV: Instruments for PM2.5 exposure using EPA county threshold for emission reduction. Compares individuals with same baseline pollution who were/were not exposed to regulation.	1 μg/m3 ↑ in PM2.5 concentration over a decade → the probability of a dementia diagnosis ↑ 2.15 p.p. (11%).	The effects are stronger for individuals with lower baseline exposure to PM2.5, older individuals, women, those with more dementia risk factors, and Black people.
Burke et al. (2018). Effects of temperature on suicide in the U.S. and Mexico.	CDC Vital Stats. 1968-2004; U.S weather from PRISM. Instituto Nacional de Estadística y Geografía (Mexican suicide rates); weather from Berkeley Earth Surface Temperature Dataset, University of Delaware Terristrial Precipitation. N = 1.4M. Plus 600M+ Tweets.	FE: county(municipality)-by-month and state-by-year FE control isolate random fluctuations around county-month temperature means, control for regional changes over time.	1°C ↑ in monthly temperature → U.S. suicide rate ↑ 0.68%, Mexican suicide rate ↑ 2.1%. Probability a Tweet contains depressive language ↑ 0.36-0.79%. The effect has been stable, if not increasing, for decades.	The effects are similar across places with higher/lower baseline temperatures and do not differ with income or access to air conditioning. No heterogeneity by age, sex, suicide method, county population size, or state-level gun ownership in the U.S.
Carleton (2017). Effects of crop-damaging temperatures on suicide in India.	Suicides from India's National Crime Records Bureau, 1967-2013. Crop yields 1956-200 from Duflo and Pande (2005). Gridded weather from National Centers for Environmental Predictin. N = 1,434 state-years.	FE: State fixed effects control for time-invariant characteristics of states, year fixed effects control for time trends share across states. Compare effects across growing and non-growing season.	For days > 20°C, a 1 SD ↑ in heat exposure during growing season → annual suicide rates ↑ 3.5%. No effect for temperature in non-growing season. This mirrors crop yield effects: 1 SD ↑ in heat exposure → crop yield ↓ 1.3%; no effect for non-growing season.	No evidence of adaptation: The effects are stronger in southern states, which are hotter at baseline. They are also no stronger in poorer states and they do not decrease over time. Isolating longer-term changes rather than year-to-year fluctations produces larger estimates.
Chen et al. (2024). Effects of air pollution on mental health.	China Family Panel Studies 2014. Data on thermal inversions from NASA. N = 28,268.	IV: Uses thermal inversions, which trap pollutants at the ground level, as an instrument for PM2.5 exposure.	1 μg/m3 ↑ in PM2.5 concentration over the past month: mental health index ↓ 3.9% (0.03 SD), severe mental illness ↑ 9.6% (0.02 SD). Probability of exercise over the past week ↓ 3%; past-month physical health ↓ 0.7%.	The effect sizes of exposure over more shorter windows are smaller, up to a precise null for conditions on the day of survey -- generally populations more likely to work outside.

Paper / Research question	Data	Methods	Results	Heterogeneity
Currie and Saberian (2025). Effects of wildfires on mental health.	Canada's Hospital Mental Health Database, 2006-2018. Wildfire locations and evacuations from Natural Resources Canada. Air pollution from Environment Canada. N = 301,619 census division-days	Descriptive: Effect of No. upwind/downwind fires within different distance bands on hospital admissions for MH conditions. IV: LASSO predictors of exposure to pollutants from upwind fires. DiD: Changes in outcomes before vs. after an evacuation event.	Fire within 100km → anxiety/SUD hospitalizations ↑ 0.898 (2%) and 0.745 (1%). Smaller 200-300km; null beyond. Effects for upwind fires up to 500km. Interquartile range ↑ in PM2.5 from wildfires → anxiety, SUD hospitalizations ↑ 3% and 2.5%; adjustment disorders ↑ 46%. Evacuations → 4.3% and 6.5% ↑ in anxiety, SUD hospitalizations, persisting 10 weeks. Wildfire tweets 500-200km → anxiety hospitalizations ↑ 0.03%.	The effects are generally stronger for individuals with respiratory or cardiovascular conditions. The effects are also stronger for the elderly and for males.
Cutler and Peterson (2025). Effects of pollution and education on the decline in the prevalence of dementia.	Health Retirement Survey, 2000-2020. PM2.5 from Meng et al. (2019). Power plant-level emissions data from EPA. Historical data on higher education institutions from U.S. Census Bureau.	IV: Fix the output of each power plant in base year, allow emission per unit of power to vary, isolating exogenous policy shocks, rather than demand. Instruments for education using higher education availability in home state at 17.	1 SD ↑ in same-year PM2.5 exposure → dementia ↑ 1.5 p.p. (17%). Five-year exposure has no significant effect. Additional year of education → dementia ↓ 2.3 p.p. (26%). The two effects seem operate independently, with similar 2SLS results including both instruments.	The effects of pollution and education on dementia grow with age. They do not seem to differ with genetic predisposition for dementia.
Dinkelman (2017). Effects of drought exposure during infancy on later-life outcomes in rural South Africa.	10% sample of the 1996 South African Census merged with rainfall from 1,000 weather stations. N = 655,532 individuals who live(d) on "homelands" — rural reservations confining Black South Africans under Apartheid.	FE: District fixed effects estimate off within-district drought fluctuations; identification aided by severely limited Apartheid-era migration.	Mean drought exposure during years 0-4 raises the chance of disability by 0.186 p.p. (3.5%) and the number of disabilities by 0.0022 (3.8%). Odds of mental disability rise 7.4% for men and 2.8% for women. Effects on sight, physical, and hearing/speech disabilities are similar.	Effects on disability roughly twice as strong for men. Stronger among male residents of the oldest homelands (greater mobility restrictions). Effects persist for cohorts exposed after homeland reintegration, though the homeland-age heterogeneity disappears.
Fan et al. (2025). Effects of air pollution on mental health in the U.S.	Pharmaceutical claims, aggregated across insurers, from Truven MarketScan, 2005-2006. PM2.5 concentrations from the EPA, thermal inversions from NASA.	IV: Uses the occurrence of thermal inversions,as an instrument for PM2.5 exposure. N = 20,923 MSA-weeks.	1 SD ↑ in PM2.5 over the last week → to a 5.8% ↑ in local antidepressant usage in the current week.	The effects are concentrated among older adults (40-64) and in areas with high baseline levels of pollution.
Fritz (2026). Short-term effects of heat and humidity stress in India.	WHO Study on Global Ageing and Adult Health, India, cross sectional, 4 waves 2002-2020. Wet bulb and dry bulb temperature from NASA. N = 37,371.	FE: District FE isolate within-region variation in temperatures, year-month by climate zone FE difference out shared regional time trends.	One more day with wet bulb > 27°C in prior month → severe depression ↑ 4%. Null for anxiety. Two-plus consecutive > 27°C → severe depression ↑ 32%. Pattern doesn't appear for dry bulb temperature.	Strongest for exposure in previous two weeks. Effects strongest for workers, men, older people, rural residents, and those with less education. Evidence for both cognitive impairment and sleep channels.

Paper / Research question	Data	Methods	Results	Heterogeneity
Gong et al. (2025). Effects of prenatal heat on mental health in China.	China Labor Force Dynamics Survey 2016-2018. Weather from Chinese Academy of Sciences. N = 10,482.	FE: Birth city by birth year FE control for city-specific differences over time. Birth city by month FE account for city-specific seasonality. Birth year by birth month, province by birth year FE account for year-specific seasonality, regional trends.	Ten > 90°F days in utero → unhappiness ↑ 0.06 SD, life dissatisfaction ↑ 0.08SD, depression ↑ 0.08SD in adulthood. Physical health, hourly income, social trust, social support ↓.	The effects are stronger for exposures in the second and third trimesters and monotonic with temperature. Larger for older respondents, women, and rural residents. Larger for children whose parents are single, have less education, and belong to lower occupational classes.
Hou et al. (2023). Effects of temperature on mental health in China.	China Family Panel Studies panel 2010-2018. Temperature from the National Meteorological Information Center of China. N = 41,416.	FE: Individual FE isolate within-individual changes in temperature exposure. County, year-month FE control for time-invariant differences across counties, shared time trends.	1 SD ↑ in past-week temperature → mental health index 0.12 SD worse, severe mental health ↑ 0.08 SD. Worse-quality sleep is a potential mechanism. Air conditioning moderates the temperature-MH relationship.	No significant heterogeneity by gender, age, rural status, or education. Relationship fairly monotonic across temperature bins. Effects larger for older respondents, women, rural-born individuals, single-parent households, lowe
Janzen (2025). Effects of temperature on mental-health helpline calls.	Calls from TelefonSeelsorge, 2018-2020. Weather from Deutscher Wetterdienst; PM2.5 from German Federal Environmental Agency. N = 21,138 counseling-center-days.	FE: Call center and year-month FE isolate temperature deviations from local and seasonal means.	Relative to 10-15°C days, call volume ↑ 2.3% on days < 0°C and ↑ 3.7% on days > 25°C. The effects are insignificant between 0-25°C.	The hot-day effect is twice as strong for men than for women, no cold-day effect for men. The cold-day effect strongest for people 50+; heat effect driven by younger people.
Molitor et al. (2023). Effects of wildfire smoke on suicide.	Satellite-based wildfire smoke plumes from Brey et al. (2018), CDC suicide data, and ground-level pollution from Van Donkelaar (2016). N = 484,848 county-months across 3,108 counties.	FE: County and month-year FE isolate within-county deviations from smoke exposures means, while controlling for seasonality and long-term trends. 2SLS: Use predicted smoke-driven PM2.5 concentrations as instrument.	In rural counties, an additional wildfire smoke day → suicides ↑ 0.11 deaths per million (0.8%); no effect in urban counties. The 2SLS estimate: a 1 μg/m3 increase in wildfire-derived PM2.5 in a rural county increases the monthly suicide rate by 0.27 deaths per million (2%).	In rural counties the effects are stronger among men, those below 65, whites, and those with a HS education or less — groups most likely to have high exposure to outdoor air.
Mullins and Srivastava (2025). Effects of temperature on MH text service volume.	Call-level data from the Crisis Text Line, 2016-2019. Weather data from PRISM Climate Group. N = 621,065 county-days.	FE: County and year-by-month FE isolate temperature deviations from county and seasonal means.	Relative to 18-21°C days, 21-24°C days → with 1.3-1.7% ↑ in conversation volume. 30°C + → conversation volume ↑ 5.5-9.3%. 12-15°C days → calls ↓ 2%. Null for < 9°C days. Counselor-assessed severity of texters' conditions also ↑ on hotter days.	Null for bullying or gender/sexual identity. High min. (nighttime) temperatures matter more than high max. temperatures → sleep channel. Little age, gender heterogeneity, though effects of >30°C days stronger for women. Effects driven by individuals in areas with lower baseline temperatures.
Mullins and White (2019). Effects of temperature on mental health.	PRISM Climate Group daily weather 1960-2016, admin data on California hospitalizations 2005-2016, CDC Vital Statistics 1960-2016. N = 8,294 county-mo. (hosps). N = 2,096,460 county-mo. (suicides).	FE: County-by-month fixed effects isolate random fluctuations in temperate around the averages for each county in each month.	MH ↓ monotonically with temperature. Suicide and ED visit for mental health rates per 100,000 are 0.24% and 0.3% ↑ when temperature > 80°F and 0.43% and 0.39% ↓ when temperature < 30°F or 40°F, respectively. Smaller, though significant, effects on self-reported MH.	ED visit effects do not vary with access to care, income, or baseline climactic conditions. None of these factors, nor the presence of mental health insurance parity laws nor air conditioning penetration drive significant heterogeneity in suicide effects.

