Mental Healthcare Facilities and Mortality: Evidence from Local Access and Insurance Expansion

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Abstract

Do mental health treatment facilities save lives? Despite rising mental health mortality and substantial policy investments, causal evidence remains absent. Using County Business Patterns data and within-county variation from 1999-2016, I provide the first evidence that each additional facility reduces mental and behavioral disorder mortality by 0.079%, with a 10% increase in facilities lowering mortality by 2%. Three key findings emerge: (1) facility closures increase mortality ten times more than openings reduce it, revealing profound market asymmetries; (2) Medicaid expansion amplifies facility effectiveness by 26% in high-uninsurance counties, demonstrating insurance-infrastructure complementarity; (3) facilities operate through multiple mechanisms, serving as gateways to disability programs and prescription access. Effects are largest for the elderly and less-educated populations. The Sun and Abraham (2021) heterogeneity-robust estimates confirm immediate, persistent mortality reductions with no pre-trends. Results indicate that coordinated policies addressing both insurance coverage and treatment infrastructure are essential for reducing mental health mortality.

JEL Classifications: H51, I10, I12, I13, I18, J24, R12

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1 Introduction

Mental health disorders have emerged as one of the most pressing public health challenges of our time, yet we know surprisingly little about whether expanding treatment infrastructure can prevent deaths. Between 1999 and 2016, deaths from mental and behavioral disorders in the United States increased fivefold, from 30,000 to over 120,000 annually, even as the number of mental health treatment facilities grew by 50 percent. This paradox raises a fundamental question: does local access to mental health treatment facilities save lives, or are we witnessing a failure of healthcare infrastructure to address a deepening crisis?

This paper provides the first causal evidence that mental health treatment facilities substantially reduce mortality, with effects that are amplified when combined with insurance coverage expansions. Using establishment-level data from County Business Patterns spanning 1999-2016, I exploit within-county variation in mental health facilities to identify their impact on mortality from mental and behavioral disorders (MBD). Each additional facility reduces MBD mortality by 0.079 percent, representing a 0.25 percent decline relative to the pre-treatment mean. These estimates indicate that a 10 percent increase in facilities lowers a county's MBD mortality rate by 2 percent. The effects are immediate, persistent, and concentrated among the most vulnerable populations: elderly individuals, those with less education, and residents of high-uninsurance areas.

The economic stakes are enormous. Mental health disorders cost the global economy 4 percent of GDP annually, approximately $2 trillion, with projections suggesting these costs will double by 2030 (Bloom et al., 2012; Chisholm et al., 2016). In the United States alone, productivity losses exceed $193 billion annually through multiple economic channels (WHO, 2021; Ettner et al., 1997; Currie et al., 2024). Mental illness reduces labor productivity by lowering the marginal product of labor: affected workers experience reduced concentration, increased absenteeism, and impaired decision-making. The wage rate penalty compounds these effects, with depressed earnings reflecting both reduced hours worked and lower hourly productivity. Labor market frictions further amplify welfare losses as mental health conditions increase job turnover, extend unemployment spells, and create matching inefficiencies. Perhaps most critically, untreated mental illness generates deadweight losses from the underutilization of human capital. Talented individuals unable to reach their productive potential represent a permanent loss to economic output.[1]

While research has examined healthcare facility closures broadly (Buchmueller et al., 2006; Freedman et al., 2023; Gujral and Basu, 2019; Carroll, 2019) and substance abuse treatment specifically (Swensen, 2015; Bondurant et al., 2018; Corredor-Waldron and Currie, 2022; Bastiaans et al., 2024), no study has

[1] Recent evidence suggests these economic costs are accelerating. Post-pandemic analyses found that mental health-related work absences increased 40 percent, while disability claims for mental health conditions rose 30 percent among prime-age workers.

causally linked mental health treatment facilities to MBD outcomes. The existing literature consistently shows that geographic barriers to healthcare access significantly impact utilization and health outcomes (Currie et al., 2023; Bradford and Maclean, 2023; Bailey and Goodman-Bacon, 2015), with particularly pronounced effects among vulnerable populations. My analysis extends these frameworks to mental health infrastructure, building on methodological innovations in analyzing establishment-level variation in healthcare services (Messel et al., 2023; Deza et al., 2022a, 2023).

My analysis reveals three key findings that reshape our understanding of mental health treatment effectiveness and extend multiple strands of the health economics literature. First, I document profound asymmetries in how facilities affect mortality: closures increase deaths by 0.124 per 100,000 residents while openings reduce deaths by only 0.013 per 100,000 in the full specification, a tenfold difference. This asymmetry, the first documented in mental healthcare markets, aligns with recent evidence from Corredor-Waldron and Currie (2022) on hospital closures but reveals even larger magnitudes. The pattern suggests that maintaining existing infrastructure may be more crucial than geographic expansion, as facility closures disrupt established therapeutic relationships that cannot be quickly rebuilt elsewhere (Frank, 2006; Mojtabai et al., 2011).

Second, I provide novel evidence that insurance expansion and treatment facilities are strong complements in reducing mortality, contributing to the growing literature on healthcare access and insurance interactions (Finkelstein, 2007; Miller, 2012; Sommers et al., 2013, 2016). Exploiting quasi-experimental variation from Medicaid expansion under the Affordable Care Act, I implement a triple-difference design interacting facility access with state expansion decisions and baseline county uninsurance rates. This is the first study to examine how insurance expansion modifies the relationship between mental health infrastructure and mortality. In high-uninsurance counties, Medicaid expansion amplifies the mortality-reducing effect of facilities by an additional 0.081 deaths per 100,000 residents, a 26 percent increase in effectiveness. This complementarity reveals that neither insurance nor infrastructure alone maximizes health benefits. Coordinated policies addressing both dimensions are essential, consistent with theoretical predictions about healthcare market equilibrium (Acemoglu and Finkelstein, 2008; Clemens and Gottlieb, 2014).

Third, I uncover important mechanisms through which facilities reduce mortality beyond direct treatment provision, advancing our understanding of mental healthcare production functions (Grossman, 1972; Frank and McGuire, 2000; Dave and Mukerjee, 2011). Mental health facilities serve as gateways to broader support systems, increasing disability program participation by 1.4 percent per facility by providing the diagnostic documentation necessary for benefit determination (Messel et al., 2023; Maestas et al., 2013; Deshpande, 2016). In states that expanded Medicaid, facilities in areas with high uninsured populations generate 280 additional antidepressant prescriptions per 100,000 residents, suggesting that insurance unlocks latent demand for pharmacological treatment (Olfson et al., 2014; Wang et al., 2009; Blazer, 2003). These mechanisms, documented here for the first time in an integrated framework, help explain why facility effects extend beyond mental health-specific mortality to reduce all-cause deaths by 1.55 per 100,000 residents (Walker et al., 2015; Druss et al., 2011; Colton and Rodin, 2009).

My empirical strategy advances the methodological frontier in several ways, building on recent innovations in healthcare access research (Swensen, 2015; Bondurant et al., 2018; Deza et al., 2022a; Bradford and Maclean, 2023; Fischer et al., 2024; Alexander and Richards, 2023). The baseline difference-in-differences approach leverages within-county variation in facility counts over time, controlling for county and state-by-year fixed effects to account for time-invariant local characteristics and state policy changes. To address concerns about heterogeneous treatment effects in staggered adoption settings (Goodman-Bacon, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021), I implement the Sun and Abraham (2021) interaction-weighted estimator, the first application of this method to mental health infrastructure. The event study results reveal no pre-trends and show immediate, persistent mortality reductions following facility openings, with effects of 1.3 to 1.8 deaths prevented per 100,000 residents, representing up to a 50.5 percent reduction relative to pre-treatment means.

The validity of these estimates is supported by multiple robustness checks that address key identification concerns raised in the healthcare access literature (Buchmueller et al., 2006; Bailey and Goodman-Bacon, 2015; Chatterji et al., 2024). I find no effects on placebo outcomes unrelated to mental health, such as transport accidents or surgical complications, confirming that results capture mental health-specific impacts rather than broader healthcare trends. To validate that facility counts represent real treatment capacity, I show that each facility increases mental health employment by 3 percent, approximately 8 to 10 workers, including psychiatrists, psychologists, social workers, and support staff. This employment response, documented using the imputed data from Eckert et al. (2020), provides the first evidence that mental health facility counts in administrative data correspond to meaningful expansions in treatment resources, addressing measurement concerns raised by Finkelstein (2007); Chay and Greenstone (2005).

The heterogeneous effects I document reveal important disparities in who benefits from expanded access, extending the healthcare disparities literature (Currie et al., 2023; Gupta et al., 2024; Fadlon et al., 2025; Honberg et al., 2011). Effects are particularly pronounced for organic mental disorders, with mortality reductions 50 percent larger than for other conditions. Elderly populations experience the strongest benefits, consistent with their higher baseline mortality risk and greater barriers to traveling for care (Bailey and Goodman-Bacon, 2015; Currie et al., 2024). Less-educated individuals experience twice the mortality reduction of those with a college education, suggesting that geographic proximity particularly matters for populations with limited resources to overcome distance barriers (Deza et al., 2022a; Simpson et al., 2022; Barker et al., 2022). These patterns demonstrate that mental health treatment exhibits even stronger proximity gradients than general medical care.

This research makes several contributions to our understanding of mental healthcare markets and policy. First, it provides the first causal evidence linking mental health treatment infrastructure to population mortality, filling a critical gap given that prior work focused on either general healthcare (Buchmueller et al., 2006; Gujral and Basu, 2019) or substance abuse treatment (Swensen, 2015; Bondurant et al., 2018). Second, it documents previously unknown complementarities between insurance coverage and treatment infrastructure, with immediate relevance for ongoing debates about Medicaid expansion and mental health parity (Lang, 2013; Dave and Mukerjee, 2011; Maclean and Saloner, 2019; Popovici et al., 2017). Third, it reveals fundamental asymmetries in mental healthcare markets that challenge standard economic models assuming symmetric adjustment costs (Corredor-Waldron and Currie, 2022; Cummings et al., 2017).

The policy implications are profound and timely. My results suggest that facility closures should be prevented at almost any reasonable cost, as the mortality consequences far exceed what symmetric models would predict. The complementarity between insurance and infrastructure implies that states with expanded Medicaid should prioritize mental health facility development to maximize mortality benefits. At the same time, areas without coverage expansion may see limited returns from infrastructure investments alone. The gateway effects on disability programs and prescription access suggest that mental health facilities generate positive fiscal externalities that partial equilibrium analyses miss (Messel et al., 2023).

2 Background

2.1 Mental Health Crisis and Mental Behavioral Disorder Mortality

The United States faces an unprecedented crisis in mental health outcomes, characterized by a striking empirical puzzle. Despite significant expansion in treatment infrastructure, deaths from mental and behavioral disorders (MBD) have risen dramatically. Between 1999 and 2016, annual MBD deaths increased nearly fivefold from approximately 30,000 to over 120,000 (Figure 1). This surge in mortality has occurred even as the number of mental health treatment facilities grew from 12,000 to over 18,000 (Figure 2).[2]

This apparent disconnect between expanding treatment capacity and deteriorating health outcomes suggests potential mismatches in both the geographic distribution of mental health services and insurance coverage for accessing them. While national trends show infrastructure growth, significant local variation exists in facility access. Figure 3a reveals substantial heterogeneity across counties, with some areas experiencing facility closures despite the overall upward trend. This pattern aligns with Buchmueller et al. (2006)'s finding that local access to healthcare facilities critically influences both utilization and

[2]These statistics are derived from International Classification of Diseases (ICD-10) codes specifically referencing mental and behavioral disorder deaths. According to the National Institute of Mental Health, mental illness affects approximately one in five U.S. adults, with mortality consequences extending beyond direct mental health causes to include excess deaths from suicide, substance abuse, and comorbid physical conditions (Walker et al., 2015; Druss et al., 2011).

outcomes, particularly when combined with adequate insurance coverage.

2.2 Geographic Access, Insurance Coverage, and Treatment Utilization

The distribution of mental health facilities shows substantial geographic and temporal variation that interacts critically with insurance coverage patterns. The average U.S. county has 5.3 facilities per 100,000 residents (Table 1), but this masks considerable heterogeneity: rural counties average 2.1 facilities per 100,000 while urban counties average 7.8. This variation creates a unique setting for studying how treatment availability affects health outcomes, particularly when combined with insurance expansions that remove financial barriers to care.

The demographic pattern of MBD deaths indicates potential mismatches between service availability, insurance coverage, and population needs. While individuals aged 65 and older experience the highest mortality rates (26.51 per 100,000), working-age adults face significant barriers to both treatment access and insurance coverage. Prior to the ACA, approximately 20 percent of adults with mental illness were uninsured, with rates exceeding 30 percent in some states (Grooms and Ortega, 2019). These disparities reflect differences in both physical access to facilities and financial ability to utilize available services.

2.3 Treatment Delivery and Insurance Market Interactions

Mental health treatment in the United States operates through a complex network of outpatient and residential facilities whose effectiveness depends critically on patients' ability to pay for services. Treatment episodes typically include diagnostic assessment, medication management, psychotherapy, and support services. Most care (90 percent) occurs in outpatient settings, where the availability of insurance coverage determines treatment intensity and duration.[3]

The complementarity between physical infrastructure and insurance coverage creates important policy implications. Sommers et al. (2016) find that Medicaid expansion increased mental health treatment utilization by 25 percent in areas with adequate facility capacity but had minimal effects in underserved areas. This suggests that neither insurance expansion nor facility development alone maximizes health benefits; coordinated policies addressing both dimensions of access are necessary for improving population mental health outcomes.

[3] According to SAMHSA (2020), insured patients receive 2.5 times more outpatient mental health visits than uninsured patients, even when facilities are geographically accessible. The ACA's essential health benefits provisions specifically require coverage for mental health and substance abuse services at parity with medical care.

2.4 Mental Health Treatment Infrastructure and Employment

The mental health treatment sector has evolved significantly since the era of deinstitutionalization, shifting toward community-based care delivery (Frank, 2006). This transition produced substantial variation in facility locations over time, with distinct waves of openings and closures across counties. Importantly, these facility changes represent real expansions in treatment capacity: each additional facility increases mental health employment by approximately 3 percent, translating to 8 to 10 additional mental health workers including psychiatrists, psychologists, social workers, and support staff (Eckert et al., 2020).[4]

The industry's structure exhibits important features that influence service provision. Treatment facilities are predominantly privately owned (87 percent), split between non-profit (60 percent) and for-profit (27 percent) organizations, with public facilities comprising the remaining 13 percent. The Affordable Care Act's Medicaid expansion fundamentally altered this financing landscape by providing comprehensive mental health coverage to millions of previously uninsured Americans (Glied and Frank, 2016), though capacity constraints remain a significant barrier to care delivery even with expanded insurance coverage.

2.5 Policy Environment: From Parity Laws to the Affordable Care Act

The policy landscape for mental health has undergone a dramatic transformation, shifting from state-level parity laws to comprehensive federal reform under the Affordable Care Act. While earlier state parity legislation studied by Popovici et al. (2017); Lang (2013) attempted to equalize coverage between mental and physical health services, implementation varied widely, and many individuals remained uninsured. The ACA fundamentally restructured mental health access through two mechanisms: Medicaid expansion, which extended coverage to adults below 138 percent of the federal poverty level, and essential health benefits requirements mandating mental health coverage in all insurance plans.

The staggered implementation of Medicaid expansion across states, following the Supreme Court's 2012 ruling making expansion optional, creates quasi-experimental variation for identifying policy effects. By 2016, 31 states had expanded Medicaid, with expansion particularly benefiting individuals with mental illness who previously faced both geographic and financial barriers to treatment (Maclean and Saloner, 2019). Evidence from early expansion states suggests that insurance coverage amplifies the mortality-reducing effects of mental health facilities, with the largest benefits in counties with high pre-expansion uninsurance rates.

[4] Following Swensen (2015) and Bondurant et al. (2018), this variation provides identification for estimating causal effects while accounting for underlying mental health trends. The employment response validates that facility counts capture meaningful changes in treatment capacity rather than administrative reorganizations.