Paper / Research question	Data	Methods	Results	Heterogeneity
Pasha et al. (2023). Effects of early-life rainfall shocks on adult mental health in Indonesia.	Indonesian Family Life Survey rounds 4-5 (2007, 2014), with station-level daily rainfall and temperature. N = 4,653 non-migrants born 1986-2000.	FE: Community, district-by-birth-year, and survey-year FE, exploiting within-community rainfall variation, controlling for cohort effects. Shocks defined as Z-scores > 0.7 SD from a 10-year community moving average.	Null prenatal effect. Postnatal positive rainfall shocks at ages 0-1 → CES-D scores ↑ 13%, and year-2 shocks → depression ↑ 6 p.p. (>26% over mean). Prenatal stress and income shock pathways ruled out; infectious disease (dengue) partially supported.	All significant effects driven by females; none for males. Stronger in rural areas.
Persico and Marcotte (2026). Effects of air pollution on suicide in the U.S.	CDC Vital Statistics, 2003-2010, suicide hospital records for AZ, NY, WA, 2003-2016 from Healthcare Cost and Utilization Project; CDC/NOAA pollution and temperature. N = 8,262,736 county-days.	IV: Wind direction as an instrument for local PM2.5; isolate outside-county changes in pollution, which might be correlated with local economic activity.	1 μg/m3 ↑ in PM2.5 concentration→ 0.49% ↑ in daily suicides, a 0.5% ↑ in the daily suicide rate, a 0.4% ↑ in all-cause deaths Suicide-related hospitalizations ↑ 50.5%; days with depressive symptoms ↑ 2% in survey data.	Little heterogeneity by race; signs that effects are stronger in counties that are more rural and those that have higher poverty rates, baseline pollution, and weaker gun laws. The largest affects are for those over 55.
Thies (forthcoming). Effects of in-utero air pollution on socio-emotional skills in childhood in Germany.	German Socio-Economic Panel (SOEP): children 5-10 born 2000-2014, linked to satellite PM2.5 (van Donkelaar et al. 2021). N = 8,253.	IV: Uses nighttime thermal inversions as an instrument for PM2.5.	A 1 μg/m3 ↑ in prenatal PM2.5 → neuroticism ↑ 0.135 SD and internalizing behavior ↑ 0.185 SD. No effects on other Big Five traits, externalizing/prosocial behavior, or cognitive skills.	Strongest for already-vulnerable children. Driven by trimesters 2-3; no postnatal or pre-conception effect. Internalizing larger for boys. No heterogeneity by age, maternal education, income.
Wen et al. (2026). Effects of roadway noise and nighttime light (ALAN) on mental health.	National Transportation Noise Maps, 2016-2020. NASA/NOAA VIIRS annual nighttime lights. National Cancer Institute's HINTS 2014, 2017–2020 (9-digit zip). Traffic air pollution from NASA DARTE. N = 14,030 (noise), N = 8,010 (light).	Instrument for road noise (and traffic air pollution) using wind speed, max wind speed, wind direction × county FE, area and road ruggedness, and annual average temperature. Instrument for ALAN using nighttime cloud cover.	1 dB (2%) ↑ road noise → psychological distress (PHQ-4) ↑ 0.0022 SD, ~11% ↑ in mild symptoms. 3% ↑ ALAN → distress ↑ 0.0026 SD; ~13% ↑ in mild symptoms. Both estimates are conditional on each other and on CO2 and PM2.5 within 1 km. 1 dB ↑ county road noise → sleep ↓ 2.3 min (weekend sleep ↓ 5.1 min). ALAN has no significant effect on sleep.	The noise effect does not vary with the local density of clean-energy/EV fueling stations. There is no significant noise effect for hearing-impaired individuals (low power). Traffic CO2 is significant only when measured within 5 km. Results hold with a ground-based (NELM) skyglow measure. They do not hold with a point (centroid) noise measure.
Xie et al. (2023). Effects of a public air-pollution monitoring system on mental health.	China Family Panel Studies, 2010-2016, and pollution and thermal inversions from NASA. N = 93,091 responses from N = 32,219 respondents.	DiD: Staggered rollout of air pollution monitoring; compares pre/post outcomes in non-/treated cities. IV: Thermal inversions as an IV for pollution.	100% (2 SD) ↑ PM2.5 in prior month → MH index 0.28 SD worse. After monitoring, gradient ↑ 0.49 SD (175%). The effects are fairly consistent across measures of MH.	Information effect larger for those 50+. Stronger for urban and more educated residents; few gender differences. Stronger for those with a higher baseline susceptibility to mental illness.
Zhang et al. (2017). Effects of air pollution on well-being.	China Family Panel Studies, 2010-2014. Air quality from Ministry of Environmental Protection of China. Weather from NOAA. N = 53,418.	FE: Individual and county FE isolate within-individual changes in well-being caused by fluctuations in pollution around county-level means.	Air pollution index ↑ 1 SD → hedonic unhappiness ↑ 4.4%, index of depression ↑ 3.4%, depressive symptoms ↑ 5.0%. Null effects on a measure of overall life satisfaction.	Stronger for younger people. Stronger happiness effects for men; reverse for MH. Richer, more educated less affected. Stronger in areas with higher baseline pollution.

Table 6: Trauma, Family Shocks, and Mental Health				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A: Family shocks				
Adhvaryu et al. (2026). Effects of child cancer diagnosis on parental mental health.	Danish registers: universe of child cancer diagnoses, linked to parental income and government transfers. N = 3,203 households w/ diagnosis, matched to 1,153,342 controls.	DiD: Compares parental outcomes in families with a cancer diagnosis to observationally similar matched households, before vs. after diagnosis.	Mothers' and fathers' therapy use → ↑ ~100% in the first two years post-diagnosis, fading after 6 years. Sharp ↓ in market income (stronger for mothers) and labor-force participation (mostly mothers); large ↑ in government benefits, effectively protect total income.	MH effects (but not labor effects) are mostly driven by severe cases where the child dies within 5 years. Few differences by educational background. Fertility ↑, but only if child dies.
Altındağ et al. (2026). Effects of parental dementia and death on adult children's mental health.	Danish registers, 1980-2018, linking adult children to parents. N = 36,112 children of a parent who died with dementia (ADRD) in 2005-2011, matched to 36,112 placebo controls and a comparison group of 195,687 children whose parent died without ADRD.	Event study: Individual and calendar-year fixed effects around parental death (10 years before to 7 years after), with nearest-neighbor propensity-score-matched controls; non-ADRD parental deaths used as a general-bereavement benchmark.	Women's MH visits → ↑ 10% 4-5 years before death, 14.6% 2-3 years before, 28.3% in the three years around death; MH drug use → ↑ 3.8% and 7.4% in same windows. Men's effects smaller, concentrated near death: visits ↑ 16.7%, drugs ↑ 6.6% around death, persist 7 years. No effects on labor market, physical health. Effects converge to counterfactual trends 5-7 years after death.	Effects largest and most persistent for women who lost a parent at or before age 50. More persistent increases for college-educated individuals. Only children show suggestively higher medication use, but estimates are imprecise. No differences by parent's partnership status.
Anukriti et al. (JDE 2026). Effects of son-preference on women's mental health.	Survey of reproductive age women and co-residing mothers-in-law in Uttar Pradesh, 2023-2024. N = 1296 women.	Natural experiment: Compares mental health among DIL and MIL in families were DIL's firstborn child is/is not male.	MIL's risk of anxiety/depression is 15% lower when DIL's firstborn is male; no effect for DIL. MIL more likely to be involved in child care, younger DIL see increases in LFP.	The effects on MIL stronger when DIL is younger. MH improvements only for older DILs. Effects much stronger for MIL with only one DIL, but don't differ with son birth order. Effects decrease with age of first born.
Asuman et al. (2025). Effects of the birth of disabled child on parental mental health.	Swedish registers: care utilization and prescriptions. N = 8,079 parent-child pairs (15% children with cerebral palsy (CP), rest matched controls).	DiD: Compares pre- vs. post-birth outcomes for parents of children born with CP (undetectable) to control parents.	Mothers→ MH medication ↑ 3.3 p.p. (36%) 1 year post-birth (fades 2 years; no ↑ for fathers). Fathers → antipsychotics ↑ 1 p.p. (227%) 1 year after (fades; none for mothers), anti-anxiety ↑ 126-179% at 3-5 years; hypnotic/sedative ↑ in birth year, 5 years later. Mothers' antidepressants ↑ 47-67%, sustained over 5 years (null for fathers). No large ↑ in healthcare interaction or addictive behaviors.	Heterogeneity marginal overall: older, higher-educated mothers show larger antidepressant ↑, while younger, less-educated fathers drive the anti-anxiety ↑. Parents living alone (both sexes) more likely to show anti-anxiety upticks. Effects stronger for more severe CP.

Paper / Research question	Data	Methods	Results	Heterogeneity
Breivik and Costa-Ramón (forthcoming). Effects of children's health shocks on parental mental health and labor-market outcomes.	Population-level admin. health and labor-market data, Finland and Norway. N = 604,856 family-years.	DiD: Compares families whose child is hospitalized to same-parent-and-child-age families hospitalized at a later date.	At 1 year, MH visits → ↑ 55% in Finland (specialist/inpatient) and 6% in Norway (primary-care diagnoses); small ↑ for Finnish fathers, null in Norway. Maternal earnings → ↓ 2.4% (Finland), 1.9% (Norway) 1yr; 4.7% and 4.6% 3yr. Maternal unemployment: null 1-2 yr, then 2.2% and 1.6% ↓ yr 3. Null for fathers. Transfers partially offset earnings losses.	When the child health shock is fatal, maternal effects are ~4x as strong (still none for fathers). Effects don't vary with municipal social-insurance level; stronger for more serious shocks (cancer, follow-up-heavy). In Finland, stronger when grandparents live further away.
Chen et al. (2026a). Effect of childhood disability on parent MH.	Linked Taiwanese registers, 2000-2020. N = 2,391 + 604,254 first-born children with/without CP, and parents.	DiD: Compares evolution in outcomes pre/post birth for parents of children with cerebral palsy, probability-weighted controls.	The birth of a CP child increases new mothers' MH diagnoses 20%, psychiatric visits 17%. Employment falls, divorces increase. Effects persist up to 10 years.	The main effects are mostly concentrated among mothers. Effects are stronger for younger and less educated parents.
Currie et al. (2024a). Effects of sibling disability on mental health.	Danish registers, 1987-2019. N = 60,405 families with two children born 1988-1999 and a third, diagnosed child born within 9 years of the second.	DiD: Compares changes in the first- vs. second-born MH gap in families where the third child is/isn't diagnosed with a mental illness (the second-born is exposed to the stressor younger and longer).	Relative to first child, second children in families with a disabled third child → MH-service use ↑ 10-20%, consistent across counseling, psychiatric visits, and prescriptions. Null on overall (incl. physical) health-care use.	Strongest when mother has less than a high-school education. Siblings with severe disabilities → psychiatric visits/medications; less severe disabilities → counseling; severity maps to MH-condition severity.
Fadlon et al. (2026). Effects of spousal death on mental health and the mediating role of income insurance.	Danish registers: health-care use and economic outcomes for the universe of households. N = 17,022 households.	DiD: Compares household heads who suddenly lose a spouse (heart attack, stroke) to heads who will, but have not yet, lost a spouse to those conditions.	MH prescriptions → ↑ 124% in the first month; 17% higher four years later. Driven by initiation and continued use of new medications in first year, not later initiation. Households retaining more income are less affected, though effects vary little with baseline income, wealth.	Medication effects are driven by the timing of the spousal death, so they occur later for those whose spouses survive longer after the initial health shock.
Fjællegaard Jensen and Zhang (2026). Effects of parental death on labor market outcomes and mental health.	Danish registers 1980-2019. N = 206,286 treated individuals aged 25-50 at sudden first parental death, 1985-2014.	Matched-control DiD: Nearest-neighbor matching; event study around sudden first parental death (heart/accidents) to address anticipation and reverse causality.	Five years post: sons' earnings ↓ 2% and daughters' ↓ 3%. MH prescriptions ↑ ~12% (men) and ~11% (women); psychologist visits ↑ 78-147%. 36% of women and 21% of men with an earnings-decline onset initiate MH treatment. Mother's death → larger effects.	Women with young children → larger (~4% vs. ~2%) earnings loss via the informal-childcare channel. Effects larger when parents live nearby, die younger, and when adult children are younger at loss. Eldercare channel operative but small. No bequest channel.
Huang et al. (2027a). Effects of Chinese migration reform on elderly MH.	China Health and Retirement Longitudinal Studies, Chinese residents 45+ 2011-2018. N = 6,191 individual-years.	FE: Use historical patterns of sent-down youth and province-level migration policies as a measure of migration exposure. Individual fixed effects.	Migration exposure increases odds that children migrate, increases transfers to older adults, and improves physical health. 1 SD of exposure: depression index ↓ 1.6%.	MH effects are stronger for elderly respondents with less education.

Paper / Research question	Data	Methods	Results	Heterogeneity
Schmidpeter (2024). Effects of stress due to child death on parental mortality.	Austrian admin. Data. N = 78,178 families exposed to child death, plus controls.	DiD: Compares parents who lose a child to non-self-harm external causes (mostly car crashes) to propensity-score-matched controls. Mediation estimates MH care's role protection against mortality.	Bereavement → paternal mortality ↑, building to 6 p.p. 13 years post-death; no effect for mothers. Mediation: MH care plays a key protective role for mothers, ↓ mortality 5-10% over 10 years; much less protection for men.	The paternal-mortality ↑ is driven by alcohol/smoking-related and circulatory deaths. Effects smaller when men have a spouse. Stronger for mothers if the lost child was a girl, for fathers if a boy.
van den Berg et al. (2017). Effects of trauma on labor income, employment status, marital status, and health.	Swedish registers (death, earnings, health, family). N = 1,811 households whose child died in a non-intentional accident + 18,110 matched controls (total 19,921).	DiD: Compares pre-post changes for parents whose children died in an accident (most likely exogenous) to matched controls.	Child loss → income ↓ 12.5% (0.15 SD) for mothers, 8.8% (0.1 SD) for fathers 6 yr later. Mothers (fathers) → divorce ↑ 9.7% (5.8%) 6 yr later. Short-run ↑ in hospitalization for both. MH-hospitalization ↑ 125% (mothers) and 63% (fathers) in loss year; persists for mothers. Fertility ↑ 201% 1yr, persisting 3 yr. Unemployment ↑ 3.5% 5 yr later; no wage effect; small ↓ maternal hours. Unemployment insurance ↓, sick/parental-leave ↑.	Effects vary little with child's gender, though strong for fathers who lose a girl, especially a young one. Little variation with family size (possibly weaker for one-child families) or with the deceased child's birth order.
Panel B: Exposure to violence and disaster				
Andrabi et al. (2026). Effects of an earthquake on poverty-MH gradient.	126 randomly-sampled villages in 4 districts of Pakistan most affected by 2005 earthquake. N = 4,616 respondents.	Natural experiment: Earthquake in area with many faults, but little earthquake expectation; assume distance to epicenter is quasi-random.	Little direct effect on mental health. Within 20km of epicenter: 10th → 90th percentile consumption → MH ↑ 0.18 SD. No effect further away.	Gradient doesn't appear for most severe MH conditions. Gradient not explained by experiencing an earthquake death.
Bharadwaj et al. (2021). Mental health and other effects of surviving a mass shooting.	Norwegian admin. registers. N = 9,032 survivors + matched controls; 12,054 survivor family members + controls; 59,223 school peers + controls.	DiD: Compares survivor outcomes before vs. after the 2011 Norway mass shooting to coarsened-exact-matched control group.	Survivors' MS GPA ↓ 0.53 SD (null exam scores), completing 1st and 3rd HS years ↓ 23.4% and 31.3%, HS-diploma odds ↓ 14.3%, college enrollment/completion ↓ 10%. GP visits during HS ↓ 60.9%; psych. diagnoses ↑ 385% over 5 years. At 7 yrs, employment ↓ 5.2% (null earnings). Psych. diagnosis ↑ 67.0%, 52.7%, and 25.9% for survivor mothers, fathers, siblings over 5 yr. Null effects on parents' economic/marital outcomes, siblings' school performance, school peers.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Bhuller et al. (2024). Effects of domestic violence on victim and victim child mental health.	Norwegian registers merged to all police reports of domestic violence, 2001-2015. N = 17,163 domestic-violence events.	FE: Within-family comparison of outcomes before vs. after a report. DiD: Not-yet-victimized families as controls to difference out time trends.	Domestic-violence incident → victim MH visits ↑ 35%, 7% over 4 years. Children's visits ↑ 19%, 15% higher 4 years later. By two years: marriage rates ↓ 50%, probability of remaining in the same municipality ↓ 4%, household expenditure ↓ 9%, and spousal earnings ↓ 43%.	Initial effects strongest for "social problems" and anx./mood disorders; also longest-lasting (no long-term addiction/dep.). Children's initial, long-term effects on mood, sleep, anxiety; long-term dep. Victim effects stronger with better baseline MH, longer relationships (no differences for kids).
Cassar et al. (2026). Effects of childhood abduction on mental health in Uganda.	Survey conducted among women in a conflict-affected subcounty in Uganda, 2022. N = 541.	Natural experiment: Assume that women abducted by a rebel group 1986-2006 were randomly selected. Village FE, controls for age, survey wave.	Abduction→ depression ↑ 17.5 p.p. (29%). Stress index ↑ 4.5%. Education ↓. Little effect on economic outcomes, marital status. Fertility ↑. Social support ↓.	MH effects stronger for women abducted younger. Education effects stronger for women adopted older. Income ↓ for younger-abducted. Fertility driven by women abducted older.
Deb and Gangaram (2024). Effects of school shooting exposure on mental health and other outcomes.	School shootings (Center for Homeland Defense and Security) matched to BRFSS (cross-sectional), 2003-2012. N = 319,945, 23-32 y/o at survey.	FE: Compares individuals who were 11-17 when a school shooting occurred in their county as treated to those older than 17 at the time of the shooting and to all respondents from non-exposed counties.	For both sexes, exposure → no significant effect on self-reported MH, but → ↑ drinking and smoking (men only), ↓ educational attainment (mostly women), and worse labor-market prospects. No effect on out-migration.	Effects fade with time since exposure.
Dustmann and Fasani (2016). Effects of local area crime rates on residents' mental health.	British Household Panel Survey (BHPS), 2002-2008, linked to quarterly Home Office crime statistics. N ≈ 35,000 individual-years (~9,400 individuals, urban); validation with English Longitudinal Study of Ageing (ELSA), N ≈ 16,600 (PSH) and 13,700 (CASP-19).	FE/FD: Individual FE (first-difference) address sorting of distressed individuals into high-crime areas; movers treated as separate individuals; robustness to an IV instrumenting crime with first-wave area crime.	1 SD ↑ in local crime → GHQ mental-distress index ↑ 8-15% SD. Driven by property crime; violent crime matters only at a broader geographic level. Effect 1 SD crime ↑ is 2-4x larger than a 1 SD ↓ in local employment. Effects manifest as ↑ anxiety and depression, and appear temporary. No effects on long-term MH diagnoses, GP visits, or hospitalization.	Effects more than twice as large for women as men across total, property, and violent crime; the gap is robust to age, education, and children. No significant heterogeneity by age group (under 30, over 65) or education. Not significant in rural areas.
Frankenberg et al. (2026). MH effects of exposure to tsunami mortality.	Longitudinal study: 10 months before the 2004 Indian Ocean tsunami-15 years post. 14,380 respondents from exposed Indonesian provinces.	FE: Community fixed effects isolate within-community variation in exposure to close-family deaths from the tsunami.	Losing close kin → depression ↑ 0.1 SD. (0.15 SD) 2 (10) years post. Exposure to damage, no family deaths → more depressed in year 2 but not by year 10. All forms of exposure increase post-traumatic stress in both years.	The year-2 depression effects appear only for women; depression higher across genders in year 10.
Rossin-Slater et al. (2020). Effects of school shootings on youth antidepressant use.	IQVIA Xponent prescriptions filled at commercial pharmacies, 2006-2015. N = 4,130 school-area-months.	DiD: Compares antidepressant prescriptions filled within 5 miles of a school that had a shooting to areas 10-15 miles away, before vs. after.	Youth antidepressant use → ↑ 21.3% over the 2 years after fatal school shootings, 24.5% over 3 years; null for non-fatal shootings. Prescriptions per 1,000 ↑ 20.6% and 29.7% at 2 and 3 years post-fatal shooting, null for non-fatal shootings.	Areas with higher densities of non-prescribing MH providers see smaller antidepressant ↑ post-shooting. Effects don't vary with the density of prescribing providers.

Paper / Research question	Data	Methods	Results	Heterogeneity
Shui et al. (2026). Effects of mining earthquakes on MH.	Earthquakes from Royal Netherlands Meteorological Institute. Dutch Lifelines cohort study and biobank, longitudinal, 2007-2023. N = 92,338 person-waves.	FE: Individual FE isolate within-individual variation in respondents exposure to earthquakes across survey waves.	138% ↑ in earthquake exposure → 8% ↑ depression, 5% ↑ anxiety.	N/A

Table 7: Access and Quality of Care				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A: The Role of Health Insurance				
Aslim et al. (2022). Effects of Medicaid expansion on criminal recidivism.	State-level variation in Medicaid-expansion timing and scope linked to recidivism outcomes for released offenders from the National Corrections Reporting Program. N = 248,410 released prisoners.	DiD: Exploits variation in the timing and scope of state Medicaid expansions to compare recidivism among released offenders in expansion versus non-expansion states.	Medicaid coverage reduces recidivism specifically among multi-time reoffenders original convicted of violent crimes by 15%. Null/marginally significant effects for most other offender groups. Some evidence of increased referral to addiction treatment as a mechanism.	N/A
Ayyagari and Shane (2015) Effects of Medicare coverage of prescription drugs on elderly mental health.	Health and Retirement Study, 2000-2010, Americans 50+ and spouses (N = 12,251 aged 60-70); Medical Expenditure Panel Survey (cross-sectional), 2002-2011 (N = 15,294).	DiD: Exploits the Medicare eligibility cutoff at 65 years old, comparing outcomes for individuals 60-64 to those 65-70 in the years before and after the rollout of Medicare Part D in 2006.	Medicare Part D → depressive symptoms ↓ 14.8% (growing 2006-2010) and clinical depression ↓ 23-29%. IV analysis suggests a much larger LATE for those gaining coverage. Antidepressant prescriptions ↑, no effect on analgesics, antipsychotics, no ↑ in MH-care use. Out-of-pocket prescription spending ↓.	Out-of-pocket spending ↓ for those below 200% of the poverty line. Effects strongest for unmarried individuals, do not vary by race or gender, and are somewhat stronger for those with more than a HS degree. No spillovers onto non-eligible spouses.
Burns and Dague (2023). Effects of Medicaid coverage at release from prison on reincarceration and employment.	Linked Wisconsin Department of Corrections, Medicaid, and Unemployment Insurance records, 2013-2017. N=38,508 prison releases (32,384 individuals).	IV: Exploits Wisconsin's April 2014 Medicaid expansion to childless adults and a January 2015 prison-based pre-release enrollment-assistance program as instruments for Medicaid coverage at release.	Medicaid → 6-month reincarceration ↓ 2.5 p.p. (16%); employment ↑ 5.2 p.p. (25%), quarterly earnings ↑ $197. Outpatient visits, substance-use-disorder treatment, and mental health care access ↑.	Reincarceration effects concentrated among those with lower predicted need for substance-use treatment; larger among those reporting financial concerns.
Carney (2021). Effects of insurance coverage for mental health care on birth outcomes.	Vital Statistics birth records, 1990–2003; HCUP National Inpatient Sample hospital admissions, 1993–2003; Behavioral Risk Factor Surveillance System survey data, 1993–2005. N = 2,369,367 births.	DiD: Exploits the staggered rollout of state mental health parity laws requiring private insurers to cover mental health care on par with physical health care.	Among mothers most likely privately insured, parity laws → very-low-birth-weight probability ↓ 3%, gestation length ↑ 0.28 weeks (0.1%), low-APGAR probability ↓ 6%. No effect for those least likely privately insured. Possibly driven by 20% and 23% ↓ in MH diagnoses during pregnancy and labor.	Birth-outcome effects are concentrated among women most likely to be privately insured — those with 12 or more years of education who are married.
Chorniy et al. (2018). Effects of the switch to managed care on MH diagnoses.	A 60% random sample of South Carolina Medicaid enrollees under 17 who were enrolled during 2005-2015. N = 577,209 observations over N = 2,960,843 child-years.	FE: Child fixed-effects models isolate the effects of within-child changes in diagnosis rates before and after switching to managed care plans.	Managed care → ADHD diagnosis ↑ 0.7 p.p. (11.6%) and anx./dep. diagnosis ↑ 12.5%, plus ↑ in physical conditions. 17.4% ↑ in patient risk-adjustment scores (thus managers' reimbursements). ↑ in screenings and vaccinations, sick visits ↑ 9.6%, and ER visits ↑ 7.68% (null on hospitalizations).	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Cowan and Hao (2021). Effects of ACA Medicaid expansion on the mental health of college students.	State-level Medicaid expansion linked to University of Michigan's Healthy Minds Study, 2010-2017. N = 175,322 college students under 25.	DiD: Compares disadvantaged versus advantaged college students in Medicaid-expansion versus non-expansion states, before and after the 2014 ACA expansion.	Medicaid expansion → 144% ↑ in public insurance among low-SES students. Low-SES students see 21% ↑ in MH drugs, 24% ↑ in MH diagnoses. Null effects on self-reported MH, risky health behaviors, academic	Effects concentrated among disadvantaged students (by family background).
Currie and Musen (2025). Effects of Medicaid prior authorization on off-label antipsychotic prescribing.	IQVIA LRx data on prescriptions filled in 90% of retail pharamcies 2006-2019, combined with hand-collected data on timing of state-level prior authorization changes. N = 12,508 prescribers.	DiD: Exploit the staggered timing of the rollout of prior authorization requirements for prescribing antipsychotics to children under 5, comparing treated states to not-yet-treated states (there was little anticipation of the changes).	Prescribers cut prescribing to 3-5 y/o Medicaid children by 30%, and prescribers writing any antipsychotic for this group ↓ 15.8%. No change for privately-insured. State-level aggregation is similar: Rx to 3-5 y/o on Medicaid ↓ 20%, null for privately-insured.	Steeper for providers more baseline antipsychotic prescribing. Stronger for pediatricians, nurse practitioners, and family-medicine; insignificant (weakly significant) for child (general) psychiatrists. No variation by local practitioner/prescriber availability.
Deza et al. (2024). Effects of losing Medicaid coverage on crime.	FBI Uniform Crime Reports (police-agency level), Tennessee, 2002-2007, linked to county-level pre-disenrollment Medicaid coverage rates (4.0%-40.7% across counties).	DiD: Exploits Tennessee's 2005 TennCare disenrollment - one of the largest Medicaid contractions in U.S. history, affecting about 170,000 adults - comparing counties by pre-policy Medicaid coverage rates before and after disenrollment.	Counties at the 75th percentile of pre-policy Medicaid coverage: total crime ↑ 2.61% relative to 25th-percentile counties after disenrollment, driven by a 4.42% ↑ in non-violent crime/theft; violent crime ↑ only 0.49% (imprecisely estimated). Mechanism analysis: rising poverty, delayed medical care, reduced behavioral-health treatment, and increased overdoses.	Effects driven by non-violent, income-generating crime rather than violent crime.
Ejrnæs et al. (2026). Effects of reduced barriers to psychotherapy on secondary education completion.	Danish administrative register data linking personal and parental characteristics, mental health care utilization, prescriptions, and educational outcomes, 2015–2019, for individuals aged 18–24. N = 2,140,814 person-year observations on 734,251 individuals.	DiD and IV: Exploits a 2018 reform eliminating co-payments for psychotherapy treatment of anxiety and depression among 18–21 year-olds, comparing birth cohorts just above and below the reform's age cutoff, combined with an instrument for psychotherapy use based on general practitioners' referral propensity, net of patient composition.	Eliminating co-payments → ↑ secondary education completion 1 p.p. among women; null for men. 37% ↑ psychotherapy visits (intensive margin) 19% ↑ (extensive margin). GP with a higher referral propensity → completion ↑ 0.6 p.p. for both men and women; psychotherapy use ↑ 20–21%. IV: additional psychotherapy visit → odds completing secondary education ↑ 12.5 p.p. for women; 24 p.p. for men.	Effects are concentrated among youth from low socioeconomic backgrounds and those with a parental history of mental health diagnoses. High-SES youth show ceiling effects and possible substitution toward private psychotherapy. Individuals with a prior personal mental health diagnosis see large increases in psychotherapy use but no corresponding educational gains.
Finkelstein et al. (forthcoming). Experimental evidence on the effect of Medicaid coverage on crime.	Oregon Health Insurance Experiment (2008 Medicaid lottery) linked to Oregon Judicial Information Network records on criminal cases, charges, and convictions, 2007-2010. N=74,922.	RCT/IV: Uses random lottery assignment as an instrument for Medicaid enrollment (same design as Finkelstein et al. 2012), estimating intent-to-treat and local-average-treatment-effect impacts.	No statistically significant effect of Medicaid on any criminal case, charge, or conviction, overall or by type. The 95% confidence intervals rule out most of the statistically significant crime-reducing estimates in the quasi-experimental literature, including for high-risk subgroups.	No significant effects by sex, age, English-language status, prior criminal history, or pre-existing mental health condition (proxied by pre-lottery ED visits with a mental-health/substance-use diagnosis) - the subgroup other studies find the largest effects for.