2.6 Economic Implications and Asymmetric Market Dynamics

The economic impact of mental health treatment access extends far beyond direct treatment costs. Mental health disorders reduce economic output through four primary channels. First, reduced labor productivity manifests as workers with mental health conditions experience lower marginal product of labor, with studies indicating productivity losses of 20 to 40 percent (Ettner et al., 1997). Second, wage rate penalties create a vicious cycle where mental health conditions depress earnings through both reduced work hours and lower hourly wages. Third, labor market frictions compound these losses as mental health conditions increase job separation rates and extend unemployment duration. Fourth, the deadweight loss from the underutilization of human capital represents a permanent reduction in economic potential when talented individuals cannot access treatment.

Market failures in mental health treatment provision necessitate careful policy design. The asymmetric effects of facility openings versus closures, with closures causing mortality increases ten times larger than the reductions from openings, indicate substantial adjustment frictions and the importance of maintaining existing infrastructure. Mental health facilities also serve as gateways to social safety nets, with each additional facility increasing disability program participation by connecting individuals to necessary diagnostic and documentation services (Messel et al., 2023). These market imperfections, amplified by the complementarity between insurance and infrastructure, provide an economic rationale for coordinated public intervention addressing both dimensions of access.

3 Conceptual Framework

Figure 5 presents the conceptual framework guiding this analysis. The framework builds on the Grossman (1972) model of health production but extends it to incorporate unique features of mental healthcare markets: the complementarity between physical infrastructure and insurance coverage, asymmetric adjustment costs, and multiple pathways through which facilities affect mortality.

3.1 Primary Pathway and Insurance Complementarity

Panel A illustrates the primary mechanism through which mental health facilities reduce mortality. Facilities improve treatment access, which directly reduces mental and behavioral disorder mortality. However, this relationship is critically moderated by insurance coverage. The complementarity between facilities and insurance operates through two channels. First, insurance removes financial barriers that prevent individuals from utilizing geographically accessible facilities. Second, insured patients receive more intensive treatment, with evidence showing 2.5 times more outpatient visits than uninsured patients even when facilities are available.

This complementarity is not merely additive but multiplicative. My empirical results confirm that Medicaid expansion amplifies facility effectiveness by 26 percent in high-uninsurance counties. Neither insurance without nearby facilities nor facilities without insurance coverage maximizes health benefits. This finding challenges traditional approaches that treat infrastructure and insurance as separate policy levers, suggesting instead that coordinated interventions are essential for improving population mental health.

3.2 Asymmetric Market Dynamics

Panel B depicts the striking asymmetry in how facility changes affect mortality. While facility openings produce modest mortality reductions, facility closures generate mortality increases that are ten times larger. This asymmetry arises from fundamental differences in how markets adjust to entry versus exit.

When facilities open, individuals gain an additional treatment option but may continue with existing providers or self-care strategies. The marginal benefit depends on the quality differential between the new facility and existing alternatives. In contrast, facility closures force immediate disruption for all existing patients. Established therapeutic relationships, often developed over years, cannot be instantly replicated. The search costs for finding and establishing care with new providers are particularly high for individuals with mental illness, who may struggle with the cognitive and emotional demands of navigating healthcare systems while symptomatic.

This asymmetry has profound policy implications. Standard cost-benefit analyses that assume symmetric effects would substantially underestimate the welfare losses from closures while overstating the benefits of geographic expansion. My results suggest that preventing closures in areas with existing coverage should take priority over opening new facilities in already-served markets.

3.3 Key Mechanisms

Panel C identifies three mechanisms through which facilities affect mortality beyond direct treatment provision. First, facilities serve as gateways to disability programs, with each additional facility increasing SSI/SSDI participation by 1.4 percent. Mental health providers supply the diagnostic documentation and longitudinal treatment records required for successful disability applications. For individuals with severe mental illness, this gateway function connects them to income support and Medicare/Medicaid coverage that may be life-saving.

Second, facilities enable prescription access, particularly when combined with insurance coverage. In Medicaid expansion states, facilities in high-uninsurance areas generate 280 additional antidepressant prescriptions per 100,000 residents. This mechanism is especially important for elderly populations managing complex medication regimens and for conditions where pharmacological treatment significantly reduces mortality risk.

Third, the employment validation mechanism confirms that facility counts represent real treatment capacity. Each facility increases mental health employment by 3 percent, translating to 8-10 additional workers including psychiatrists, psychologists, social workers, and support staff. This first-stage relationship validates that administrative facility counts correspond to meaningful healthcare resources rather than empty establishments.

3.4 Implications for Policy and Research

This conceptual framework advances our understanding of mental healthcare markets in several ways. It demonstrates that mental health facilities are not simply production units converting inputs to health outputs, but complex organizations embedded in insurance systems and social support networks. The framework's emphasis on complementarities and asymmetries provides a richer foundation for policy design than traditional models assuming additive effects and symmetric adjustments.

The framework generates testable predictions that my empirical analysis confirms: facilities should increase employment if they represent real capacity; insurance expansion should amplify facility effects if complementarity exists; and closures should have larger effects than openings if adjustment costs are asymmetric. The validation of these predictions strengthens confidence in the framework and its policy implications.

4 Data

4.1 County Business Patterns

I measure access to mental health treatment using establishment counts from the U.S. Census Bureau's County Business Patterns (CBP). The CBP data are derived from annual tax returns submitted to the Internal Revenue Service (IRS) and capture nearly all establishments operating during the week of March 12th each year. These data have been extensively used in recent economic research to study the effects of healthcare access (Deza et al., 2022a,b; Swensen, 2015; Bondurant et al., 2018).

Following the literature, I identify mental health treatment facilities using North American Industry Classification System (NAICS) codes. Specifically, I include establishments classified under NAICS codes

621112 (offices of physicians, mental health specialists) and 621330 (offices of mental health practitioners except physicians). Each establishment represents a single physical location where mental healthcare services are provided, and establishments can only be assigned one NAICS code.

While these establishments primarily focus on mental healthcare, they may also provide substance use disorder (SUD) treatment services. This comprehensive classification allows me to capture the full spectrum of mental health treatment facilities available in each county. Consistent with previous studies (Swensen, 2015; Bondurant et al., 2018), I lag facility counts by one year in my regression analyses to account for the time required for facility establishment, patient access, and potential improvements in mental health outcomes.

My analytical sample includes 53,498 county-year observations spanning 1999 to 2016. This extensive coverage enables me to examine how changes in local access to mental health treatment facilities affect mortality outcomes while controlling for time-invariant county characteristics and common temporal shocks that might influence both facility location decisions and mortality patterns.

4.2 Mental Health Employment Data

To establish the relationship between facility openings and actual healthcare provision, I utilize employment data from the County Business Patterns following the imputation methodology developed by Eckert et al. (2020). The CBP employment data present unique challenges as the majority of county-industry cells have suppressed values to protect establishment confidentiality. Eckert et al. (2020) address this limitation through a linear programming method that exploits the hierarchical adding-up constraints implicit in the data structure to impute missing employment values.[5]

For my analysis, I extract employment data for mental health establishments using NAICS codes 621112 and 621330, consistent with my facility count measures. These employment figures capture the lower bound of full-time and part-time employees working in mental health treatment facilities during the payroll period that includes March 12th of each year. The employment data serve as my first-stage outcome, allowing me to verify that facility openings translate into increased mental healthcare capacity as measured by sectoral employment. This validation is crucial for establishing that changes in facility counts represent meaningful expansions in treatment availability rather than merely administrative changes or establishment reorganizations.

[5] Eckert et al. (2020) develop a comprehensive imputation procedure that leverages the nested structure of industry classifications and geographic aggregations in the CBP data. Their method ensures that imputed values satisfy all disclosed totals and subtotals while minimizing deviations from observed patterns.

4.3 Vital Statistics Mortality Data

My outcome of interest is the mortality rate from mental and behavioral disorders (MBD), which I measure using restricted-access Multiple Cause of Death data files from the National Center for Health Statistics (NCHS) for the period 1999 to 2016. These data capture all recorded deaths in the United States and provide detailed geographic identifiers at the county level, allowing me to track mortality patterns across space and time.

I examine deaths attributed to eight distinct diagnostic categories defined by the International Classification of Diseases, 10th Revision (ICD-10): organic mental disorders (F00-F09), substance use disorders (F10-F19), schizophrenia and psychotic disorders (F20-F29), mood disorders (F30-F39), anxiety disorders (F40-F48), behavioral syndromes (F50-F59), personality disorders (F60-F69), and intellectual disabilities (F70-F79). I also construct an aggregate measure of total MBD mortality to estimate the overall impact on mental health-related deaths.[6]

To construct my dependent variables, I aggregate death counts at the county-year level and normalize them by county population (per 100,000 residents), using annual population estimates from the U.S. Census Bureau. This normalization ensures that my mortality rates are comparable across counties of different sizes and over time, which is crucial for identifying the causal effects of interest.

4.4 Medicare Part D Prescription Data

To examine mechanisms through which access to mental health facilities affects outcomes, I incorporate Medicare Part D prescription drug data from 2013 to 2016. These administrative data, provided by the Centers for Medicare and Medicaid Services (CMS), contain comprehensive information on prescription drug claims for Medicare beneficiaries, covering approximately 70 percent of all Medicare enrollees during this period (Centers for Medicare & Medicaid Services, 2023).

I focus on prescriptions for nine major antidepressant medications that account for the vast majority of depression treatment in the United States: sertraline, escitalopram, trazodone, bupropion, fluoxetine, citalopram, duloxetine, venlafaxine, and amitriptyline. These medications span multiple pharmacological classes, including selective serotonin reuptake inhibitors (SSRIs), serotonin-norepinephrine reuptake inhibitors (SNRIs), and tricyclic antidepressants, representing both first-line and adjunctive treatments for depression and anxiety disorders (Cipriani et al., 2018).

The Medicare Part D data are aggregated to the state-year level to ensure sufficient statistical power while

[6]Classification includes dementia in Alzheimer's disease (F00*) and dementia in other diseases classified elsewhere (F02*), based on ICD-10 Chapter V: Mental and Behavioral Disorders (World Health Organization, 2019).
Mental and Behavioural Disorders (ICD-10 Section V)

maintaining geographic variation. I construct my prescription access measure as the total number of antidepressant claims per state-year, which provides a direct measure of realized access to pharmacological mental health treatment. This outcome complements my mortality analysis by capturing an intermediate mechanism through which facility expansion may improve mental health outcomes. The prescription data are particularly valuable as they reflect actual treatment utilization rather than merely potential access, allowing me to trace the causal chain from facility availability through treatment uptake to ultimate health outcomes.

4.5 Additional Data Sources

I use data from several sources to account for differences between counties that experience changes in mental health treatment facility access and those that do not. I gather time-varying county-level information from the National Institute for Health Surveillance (SEER) (Surveillance, Epidemiology, and End Results , SEER) and the Regional Economic Information System (REIS) (Bureau of Economic Analysis, BEA). I obtain data on personal income from REIS, including per capita net earnings, welfare receipts, and employment to population ratios, to capture each county's economic conditions that might influence both mental health outcomes and facility locations. SEER provides population counts by age group, which is crucial for controlling for demographic factors that could affect mental health treatment needs and mortality patterns. I also use the 1993 rural-urban continuum codes from the U.S. Department of Agriculture to identify rural and urban counties, as access to mental health facilities may vary systematically with urbanization levels.

To examine heterogeneous treatment effects by insurance coverage, I incorporate county-level health insurance data from the Small Area Health Insurance Estimates (SAHIE) program administered by the U.S. Census Bureau (U.S. Census Bureau, 2021). The SAHIE provides model-based estimates of health insurance coverage for all counties, utilizing data from the American Community Survey, administrative records, and demographic information to produce reliable estimates even for areas with small populations. I use the 2013 baseline uninsurance rates to capture pre-Affordable Care Act variation in insurance coverage across counties. This baseline measure is particularly valuable as it reflects longstanding differences in healthcare access that predate both Medicaid expansion and the individual mandate, allowing me to identify counties where expanded mental health treatment facilities might have the greatest impact due to previously limited access to care.

To examine heterogeneous treatment effects and policy interactions, I incorporate information on state Medicaid expansion decisions under the Affordable Care Act. Following Carey et al. (2020), I classify states based on their expansion status and timing, creating indicators for states that expanded Medicaid between 2014 and 2016. This policy variation allows me to explore whether the effects of mental health facility access differ based on the insurance coverage environment, as Medicaid expansion substantially increased coverage for mental health and substance abuse treatment services (Maclean and Saloner, 2019). The combination of baseline uninsurance rates and Medicaid expansion timing creates rich variation that helps identify how insurance access modulates the relationship between treatment facility availability and health outcomes.

4.6 Analytical Sample Construction

My analytical sample includes 48 U.S. states from 1999 to 2016. I measure treatment availability using the number of mental health treatment facilities in each county year. I identify these facilities using the North American Industry Classification System (NAICS) codes 621420 (Outpatient Mental Health and Substance Abuse Centers) and 623220 (Residential Mental Health and Substance Abuse Facilities).

To ensure clean identification of treatment effects, I exclude counties in Alaska and Hawaii, as well as those with inconsistent identifiers. I also dropped counties that never reported any mental health treatment facilities during the sample period, as these counties do not contribute to identifying the treatment effect. The final sample consists of 53,498 county-year observations spanning 1999 to 2016.

My main treatment variable is the number of mental health treatment facilities in county c in year t. For each county-year observation, I measure treatment intensity based on the total count of facilities with the relevant NAICS codes. Since my empirical specification controls for population, this measure can be interpreted as per capita access to mental health treatment facilities.

For my triple-difference analyses examining insurance coverage heterogeneity, I classify counties based on their 2013 baseline uninsurance rates from SAHIE. Within each state, I calculate the median uninsurance rate and create an indicator for counties above this threshold. This within-state comparison ensures that I am comparing counties facing similar state-level policies and healthcare markets but differing in their baseline insurance coverage gaps. The resulting classification yields 2,440 counties with sufficient data for the heterogeneity analysis, balanced across high and low uninsurance categories within states.

For mechanism analyses using Medicare Part D data, I construct a state-year panel covering 2013 to 2016, yielding 144 state-year observations across 36 states that expanded Medicaid during this period. This subsample allows me to examine how insurance expansion interacts with facility availability to affect prescription drug utilization, providing evidence on the complementarity between treatment infrastructure and insurance coverage in improving mental health outcomes. The combination of facility counts, baseline uninsurance rates, and Medicaid expansion timing creates a rich empirical setting to disentangle the effects of treatment availability from insurance access while examining their interaction effects on mental health outcomes and mortality.

5 Methods

5.1 Empirical Strategy

I exploit within-county variation in mental health treatment facility presence to identify their effect on mortality outcomes. This approach builds on established research examining the health effects of treatment access (Swensen, 2015; Bondurant et al., 2018).[7] The empirical strategy leverages temporal within-county variation from facility openings and closings while accounting for time-invariant county characteristics and aggregate shocks.

5.2 Baseline Specification

My baseline specification estimates the relationship between mental health treatment facilities and MBD mortality using a two-way fixed effects (TWFE) model:

$$\text{Mental Behavorial Disorder Mortality}_{ct} = \alpha_c + \eta_t + \beta \text{Mental Health Treatment Facilities}_{c,t-1} + \varepsilon_{ct} \quad (1)$$

where $\text{Mental Behavioral Disorder Mortality}_{ct}$ represents the mortality rate from mental and behavioral disorders per 100,000 residents in county c in year t. The main explanatory variable, $\text{Mental Health Treatment Facilities}_{c,t-1}$ allowing for delayed mortality responses to changes in treatment access.[8] This measures the number of mental health treatment facilities in county c in year $t-1$. The model includes county fixed effects (α_c) to absorb time-invariant county characteristics that might correlate with both facility locations and mortality outcomes, such as persistent differences in healthcare and year-fixed effects (η_t) to control for common temporal shocks. Standard errors are clustered at the county level to account for serial correlation in outcomes within counties over time.

5.3 Extended Specification with County-Level Controls

To account for potential confounding from state-specific policy changes, local economic conditions and time-varying county characteristics, I extend the baseline model:

[7] This identification strategy has been effectively employed in related healthcare contexts. Swensen (2015) uses it to study substance abuse treatment facilities, while Bondurant et al. (2018) examines access to drug treatment.

[8] The one-year lag structure follows Swensen (2015) and helps mitigate potential simultaneity bias between facility locations and current-period health outcomes.

$$\text{Mental Behavioral Disorder Mortality}_{ct} = \alpha_c + \gamma_{st} + \beta\text{Mental Health Treatment Facilities}_{c,t-1} + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \quad (2)$$

State-by-year fixed effects (γ_{st}) absorb time-varying state-level factors like Medicaid expansion or mental health parity laws that could affect both treatment access and mortality outcomes. The vector $\mathbf{X}_{ct}$ includes county-year varying controls for demographic composition and economic conditions that might independently influence mental health outcomes.[9]

5.4 First-Stage Validation: Facilities and Healthcare Employment

A fundamental concern in interpreting facility counts as meaningful changes in healthcare access is whether these establishments represent actual increases in mental healthcare resources rather than administrative reorganizations or empty storefronts. To validate that facility openings translate into expanded treatment capacity, I estimate the relationship between mental health facilities and sectoral employment:

$$\ln(\text{MH Employment per 100k})_{ct} = \alpha_c + \gamma_{st} + \delta\text{Mental Health Facilities}_{ct} + \mathbf{X}'_{ct}\phi + \nu_{ct} \quad (3)$$

where $\ln(\text{MH Employment per 100k})_{ct}$ represents the natural log of mental health employment per 100,000 residents in county c and year t, constructed using the imputed County Business Patterns data from Eckert et al. (2020).[10] This specification parallels the mortality analysis but uses contemporaneous facility counts since employment adjustments should occur immediately upon facility opening, unlike health outcomes which require time to manifest.[11]

The first-stage analysis serves three critical functions in the research design. First, it validates that the facility measure captures real changes in healthcare provision capacity rather than merely counting administrative entities. Second, it provides a quantitative benchmark for the magnitude of treatment expansion

[9] Demographic controls from SEER include population shares by age groups, race/ethnicity, and gender. Economic indicators from BLS and CBP capture local business conditions that could affect both healthcare access and mental health.

[10] The log transformation addresses the skewed distribution of employment across counties while preserving zeros through the $\ln(x+1)$ transformation. The coefficient δ can be interpreted as the percentage change in employment from one additional facility, scaled by 100 for log models.

[11] Mental health employment in these facilities encompasses a diverse workforce essential for comprehensive treatment delivery. This includes psychiatrists who provide medical management and psychopharmacology (Olfson et al., 2014; Glied and Frank, 2016), clinical psychologists offering psychotherapy and psychological assessments (Norcross and Karpiak, 2017). These psychiatric nurse practitioners increasingly serve as primary prescribers particularly in underserved areas (Phoenix, 2019). These licensed clinical social workers provide the majority of mental health services in the United States (Heisler et al., 2022), mental health counselors specializing in various therapeutic modalities (Hill, 2007), psychiatric nurses managing inpatient and intensive outpatient care (Ameel et al., 2019), peer support specialists who improve treatment engagement and recovery outcomes (Zuccarini and Stiller, 2024), and administrative staff coordinating care and insurance authorization (Cutler et al., 2010). The employment measure thus captures the full complement of personnel required for mental health facilities to deliver effective treatment, from direct clinical care to essential support services.

represented by each additional facility. Third, it strengthens the causal interpretation by demonstrating that the mechanism operates through increased healthcare resources, consistent with standard models of healthcare production (Grossman, 1972; Acemoglu and Finkelstein, 2008; Finkelstein, 2007).

For the event study framework, I extend the first-stage analysis to examine dynamic employment responses:

$$\ln(\text{MH Employment per 100k})_{ct} = \alpha_c + \eta_t + \sum_{k=-5,k\neq-1}^{2} \delta_k \mathbf{1}[\text{Years Since Opening} = k]_{ct} + \mathbf{X}'_{ct}\phi + \nu_{ct} \tag{4}$$

This specification traces employment changes around facility openings, where $k = 0$ represents the opening year and $k = -1$ serves as the omitted reference category. The pre-treatment coefficients ($k < 0$) test for anticipatory hiring or differential trends, while post-treatment coefficients ($k \geq 0$) reveal the persistence of employment effects.[12]

5.5 Event Study Analysis

To strengthen the causal interpretation of my results, I complement the TWFE analysis with an event study framework that examines the dynamic effects of changes in mental health treatment access. The event study specification is:

$$\text{Mental Behavioral Disorder Mortality}_{ct} = \alpha_c + \eta_t + \gamma_{st} + \sum_{k=-5,k\neq-1}^{5} \beta_k \,\text{Mental Health Treatment Facilities}_{c,t-k} + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{5}$$

where the coefficients β_k trace out the temporal path of mortality responses to changes in mental health treatment access relative to the year before a facility opens (k = -1), which serves as the baseline period. This specification serves two key purposes. First, it allows me to assess whether mortality trends differ between counties that experience changes in facility access and those that do not prior to facility openings, providing a test of the parallel trends assumption underlying my main specification. Second, it reveals the dynamic pattern of treatment effects, showing how mortality responses evolve in the years following changes in facility access.

The event study approach advances the baseline TWFE model by providing a richer understanding of treatment effect dynamics. By examining effects up to four years before and after changes in facility

[12]Following Jacobson et al. (1993) and Autor et al. (2007), examining employment dynamics provides insights into both the timing of resource expansions and potential adjustment frictions in healthcare labor markets.

access, I can evaluate both the immediate impact of mental health treatment facilities and any adaptation in mortality responses over time. Importantly, this specification also helps address potential concerns about anticipatory effects or delayed responses that might not be captured in the baseline model.

The event study sample is restricted to two specific county groups. Following Messel et al. (2023) treatment counties experience exactly one increase in mental health establishments, with no decreases over the study period. Control counties maintain the same number of mental health establishments throughout, experiencing no changes. This clear distinction between treatment and control counties helps establish a clean comparison for analyzing the causal effects of changes in mental health facility availability.[13]

5.6 Identification and Threats to Validity

Following Deza et al. (2022a), the identifying assumption of Equation 2 can be expressed as:

$$Cov(\text{Mental Health Treatment Facilities}_{c,t-1}, \varepsilon_{ct} | \mathbf{X}_{ct}, \alpha_c, \gamma_{st}) = 0 \tag{7}$$

The number of mental health facilities per county is uncorrelated with the error term after conditioning on county-level characteristics, county fixed-effects, and state-by-year fixed-effects. While this specification addresses several potential confounders, I discuss key threats to identification and empirical strategies to address them.

A primary threat is reverse causality: changes in mental health and behavioral disorders could drive changes in facility openings through demand-side effects. Healthcare providers might strategically locate in areas experiencing increasing MBD prevalence.[14] I address this by lagging the facility measure by one year, which helps mitigate simultaneous feedback effects. The first-stage employment results provide additional evidence against pure demand-driven explanations, as immediate employment responses suggest supply-side expansions rather than gradual demand accumulation.

A second threat to validity is that changes in both mental health facilities and MBD rates could be responding to unobserved time-varying county-level factors. For instance, counties experiencing economic

[13] I also estimate a contemporaneous event study specification:

$$\text{Mental Behavioral Disorder Mortality}ct = \alpha_c + \eta_t + \gamma_{st} + \sum_{k=-5, k\neq -1}^{5} \beta_k, \text{Mental Health Treatment Facilities}_{c,t+k} + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{6}$$

where the key difference from the main specification is that facilities are now measured at time $t+k$ rather than $t-k$, allowing me to examine both anticipatory effects ($k<0$) and contemporaneous impacts (k ≥ 0). This complements the main lagged specification by testing for potential anticipatory responses to facility changes. Following Malani and Reif (2015) and Angrist and Pischke (2009), examining both contemporaneous and lagged effects provides a more complete picture of the treatment dynamics.

[14] Similar concerns have been raised in studies of healthcare access. See Shannon et al. (1986) and Bailey and Goodman-Bacon (2015).

growth might simultaneously see increases in healthcare infrastructure and changes in mental health outcomes through various channels (e.g., stress levels, substance use, or access to insurance). The rich set of time-varying controls $\mathbf{X}_{ct}$ partially addresses this concern by accounting for observable economic and demographic shifts.[15]

The inclusion of state-by-year fixed effects γ_{st} addresses concerns about state-level policy changes that might affect both facility operations and mental health outcomes, such as Medicaid expansion, insurance mandates, or changes in licensing requirements. These fixed effects flexibly absorb any state-specific shocks or policy changes that could confound our relationship of interest.

Finally, I note that the county-level analysis captures the relevant geographic market for mental healthcare services, as evidence suggests that most individuals seek mental health treatment within their county of residence (Schmitt et al., 2003; Lindrooth et al., 2006). This helps ensure that the facility measure appropriately captures meaningful variation in access to mental healthcare.

5.7 Summary Statistics

Table 1 presents summary statistics for mental health treatment facilities and mental health-related mortality across U.S. counties from 1999-2016. The average county has approximately 53 mental health treatment facilities, with a net opening rate of 0.35 and a net closing rate of 0.24. When normalized by population, counties average 5.16 facilities per 100,000 residents.

Mental and behavioral disorder (MBD) deaths per 100,000 population exhibit stark demographic patterns. The elderly population (ages 65+) experiences substantially higher mortality rates at 26.51, while younger age groups show markedly lower rates: 0.03 for those under 19, 0.27 for ages 20-34, 0.99 for ages 35-49, and 1.63 for ages 50-64. The overall MBD death rate averages 29.42 across all groups.

Racial differences are notable in the data, with White populations showing an average MBD death rate of 26.49, compared to 2.50 for Black populations and 0.42 for other racial groups. The sample encompasses 3,022 counties, resulting in 60,418 county-year observations over the study period.

[15] Following Dave et al. (2021), I include comprehensive economic indicators to capture local market conditions that might influence both healthcare provision and mental health outcomes.

6 Results

6.1 First-Stage Evidence: Facilities and Healthcare Employment

Before examining mortality outcomes, I first validate that mental health facility counts represent meaningful expansions in treatment capacity rather than administrative reorganizations. Table A2 presents estimates from Equation 3, examining the relationship between facility counts and mental health employment.

The results provide strong evidence that facilities translate into real healthcare resources. Column 1 shows that each additional mental health facility increases sectoral employment by 3.35 percent in the baseline specification with county and year fixed effects. This effect remains stable across increasingly demanding specifications. Adding state-by-year fixed effects (Column 2) leaves the estimate unchanged, while incorporating demographic controls (Column 3) yields a coefficient of 2.94 percent. The full specification with economic controls (Column 4) produces an estimate of 2.90 percent, statistically significant at the 1 percent level across all specifications.

Figure 6 presents the dynamic employment response around facility openings. The event study reveals no pre-treatment trends in employment, supporting the exogeneity of facility timing. Employment increases sharply at the time of facility opening, with effects persisting through the post-treatment period. The immediate employment response validates that facility openings represent actual expansions in treatment capacity, with the average facility increasing mental health employment by approximately 3 percent, translating to roughly 8-10 additional mental health workers per facility based on average establishment sizes in the sector.[16]

6.2 Main Results: Mental Health Facilities and MBD Mortality

Having established that facilities represent real treatment capacity, I now examine their effect on mortality from mental and behavioral disorders. Table 2 presents the baseline estimates across diagnostic categories. An additional mental health facility reduces overall MBD mortality by 0.066 percent (Column 1), with this effect remaining robust at 0.061 percent when examining specific diagnostic subcategories (Column 2). The mortality reductions are particularly pronounced for organic mental disorders (F00-F09) and schizophrenia/psychotic disorders (F20-F29), conditions where timely treatment and medication management are especially critical for preventing fatal outcomes.

[16] The employment elasticity of approximately 0.03 aligns with industry reports suggesting that outpatient mental health facilities employ 8-15 workers on average, while residential facilities employ 20-30 workers (U.S. Bureau of Labor Statistics, 2022). The persistence of employment effects indicates these are permanent expansions rather than temporary staffing adjustments.

Table 3 examines the robustness of these findings across specifications. The baseline two-way fixed effects model yields a 0.066 percent reduction in MBD mortality per additional facility. This effect remains stable at 0.064 percent when adding state-by-year fixed effects to account for state-level policy changes. The preferred specification with full demographic and economic controls produces the strongest effect, showing a 0.079 percent reduction in MBD mortality. All estimates are precisely estimated with standard errors clustered at the county level.

The economic magnitude of these effects is substantial. At the sample mean of 30.9 MBD deaths per 100,000 population, the preferred estimate implies that each additional facility prevents approximately 0.024 deaths per 100,000 residents annually. For the average county with 100,000 residents, this translates to one life saved every four years per facility.

6.3 Spillover Effects on Overall Mortality

Mental health conditions often contribute to mortality through multiple pathways beyond direct mental health causes, including suicide, substance abuse complications, and exacerbation of physical health conditions (Walker et al., 2015; Druss et al., 2011). To capture these broader health impacts, Table 4 examines the effect of mental health facilities on all-cause mortality.

The results reveal substantial spillover benefits. Column 1 shows that an additional mental health facility reduces overall mortality by 1.73 deaths per 100,000 population in the baseline specification. This effect grows to 1.56 deaths per 100,000 when adding state-by-year fixed effects (Column 2) and demographic controls (Column 3). The full specification (Column 4) yields a reduction of 1.55 deaths per 100,000, significant at the 1 percent level.

Notably, the overall mortality reduction (1.55 deaths per 100,000) is substantially larger than the MBD-specific reduction (0.024 deaths per 100,000), indicating that mental health treatment prevents approximately 65 non-MBD deaths for every MBD death prevented. This ratio aligns with evidence that untreated mental illness contributes to premature mortality through reduced adherence to medical treatment, increased risk-taking behaviors, and physiological stress responses that exacerbate cardiovascular and other chronic conditions (Colton and Rodin, 2009; Matthews et al., 2018). These spillover effects underscore that mental health treatment infrastructure represents a critical component of the broader public health system.

6.4 Dynamic Effects: Evidence from Event Studies

To examine the temporal evolution of treatment effects and validate the parallel trends assumption, I implement the heterogeneity-robust event study approach of Sun and Abraham (2021). This methodology addresses potential biases in traditional two-way fixed effects models when treatment timing varies and effects are heterogeneous across cohorts.

Figure 7 presents the results. Panel 7a shows the lagged specification where facilities affect mortality with a one-year delay, while Panel 7b presents contemporaneous effects. Both specifications reveal no differential trends in the pre-treatment period, with coefficients statistically indistinguishable from zero for $t < 0$. This absence of pre-trends supports the identifying assumption that facility openings are not endogenously timed to coincide with mortality changes.

Following facility entry, mortality reductions emerge immediately and persist over time. The lagged specification yields a cumulative treatment effect of 1.8 deaths per 100,000 population by year five, representing a 50.5 percent reduction relative to the pre-treatment mean. The contemporaneous specification shows similar immediate impacts with modest attenuation over time. The persistence of effects suggests that mental health facilities provide sustained benefits through ongoing treatment relationships rather than merely addressing acute crises.

Table A5 presents the corresponding regression estimates, confirming that the visual patterns are statistically significant. The average treatment effect across all post-treatment periods is -1.3 to -1.8 deaths per 100,000 residents, substantially larger than the traditional TWFE estimates. This difference highlights the importance of accounting for treatment effect heterogeneity, as the TWFE estimator can underweight periods with larger treatment effects when timing varies across units.[17]. The Sun and Abraham (2021) estimator avoids these issues by using only clean comparisons between treated and not-yet-treated units.

6.5 Robustness

I conduct several analyses to validate the causal interpretation of my main findings. First, as shown in Table 3, the estimated effects are robust to increasingly demanding specifications. The impact remains stable and statistically significant when progressively adding state-by-year fixed effects and socioeconomic controls, with the full specification indicating a 0.079% reduction in MBD mortality per additional facility.

The event study analysis in Figure A2 provides two crucial robustness checks. Panel (a) augments the baseline specification with lagged mortality rates to account for pre-existing trends in health outcomes.