Paper / Research question	Data	Methods	Results	Heterogeneity
Giuntella and Lonsky (2020). Effects of DACA-induced health insurance coverage on mental health.	American Community Survey (labor/insurance), 2005-2015 (N = 395,902); National Health Interview Survey, 2005-2016 (N = 583,051); California Health Interview Survey, 2003-2015 (N = 106,247).	DiD: Leverages the fact that only some non-citizens were eligible for DACA; compares outcomes of eligible and non-eligible non-citizens before and after the DACA rollout in 2013.	Depression among immigrants in poverty ↓ 36% and physical health ↑ overall; in CA, distress for below-poverty immigrants ↓ 54%. Post-2012, insurance coverage ↑ 3% (mostly individually-purchased, not Medicaid); in NY and CA, (recipients gained Medicaid eligibility) public coverage ↑ 17%, ↑ 6.2% overall. Care delays ↓ nationally; care access ↑ in CA. No national ↑ in care use.	N/A
Guldi and Hamersma (2023). Effects of Medicaid coverage during pregnancy on maternal mental health.	National Maternal and Infant Health Survey: 1988 U.S. births with 1- and 3-year follow-ups; NCHS Vital Statistics birth records (near-universe of 1988 births); state Medicaid income-eligibility thresholds from Hill (1992). N = 11,532 births.	FE: State fixed-effects isolate within-state changes in Medicaid eligibility thresholds, with month-year of conception fixed-effects differencing out time trends common across states.	More Medicaid eligibility → ↑ in prenatal care; null on most birth outcomes. At 1 year, some ↓ maternal depression. Null on hospital readmission, infant death, child apnea, breastfeeding initiation. After 3 years, a 10% ↑ in eligibility threshold → maternal-depression index ↑ (improvement) 1-3%. Null on maternal, child health, child insurance, labor supply. Marginally significant ↑ infant	Authors find some evidence that unmarried and less-educated mothers may be more sensitive to increases in Medicaid access, though large standard errors prevent any strong conclusions.
He and Barkowski (2020). Effects of ACA Medicaid expansion on crime.	FBI Uniform Crime Reports, state-level (2010-2016) and border-county-level (2010-2014, 2016) samples; American Community Survey demographic and economic controls.	DiD: Compares crime rates in ACA Medicaid-expansion versus non-expansion states and border counties, with event-study specifications around the January 2014 expansion date.	Expansion is associated with reductions in vehicle theft (10.4%), homicide (8.1%), robbery (6.3%), burglary (3.8%), and assault (2.9%). Implied welfare gains of about $10.5 billion per year, offsetting roughly one-seventh of expansion costs. Effects concentrated in 2014 at the state level but persisted through 2016 in border counties.	N/A
Hegland (2025). Effects of expanded medicaid coverage of mental health on crime.	Municipality-level crime data from the FBI's Uniform Crime Reporting Program, 1988-2016. County Business Patterns data, 1988-2016. N = 2,570 municipality/county-years.	DiD: Leverage staggered rollouts of Medicaid coverage for psychological treatment in 5 states, comparing areas with higher and lower poverty (Medicaid eligibility) rates.	Expanded coverage is associated with a reduction of 5.04 crimes per 1,000 people (0.15 SD). Employment in mental-health-treatment-related professions increases by 0.3 per 1,000 people (0.32 SD).	N/A
Jácome (2024). Effects of losing Medicaid coverage on criminal involvement.	Linked South Carolina admin. records (Medicaid coverage, MH status, justice interactions). N = 31,027 low-income men born 1990-1993 ever enrolled in Medicaid.	Triple-diff: Exploits the cutoff of Medicaid coverage through the Children's Health Insurance Program at age 19. Compares individuals with/without a mental illness who were/were not enrolled in Medicaid, before/after they turn 19.	A year after losing coverage, young men with MH histories → probability of being incarcerated ↑ 0.9 p.p. (19%) and of ever being incarcerated ↑ 2.5 p.p. (22%).	Larger ↑ for men who accessed MH care pre-loss, especially those who filled prescriptions. Effects for property and violent offenses, none for drug offenses. Driven by those with behavioral diagnoses (conduct, oppositional-defiance, substance/addictive).

Paper / Research question	Data	Methods	Results	Heterogeneity
Ma et al. (2020). Effects of free GP care on elderly mental health.	Panel data on physical and mental health from the Irish Longitudinal Study on Ageing, 2009-2016. N = 6,940 individuals ages 50-90.	DiD: Leverages the fact that GP fees became free for individuals over age 70 beginning in 2015. Compares pre-/post-2015 health outcomes for individuals above/below 70 years of age.	The elimination of GP fees does not seem to have a significant effect on perceived quality of life, life satisfaction, depression, or worry. However, percieved stress decreases by 6% for those affected by the fee elimination.	The decreases in stress only appear among individuals in the lowest income tercile and among those with a chronic condition. They also seem to be concentrated among those who are single.
Mann et al. (2024). Effects of Medicaid gender-affirming care coverage on the mental health of transgender people.	CDC BRFSS: cross-sectional, 2014-2020; state policies from Movement Advancement Project; Medicaid State Drug Utilization Data. N = 1,215,080.	Triple-diff: Compares MH between low- and high-income (Medicaid-eligible/ineligible) transgender individuals in states with/without mandatory Medicaid coverage of gender-affirming care, before vs. after rollout.	Medicaid coverage of gender-affirming care → mental-distress incidence ↓ 13% and poor-MH days ↓ 1.6 (14.6%) two years later, growing through the post-period. Hormone-drug take-up ↑ ~9.5%, suggesting MH gains were driven by ↑ use of gender-affirming care.	N/A
Marcotte and Rakus (2026). Effects of medicaid expansion on suicide rates.	CDC mortality and Medicaid-coverage data by state and age group. Medicaid expansion dates from Kaiser Family Foundation. N = 5.634 group-state-years.	FE: Isolates within-state changes in Medicaid coverage. Alternatively allows heterogeneous effects of age-group specific eligibility changes.	Each 1 p.p. ↑ in Medicaid coverage → suicide mortality ↓ 1% (0.05 SD) among 15-19 y/o and 0.25% among 20-24 y/o. Null for 25-45. Small ↑ for 45-55 and small ↓ for 60-64.	N/A
Messel et al. (2023). Effects of expanding access to mental health services on disability program applications and awards.	County-level variation in the number of mental health treatment establishments linked to SSI and SSDI application and award records.	Panel/IV-style design: Exploits county-level changes in mental health establishment availability over time to estimate effects on disability-program applications and awards.	10% ↑ in county mental health establishments → SSI applications ↑ 1.2%; SSDI applications ↑ 0.7%.	Award effects concentrated in higher-poverty counties; no significant award effect elsewhere.
Ortega (2023). Effects of the Affordable Care Act medicaid expansion on mental health.	Mental-health admissions from SAMHSA; CDC Vital Statistics mortality. All 2007-2019. N = 442 state-years.	DiD: Compare outcomes in expansion versus non-expansion states, before and after the expansion.	Medicaid expansion → Medicaid MH admissions ↑ 31%, Medicaid prescriptions ↑ 63%, and overall stress/anx./de. diagnoses ↑ 35% one year post. No effect on non-Medicaid admissions or facility counts; facilities accepting Medicaid ↑ 1.8%. Some short-term ↓ in suicides (up to 4%).	Not much evidence of significant heterogeneity in the admissions effects.
Packham and Slusky (2023). Effects of simplified Medicaid re-enrollment at release on recidivism.	Linked South Carolina criminal-justice and Medicaid claims records, 2007-2020. N>137,000.	RDD: Exploits South Carolina's July 2016 policy simplifying Medicaid re-enrollment for recently incarcerated individuals, comparing those released just before and after the policy change.	Medicaid enrollment ↑ 10.4 p.p, modest ↑ outpatient-care utilization; null effect on recidivism at 1 and 3 years post-releases. The authors attribute the null result to weak implementation (limited staffing and outreach) rather than a true absence of a	No significant effects across the crime categories examined.