[17]The traditional TWFE event study results, presented in Appendix Figure A1, show qualitatively similar patterns but smaller magnitudes, consistent with the negative weighting problem identified by Goodman-Bacon (2021)

Panel (b) includes lagged controls for mental health establishments to address potential dynamic selection in facility placement. Both specifications maintain the core controls from my primary event study analysis: county and year fixed-effects, state-by-year fixed effects, and demographic and economic characteristics. Across both specifications, I observe no significant pre-trends in the years preceding facility changes, while the treatment effects emerge sharply after facility establishment and persist over time. The parallel patterns across both specifications with lagged outcome controls (Panel A) and lagged establishment controls (Panel B) provide strong support for my identification strategy.

A key concern is that mental health facility locations might correlate with broader healthcare infrastructure. For instance, hospitals might be substitutable for mental health treatment facilities. To address this, Table A7 presents estimates that explicitly control for hospital establishments. The results remain stable: an additional mental health facility reduces MBD mortality by 0.079% (Column 1), nearly identical to my baseline estimates. This robustness extends to diagnostic subcategories, with particularly strong effects for organic mental disorders (F00-F09). Importantly, controlling for general healthcare access does not meaningfully alter my conclusions, suggesting that mental health facilities have distinct effects beyond overall healthcare infrastructure.

Finally, to rule out that my findings reflect broader local health trends or changes in mortality reporting, I examine other causes of death that should be unrelated to mental health treatment access. In Table A8, I investigate the effects on three placebo outcomes: non-mental-health-related deaths, transport accidents, and deaths from medical/surgical care. The estimates are small in magnitude and statistically insignificant across all outcomes. These null effects on unrelated mortality measures, combined with the hospital control analysis and event studies, strongly support a causal interpretation of our main results rather than a spurious correlation with broader mortality trends or healthcare changes.

6.6 Heterogeneous Effects

While the average effects documented above provide evidence that mental health treatment facilities reduce mortality, these effects may vary systematically across population subgroups. Understanding such heterogeneity is crucial for both identifying vulnerable populations and informing targeted policy interventions. In this section, I examine how the effects of mental health treatment facilities vary across facility types, age groups, education levels, race, and gender.

Table 7 examines heterogeneity by facility type, revealing meaningful differences in treatment effectiveness. Outpatient mental health facilities (Panel A) yield consistently larger and more precisely estimated reductions in MBD mortality than residential facilities (Panel B). Specifically, an additional outpatient facility reduces MBD mortality by 0.126 deaths per 100,000 population (0.4% of the pre-treatment mean) in the preferred specification with full controls. In contrast, the effect of residential facilities is smaller

(-0.090 deaths per 100,000) and only marginally significant. This pattern suggests that the accessibility advantages of outpatient care lower barriers to entry, greater geographic distribution, and fewer disruptions to patients' daily lives may enhance treatment efficacy. The larger impact of outpatient facilities aligns with evidence that continuity of care and community integration improve mental health outcomes (Drake et al., 2001; Fortney et al., 2011).

Table 8 presents estimates of facility effects across age groups. The results reveal meaningful heterogeneity, with particularly pronounced effects among elderly populations. An additional facility reduces MBD mortality by 0.27% for individuals over 65, compared to the average impact of 0.26% across all ages. This heightened response among older adults aligns with their greater baseline vulnerability to mental health conditions and potentially greater sensitivity to geographic access barriers. Interestingly, while effects are modest and statistically insignificant for those under 19, they become progressively larger and more precisely estimated through middle age. This suggests that facility access may be especially valuable for working-age adults who face time constraints in seeking treatment.

The effects also vary substantially by educational attainment. As shown in Table 9, the mortality reduction from an additional facility is most pronounced among those with a high school education or less, where each facility reduces MBD mortality by 0.43%. In contrast, the effect for those with some college education is both smaller in magnitude (0.08%) and statistically insignificant. This pattern suggests that geographic access barriers may be particularly binding for less-educated populations, perhaps due to more limited transportation options or lower awareness of alternative treatment locations.

Examining heterogeneity by race in Table 10 reveals another dimension of variation in treatment facility effects. While the impact is significant and negative for White populations (-0.35%), the estimates for Black populations, though similar in magnitude, are less precisely estimated. This imprecision may reflect both the smaller sample sizes for minority populations and potentially greater variation in facility quality or accessibility across predominantly minority communities. Finally, Table 11 explores differences in facility effects by gender. The estimates indicate remarkably similar percentage impacts on male (-0.26%) and female (-0.25%) mortality rates despite well-documented differences in mental health treatment-seeking behavior across genders. This symmetry suggests that geographic access may be an equally important determinant of treatment utilization for both men and women, even if their baseline propensities to seek care differ.

These heterogeneity patterns suggest that the benefits of expanded mental health treatment access are not uniformly distributed across the population. The particularly large effects among elderly and less-educated populations highlight how geographic access barriers may interact with other dimensions of healthcare disparities. These findings have important implications for targeting mental health infrastructure investments, suggesting potential returns to prioritizing facility expansion in areas with larger elderly and lower-education populations.

6.7 Asymmetric Responses to Facility Changes

The heterogeneous effects documented above reveal how treatment facilities' impact varies across population subgroups. A related but distinct question is whether the effects themselves vary with the direction of change in facility access. Understanding such asymmetries is crucial for policy, as the welfare implications of facility closures may not simply mirror those of facility openings.

Table 5 presents estimates that separately identify the effects of facility openings and closings on mortality. The results reveal striking asymmetries that have important implications for mental health policy. Panel A examines the effect of facility openings. The baseline specification shows that adding a treatment facility reduces MBD mortality by 0.088 deaths per 100,000 residents, though this effect is imprecisely estimated. As controls are added, the magnitude diminishes slightly to 0.059 deaths in Column 2 and 0.058 deaths in Column 3. The full specification with state-by-year fixed effects and all controls (Column 4) yields a negligible and statistically insignificant effect of -0.013 deaths per 100,000.

In sharp contrast, Panel B reveals that facility closures have devastating consequences for population health. The loss of a mental health facility increases MBD mortality by 0.115 deaths per 100,000 residents in the baseline specification, with this effect significant at the 1 percent level. The magnitude remains remarkably stable across specifications: 0.104 deaths when adding controls (Column 2), 0.105 deaths with demographic controls (Column 3), and 0.124 deaths in the full specification (Column 4). All closure effects are precisely estimated with p-values below 0.05.

The asymmetry between openings and closures is both statistically and economically significant. The formal test for asymmetry reported at the bottom of the table decisively rejects the null hypothesis that opening and closing effects are equal in magnitude ($p < 0.05$). The closing effect is approximately ten times larger than the opening effect in the full specification, suggesting profound adjustment frictions in mental healthcare markets.

Figure 8 provides dynamic evidence of these asymmetric effects using the Sun and Abraham (2021) heterogeneity-robust estimator. Panel (a) shows that facility openings have modest, statistically insignificant effects on mortality that remain close to zero throughout the post-treatment period. In contrast, Panel (b) reveals that facility closures lead to immediate and persistent mortality increases, with effects reaching 1.5 deaths per 100,000 by year 2 post-closure. The event study confirms no pre-trends for either openings or closures, validating the causal interpretation of these asymmetric effects.

This asymmetric response aligns with recent evidence from Corredor-Waldron and Currie (2022) on hospital closures and extends their findings to mental healthcare settings. The pattern suggests several mechanisms may be at work. First, when facilities close, existing patients face immediate disruption to established treatment relationships, which are particularly crucial for managing chronic mental health conditions (Glied and Frank, 2016). The therapeutic alliance between patient and provider, developed over months or years, cannot be instantly replicated elsewhere. Second, the search costs of finding alternative providers may be prohibitive for individuals already struggling with mental illness, leading to treatment discontinuation rather than substitution (Mojtabai et al., 2011).

The asymmetry is particularly concerning given the vulnerability of the populations most affected by facility changes. Our earlier heterogeneity analysis identified elderly and less-educated individuals as experiencing the largest mortality reductions from facility access. These same populations likely face the highest costs when transitioning to new providers, including transportation barriers, difficulty navigating insurance networks, and challenges establishing care with providers who may have long wait times for new patients (Cummings et al., 2017).

7 Insurance Expansion, Mental Health Treatment Access, and Mortality

While my county-level analysis establishes that mental health treatment facilities reduce mortality from mental and behavioral disorders, an important question remains: how do insurance coverage expansions affect this mortality-reducing impact of treatment infrastructure? This section examines whether Medicaid expansion under the Affordable Care Act amplifies the life-saving effects of mental health facilities, providing evidence on critical complementarities between insurance access and treatment availability in preventing deaths from mental and behavioral disorders.

7.1 Medicaid Expansion Background

The Affordable Care Act's Medicaid expansion, implemented beginning in January 2014, represents one of the largest insurance coverage expansions in U.S. history. The expansion extended eligibility to all adults with incomes below 138 percent of the federal poverty level, regardless of family status or disability status (Sommers et al., 2013; Wherry and Miller, 2016). Crucially for mental health mortality, the expansion included comprehensive coverage for mental health and substance abuse treatment as essential health benefits, with strong parity provisions ensuring coverage comparable to physical health services (Glied and Frank, 2016; Beronio et al., 2014). This comprehensive mental health coverage is particularly important given that untreated mental illness is a leading cause of preventable death through suicide, substance abuse complications, and chronic disease interactions (Walker et al., 2015; Colton and Rodin, 2009).

However, the Supreme Court's 2012 decision in *National Federation of Independent Business v. Sebelius* made expansion optional for states, creating substantial variation in implementation timing. As illustrated in Figure 4, by 2016, 31 states and the District of Columbia had expanded Medicaid, while 19 states had not. Table A12 details the expansion timing, with most expansion states implementing in January 2014, though several states expanded later, including Pennsylvania (January 2015), Indiana (February 2015), Alaska (September 2015), Montana (January 2016), and Louisiana (July 2016).[18]

This staggered implementation creates plausibly exogenous variation in insurance coverage that I exploit to examine how expanded insurance access affects the mortality-reducing impact of mental health treatment infrastructure. The expansion is particularly relevant for preventing mental health-related deaths given the high rates of uninsurance among individuals with mental illness prior to the ACA and evidence that insurance coverage improves mental health treatment utilization and reduces mortality (Guth et al., 2020; Ortega, 2023; Sommers et al., 2013).

7.2 Triple-Difference Identification Strategy

To identify how insurance expansion affects the relationship between mental health facilities and mortality, I implement a triple-difference (DDD) specification that exploits three sources of variation: (1) within-county changes in mental health facilities over time, (2) state-level variation in Medicaid expansion decisions, and (3) cross-sectional variation in baseline uninsurance rates that determines treatment intensity. This approach allows me to test whether insurance expansion enhances the mortality-reducing effects of mental health facilities by removing financial barriers to accessing available treatment.

The baseline DDD specification takes the form:

$$\begin{aligned}\text{MBD Mortality}_{ct} = {} & \beta_0(\text{MH Facilities}_{c,t-1} \times \text{Post-Expansion}_{st}) \\ & + \beta_1(\text{MH Facilities}_{c,t-1} \times \text{High Uninsured}_c) \\ & + \beta_2(\text{MH Facilities}_{c,t-1} \times \text{Post-Expansion}_{st} \times \text{High Uninsured}_c) \\ & + \mathbf{X}'_{ct}\theta + \alpha_c + \gamma_{st} + \varepsilon_{ct} \end{aligned} \tag{8}$$

Where $\text{MBD Mortality}_{ct}$ represents mental and behavioral disorder deaths per 100,000 residents, $\text{MH Facilities}_{c,t-1}$ is the lagged count of mental health treatment facilities, $\text{Post-Expansion}_{st}$ indicates post-2014 periods in states that expanded Medicaid, and High Uninsured_c indicates counties with above-median baseline uninsurance rates within their state.[19]

[18]Early expansion states that expanded under Section 1115 waivers before 2014 are coded as expansion states throughout the sample period, following Wherry and Miller (2016). These include California, Connecticut, Delaware, Massachusetts, Minnesota, New Jersey, New York, Vermont, and Washington, plus the District of Columbia.

[19]Using within-state variation in uninsurance rates ensures comparisons between counties facing similar state policies and

β_0 captures the effect of mental health facilities on mortality in expansion states after Medicaid implementation, averaging across all counties regardless of baseline uninsurance. This coefficient identifies the overall impact of facilities when insurance coverage has been expanded. β_1 identifies heterogeneity in the facility-mortality relationship by baseline uninsurance rates, pooling across expansion and non-expansion states. This tests whether facilities are more effective in areas with historically limited insurance access.

β_2 is the coefficient of primary interest, capturing the additional mortality reduction from mental health facilities in high-uninsurance counties within expansion states after Medicaid implementation. A negative coefficient indicates that the life-saving effects of mental health facilities are amplified when combined with expanded insurance coverage in areas with the greatest coverage gaps. This complementarity could arise through multiple channels: insurance enables individuals to afford treatment at existing facilities, reduces delays in seeking care that could prove fatal, and facilitates ongoing treatment adherence crucial for managing chronic mental health conditions (Baicker et al., 2014; Wherry et al., 2018).

The specification includes county fixed effects (α_c) and state-by-year fixed effects (γ_{st}), ensuring identification comes from within-county variation in facilities interacted with policy-induced insurance changes. The vector $\mathbf{X}_{ct}$ includes time-varying demographic and economic controls. Standard errors are clustered at the state level to account for serial correlation and the state-level nature of the expansion decision (Bertrand et al., 2004; Cameron et al., 2008).

7.3 Event Study Specification

To examine the dynamic evolution of insurance-facility complementarities and test for differential pretrends, I extend the DDD framework to an event study design:

$$\begin{aligned} \text{MBD Mortality}_{ct} = &\sum_{k=-5, k\neq -1}^{1} \delta_k (\text{MH Facilities}_{c,t-1} \times \mathbf{1}[\text{Year} = 2014+k]_t \times \text{Expansion}_{st}) \\ &+ \mathbf{X}'_{ct}\theta + \alpha_c + \gamma_{st} + \varepsilon_{ct} \end{aligned} \tag{9}$$

where $\mathbf{1}[\text{Year} = 2014+k]_t$ indicates year t is k years from 2014, with $k = -1$ (year 2013) as the omitted reference category. The coefficients δ_k trace out how the differential effect of facilities in expansion versus non-expansion states evolves around Medicaid implementation.[20]

healthcare markets. The median split provides a transparent, nonparametric approach that avoids functional form assumptions about the relationship between baseline uninsurance and treatment effects (Finkelstein, 2007; Miller, 2012).

[20] This event study approach follows Goodman-Bacon (2021) and Sun and Abraham (2021) in addressing concerns about heterogeneous treatment effects and negative weighting in two-way fixed effects models with staggered treatment timing.

The pre-treatment coefficients ($k < 0$) provide a test of the identifying assumption that the mortality effects of facilities would have evolved similarly in expansion and non-expansion states absent Medicaid expansion. Statistically insignificant pre-treatment coefficients support this parallel trends assumption. The post-treatment coefficients ($k \geq 0$) reveal whether the complementarity between insurance and facilities in preventing deaths emerges immediately or strengthens over time as newly insured individuals establish care relationships and receive consistent treatment for previously untreated conditions.

7.4 Identifying Assumptions and Robustness

The DDD identification strategy relies on three key assumptions. First, in the absence of Medicaid expansion, the relationship between mental health facilities and mortality would have evolved similarly in expansion and non-expansion states. The event study's flat pre-treatment coefficients support this parallel trends assumption, indicating no differential mortality trends prior to expansion.

Second, baseline uninsurance rates must be uncorrelated with other factors that differentially affect the facility-mortality relationship over time. This assumption is plausible given that 2013 uninsurance rates reflect longstanding differences in state policies, labor markets, and demographics that predate the ACA (Courtemanche et al., 2017). Moreover, using within-state variation in uninsurance rates helps control for state-level confounders that might affect mortality patterns.

7.5 Results: Insurance Expansion, Mental Health Treatment Access, and Mortality

Having established that mental health facilities reduce mortality and that these effects vary across populations, I now examine how insurance expansion affects the relationship between treatment facilities and mortality outcomes. Table 6 presents estimates from the triple-difference specification exploiting variation from Medicaid expansion under the Affordable Care Act.

Column 1 shows that mental health facilities in expansion states reduce mortality by 0.063 deaths per 100,000 residents post-expansion, though this effect is imprecisely estimated. Column 2 reveals substantial heterogeneity: in counties with above-median baseline uninsurance rates, facilities reduce mortality by an additional 0.117 deaths per 100,000 ($p < 0.01$), representing a 0.38 percent reduction relative to the pre-treatment mean.

The key result appears in Column 3. The triple interaction coefficient of -0.081 ($p < 0.01$) indicates that mental health facilities prevent an additional 0.081 deaths per 100,000 residents in high-uninsurance counties within expansion states after Medicaid implementation. This represents a 0.26 percent additional mortality reduction beyond the baseline facility effect, providing strong evidence that insurance expansion amplifies the life-saving impact of mental health treatment facilities.

Figure 9 presents the dynamic evolution of these interaction effects from the event study specification in Equation 9. The pre-treatment coefficients for years -5 through -1 are small and statistically indistinguishable from zero, supporting the parallel trends assumption. Following Medicaid expansion in 2014, the interaction effect emerges immediately and grows over time. By year 1 post-expansion, the differential effect of facilities in expansion states reaches -0.09 deaths per 100,000, representing a 0.2 percent reduction. This effect strengthens over time, consistent with gradual enrollment in Medicaid and the time required for newly insured individuals to establish care relationships at existing facilities.

7.6 Implications for Mental Health Policy

These results demonstrate that insurance expansion and mental health facilities are complements rather than substitutes in reducing mortality. The complementarity has critical implications for policy design and resource allocation. States considering Medicaid expansion should assess their existing mental health infrastructure to maximize the mortality benefits of coverage expansion. Conversely, investments in new facilities may yield limited returns in areas with high uninsurance rates unless accompanied by coverage expansion efforts.

The magnitude of the interaction effect is economically meaningful. For a high-uninsurance county with the sample mean of 3 facilities, Medicaid expansion prevents approximately 0.24 additional deaths per 100,000 residents annually through enhanced facility effectiveness. This finding challenges the traditional supply-side versus demand-side policy debate in healthcare, suggesting that optimal mental health policy requires coordinated investments in both treatment infrastructure and insurance coverage.

From a federal perspective, these results validate the ACA's dual approach of expanding insurance while investing in healthcare infrastructure. The 0.26 percent additional mortality reduction from the interaction of these policies represents lives saved that neither intervention alone would achieve, underscoring the importance of comprehensive rather than piecemeal approaches to mental healthcare reform.

8 Mechanisms

The documented mortality reductions from mental health facilities raise important questions about the pathways through which treatment access improves health outcomes. In this section, I examine three key mechanisms: disability program participation that connects individuals to social safety nets, prescription drug utilization that enables pharmacological treatment, and the interaction with insurance expansion that removes financial barriers to care.

8.1 Mental Health Facilities and Disability Program Participation

Mental health facilities may reduce mortality not only through direct treatment but also by facilitating access to disability benefits that provide crucial income support and healthcare coverage. Table 12 examines how mental health facilities affect Social Security disability claims among working-age adults (18-64).

The results reveal a counterintuitive but important pattern. Each additional mental health facility increases SSI disability recipients by 8.89 per 100,000 population in the baseline specification (Column 1), representing a 1.38 percent increase. This effect remains remarkably stable across specifications, ranging from 6.63 (Column 2) to 8.99 (Column 3) to 8.88 (Column 4) recipients per 100,000, all significant at the 1 percent level.

Rather than reflecting worsening mental health, this increase in disability claims likely represents improved access to diagnosis and documentation necessary for disability determination. As Messel et al. (2023) demonstrates, mental health treatment facilities serve as critical gateways to disability programs by providing the medical evidence required for successful applications. Individuals with severe mental illness often struggle to navigate the complex disability application process without professional assistance. Mental health providers diagnose conditions, document functional limitations, and provide the longitudinal treatment records that disability examiners require (Maestas et al., 2013; Deshpande, 2016).

The mortality benefits documented earlier may partly operate through this disability channel. SSI and SSDI provide not only income support but also access to Medicare or Medicaid, ensuring continued access to treatment. For individuals with severe mental illness, this combination of income stability and healthcare coverage can be life-saving, preventing homelessness, enabling medication adherence, and reducing suicide risk (Shinn et al., 2007; Silverman et al., 2017).

8.2 Prescription Drug Access as a Treatment Pathway

A more direct mechanism through which facilities reduce mortality is by increasing access to psychotropic medications. Table 13 presents evidence from Medicare Part D on how the interaction between facilities and Medicaid expansion affects antidepressant prescriptions.

The triple-difference coefficient of 279.6 additional antidepressant claims per 100,000 population (Column 1) indicates that mental health facilities in expansion states generate substantially more prescriptions after Medicaid implementation. This effect remains stable at 277.0 claims when adding demographic controls (Column 3) and 217.9 claims in the full specification (Column 4), all significant at the 1 percent level.

This prescription pathway is particularly relevant given my earlier finding that facility effects are strongest among elderly populations. Medicare beneficiaries often face complex medication regimens requiring careful management, and mental health facilities provide the psychiatric expertise necessary for appropriate prescribing and monitoring (Olfson et al., 2014; Wang et al., 2009). The substantial increase in antidepressant prescriptions suggests that facilities enable pharmacological treatment that would otherwise be inaccessible, particularly for depression and anxiety disorders that are prevalent among older adults (Blazer, 2003).

The magnitude of the prescription effect aligns with the mortality reductions documented earlier. Clinical trials demonstrate that antidepressant treatment reduces suicide risk by 20-30 percent among elderly patients (Craig Nelson, 2018). Given that suicide accounts for a substantial portion of mental health-related mortality, increased antidepressant access represents a plausible mechanism for the observed mortality benefits.

8.3 Insurance Expansion and Treatment Utilization

The complementarity between insurance expansion and facility access extends beyond mortality to affect disability program participation. Table 14 examines how Medicaid expansion modifies the relationship between facilities and disability claims.

The results reveal complex interactions. Column 1 shows that facilities in expansion states have no significant effect on disability claims post-expansion (0.999, $p > 0.10$). However, Column 2 indicates that facilities in high-uninsurance counties increase disability claims by 4.93 per 100,000 ($p < 0.05$), suggesting that facilities are particularly important for connecting uninsured populations to disability programs.

The triple interaction in Column 3 is negative and significant (-2.106, $p < 0.05$), indicating that Medicaid expansion reduces the facility-disability relationship in high-uninsurance areas. This seemingly paradoxical result has a logical interpretation: when Medicaid expands, individuals who previously needed disability benefits primarily for healthcare access can now obtain coverage directly through Medicaid. This reduces the incentive to pursue disability claims solely for Medicare/Medicaid eligibility (Maestas et al., 2013; Burns and Dague, 2017).

This mechanism helps explain the mortality benefits of the insurance-facility interaction documented earlier. By providing an alternative pathway to healthcare coverage, Medicaid expansion allows individuals to receive treatment without the lengthy disability determination process, enabling more timely intervention. The 2.1 reduction in disability claims per facility in high-uninsurance expansion states suggests that roughly 2 individuals per 100,000 who would have pursued disability can instead access care immediately through expanded Medicaid.

8.4 Synthesis of Mechanisms

These three mechanisms on disability program access, prescription drug utilization, and insurance-based treatment work in complementary ways to reduce mortality. Mental health facilities serve multiple functions beyond direct treatment: they connect vulnerable individuals to social safety nets, enable access to life-saving medications, and leverage insurance expansions to maximize treatment uptake.

The relative importance of each mechanism varies by population. For working-age adults with severe mental illness, the disability pathway may be most critical, providing both income support and healthcare access. For elderly populations, the prescription mechanism dominates, with facilities enabling appropriate pharmacological management. In high-uninsurance areas, the insurance interaction is paramount, with Medicaid expansion unlocking latent demand for mental healthcare.

Together, these mechanisms explain why mental health facilities have such pronounced effects on mortality, particularly for vulnerable populations. They also underscore why the complementarity between insurance and infrastructure is so important: facilities without insurance coverage can only partially activate these mechanisms, while insurance without facilities cannot deliver the specialized care needed to prevent mental health-related deaths.

9 Discussion

This study provides the first causal evidence that mental health treatment facilities substantially reduce mortality, with effects amplified by insurance coverage expansions. Using county-level variation in mental health facilities from 1999-2016, I find that each additional facility reduces MBD mortality by 0.079 percent, representing a 0.25 percent decline relative to the pre-treatment mean. A 10 percent increase in facilities lowers a county's MBD mortality rate by 2 percent. These effects extend beyond mental health-specific deaths, reducing all-cause mortality by 1.55 per 100,000 residents, underscoring the broader health impacts of mental healthcare infrastructure.

Three key findings reshape our understanding of mental healthcare markets. First, the profound asymmetry between facility openings and closures, with closures causing mortality increases ten times larger than the reductions from openings, reveals substantial adjustment frictions that standard models miss. This asymmetry suggests that maintaining existing infrastructure should be prioritized over geographic expansion, particularly given the irreversible disruption of therapeutic relationships when facilities close (Corredor-Waldron and Currie, 2022; Frank, 2006).

Second, the complementarity between insurance and infrastructure fundamentally alters the policy calculus for mental healthcare. In high-uninsurance counties, Medicaid expansion amplifies facility effectiveness by an additional 26 percent, demonstrating that neither insurance nor infrastructure alone maximizes health benefits. This finding has immediate relevance as states continue debating Medicaid expansion, suggesting that expansion states should prioritize facility development. In contrast, non-expansion states may see limited returns from infrastructure investments without addressing coverage gaps (Sommers et al., 2016; Maclean and Saloner, 2019).

The mechanisms underlying these effects extend beyond direct treatment provision. Facilities serve as gateways to disability programs, increasing participation by 1.4 percent per facility, and enable prescription access, generating 280 additional antidepressant claims per 100,000 residents in expansion states. These pathways help explain why facility effects are particularly pronounced among elderly populations and those with lower education, groups that face the greatest barriers to navigating complex healthcare systems independently (Messel et al., 2023; Gupta et al., 2024).

The economic implications are substantial. With mental health disorders costing 4 percent of global GDP annually through reduced productivity, labor market frictions, and human capital underutilization, the mortality reductions documented here represent only part of the social returns to mental health infrastructure (Bloom et al., 2012; Ettner et al., 1997).

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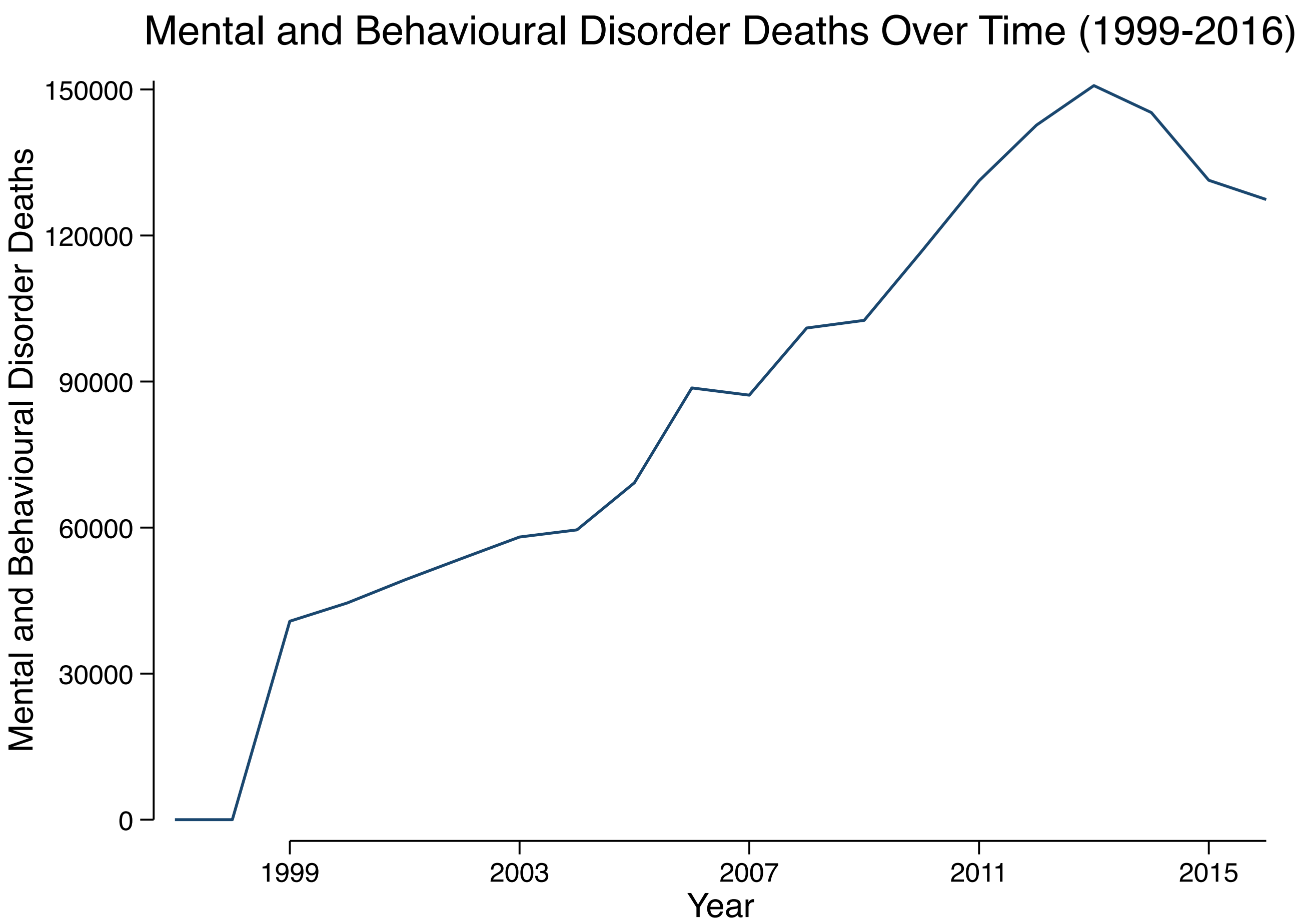
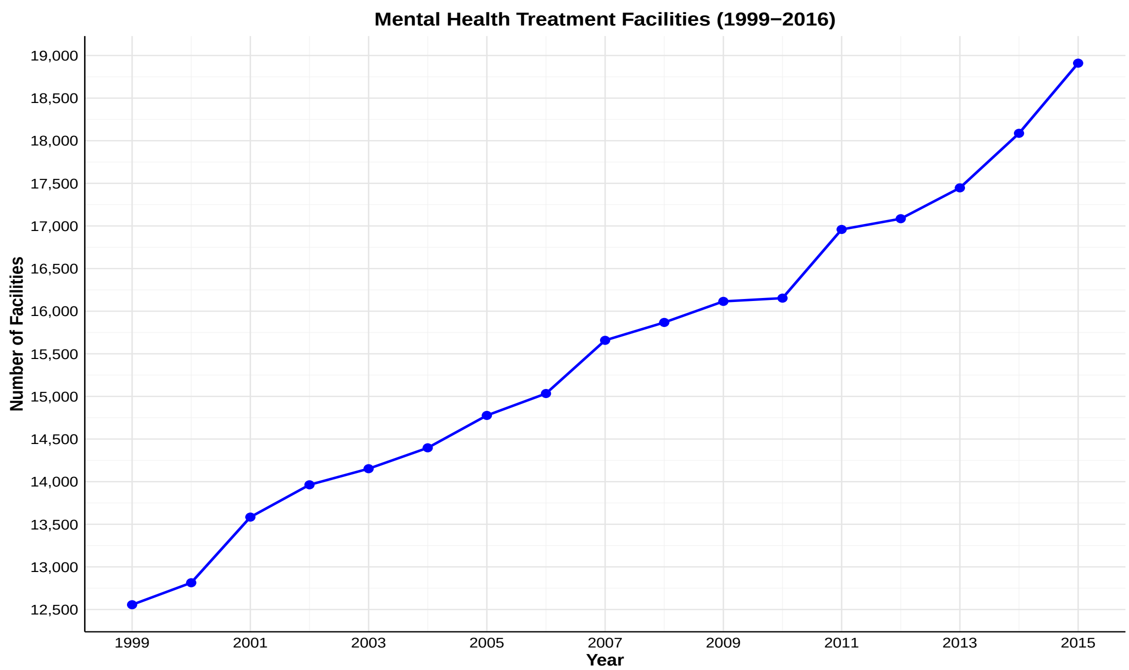
Figures