Paper / Research question	Data	Methods	Results	Heterogeneity
Serena (forthcoming). Effects of insurance coverage of psychotherapy on health, suicide, and labor market outcomes.	Administrative health, labor market, and socioeconomic data encompassing all citizens of Denmark 2000-2016. N = ERYOR.	i) RDD: Examine outcomes on either side the 38-y/o cutoff to receive 60% coverage for psychotherapy. Ii) DiD: Examine difference in the changes in outcomes for eligible/non elidgible cohorts after the coverage was introduced. iii) RDD: Compare individuals who experience mental health shocks right before or right after their 38th birthday.	Coverage → psychotherapy ↑ 65%, psychiatric hospitals ↓ 7%. DiD estimates: +88% and -7% respectively; PCP MH consultations ↑ 6%; n private psychiatrist use null. Antidepressants ↑ ~3.5%. Suicide attempts ↓ 20% for 18-37 y/o, but RDD effects at 37 are null. Coverage during shock→ psychotherapy share ↑ 150%, with no employment effect. Coverage also ↓ spending on somatic prescriptions (7.5%) and inpatient	Offsets in hospital utilization are driven by the bottom tercile of earners, along with women, who also drive much of the increase in psychotherapy.
Solomon and Dasgupta (2022). Effects of state mental health parity laws on young adults' mental health and educational outcomes.	CDC suicide rates (N = 561 state-years); cross-sectional MH from CDC BRFSS, 1998-2008 (N = 458,013); college outcomes from NLSY97 (N = 12,737). Parity laws from Lang (2013).	DiD: Compares pre-post passage outcomes in states with mental health parity laws to those in states that have not passed them.	A full MH parity law → college-aged suicide rate ↓ 3%, poor-MH-days incidence ↓ 4.2%, and GPA ↑ 4.24% among college students, with no effect on drop-out. GPs visits ↑ and financial stress ↓.	The improvement in GPA following the passage of parity laws is concentrated among women.
Vogler (2020). Effects of ACA Medicaid expansion on violent crime.	FBI Uniform Crime Reports, state-level, 2009-2018.	DiD: Compares crime rates in ACA Medicaid-expansion versus non-expansion states.	Expansion states → 5.3% ↓ annual violent crime; implied cost savings of about $4 billion per year.	Effect concentrated in aggravated assault rather than other violent-crime subtypes. Suggestive evidence of larger crime reductions in states with no SUD/MH benefit exclusion.
Wen et al. (2017). Effects of pre-ACA HIFA-waiver Medicaid expansions on crime.	County-level FBI Uniform Crime Reports linked to state HIFA-waiver Medicaid-expansion timing (pre-ACA period). N = 22,328 county-years	DiD: Exploits staggered state adoption of HIFA-waiver Medicaid expansions to compare crime rates before and after expansion.	Expansion → robbery ↓ 1.3%, aggravated assault ↓ 1.3% and larceny theft ↓ 0.6%. Substance use treatment rate ↑ 20%; substance use disorder prevalence decrease.	N/A
Panel B: The Role of Broader Care Availability				
Ali et al. (2026). Effects of MH/SU treatment facilities on child maltreatment.	National Child Abuse and Neglect Data System maltreatment reports, 2004-2022. Behavioral health treatment centers from Census Bureau County Business Patterns. N = 19,636 county-years.	FE: County and year fixed effects isolate within-county changes in the number of treatment centers while controlling for common time trends.	An additional 7 treatment centers → 0.7% fewer child maltreatment reports, 0.4% fewer injury deaths among children.	Largest reduction for educator reports; decreases in recommendations for family support, counseling, housing, and SUD treatment services. Decreases in physical abuse, sexual abuse, neglect, null for emotional maltreatment. Larger in states with weaker child safety net.
Alsan and Yang (2025). The hidden health care crisis behind bars: a randomized trial to accredit U.S. jails.	RCT across 44 U.S. jails; staff surveys and administrative records on care-quality compliance, in-custody mortality, and recidivism.	RCT: Random offer of health care accreditation (National Commission on Correctional Health Care standards) to jails; compares offered vs. control facilities.	Accreditation → care standard compliance ↑11–15%; largest gains in compliance with MH screening requirements. Mortality ↓ to about one-third of the control-group rate; suggestive 44–45% reduction in six-month recidivism.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Bhuller et al. (2025). Mental health effects of rehabilitation-oriented correctional sentencing.	Linked Norwegian administrative correctional and health records, 2006-2014. N = 22,498 cases decided between 2011 and 2014.	DiD event study: Outcomes for sentenced defendants are compared to others that receive the same sentence, but at a later time.	5 years after an incarceration event, the odds of a health care visit are 5 p.p. (10%) lower, driven by an 8. p.p. (30%) drop in MH visits with no (or even slightly positive) effects on physical health visits. There is also a 4.5 p.p. (57.7%) decrease in ED admissions and a 2.4 p.p. (85.7%) decrease in MH-related ED visits.	The decreases in MH visits driven by inmates at more rehabilitative "open" prisons. Defendants who receive only fines see no effect, while non-custodial punishments that include rehabilitative services (electronic monitoring/probation) generate similar effects. Declines larger for those with better pre-sentencing MH.
Costantini (2025). Effects of delays in mental health treatment on long-term mortality.	Administrative data from the VA hospital system 2001-2015. N = 621,289 individuals arriving at the ED with a mental health condition.	IV: Instruments for a veteran's received waiting time before a follow-up appointment using the average wait time for individuals arriving at the same hospital, with the same diagnosis, in the same 2-week period.	A 1 SD ↑ in wait time → 2-year mortality ↑ 0.11 p.p. (1.5%), up to 0.14 p.p. (1.9%) at 5 years. Driven by ↑ odds of missing the second appointment (2 p.p., 5.6%), interim MH-drug prescribing (1.2 p.p., 4%), and receiving MH care exclusively from a PCP (0.27 p.p., 11%).	The mortality results are driven by patients with substance use disorder or psychosis.
Costantini (2026). The relative efficacy of housing- and treatment-first programs for mentally ill veterans.	Administrative data from the VA on veteran mental health and homelessness status (based on NLP analysis of 50 million clinical notes), all VA interactions, and mortality. N = 300,000 unhoused veterans with a mental illness.	IV: Exploits the quasi-random timing of arrival at a VA clinic, instrumenting for receipt of housing vouchers using length of the voucher waitlist at arrival and instrumenting for entrance into "treatment-first" transitional housing based on the availability of a program-specific specialist.	Voucher → 4.6 p.p. (69.7%) ↓ in three-year mortality; "treatment first" null. Three quarters later, voucher program → 34 p.p. ↑ in stable housing; much smaller effects for the "treatment first" program. Engagement with VA homelessness services ↑ for both; stronger for voucher. Transitional housing: MH visits ↑, fading after 2 years; vouchers no effect.	Voucher mortality effect driven by exposure to the elements, assaults, and especially HIV, Hepatitis B, and Hepatitis C, suggesting decreases in drug and alcohol use. There is some evidence that the "treatment first programs" that place the least stringent requirements on housing access and guarantee housing for a longer period are more effective.
Deza et al. (2022). Effects of the availability of mental health facilities on crime.	FBI Uniform Crime Reporting program (1999-2016); County Business Patterns (1998-2015). N = 15,803 county-years.	TWFE: Identify the effects of treatment access from fluctuations in the number of mental health facilities within a given county across years.	Ten additional facilities decrease the social costs of juvenile arrest by 2.3%-2.6%.	The effects are driven by non-physician offices and by boys, white people, and older juveniles.
Dias and Fontes (2024). The effects of community mental health care centers on care utilization and crime in Brazil.	Administrative heath, mortality, and crime data outcomes data from Brazil. N = 53,034 municipality-years.	DiD: Leverage the staggered implementation of community mental health centers (designed as substitutes for inpatient care) across municipalities.	Treatment → supply of MH professionals ↑ 46% and outpatient MH procedures ↑ 113%. No effect on psychiatric-bed counts, though inpatient MH admissions ↓ 7.5% and associated public expenditure ↓ 15%. No mortality effect, though homicides ↑ 7.7%.	Largest utilization ↑ among psychiatrists (vs. psychologists, occupational therapists, social workers). Inpatient-admission ↓ strongest among the longest stays and schizophrenia patients.

Paper / Research question	Data	Methods	Results	Heterogeneity
Emanuel et al. (2025). Effects of involuntary MH hospitalization on suicides, overdoses, and criminality.	Administrative data on all involuntary hospitalizations, criminal charges, and deaths by overdose or suicide in Allegheny County, PA. N = 16,630 involuntary hospitalization evaluations, 2014-2023.	IV: Exploits the quasi-random assignment of patients to emergency-room physicians, using physician propensity to involuntarily hospitalize as an instrument for the receipt of involuntary hospitalization.	10 p.p. ↑ in physician's tendency to hospitalize →2.6 p.p. (78.9%) ↑ in violent crime in following 3 months; no effect on overall (non-violent) criminal charges. 0.98 p.p. (89.1%) ↑ in the odds of death by suicide or overdose in the next three months. Lower earnings and increased housing instability.	Little heterogeneity by provider type (physicians versus psychiatrists), gender. More experienced (10+ years) physicians see smaller increases in the probability of violent crime. Increases in violent crime are larger among patients with substance use disorders and patients are referred by a relative rather than police.
Golberstein et al. (2023). Effects of school-based mental health services on youth outcomes.	Administrative education, juvenile detention, and Medicaid records from Minnesota, 2001-2018. N = 2,528,624.	DiD: Exploits staggered implementation of school-based mental-health (SBMH) clinicians across schools, bolstered by school-level matching on observables.	SBMH → null on attendance, test scores, and suspensions. Justice involvement ↓ 25%; outpatient MH services/ drugs ↑ 7% (among Medicaid students), driven by therapy ↑ 13%. Reported 12-month suicide attempts ↓ 15%.	SBMH → ↓ test scores for American Indian, Black, K-5, free-lunch-eligible, and child-welfare-involved students; ↑ for those not free-lunch-eligible. Suicide effects stronger for white students.
Hansen et al. (2026). Efficacy of suicide hotlines.	State-level suicide mortality data and 988 crisis-line operational records for all U.S. states, spanning the July 2022 rollout of the National Suicide Hotline Designation Act (988). N = 1,530 state-years.	DiD: Exploits pre-existing cross-state variation in crisis-line capacity gaps, measured by the number of pre-988 calls routed to a state but left unanswered in-state, to compare states with larger versus smaller capacity gaps before and after the July 2022 rollout.	States with larger baseline capacity gaps answer significantly more calls and see larger increases in in-state answer rates after the rollout, but these operational gains do not translate into detectable reductions in suicide mortality or improvements in broader population mental health outcomes.	N/A
Hjalmarsson and Lindquist (2026). Diagnosing ADHD in prison: post-release outcomes for inmates and their families.	Swedish prison registers matched to non-prison health, crime, and labor market registers, 2009–2013. N ≈ 37,000 prison spells (26,000 individuals); core sample restricted to >32,000 spells with no pre-prison ADHD history, of which 950 receive a new in-prison diagnosis.	Pre/post dynamics around prison entry and release; spell-level OLS controlling for demographics, health, and criminal history; repeat-offender fixed effects (diagnosed in a later but not an earlier spell); controls for self-reported motivation (subsample); static and dynamic DiD against a matched, reweighted comparison group.	In-prison ADHD diagnosis → ADHD medication take-up ↑ 14.3 p.p., ADHD diagnosis ↑ 4.9 p.p. (~50%). No reduction in crime (overall or by category) or improvement in employment or earnings.	Patterns are consistent across subgroups defined by gender, Swedish citizenship, age, and alcohol/narcotics conviction history. Children and siblings of newly diagnosed inmates with no prior ADHD history are also more likely to be treated for ADHD after the inmate's prison spell, with no corresponding reduction in their own crime.
Prudon (2025). Effects of mental health treatment wait times on employment outcomes.	Administrative health care and labor market data for every Dutch individual, 2012-2019. N = 524,707 individuals meeting sample restrictions.	IV: Instruments for an individual's waiting time with the average waiting time in a given region, with region fixed effects isolating variations in each region over time.	A one-month (0.5 SD) ↑ in wait time → employment ↓ 2 p.p. over eight years and disability-benefit receipt ↑ 1 p.p. Cumulative care minutes ↑ 150 (9%), spending ↑ €875 (12%), and pharmaceutical use ↑ 3 p.p. (6%).	The effects of longer waiting times are significantly stronger for individuals with a migration background or lower educational attainment.
Shakya and RoyChoudhury (2026). Access to MH care and suicide rates.	CDC Vital Stats 2016-2019. Providers from the National Plan and Provider Enumeration System. N = 12,554.	IV: Use the passage of expanded psychologist scope-of-practice laws as an instrument for local availability of MH care.	1% ↑ in access (0.3 providers w/i 70 miles) → 0.3% decrease in suicide rate.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Williams et al. (2026). Effects of SU treatment wait times.	Norwegian administrative registers covering all outpatients entering specialist treatment for cannabis use disorders (CUDs) in 2009-2010, followed through 2013. N = 2,576 individuals across 3,537 treatment episodes (76% male, average age 26).	2SLS: Instruments wait time with the average wait time among CUD patients in neighboring health trusts, exploiting the staggered 2008-2012 rollout of Norway's National Action Plan and common labor-market shocks across neighboring treatment facilities.	A 10-day delay decreases probability on exiting treatment within a year by 2.4%, increases total treatment days 3.7%. Decreases odds of employment and days worked.	Effects on treatment continuation are larger for male and younger patients. Patients without a co-occurring mental health diagnosis respond substantially more strongly to waiting, consistent with a severity-based mechanism.
Panel C: The Role of Providers				
Berndt et al. (2015). Measuring heterogeneity in prescribing of antipsychotics.	IMS Xponent prescriptions: 10% random sample of 1996 prescribers; 2007 cross-section. N = 2,867 prescribers.	Descriptive: Measures how far each prescriber's drug portfolio deviates from national market shares, regresses on correlates. Also builds a model of prescribing: tradeoff between learning one drug deeply vs. offering variety.	Divergence from national market shares for ~95% of prescribers; ~75% have portfolios significantly more concentrated than national shares. Model: low-volume prescribers concentrate in a few drugs based on first patients' symptoms. Regressions confirm: a 1 log-pt ↑ in Rx volume → 31% ↓ deviation from market, concentration ↓ 11.2%.	Among older prescriber cohorts, the highest-volume prescribers prescribe the largest shares of older drugs (suggestive of pharmaceutical advertising). Among younger cohorts (too young for old-drug advertising), volume is still associated with higher old-drug shares, which marketing can't explain.
Cuddy and Currie (2020). Measuring variation in follow-up mental health care and prescribing.	Children covered by Blue Cross Blue Shield for at least 1 year, 2012-2018. N = 202,066 with a first mental health claim between 10-17 years old.	Descriptive: Examine the kinds of care children receive in the period after their first MH-related claim.	29.4% get no follow-up 3 mo post-claim; 45% receive "red-flag" Rx, conditional on Rx. Varies widely from 10th-90th-percentile ZIP codes: 50-90% for 3-mo follow-up, 0-100% for red-flag Rx. Also wide variation in therapists access. Treatment within 3 mo ↑ 1 p.p. (1.4%) per year of age; red-flag Rx ↑ 1.4 p.p. (3.1%). Girls are 1.7 p.p. (2.4%) likelier treated and 0.8 p.p. (1.8%) likelier to get red-flag Rx. Supply-side explains little cross-ZIP	First claim was in a hospital → 2.9 p.p. (4.1%) likelier to get follow-up and 2.8 p.p. (6.1%) likelier red-flag Rx. Surprisingly, first claim ER visit → 12.3 p.p. (17.6%) less likely to get follow-up and 2.7 p.p. (6%) less likely red-flag Rx. Recent (6-month) hospitalization → 2.8 p.p. (6.3%) likelier red-flag Rx (no follow-up effect); the top quartile of past-6-month spending → 4.9 p.p. (7%) likelier follow-up and 8.3 p.p. (18.4%) likelier red-flag Rx.
Currie and MacLeod (2020). Effects of the breadth of provider's MH prescription portfolio on patient outcomes.	Blue Cross Blue Shield insurance claims plus IQVIA retail-pharmacy data. N = 450,802 members prescribed an antidepressant; 5,409,124 member-months.	FE: Patient FE identify the effects of doctors who prescribe more widely or violate guidelines from outcome changes among patients who switch doctors.	0.25-unit ↑ dispersion (~IQR) → care costs ↓ 2.1%, non-drug costs ↓ 4%, ER ↓ 5%, null on MH ER. Viol. UK guidelines → null. Viol. Canada (US) guidelines → costs ↑ 48% (28.2%), non-drug ↑ 41.6% (29.1%), ER ↑ 17% (13%), MH ER ↑ 20% (20%). Drug cocktails → costs ↑ 51%, non-drug ↑ 36.3%, ER ↑ 21%, MH ER ↑ 20%.	Among patients likelier to have seen psychiatrists, null effect on total costs but ER visits ↓ 10% and MH ER ↓ 14.7%. For those less likely to have seen skilled providers, costs ↓ 3.8% (total) and 5.6% (non-drug), null on hospitalizations, but MH ER ↑ 9.7%. For guideline violations, little difference for patients seeing psychiatrists vs. not.