Figure 1: Trend of Mental and Behavioral Disorder Deaths, 1999-2016



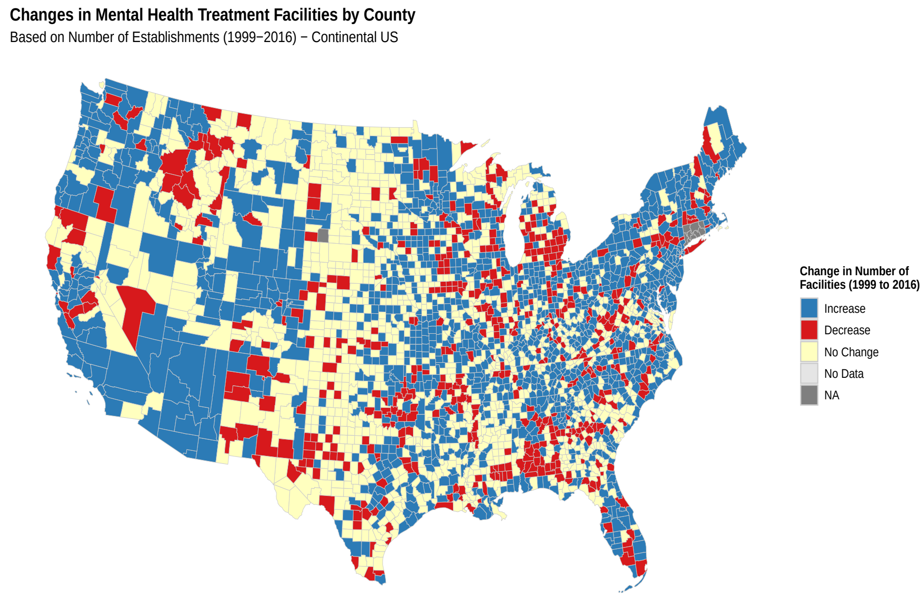
Notes: This figure plots the aggregate annual number of deaths from Mental and Behavioral Disorders (MBDs) in the United States from 1999 to 2016. Data are from the restricted-access Multiple Cause of Death (MCOD) files from the National Center for Health Statistics (NCHS). The MBD mortality measure is an aggregate of deaths with an underlying cause falling under the International Classification of Diseases, 10th Revision (ICD-10) codes F00-F79. The y-axis represents the total count of deaths, not a rate.

Figure 2: Temporal Variation of Mental Health Treatment Facilities

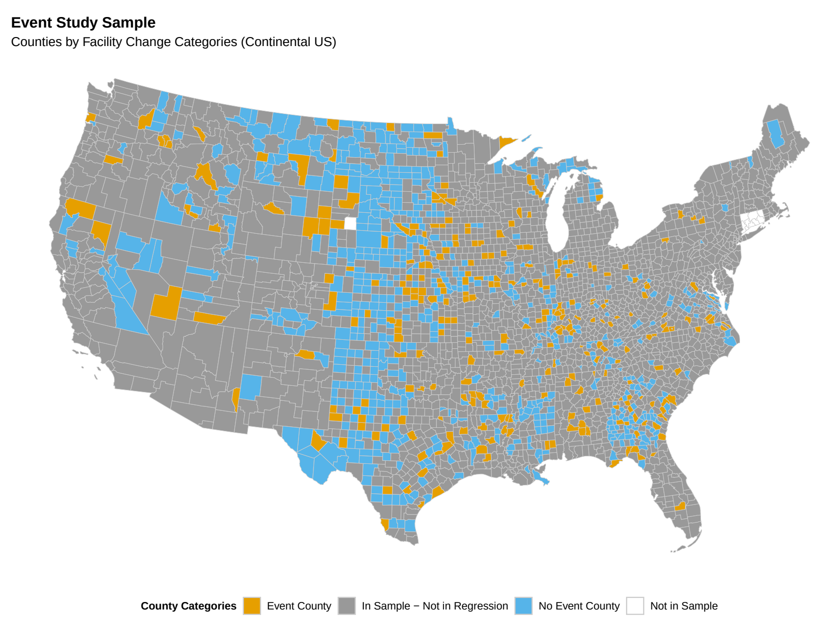


Note: Data on the county's mental health facility treatment comes from the County Business Patterns. A county is designated as having access to mental health services if it has any establishment that provides these services at a given year. The sample is restricted to 1999-2016. The figure presents mean establishment trend over time. A county is designated as having "net access" if it goes from having no mental health treatment facilities to having some for the rest of the sample period. Section 4.1 presents more information on these data.

Figure 3: Spatial Variation in Access to Mental Health Treatment Facilities



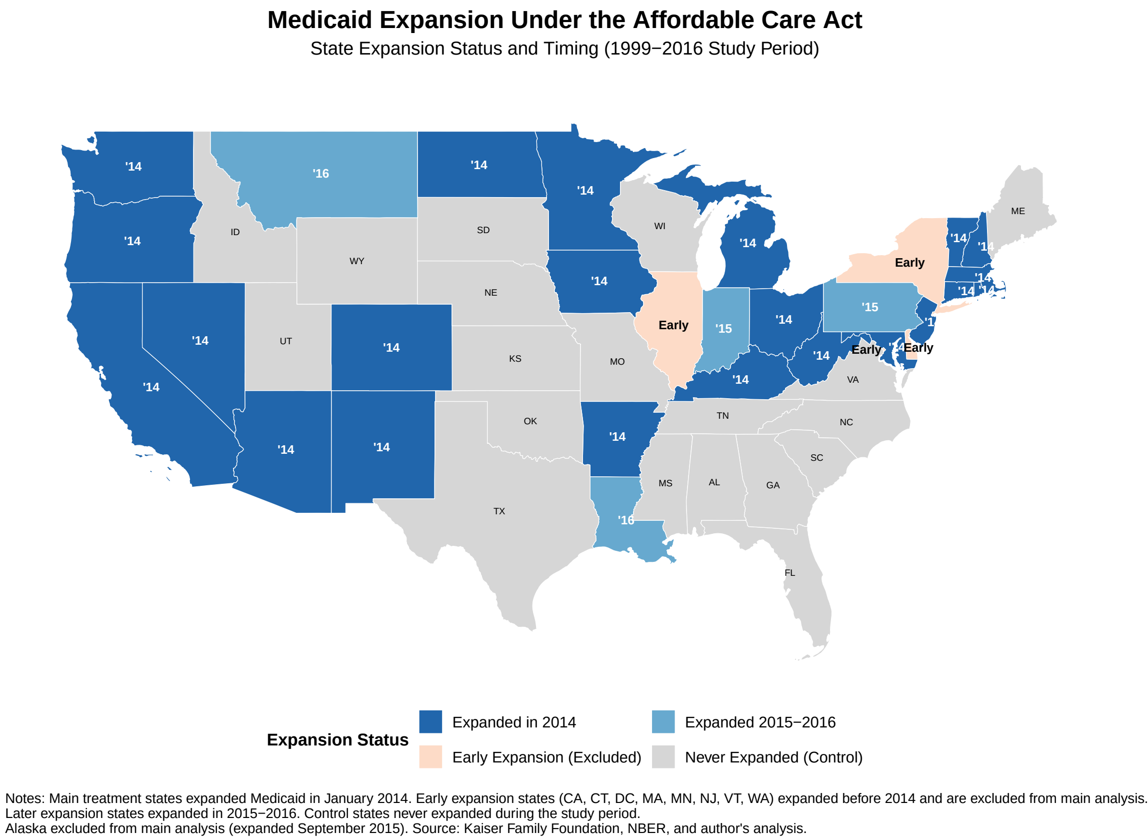
(a) Spatial Variation in Mental Health Treatment Facilities



(b) Spatial Variation in Mental Health Treatment Facilities: Event Study Sample

Note: Data on mental health treatment facilities comes from the County Business Patterns. The top panel (a) displays the spatial distribution of changes in mental health treatment facilities across U.S. counties between 1999 and 2016. Section 4.1 presents more information on these data. Counties are categorized by whether they experienced an increase (blue), decrease (red), or no change (yellow) in the number of facilities over this period. The bottom panel (b) shows the event study sample classification, where “Event Counties" (orange) represent those that experienced exactly one change in facilities during the study period, “No Event Counties" (light blue) had no changes, and “In Sample - Not in Regression" (gray) experienced multiple changes. The sample consists of 275 event counties, 653 no-event counties, and 2,202 counties with multiple changes, while 92 counties were not in the sample. Alaska and Hawaii are included in the analysis but shown as insets due to their geographic separation from the continental United States.

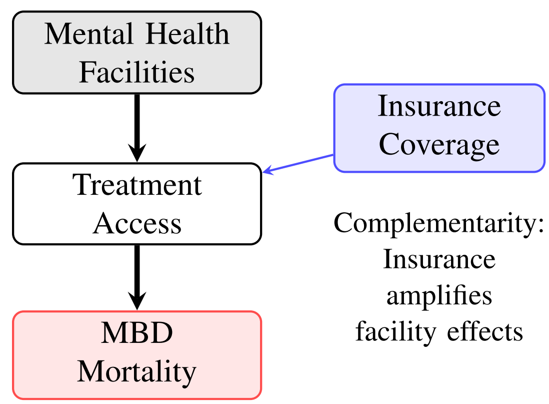
Figure 4: Medicaid Expansion Status and Timing Under the ACA



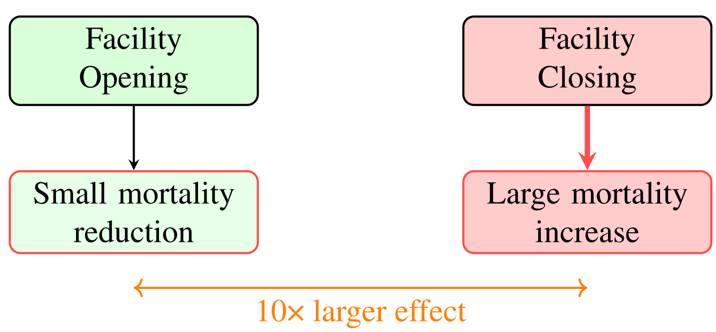
Notes: This figure illustrates the state-level timing of Medicaid expansion under the Affordable Care Act (ACA). States are categorized based on their expansion status and timing. The main treatment group consists of states that expanded in 2014. "Early Expansion" states adopted Medicaid expansion prior to 2014 under Section 1115 waivers and are excluded from the main analysis. "Control" states did not expand Medicaid during the study period. Year labels on the map indicate the year of expansion. Data on expansion timing are compiled from the Kaiser Family Foundation and the National Bureau of Economic Research (NBER).

Figure 5: Conceptual Framework. Panel A shows the primary pathway through which mental health facilities reduce mortality via improved treatment access. Insurance coverage acts as a complementary input that amplifies facility effectiveness. Panel B illustrates the asymmetric response to facility changes: closures cause mortality increases ten times larger than the reductions from openings, reflecting disruption costs and adjustment frictions in mental healthcare markets. Panel C depicts the three key mechanisms through which facilities affect mortality: serving as gateways to disability programs, enabling prescription access, and validating real treatment capacity through employment effects.

Panel A: How Mental Health Facilities Affect Mortality



Panel B: Asymmetric Effects



Panel C: Mechanisms

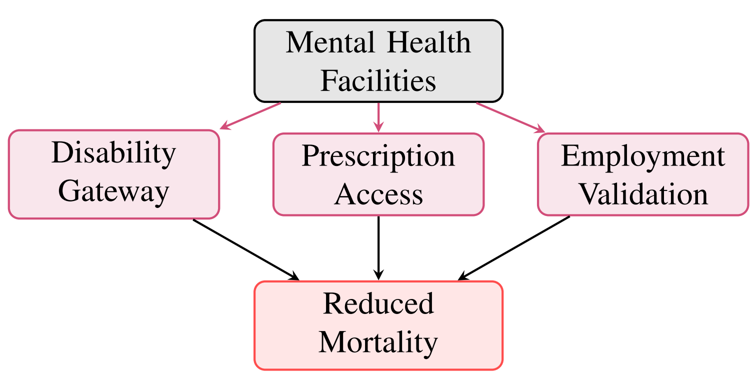
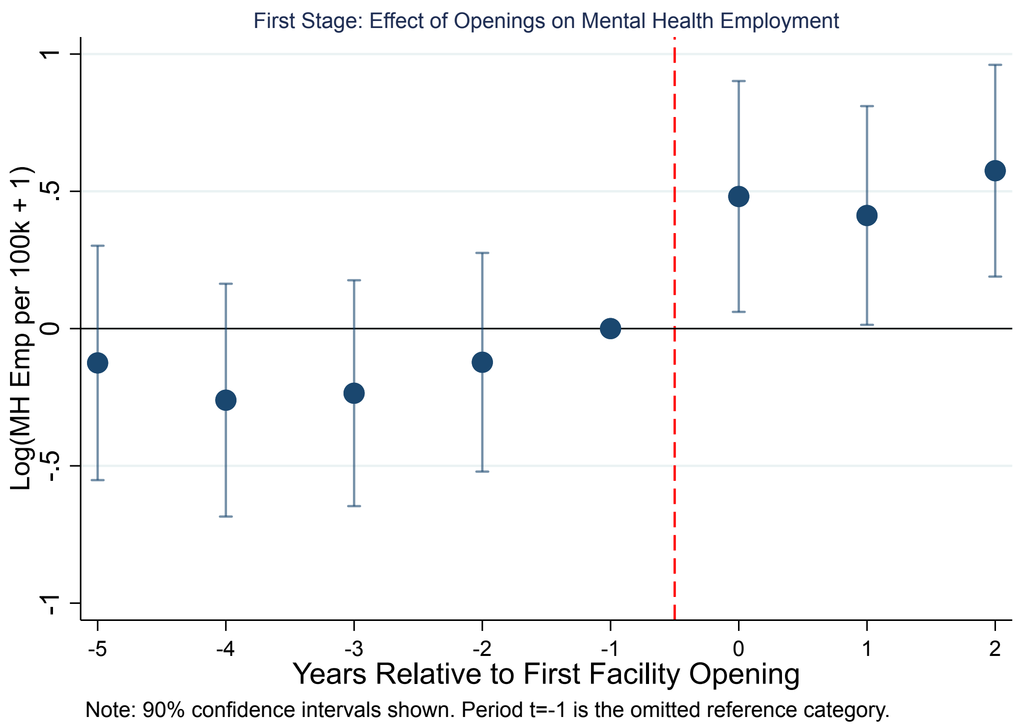
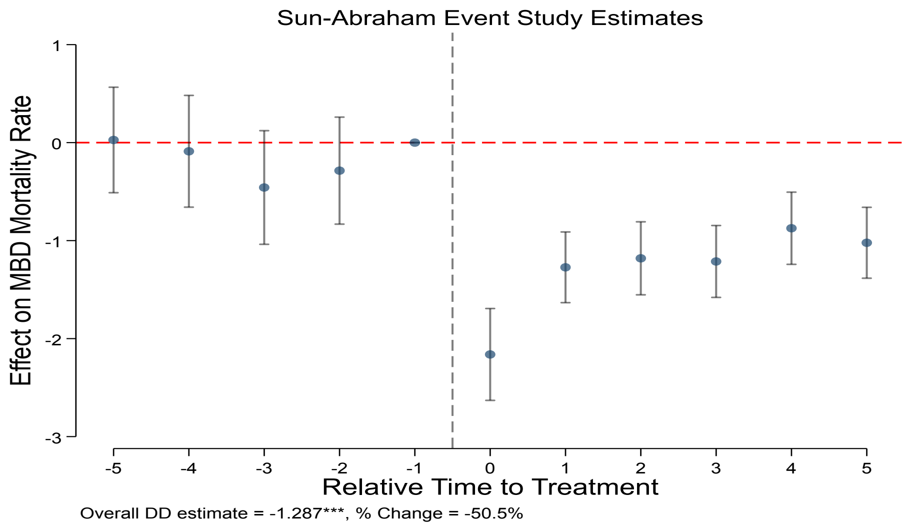