Paper / Research question	Data	Methods	Results	Heterogeneity
Currie and Zhang (2025). Effects of PCP effectiveness on short-term mental and physical health.	Administrative health records from the Veteran's Health Administration. N = 802,777 veterans assigned to 7,548 PCPs.	IV?: Exploits the mostly-random assignment of new patients in the VA system to PCPs, whose efficacy over three dimensions -- MH, circulatory conditions, ambulatory-care sensitive conditions (ACSC) -- is measured using a Bayes jackknifed value-added measure.	1 SD higher MH, circulatory, ACSC effectiveness → 3-year mortality ↓ 3.6-4.2%, 1-year, 3-year costs ↓ 2.48-5.4%, encounters ↓ 2-3%. Three years: MH effectiveness → suicides ↓ 13.3%, external-cause deaths ↓ 8.7%, cancer deaths ↓ 3.4%, and heart deaths ↓ 4.0%. Circulatory and ACSC → deaths ↓, no suicide effect. MH effectiveness → MH visits ↓ 8.1%. All three → ↓ referrals and tests/images, ↑ screening guideline	N/A
Currie et al. (2024b). Socioeconomic gradients in MH drug prescribing in Ontario.	Ontario admin. prescriptions during universal drug coverage, 2018-2019, plus hospitalization and cost data. N = 3,530,010 MH prescriptions to 237,835 youth.	FE: Includes control for patient's medical history and provider FE, isolating within-doctor differential prescribing to patients from different socio-economic groups with the same medical histories.	Low-income children receive 49.4% more antipsychotics, 11.0% benzodiazepines, 9.6% mood stabilizers, and 1.2% ADHD drugs; SSRIs 8.9% less likely; other antidepressants 10.7% likelier. Cocktails of 2+, 3+, or 4+ are 9.7%, 28.9%, and 37.1% likelier.	In general, there are similar but smaller effects for a slightly higher income group. There seems to be little heterogeneity by gender.
Currie, et al. (2024c). Sources of variation in inappropriate mental health prescribing to children.	IQVIA data on prescriptions filled at retail pharmacies. N = 7,013,737 first-time MH prescriptions to children under 18.	Models doctor decision making w/r/t mental health prescribing, with own training, same-ZIP providers' training, and ZIP-level residual (beyond provider training) as main explanatory factors.	Both a physician's own training and the typical training of doctors in her ZIP strongly predict whether she writes "red-flag" prescriptions to under-18s, evidence of both training/cohort effects and local practice-area spillovers.	Spillovers (and, slightly, training effects) are much stronger for nonpsychiatrist prescribers, especially for prescriptions to too-young patients, for benzodiazepines, and of multiple drugs on the same day.
Ding (2026). Estimating geographic variation in mental health treatment utilization and drug prescribing, and its effects on outcomes.	A 20% sample of Medicare enrollees 2006-2018. N = 6,2448,950.	DiD: compares patients who move between hospital referral regions with different levels of mental health service and drug use.	Moving to area with 1 SD higher service utilization → own utilization ↑ 0.46 p.p. (4.3%), while 1 SD higher drug utilization → drug use ↑ only 0.151 p.p. (0.6%). A 1 SD higher service-utilization area → self-harm ED visits ↓ 13.6%; 1 SD higher drug utilization has null effects.	There are much smaller place-based effects for schizophrenia-related treatment, as compared to treatment for anxiety and depression. There are larger place-effects for services rendered at hospitals, offices of mental health professionals, and PCP offices.
Douven et al. (2019). Effects of treatment provider altruism on mental health outcomes.	Administrative data on all mental health treatment episodes in the Netherlands, 2008-2010. N = 208,117 treatment episodes across N = 1,614 treatment providers.	Descriptive: Self-employed Dutch MH providers earn flat fees that step up at set minute intervals. Provider "altruism" measured by how often a provider stops treatment right after threshold, then regresses patient outcomes on it.	A 1 SD increase in provider altruism is associated with a 0.5% increase in provider-assessed mental health at the end of the treatment period and 40 (3.5%) fewer minutes of total treatment duration.	N/A
Marquardt (2021). Measuring variation in provider's ADHD diagnosis rates.	Doctor notes for N = 12,311 pediatric patients in Arizona, written by 129 physicians.	Controlling for observables: Trains an ML model on patient notes to estimate each patient's ADHD symptom match, then regresses observed diagnosis on symptom match with physician FE (prescribing intensity) and physician-specific slopes (diagnostic compliance).	Median intensity is negative (less Rx than symptoms suggest). Median compliance is 0.44 (44% ↑ in diagnosis moving from the least to most symptom-matched patient). At median, 1 SD ↑ intensity → diagnosis ↑ 19 p.p. (549%); 1 SD ↑ compliance → ↑ 16.5 p.p. (478%).	Diagnostic intensity is higher and compliance is lower among male doctors, and the same pattern holds among doctors with 15-25 years of experience, though not those with 5-15 years, 25-25 years, or 35+ years. Med school rank does not seem correlated with either measure.

Paper / Research question	Data	Methods	Results	Heterogeneity
Marquardt (2026). ADHD diagnoses: modelling doctor decision-making.	Doctor notes and visit summaries for N = 36,193 unique patient encounters at a large healthcare center in Arizona, 2014-2017.	Model: Models the 3-stage ADHD-diagnosis process: parents' choice to schedule a consultation, doctors' updating during it and diagnosis using an ex-ante, gender-specific threshold. Uses ML on doctors' notes to identify assessment visits and quantify symptom overlap.	Higher symptom match explains 46-55% of the male-female diagnosis gap; higher symptom variance among boys. Providers weight DSM-V overlap more when diagnosing female patients (narrowing gap 7%), but have higher diagnostic thresholds for them → 55-64% of the gap. Utilization cost barely affects the gap.	N/A
Persson et al. (2025). Family spillovers in ADHD diagnoses.	Administrative health, labor market and family structure data for the entire Swedish population, including identifiers for an individuals' cousins. N = 1,122,722 cousin pairs born between 1985-2001.	RDD: Exploits school-entry cutoffs, compares children born just before/after the Jan. 1 cutoff (close in age, enter school a year apart). Compares ADHD diagnosis rates among younger cousins born the same day whose older cousins fell just before/after the cutoff.	Older cousins born pre-cutoff are 17.6%/16.1% likelier diagnosed/medicated for ADHD. Younger cousins whose older cousins were born just before are 9.1%/5.8% likelier diagnosed/medicated. Older-cousin diagnosis → 0.6 additional diagnoses for younger cousins. No effects (perhaps small negative) on younger cousins' long-term education or earnings.	Younger cousin is born before the cutoff → both cousins' diagnosis odds and the older cousin's odds of being diagnosed second ↑, so spillovers go both ways. Spillovers appear only when >= 1 linking parent is a woman (none when both men), pointing to communication channel. Stronger in lower-income, Swedish-born, and lower-education families.
Shapiro (2018). Effects of pharma company detailing on off-label prescription of antipsychotics.	Monthly data on the prescribing behavior -- along with interactions with pharmaceutical sales reps -- for a sample of PCPs and psychiatrists, 2001-2006. N = 52,613 physician-months.	FE: Physician FE isolate within-physician variation in detailing for AstraZeneca's Seroquel, plus within-physician discontinuities around two "information shocks" (evidence of efficacy). Models let detailing effects change after shocks and vary with whether a visit coincided with a shock.	Detailing → Rx of Seroquel ↑ 29.1% and Rx off-label ↑ 20.2%. Information shocks: no effect alone, but coincident detailing → ↑ off-label Rx (both) and ↑ total Rx (second shock). Detailing between shocks → ↑ off-label Rx, not total; detailing after second → both ↑. Coincident-detailing effect never larger, so information not primary channel.	Heterogeneity analyses are underpowered, but there is evidence that detailing has much smaller effects on Rx among physicians who have a larger share of children in the client pools
Shapiro (2022). Effects of antidepressant advertising on mental health and labor market outcomes.	Nielsen Media advertising data; insurance claims and employment from Truven MarketScan, 2007-2010. N = 518,284.	RDD/border strategy: Exploits the borders of major TV markets to isolate exogenous differences in the penetration of direct-to-consumer antidepressant advertising.	A 10% ↑ in antidepressant advertising over six months → days absent ↓ 0.013 (5.8%). Null for therapist visits, non-adherence, market outcomes (prices, generic use, drug switches).	The effects of advertising on labor supply mostly affect individuals who have missed work recently (i.e. those who might be most likely to be depressed).
Swagel (forthcoming). Drivers of across-region and across-provider variation in ADHD med and antidepressant prescribing.	Blue Cross Blue Shield private insurance claim data. N = 11,495,405 children, 47,427,135 child-years.	AKM model: Decomposes patient-, place-, and provider-level variation in PCP ADHD and antidepressant prescribing, identified from child and provider moves across regions and children switching providers within regions.	Non-provider supply-side explains 50% (ADHD), 40% (antidep.) regional variation. Provider propensities explain 20% of antidep. variation, cut against ADHD variation. Cross-provider variation 15x (ADHD) to 36x (antidep.) larger than cross-region; propensities explain 30% (ADHD), 45% (antidep.), other supply-side 2-3.5%. 20% provider variation: assortative matching of high-propensity providers to high-need kids.	Providers' prescribing intensity varies widely across conditions: 24% of providers are in the top two quintiles for one condition and the bottom two for the other. Female providers, pediatricians, and higher-ranked-med-school graduates prescribe more ADHD meds and fewer antidepressants. U.S.-trained physicians have higher propensities for both vs. internationally-trained.

Table 8: Mental Health Treatments				
Paper / Research question	**Data**	**Methods**	**Results**	**Heterogeneity**
Panel A: Therapy				
Angelucci et al. (2026). Effects of access to an AI-powered mental health app on mental health, behavior, and labor-market outcomes.	N = 1,964 low-to-medium income women in Mexico, age 18-50, with at least some anxiety/depression symptoms.	RCT: Randomizes free access to an AI CBT app (and, in a second experiment, access duration).	Over 6 mo, MH improves 0.29 SD and severe-symptom prevalence ↓ 27%. Labor-market index ↑ 0.10 SD, missed work ↓ ~16; better sleep, healthful behaviors. Therapy attendance ↑ 35%; therapy accounts for at most 5% of MH effect. Use: 81% week one → <10% by six mo; 3→ 6 mos access: use ↑ 39%, no additional MH gains.	Psychotherapy-use increase concentrates among moderate- and severe-baseline-distress participants (+7-8 p.p.), small and insignificant for mild distress. Mental health gains occur across all baseline-distress groups but are largest for moderate distress.
Arbour (2022). Can recidivism be prevented from behind bars? Evidence from a behavioral program.	Quebec Ministry of Public Security admin. records, 2007–2019 (DACOR corrections files; LS/CMI risk evaluations, 2007–2017) on participation in Parcours, a CBT program delivered in 11 prisons. N = 6,142 male inmates (995 participants, 5,147 non-participants).	IV: Instruments participation with the historical recommendation rate of the probation officer each inmate is randomly assigned to, isolating variation in program take-up unrelated to inmate selection; 2SLS with prison, year, and crime-type fixed effects.	OLS estimates understate the effect (3–6 p.p. reduction in recidivism) relative to IV: the program reduces recidivism by 15 p.p. (75%) at 6 months, 19 p.p. (61%) and 17 p.p. (40%) at 1 and 2 years post-release, and reduces the number of subsequent offenses by 0.35–0.55 per year.	Causal-forest estimates show little heterogeneity by age, crime type, or prior conviction history; compliance with the probation officer's recommendation declines with age, so younger inmates contribute more to the identified effect.
Baird et al. (2025). Effects of interpersonal therapy and cash transfers on MH and human capital.	Data collected from an RCT among ugandan women ages 13-19 with moderate or severe depression. N = 1,919.	RCT: Cluster-randomized trial of a 14-week course of "interpersonal therapy," cross randomized with cash transfers of $69.	No depression at endline ↑ 0.14 SD, GHQ↑ 0.15 SD; 1 yr later ↑ 0.12-0.14 SD higher, fades by 30 mo. Adding cash worsens: no depression 12 mo 0.2-0.23 SD ↓ vs. therapy; PHQ/GHQ ~0.18 SD ↓, through 30 mo. No effects on human-capital/family-formation.	N/A
Baranov et al. (2020a). Effects of therapy on perinatal depression symptoms, financial empowerment, parental investments.	Women in the third trimester of pregnancy, assessed for clinical depression, in Punjab, Pakistan. N = 903.	RCT: A course of CBT therapy administered over 16 home visits in 12 months.	7 years post: 17% less likely depressed; depression severity ↓ 0.18 SD (vs. 61%, 0.66 SD at one year). Financial-empowerment ↑ 0.29 SD, monetary parental investments ↑ 0.28 SD; time investments ↑ 0.2 SD. No effects on parenting style, fertility, or children's development.	The effects are roughly twice as strong for mothers of girls.
Baranov et al. (2020b). Effects of a light-touch gratitude intervention on mental health.	N = 220 residents of Kibera, a large slum outside of Nairobi, Kenya.	RCT: A 16-day course of the "County Your Blessings" protocol, designed to promote gratitude. At endline, some participants also engaged in one-time activities designed to promote self-affirmation and aspirations.	No effect on psychological-well-being index (but gratitude ↑ 0.43 SD); negative but insignificant on sleep-quality, aspirations, beliefs, and intentions. No effects on beliefs/aspirations, and null-to-slightly-detrimental effects for cognitive control. Less likely to return to the administering center.	With the caveat that they are underpowered to analyze heterogeneous effects, authors don't find any subgroups for whom the treatment had beneficial effects on psychological well-being.

Paper / Research question	Data	Methods	Results	Heterogeneity
Barker et al. (2022). Effects of cognitive behavioral therapy on health, economic self-perceptions.	Individuals from poor rural households in Ghana. N = 7,227.	RCT: 12 weekly 90-minute cognitive behavioral therapy group sessions.	CBT → MH-index ↑ 0.15 SD, psychological distress ↓ 6 p.p. (10%), moderate distress ↓ 6 p.p. (20%), severe distress ↓ 4 p.p. (23%), and bad-MH days ↓ 0.53 (10%). Physical-health ↑ 0.13 SD and socio-emotional-skills ↑ 0.27 SD. Economic-self-perception ↑ 0.2 SD, mostly 0.36 SD ↑ expected future economic	Authors emphasize that the program was equally effective in improving mental and physical health for individuals with both low and high baseline mental distress. The economic perception results are more so driven by those with high baseline distress.
Bhat et al. (2022). Long-run effects of psychotherapy on depression, beliefs, and economic outcomes.	Depressed adults in India. N = 775.	RCT: Healthy Activity Program: 6-8 weeks of non-specialist therapy to those with moderate-severe depression. Thinking Healthy Program Peer-Delivered: roughly monthly peer-administered therapy for pregnant women with moderate depression, over 7-12 months.	Pooling the two trials: 4-5 years later, PHQ-9 scores ↓ 0.15 SD mild/moderate depression ↓ 8-11 p.p. (13-33%). 8 p.p. (50%) fewer overconfident assessments of work ability. Self-reported patience ↑ 0.18 SD and altruism ↑ 0.21 SD. No effects on consumption or labor outcomes.	The effects on PHQ-9 scores and incidence of moderate/mild depression are entirely driven by the HAP, with decreases of 0.23 SD decrease in PHQ-9 and 13 p.p. (52%). There don't seem to be any patterns to the within-intervention heterogeneous effects.
Blattman et al. (2017). Effects of cognitive behavioral therapy and cash on criminality in Liberia.	At-risk men 18-35 in Monrovia, Liberia. N = 999.	RCT: Eight weeks of cognitive behavioral therapy cross-randomized with $200 grants.	Two-five weeks post, therapy alone → anti-social-behavior ↓ 0.25 SD (0.31 SD with cash); cash alone: no effect. One year later, only cash + therapy had a significant effect, → anti-social behavior ↓ 0.25 SD. No effects on economic activity, behavioral traits.	The effects were strongest among highest baseline levels of antisocial behavior and lowest levels of self-control and future orientation. (Authors caution this was not part of pre-specified analysis plan.)
Blattman et al. (2023). Long-term effects of cognitive behavioral therapy and cash transfers on anti-social and economic	At-risk men 18-35 in Monrovia, Liberia. N = 999.	RCT: Eight weeks of cognitive behavioral therapy crossrandomized with $200 grants.	10 years post, therapy alone → antisocial-behavior index ↑ (improvement) 0.2 SD, 0.25 SD with cash; no impact for cash only. Cash + therapy → forward-looking time preference ↑ 0.25 SD, mental health ↑ 0.2 SD, and an economic-outcomes index ↑ 0.19 SD.	The main effects only appear, and are stronger, for men who had high levels of anti-social behaviors at baseline.
Breza et al. (2026). Effect of financial incentives, targeting on therapy uptake.	RCT conducted among college students in Chennai, India. N = 340.	Students cross-randomized into treatments that pay them $6 to attend a first therapy session and/or give them feedback on their mental health screening score.	Payments more than double initial outreach for, scheduling of, and attendance of therapy; effect on follow-up appointments insignificant. Feedback on MH score has no overall effect. Payments x feedback triples scheduling, doubles attendance.	Payment effect on outreach larger for asymptomatic patients; scheduling, attendance effect larger for symptomatic. Screening increases outreach for symptomatic patients. Payment x screening no effect for asymptomatic; scheduling ↑ 575%, attendance ↑ 450% for symptomatic.
Carías et al. (2026). The protective effects of CBT.	RCT conducted among prenatally-depressed women in rural Pakistan. N = 431 mothers surveyed during pregnancy and 6 years post, 2014-2020.	Triple-difference: Exploits randomized assignment to an earlier course of psychotherapy (Thinking Healthy Program) together with quasi-random variation in COVID-19 restriction stringency at the time of the year-6 survey.	For each additional Covid restriction, treated women saw 22.4%, 18.7%, and 31.9% decreases in anxiety scores, depressive symptoms, and days with functional difficulties relative to controls. Relative relationship quality also improved. No effect on child outcomes	No heterogeneity analysis reported; the paper's focus is on how treatment effects vary with the intensity of COVID-19 restrictions rather than with baseline patient characteristics.

Paper / Research question	Data	Methods	Results	Heterogeneity
Cronin et al. (2025). Modelling the effects of therapy and causes of its underutilization.	Longitudinal data on mental health treatment and conditions, along with labor supply and earnings, from the Medical Expenditure Panel, 1996-2011. N = 208,113 individual-periods.	Model: Creates a dynamic choice model of patient demand for therapy and antidepressants, incorporating a number of impediments (direct costs, time costs, direct disutility) to utilization. Also models the connection between mental health and earnings.	Significant disutility from both antidepressants and therapy; MH ↑ utility, wages ↓ slightly as it worsens; therapy effects heterogeneous (35% of effects 2x the mean, 35% negative effects). Counterfactual: everyone attends one therapy appt → therapy ↑ 100% and antidepressants ↑ 86% two years later, but only a 4.5% MH ↑; no labor market impact; MH gains offset by time costs, antidepressant side effects. Cutting real, implicit costs of therapy → very small MH effects.	N/A
Cuellar and Dave (2016). Effects of mental health treatment on educational outcomes for criminally-involved youth.	Administrative juvenile justice and school performance records from Washington state. N = 35,020 justice-system-involved youth screened for MH treatment.	RDD: Isolates continuous jumps in outcomes around state-defined risk score cutoffs for eligibility for different treatment programs.	Aggression-replacement (less intense) → null attendance, dropout, GPA. Functional family therapy (more intense) → absentee ↓ 5%, GPA ↓ 2.6%. Multisystemic therapy (most intense) → absentee ↓ 10%, dropout ↓ 35%, GPA null. Agg.-rep., multisystemic → HS-completion ↑.	The effects on dropouts are stronger among those screened when they are older than 17.
Edmonds et al. (2025). Effects of CBT on adolescent's MH and school outcomes.	Data collected from an RCT among adolescents at risk of school dropout in urban and semi-urban Nepal. N = 1,707.	RCT: A 4-6 session course of one-on-one cognitive behavioral therapy, followed by two family sessions.	2 months following the end of treatment, treated adolescents have 0.16 SD lower psychological Distress Index scores. There are no significant effects on school attendance or cognitive outcomes.	Driven by emotional regulation, life perspective. Reductions are greater for those flagged at baseline; still emotional-regulation and life-perspective gains for non-flagged.
Ghosal et al. (2022). The effects of a self-image intervention on behavior and self-regard among sex workers.	Sex workers in Kolkata, India. R = 467.	RCT: 8 weekly sessions designed to foster self-image and economic agency.	Immediately post: 0.83 SD ↓ ashamed of their profession, 1.88 SD ↑ high self-worth. Savings account ↑ 53 p.p. (93%) open right after, ↑ 52 p.p. (58%) 15 months post. 0.3 SD and 0.34 SD likelier to visit doctor at 3 and	Individual's with higher levels of baseline stigma see larger self-image improvements.
Haushofer et al. (2023). The effects of psychotherapy and cash transfers on economic outcomes, psych. well-being.	Low-income households in Ghana. N = 5,756.	RCT: 5 weekly 90-minute 1-on-1 cognitive behavioral therapy sessions, crossrandomized with a large $1,076 (PPP) unconditional cash transfer (in 1 or 5 installments).	Households receiving cash (cash + therapy): monthly consumption ↑ 0.22 SD (null), assets ↑ 0.41 SD (0.35 SD), household revenue ↑ 0.24 SD (0.18 SD), psychological-well-being index ↑ 0.23 SD (0.27 SD), and GHQ-12 ↑ 0.16 SD (insignificant). No significant effects for CBT only.	Cash transfers seem to have a smaller effect for households where women were the primary recipient and which had higher levels of baseline psychological distress.
Heller et al. (2017). Effects of cognitive behavioral therapy on crime, dropout rates.	Data collected from RCTs conducted among high-school age boys in Chicago, 2009-2011. N = 7497 across three studies.	RCT: Becoming a Man (BAM): 27 one-hour, once-a-week group CBT sessions over one (wave 1) or two (wave 2, 52) academic years. Juvenile Temporary Detention Center (JTDC): twice-daily group CBT sessions within a juvenile correction center.	One yr BAM → school engagement ↑ 0.14 SD (treatment year) and 0.19 SD (follow-up year). Two yrs: null yr 1, ↑ 0.1 SD yr 2. One (2) yr(s) of BAM → total, violent, "other" arrest ↓ 35%, 50%, and 43%. One yr → on-time grad. ↑ 19%. JTDC: readmission ↓ 21% 18 months later.	N/A