Figure 6: First Stage: Effect of Facility Openings on Mental Health Employment

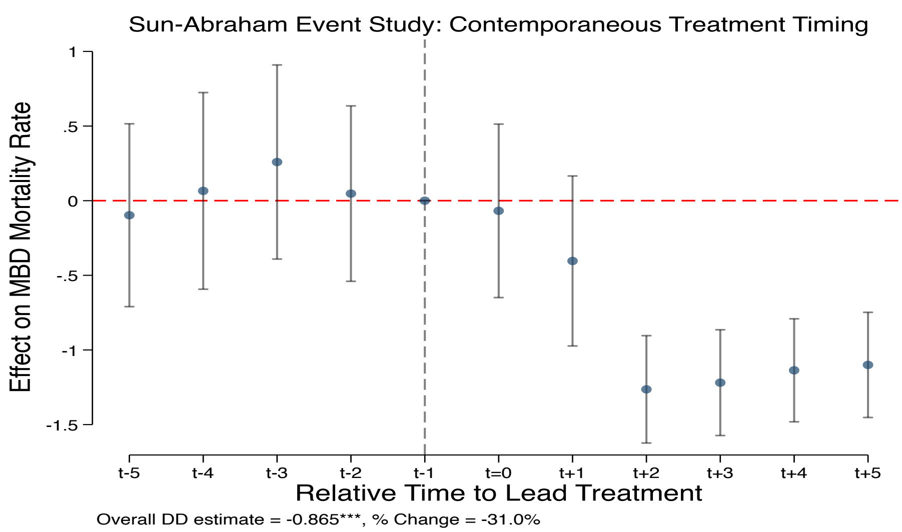


Notes: This figure plots the event study estimates from a two-way fixed effects regression of mental health facility openings on sectoral employment. The dependent variable is the natural log of mental health employees per 100,000 residents plus one. The event is defined as the first opening of a mental health facility in a county. The period t=-1 is the omitted reference category. The specification includes county and year fixed effects, as well as demographic and economic controls. Employment data are from the County Business Patterns (CBP), as compiled by Eckert et al. (2020).

Figure 7: Dynamic Effects of Local Access to MHT Treatment Facilities on Mental and Behavioral Health Disorder Mortality: Sun-Abraham Estimates



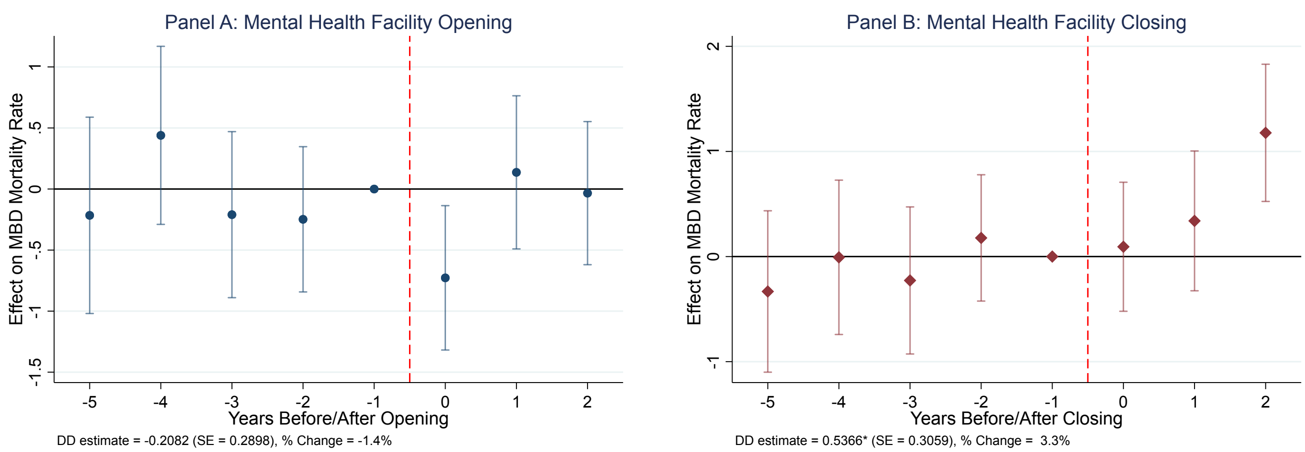
(a) Main Event Study: Lagged Treatment Effects (Sun-Abraham)



(b) Event Study: Contemporaneous Treatment Timing (Sun-Abraham)

Notes: The estimates implement the Sun-Abraham heterogeneity-robust event study estimator where the outcome variable is the mortality rate related to mental and behavioral health disorders (MBD) per 100,000 county residents. Panel 7a examines the lagged effects of treatment, showing an overall treatment effect of -1.29 (representing a 50.5% change from pre-treatment mean). Panel 7b investigates contemporaneous effects, with an overall treatment effect of -0.518 (18.8% change from baseline). Both specifications include county and year fixed-effects, and state-by-year fixed effects. The observations are weighted by county-level demographic characteristics from 1999. Additional controls include demographic composition, economic conditions, healthcare infrastructure, and other county-level characteristics. The standard errors are clustered at the county level. The data combines County Business Patterns (CBP) and Vital Statistics mortality data for the period 1999-2016. The figures display point estimates and 95% confidence intervals, with dashed vertical lines indicating the timing of treatment and horizontal lines at zero serving as reference points. These estimates account for potential heterogeneity in treatment effects across cohorts, addressing limitations of traditional two-way fixed effects models.

Figure 8: Dynamic Effects of Facility Openings and Closings on MBD Mortality: Sun and Abraham (2021) Estimates

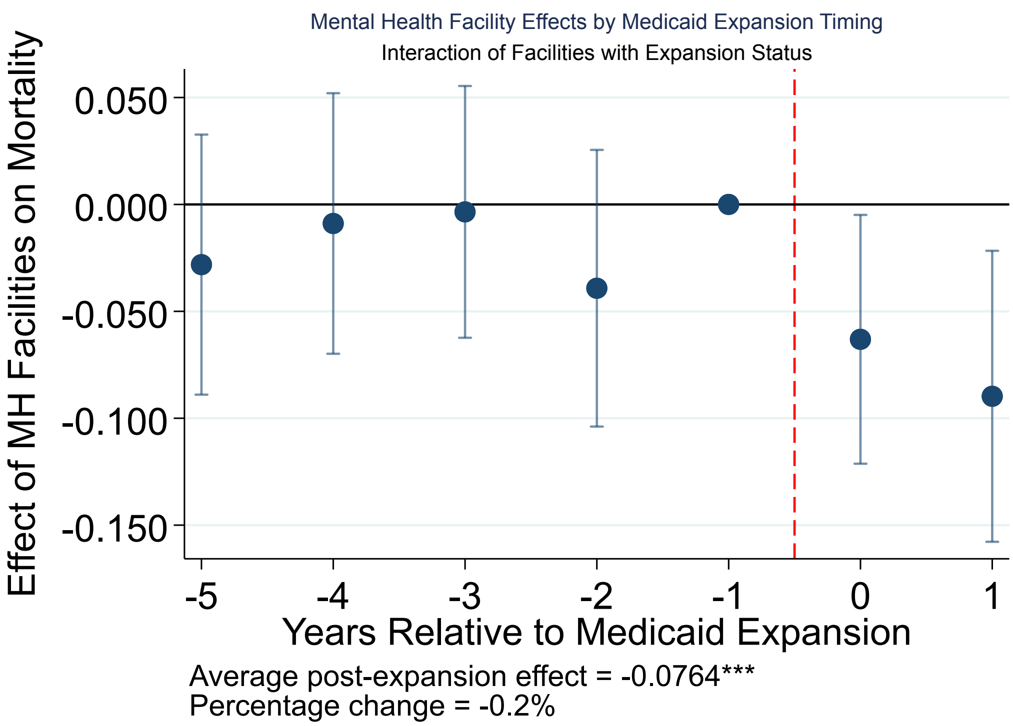


(a) Mental Health Facility Opening

(b) Mental Health Facility Closing

Notes: This figure plots event study estimates from the Sun and Abraham (2021) heterogeneity-robust estimator. The outcome variable in both panels is the mortality rate related to mental and behavioral disorders (MBD) per 100,000 county residents. Panel (a) shows the dynamic effect of the first opening of a mental health facility in a county. Panel (b) shows the dynamic effect of the first closing of a facility. The points represent the estimated average treatment effect for each period relative to the year before the event (t=-1), which is the omitted reference category. All specifications include county fixed effects, year fixed effects, state-by-year fixed effects, and demographic and economic controls. Standard errors are clustered at the county level. The data combine County Business Patterns (CBP) and Vital Statistics mortality data for the period 1999-2016.

Figure 9: Event Study of the Interaction Between Facility Access and Medicaid Expansion



Notes: This figure plots the results of a triple-difference (DDD) event study. The points represent the estimated coefficients on the interaction between the number of mental health facilities and indicators for years relative to a state's Medicaid expansion. The main treatment group consists of counties with mental health (MH) facilities located in states that expanded Medicaid in 2014. The outcome variable is the mortality rate from mental and behavioral disorders (MBD) per 100,000 county residents. Each coefficient captures the differential effect of an additional MH facility in an expansion state, for a given year, relative to the year just before the main expansion wave (t=-1, representing 2013), which is the omitted reference category. Vertical bars represent 95% confidence intervals. The specification includes all constitutive two-way interactions, county fixed effects, year fixed effects, state-by-year fixed effects, and demographic and economic controls. Standard errors are clustered at the county level. Data are from the County Business Patterns (CBP) and Vital Statistics for the period 1999-2016.

Tables

Table 1: Summary Statistics

	(Mean)	(Std. dev.)
Mental health treatment facilities		
Total facilities	53.32	95.10
Net openings	0.35	0.48
Net closings	0.24	0.43
Outpatient facilities	28.09	50.85
Inpatient facilities	24.66	44.24
Facilities (per 100,000)	5.16	3.73
MBD Deaths (per 100,000)		
All	29.42	21.40
Age under 19	0.03	0.17
Ages 20–34	0.27	0.58
Ages 35–49	0.99	1.26
Ages 50–64	1.63	1.72
Ages 65+	26.51	20.60
White	26.49	20.35
Black	2.50	3.99
Other	0.42	1.25
Counties	3,199	
County-year observations	63,650	

Notes: All statistics are weighted by county population. The sample includes all U.S. counties with available data from 1999–2016. MBD refers to Mental and Behavioral Disorder deaths.

Table 2: Baseline Model - Main Effects of Access to Mental Health Treatment Facilities on Mortality Related to Mental Health and Behavioral Disorders

	All MBD Deaths (1)	F00-F09 (2)	F10-F19 (3)	F20-F29 (4)	F30-F39 (5)	F40-F48 (6)	F50-F59 (7)	F60-F69 (8)	F70-F79 (9)
Number of Facilities	-0.06647**	-0.06146**	-0.00254	-0.00059	-0.00025	-0.00052**	-0.00059	0.00001	-0.00052
	(0.02928)	(0.02843)	(0.00368)	(0.00059)	(0.00079)	(0.00026)	(0.00043)	(0.00003)	(0.00056)
	[0.21]	[0.22]	[0.09]	[0.26]	[0.07]	[0.76]	[0.46]	[0.48]	[0.26]
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.509	0.523	0.100	0.028	0.028	0.013	0.004	0.003	0.088
N	53,498	53,498	53,498	53,498	53,498	53,498	53,498	53,498	53,498

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD). Each coefficient represents a separate regression following Equation 1. The dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* $p<.10$ ** $p<.05$ *** $p<.01$). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county and year fixed effects to control for time-invariant county characteristics and common temporal shocks. The sample covers 1998-2016 with 53,498 county-year observations. Column headers denote the dependent variable. Dependent variables are coded using ICD-10 categories: F00-F09 (organic mental disorders), F10-F19 (substance use disorders), F20-F29 (schizophrenia and psychotic disorders), F30-F39 (mood disorders), F40-F48 (anxiety disorders), F50-F59 (behavioral syndromes), F60-F69 (personality disorders), and F70-F79 (intellectual disabilities). Column 1 reports effects on total MBD mortality, while columns 2-9 show effects for specific diagnostic categories. Mortality rates and facility counts are measured at the county-year level. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 3: Main Effects - Full Specification

	(1)	(2)	(3)	(4)
Number of Facilities	-0.06647**	-0.06484***	-0.07897***	-0.07898***
	(0.02928)	(0.02353)	(0.02969)	(0.02974)
	[-0.21]	[-0.21]	[-0.25]	[-0.25]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	No	Yes	Yes	Yes
Controls				
Demographic	No	No	Yes	Yes
Economic	No	No	No	Yes
Adj. R^2	0.509	0.529	0.529	0.529
N	53,498	53,498	53,498	53,480

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD). Each column represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county and year fixed effects. Column (1) presents the baseline specification. Column (2) adds state-by-year fixed effects to account for state-specific temporal trends. Column (3) introduces demographic controls. Column (4) adds economic controls. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 4: Effect of Mental Health Treatment Facilities on Overall Mortality

	(1)	(2)	(3)	(4)
Number of Facilities	-1.73977***	-1.37340***	-1.55872***	-1.55855***
	(0.22019)	(0.22417)	(0.25482)	(0.25512)
	[-0.19]	[-0.15]	[-0.17]	[-0.17]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	No	Yes	Yes	Yes
Controls				
Demographic	No	No	Yes	Yes
Economic	No	No	No	Yes
Adj. R^2	0.874	0.881	0.882	0.882
N	53,498	53,498	53,498	53,480

Notes: This table presents estimates of the effect of mental health treatment facilities on overall mortality rates. The dependent variable is total deaths per 100,000 county residents from all causes. Standard errors clustered at the county level are reported in parentheses (* $p<0.10$, ** $p<0.05$, *** $p<0.01$). Numbers in square brackets show the percentage change relative to the pre-treatment mean of 927.41 deaths per 100,000. Column (1) includes only county and year fixed effects. Column (2) adds state-by-year fixed effects to account for differential state-level trends in mortality and mental health policy. Column (3) incorporates demographic controls including age distribution. Column (4) adds economic controls including the employment-to-population ratio. The identification strategy exploits within-county variation in facility openings and closings over time. The sample covers 1999-2016 and includes all U.S. counties with non-missing data. These results provide evidence that increased access to mental health treatment facilities is associated with reductions in overall mortality, suggesting important spillover effects beyond mental health-specific outcomes.

Table 5: Asymmetric Effects of Mental Health Facility Openings and Closings on Mortality

	(1)	(2)	(3)	(4)
Panel A: Effect of Facility Openings				
Facilities Opened	-0.08808***	-0.05972*	-0.05844*	-0.01345
	(0.03202)	(0.03490)	(0.03494)	(0.03282)
	[-0.28%]	[-0.19%]	[-0.19%]	[-0.04%]
Adj. R^2	0.526	0.526	0.526	0.549
Observations	59,455	59,455	59,435	59,435
Panel B: Effect of Facility Closings				
Facilities Closed	0.11511**	0.10383**	0.10541**	0.12423***
	(0.04821)	(0.04688)	(0.04694)	(0.04777)
	[0.36%]	[0.33%]	[0.33%]	[0.39%]
Adj. R^2	0.526	0.526	0.526	0.549
Observations	59,455	59,455	59,435	59,435
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State × Year	No	No	No	Yes
Controls				
Demographic	No	Yes	Yes	Yes
Economic	No	No	Yes	Yes
Test for Asymmetry (H_0: Opening effect = -Closing effect)				
p-value		0.054		

Notes: This table examines the asymmetric effects of mental health facility openings and closings on mortality from mental and behavioral disorders. The dependent variable is deaths per 100,000 county residents. Panel A reports the effect of facility openings (year-over-year increases), where negative coefficients indicate mortality reductions. Panel B reports the effect of facility closings (year-over-year decreases in absolute value), where positive coefficients indicate mortality increases. The asymmetry test examines whether the magnitude of opening effects equals the magnitude of closing effects. Standard errors clustered at the county level are in parentheses (* p<0.10, ** p<0.05, *** p<0.01). Percentage changes relative to the pre-treatment mean (31.56 deaths per 100,000) are in square brackets. Column (1) includes only county and year fixed effects. Column (2) adds demographic controls for age distribution. Column (3) incorporates economic controls including the employment-to-population ratio. Column (4) adds state-by-year fixed effects to account for state-specific policy changes and trends. The sample covers all U.S. counties from 1999-2016. The asymmetric response to openings versus closings has important policy implications: the harm from losing access may exceed the benefit from gaining access, suggesting that maintaining existing infrastructure is crucial for population mental health.