Paper / Research question	Data	Methods	Results	Heterogeneity
Lund et al. (2024). Meta analysis: effects of MH on labor market outcomes in low-/mid-income countries.	Meta-analysis (no primary dataset).	Meta-analysis of mental-health-treatment effects on labor-market outcomes.	On average, treating common mental disorders (e.g., depression) with psychotherapy raises a labor-market aggregate index by 0.16 SD. Treating severe disorders (e.g., schizophrenia) raises it by	N/A
Moya et al. (2024). Effect of caregiver mental health on early childhood development.	Cluster-RCT in Tumaco, Colombia (conflict-affected). N = 1,376 caregivers (714 treatment, 662 control) across 18 childcare centers, 4 cohorts (2018-2019).	CRCT: 15-session weekly psychosocial program for caregivers based on Child-Parent Psychotherapy, randomized across childcare centers for children 2-5.	8 mo: caregiver-MH ↑ 0.17 SD; caregiver interaction, and style ↑ 0.31, 0.15 SD; child MH ↑ 0.10 SD (marginal); child development ↑ 0.23 SD (all ITT). ATT for 8+ sessions: caregiver MH ↑ 0.32 SD, relationship quality ↑ 0.59 SD, development ↑ 0.46 SD. Effects grow over time.	Stronger effects for displaced caregivers and caregivers with worse baseline mental health.
Nilsson and Pougué Biyong (2025). Effects of hairdressers' active listening on mental health.	Data collected from an RCT conducted among the clients of a sample of hairdressers in Abidjan, Côte d'Ivoire. N = 73 hairdresser, N = 378 clients.	RCT: Hairdressers were randomized into a 3-day training to be mental health ambassadors.	18 mo later: talking about private matters with clients ↑ 112%, discussing difficulties ↑ 129%, positive interactions ↑ 176%. But no significant effects on clients perceptions or MH. Hairdressers 326% likelier to report own MH problems at 6 mo.	Authors find no evidence of significant heterogeneous effects.
Oparina et al. (2026). Effects of CBT and wait times in the UK.	Administrative session-by-session data for all patients who started treatment in the U.K.'s IAPT universal mental healthcare program, 2016-2018. N = 1,246,792 patients.	DiD: Compares outcomes for patients who receive therapy to other patients who receive an initial assessment for a similar condition around the same time but have not yet received therapy.	Treatment → odds of recovery ↑ 43 p.p. (82%), odds of improvement ↑ 37 p.p. (50%), and odds of deterioration ↓ 8 p.p. (140%). Reported day to day social and work-related impairment due to mental health ↓. No overall effect on employment, but initially unemployed see ↑.	Effects are of treatment are weaker for those with higher baseline severity of illness, people with long-term health conditions, non-White-British patients, and those from more deprived areas.
Orkin et al. (forthcoming). Effects of a simple psychological intervention to increase aspirations.	Data collected from an RCT among a sample of women living in poverty in rural Kenya. N = 8,300 women, with randomization across 415 villages.	RCT: Cross-randomizes a one-time, 80-minute workshop designed to increase women's aspirations with one-time $2,237 PPP cash transfers.	Workshop: aspirations ↑ 0.09 SD, future-expectations ↑ 0.09 SD; no effects on self-belief, planning, "grit," null MH index. Labor supply ↑ 5%, home-production inputs ↑ 27%, revenue ↑ 12%, non-land assets ↑ 6%, savings ↑ 22%, shift toward investment. Cash alone: larger (2-3x) effects; cash + workshop resembled cash alone.	The main effects do not vary with baseline wealth, baseline psychological indices, age, education, household size, or marital status.
Roth et al. (2026). Effects of depression stigma on health-seeking.	RCT among 1,844 U.S. adults recruited via Prolific in fall 2022 with PHQ8 depression scores of 10 or higher and no prior therapy experience.	RCT: Respondents randomized into three groups: a) receive survey data on depression stigma incidence b) guess incidence of stigma c) no information.	83% of respondents overestimated incidence of stigma. Interventions a) and b) decrease WTP for MH treatment by a similar amount (little information effect). Follow-ups show thinking about stigma increases positivity about own MH.	The WTP decline is concentrated among participants who had overestimated stigma at baseline and among the most severely depressed; participants who had underestimated stigma raise WTP once corrected.

Paper / Research question	Data	Methods	Results	Heterogeneity
Sevim et al. (2024). Effects of a mental health intervention for new mothers.	Data collected from an RCT among a sample of pregnant women in rural Punjab, Pakistan. N = 1,154.	RCT: Randomizes pregnant women in 20 out of 40 villages into 32 sessions of cognitive behavioral therapy split between a one-on-one and group therapy setting, running from the third trimester of pregnancy until the child is 3 years old.	At 6, 12, and 36 months post → maternal-MH ↑ 0.17-0.27 SD, maternal functioning ↑ 0.18-0.29 SD, largest at 36 months, consistent for stress more/less severe depression. Parental-investment index insignificant. For children, null on cognition, short-term socio-emotional gain (0.19-0.39 SD); fades by 36	For the maternal outcomes, the effects are stronger for mothers of boys. There is no heterogeneity by birth order, socioeconomic status, mother's education, and baseline depression.
Shah et al. (2024). Effects of life-skills programming on adolescent mental health.	Data collected from an RCT among 10-19-year-old girls in Tanzania, Bangladesh, and Ethiopia. N = 4,532.	RCT: Randomizes two-session goal-setting activity (Tanzania), an eight-week growth-mindset program cross-randomized with a female-empowerment program (Bangladesh), a 10-month weekly goal-setting/life-skills program cross-randomized with cash (Ethiopia).	Tanzania: goal-setting → depression ↑ 8.6 p.p. for girls not in life-skills clubs, ↓ 11 p.p. for members. Bangladesh: no MH impact alone or combined; growth mindset ↑ socio-emotional development, locus of control, driving MH-index ↑. Ethiopia life-skills → depression index ↑ (improvement) 0.113 SD, resilience, locus of control ↑; insignificant in arm that also got cash.	In Bangladesh and Ethiopia, MH impacts are larger for wealthier girls. Little heterogeneity by enrollment, gender norms, baseline MH, or mother's presence; exceptions: Bangladesh's female-empowerment program is more effective under more restrictive gender norms and negative under less restrictive ones.
Panel B: Drugs				
Albertini et al. (2025). Effects of benzodiazepine receipt, evidence from provider propensities.	Administrative data from Statistics Netherlands, matching individuals across GP records, insurance claims, a medication use database, and tax and employment rolls. N = 76,407 patients.	DiD: Within neighborhoods, residents quasi-randomly assigned to PCPs with different benzodiazepine-prescribing propensities. Compares outcomes before vs. after across patients with lower- vs. higher-propensity PCPs who experience a relative's death.	10th → 90th-percentile-propensity PCP → benzodiazepine Rx after relative's death ↑ 1 p.p. (12.2%), lasting 6 years; red-flag Rx ↑ 0.5 p.p., lasting 3 years. Higher-propensity providers → income ↓ from year 2, peaking at ~4%. MH nurses at PCP practices cut benzo., income effects ~50%.	The effects on both prescriptions and labor-market outcomes seem to be driven by patients under 50. The effects on benzodiazepine use are stronger for women (still significant for men), but decreases in secondary health care utilization and labor market effects are present only for men.
Angelucci and Bennett (2024). Effects of antidepressants, career coaching on depression symptoms and earnings.	Data collected from RCT in India. N = 1,000 depressed adults.	RCT: Cross-randomizes pharmacotherapy and "livelihoods assistance" (employment and finances counseling).	Pharmacotherapy + livelihoods assistance → PHQ-9 ↓ 0.24 points (1.6%) 26 months post. Neither had significant effect alone. No arm significantly affected work time, earnings, or parental investments.	Depressive symptoms fall more for those with worse physical health and more adverse childhood shocks. Parental investments in children over 12 ↑ 0.4 SD.
Bhalotra et al. (2026b). Effects of childhood antidepressant receipt on long-term outcomes.	Population-level Danish administrative data, including health care utilization and educational/labor market outcomes. N = 7,211 children with a first psychiatric visit between 8-15.	IV: Instruments for a child's receipt of AD using their psychiatrist's propensity to prescribe ADs.	For MH patients, AD use at 8-15 → math and Danish scores at 16 ↑ 0.52 SD and 0.4 SD. In 3 months after AD receipt, self-harm ED visits ↓ 2.9 p.p. (96.7%), null on overall/inpatient visits. 42.8% likelier enrolled in education at 18. At 25-30, employment ↑ 47.2 p.p. (100.6%), welfare receipt ↓ 31.2 p.p. (123%); earnings ↑.	No test-score differences by gender. Low-SES children see larger math gains; girls and low-SES children larger self-harm effects. Schooling effects vary little by SES/gender, though girls and high-SES children shift toward academic track, boys and low-SES toward vocational. Labor effects stronger for men and low-SES.

Paper / Research question	Data	Methods	Results	Heterogeneity
Biasi et al. (2027, forthcoming). Labor market effects of the rollout of lithium.	Administrative health and administrative data from Denmark 1995-2015. N = 2,692,479 people, N=~23,000 with BD.	Triple-Diff: Compares labor outcomes for people with BD vs. other MH conditions, relative to healthy siblings, across birth cohorts with vs. without lithium access at 20.	Lithium at 20 → odds of zero earnings ↓ 22%. No significant change for people with dep., anx., schizophrenia. BD earnings penalty, conditional on some earnings, ↓ 20%; odds of receiving disability ↓ 38%. No effect on college graduation.	No heterogeneity by gender, though BD more common, and more costly, for women. BD penalties, and treatment effects, greater for lower-SES, those with more severe cases.
Bütikofer et al. (2020). Employment effects of a FDA warning label on antidepressants.	National Survey on Drug Use and Health, 2005-2008. N = 74,576.	DiD: Uses the 2007 FDA black-box antidepressant warning for under-24s, comparing individuals with vs. without a major depressive episode.	The warning label had no aggregate employment effects, except among women 35-49, for whom employment fell 4.4 p.p. (6.1%). Those women also saw reported antidepressant use fall 7.6 p.p. (19%).	Effects only appear among women 35-49.
Chorniy (2025). Effects of ADHD medication for children.	A 60% random sample of South Carolina Medicaid enrollees, 1998-2015, linked to school and juvenile justice records. N = 52,263 whose ADHD diagnosis is identified in the data.	IV: Uses a leave-one out measure of provider's propensity to prescribe ADHD drugs an instrument for a child's receipt of those drugs.	Injury ↓ 5.7%, substance abuse ↓ 25.3%, teen pregnancy ↓ 40.3%, STDs ↓ 10.3%, arrests ↓ 11.1%, dep./anx. diagnosis ↓ 24.5%; autism diagnosis ↓ 100%. Null on grade repetition; school days missed ↓ 8.3%. Math/English HS exams↓.	Effects are more pronounced for girls; null effects on most boys' health/behavioral outcomes; HS-test-score effect concentrates among girls. Among linkable siblings, few spillovers onto non-ADHD siblings' test scores or grade progression.
Chorniy and Kitashima (2016). Effects of ADHD drugs on teen risky behaviors.	South Carolina Medicaid claims 2003-2013. N = 58,685 people.	IV: instruments for ADHD medication receipt using provider propensity to prescribe.	For children with ADHD, receiving pharmacological treatment reduces the likelihood of being treated for an STD by 3.6 p.p. (28%), the likelihood of being treated for a substance abuse disorder by 7.3 p.p., and injuries by 2.3 p.p. per year.	Treatment is more effective for older than younger cohorts, perhaps because the average ADHD case is now milder due to increased diagnosis.
Cuddy and Currie (2026). Effects of prescribing practices on adolescent health outcomes.	Blue Cross Blue Shield claims data 2012-2018. N = 45,223 children with a first anxiety or depression contact.	IV: Uses Lasso-selected, ZCTA-level measures of provider mental health practice style to instrument for receipt of drugs that are FDA approved, gray-area (non-FDA, but consistent with professional guidelines), or red-flag (neither).	Vs. children treated for anxiety/depression without drugs, FDA-approved, gray-area, and red-flag drugs → self-harm probability: -34%, -13% and +2%; on facility use -8%, -40%, and +18.5%; on medical costs +75%, -94%, and +72.8%.	No discussion of heterogeneity, but all children are privately insured so the sample is overly homogeneous relative to all children.
Currie and Zwiers (JHR 2023). Effects of postpartum antidepressant prescriptions on MH and labor market	Dutch administrative health data, 2008-2016. N = 420,000 first births.	IV: instruments for receipt of anti-depressants postpartum using local providers' propensities to prescribe to the non-childbearing 46-65 y/o age group.	Postpartum antidepressant → probability still taking 11-20 mo later ↑ 60.9 p.p. (2175%), rising to 68.7 p.p. (2290%) at 21-30 months. Probability income > 0 ↓ 82.1 p.p. (90%) 1 yr, not after. Null on MH-service use, earnings, fertility, marriage.	The employment effects are driven by women in the bottom 75% of the income distribution.
Masiero et al. (forthcoming). MH effects of a surge in swiss AD prescribing.	Private data on antidepressant sales and administrative hospital admissions data, aggregated to the region-year level, 2003-2014. N = 1,272.	IV: uses modified shift-share instrument based on company-level growth in anti-depressant sales, assigned to regions based on companies' non-pharmaceutical market shares.	A one-unit ↑ in antidepressant doses per 1,000 inhabitants/year → MH-disorder hospital admissions ↑ 2%; depression-specific admissions ↑ 6.5%. No effect on suicides.	The effects on hospital admissions for depression are stronger for teenagers (8%) and smaller for the elderly (5%).