Table 6: Medicaid Expansion, Mental HealthTreatment Facilities, and Mortality

	(1) Medicaid Expansion	(2) Uninsurance Heterogeneity	(3) Triple Interaction
MH Facilities × Post-Expansion	-0.06253***		
	(0.01988)		
	[-0.20%]		
MH Facilities × High Uninsurance		-0.11774***	
		(0.04555)	
		[-0.38%]	
MH Facilities × Post-Expansion × High Uninsurance			-0.08064***
			(0.02968)
			[-0.26%]
Interpretation:			
Column (1): Effect of facilities in expansion states post-expansion			
Column (2): Effect of facilities in high uninsurance counties			
Column (3): Additional effect in high uninsurance expansion states post-expansion			
Fixed Effects:			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State × Year	Yes	Yes	Yes
Controls:			
Demographics	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Observations	43,904	43,904	43,904
Counties	2,440	2,440	2,440
Adjusted R^2	0.505	0.505	0.505
Pre-treatment Mean		30.856	

Notes: This table examines heterogeneity in the effect of mental health (MH) treatment facilities on mortality from mental and behavioral disorders. The dependent variable is deaths per 100,000 county residents. Column (1) presents the baseline effect of MH facilities. Column (2) tests whether effects differ in states that expanded Medicaid under the ACA, where Post-Expansion equals 1 for expansion states after their expansion date. Column (3) examines heterogeneity by baseline uninsurance rates, where High Uninsurance indicates counties above their state's median uninsurance rate in 2013. All specifications include county fixed effects, year fixed effects, and state-by-year fixed effects to account for state-specific policy changes and trends. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heterogeneity by Facility Type: Effects on Mental Health Outcomes

	(1)	(2)	(3)	(4)
Panel A: Outpatient mental health facilities				
Number of facilities	-0.081^{*}	-0.108^{***}	-0.126^{***}	-0.126^{***}
	(0.048)	(0.036)	(0.043)	(0.043)
	[-0.3%]	[-0.3%]	[-0.4%]	[-0.4%]
Panel B: Residential mental health facilities				
Number of facilities	-0.070	-0.060	-0.090^{*}	-0.090^{*}
	(0.049)	(0.037)	(0.051)	(0.051)
	[-0.2%]	[-0.2%]	[-0.3%]	[-0.3%]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	No	Yes	Yes	Yes
Controls				
Demographic	No	No	Yes	Yes
Economic	No	No	No	Yes
Counties	2,973	2,973	2,973	2,972
Observations	56,471	56,471	56,471	56,452
Mean of dep. var.	31.561	31.561	31.561	31.561

Notes: This table reports the differential effects of outpatient and residential mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD). Panel A presents estimates for outpatient mental health and substance abuse centers (NAICS 621420), while Panel B presents estimates for residential mental health and substance abuse facilities (NAICS 623220). Each column represents a separate estimation, where the dependent variable is deaths per 100,000 county residents. The main explanatory variables are the lagged number of each facility type in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable (calculated as coefficient/pre-treatment mean × 100). All specifications include county and year fixed effects. Column (1) presents the baseline specification. Column (2) adds state-by-year fixed effects to account for state-specific temporal trends. Column (3) introduces demographic controls. Column (4) adds economic controls. The sample is restricted to 1999-2016.

Table 8: Effects of Treatment Facilities by Age Groups

	All Ages	Under 19	20-34	35-49	50-64	Over 65
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Facilities	-0.07898***	0.00001	-0.00154**	-0.00101	-0.00112	-0.07524***
	(0.02974)	(0.00019)	(0.00069)	(0.00174)	(0.00264)	(0.02837)
	[-0.26]	[0.02]	[-0.74]	[-0.12]	[-0.07]	[-0.27]
Fixed Effects						
County	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls						
Demographic	Yes	Yes	Yes	Yes	Yes	Yes
Economic	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.536	0.536	0.536	0.536	0.536	0.536
N	53,480	53,480	53,480	53,480	53,480	53,480

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD) by age groups. Each coefficient represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents within each age group. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for the entire population, while columns (2)-(6) show estimates for specific age groups: under 19, 20-34, 35-49, 50-64, and over 65 years old, respectively. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 9: Effects of Treatment Facilities by Education Level

	All Levels	High School or Less	Some College
	(1)	(2)	(3)
Number of Facilities	-0.07898***	-0.09526***	0.00315
	(0.02974)	(0.02152)	(0.00563)
	[-0.26]	[-0.43]	[0.08]
Fixed Effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes
Controls			
Demographic	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Adj. R^2	0.213	0.213	0.213
N	50,512	50,512	50,512

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD) by education level. Each coefficient represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents within each education group. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for all education levels combined, while columns (2)-(3) show estimates by education level: high school or less and some college, respectively. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 10: Effects of Treatment Facilities by Race

	All Races (1)	White (2)	Black (3)	Other Races (4)
Number of Facilities	-0.07898***	-0.09896***	0.01708	0.00290
	(0.02974)	(0.02737)	(0.01048)	(0.00310)
	[-0.26]	[-0.35]	[0.98]	[0.84]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes	Yes
Controls				
Demographic	Yes	Yes	Yes	Yes
Economic	Yes	Yes	Yes	Yes
Adj. R^2	0.290	0.290	0.290	0.290
N	53,480	53,480	53,480	53,480

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD) by race. Each coefficient represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents within each racial group. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for all races combined, while columns (2)-(4) show estimates by racial group: White, Black, and other races, respectively. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 11: Effects of Treatment Facilities by Gender

	All (1)	Male (2)	Female (3)
Number of Facilities	-0.07898***	-0.02919***	-0.04978**
	(0.02974)	(0.01090)	(0.01993)
	[-0.26]	[-0.26]	[-0.25]
Fixed Effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes
Controls			
Demographic	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Adj. R^2	0.467	0.467	0.467
N	53,480	53,480	53,480

Notes: This table reports the effects of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD) by gender. Each coefficient represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents within each gender group. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for all groups combined, while columns (2)-(3) show estimates by gender: male and female, respectively. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1999-2016.

Table 12: Mechanism: Effect of Mental Health Facilities on Disability Claims

	(1)	(2)	(3)	(4)
Mental Health Facilities	8.89042	6.62725	8.98873	8.87719
	(2.41119)***	(1.99641)***	(2.41433)***	(2.43903)***
	[1.38%]	[1.03%]	[1.39%]	[1.37%]
Fixed Effects:				
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	Yes
Controls:				
Demographics	No	No	Yes	Yes
Economic	No	No	No	Yes
Observations	21,140	21,140	20,811	20,804
Adjusted R^2	0.630	0.774	0.785	0.787

Notes: This table examines disability claims as a mechanism through which mental health facilities affect population wellbeing. Data from Social Security Administration county-level SSI recipient counts (2009-2016). The outcome is SSI disability recipients aged 18-64 per 100,000 population. Negative coefficients indicate that mental health facilities reduce disability claims, consistent with improved mental health treatment preventing disability. Standard errors clustered at county level in parentheses. Percentage changes relative to pre-2014 mean shown in brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table 13: Mechanism: Mental Health Prescriptions and Facility Access

	(1) Basic	(2) Year FE	(3) Demographics	(4) Full
MH Facilities × Post × Expansion	279.586 (54.667)***	279.586 (54.667)***	276.995 (49.234)***	217.894 (64.759)***
Fixed Effects:				
State FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Controls:				
Demographics	No	No	Yes	Yes
Economic	No	No	No	Yes
Observations	144	144	144	144
Adjusted R^2	0.967	0.967	0.968	0.971
Number of States	36	36	36	36

Notes: This table presents state-level evidence on the prescription drug mechanism. The outcome is antidepressant claims per 100,000 population using Medicare Part D data (2013-2016). The triple-difference coefficient captures the differential effect of mental health facilities in Medicaid expansion states after expansion, relative to non-expansion states. Medicaid expansion states are those that expanded between 2014-2016. Demographics include share under 19. Economic controls include employment-population ratio. Standard errors clustered at the state level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 14: Mechanism: Medicaid Expansion, Mental HealthTreatment Facilities & Disability Claims

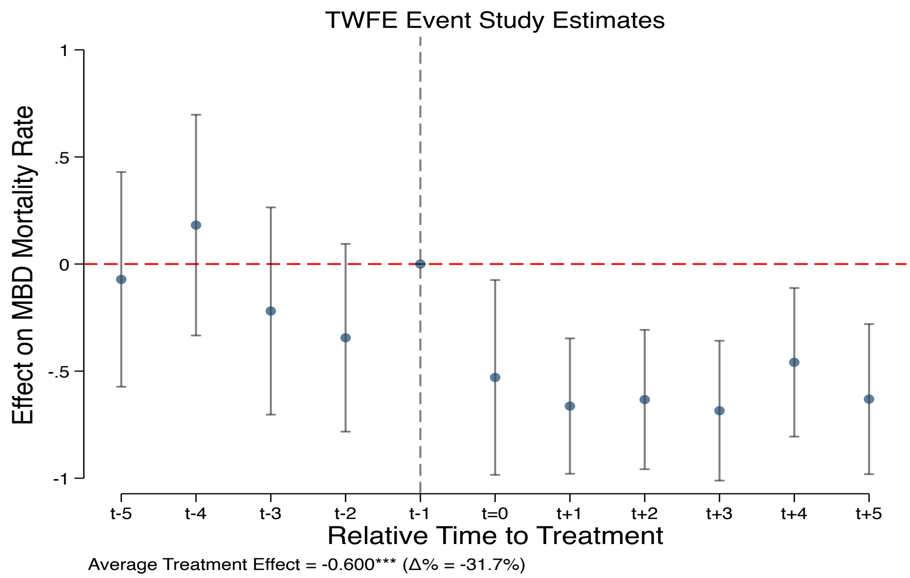
	(1) Medicaid Expansion	(2) Uninsurance Heterogeneity	(3) Triple Interaction
MH Facilities × Post-Expansion	0.99857		
	(0.84510)		
	[0.15%]		
MH Facilities × High Uninsurance		4.93246^{**}	
		(2.19795)	
		[0.74%]	
MH Facilities × Post-Expansion × High Uninsurance			-2.10602^{**}
			(0.96989)
			[-0.32%]
Interpretation:			
Column (1): Effect of facilities in expansion states post-expansion			
Column (2): Effect of facilities in high uninsurance counties			
Column (3): Additional effect in high uninsurance expansion states post-expansion			
Fixed Effects:			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State × Year	Yes	Yes	Yes
Controls:			
Demographics	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Observations	17,073	17,073	17,080
Counties	2,439	2,439	2,440
Adjusted R^2	0.783	0.783	0.781
Pre-treatment Mean		668.5	

Notes: This table examines heterogeneity in the effect of mental health (MH) treatment facilities on disability claims using Social Security Administration county-level SSI recipient data (2009-2016). The dependent variable is SSI disability recipients aged 18-64 per 100,000 population. Column (1) tests whether mental health facilities reduce disability claims more in states that expanded Medicaid under the ACA, where Post-Expansion equals 1 for expansion states after their expansion date. Column (2) examines heterogeneity by baseline uninsurance rates, where High Uninsurance indicates counties above their state's median uninsurance rate in 2013. Column (3) tests whether the effect is strongest in high uninsurance counties within expansion states post-expansion. All specifications include county fixed effects, year fixed effects, and state-by-year fixed effects to account for state-specific policy changes and trends. Standard errors clustered at the county level are reported in parentheses. Numbers in square brackets show the percentage change relative to the pre-2014 mean. The sample excludes early expansion states (CA, CT, DC, MA, MN, NJ, VT, WA) and Alaska. Negative coefficients indicate that mental health facilities reduce disability claims, consistent with effective treatment preventing disability. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

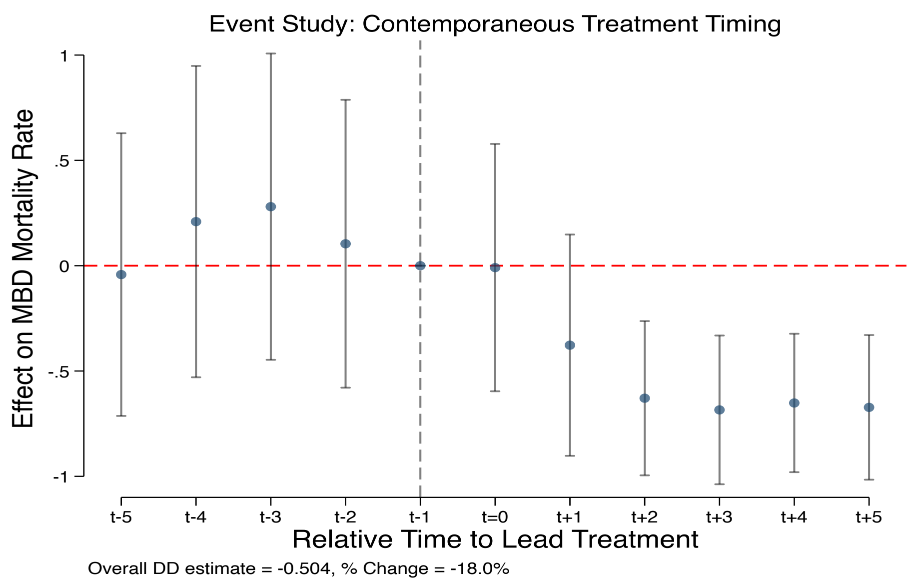
Appendices

Appendix Figures

Figure A1: Dynamic Effects of Local Access to MHT Treatment Facilities on Mental and Behavioral Health Disorder Mortality



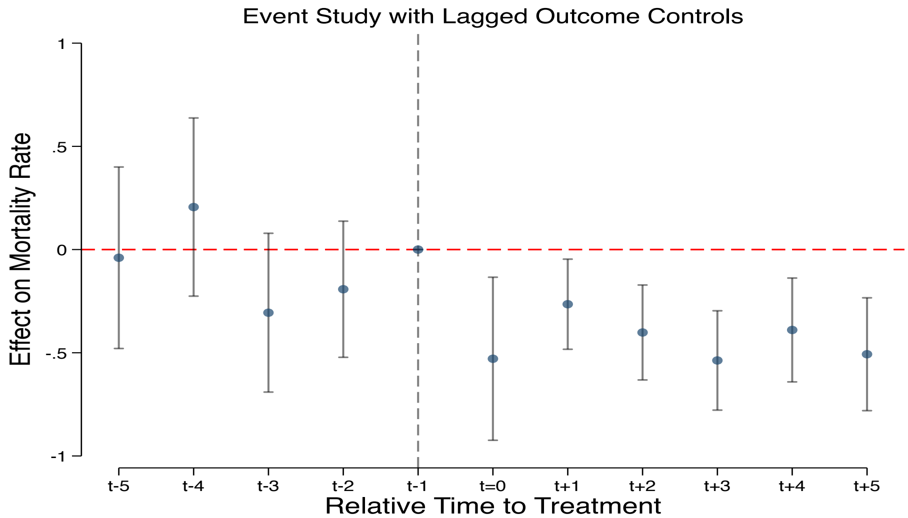
(a) Main Event Study: Lagged Treatment Effects



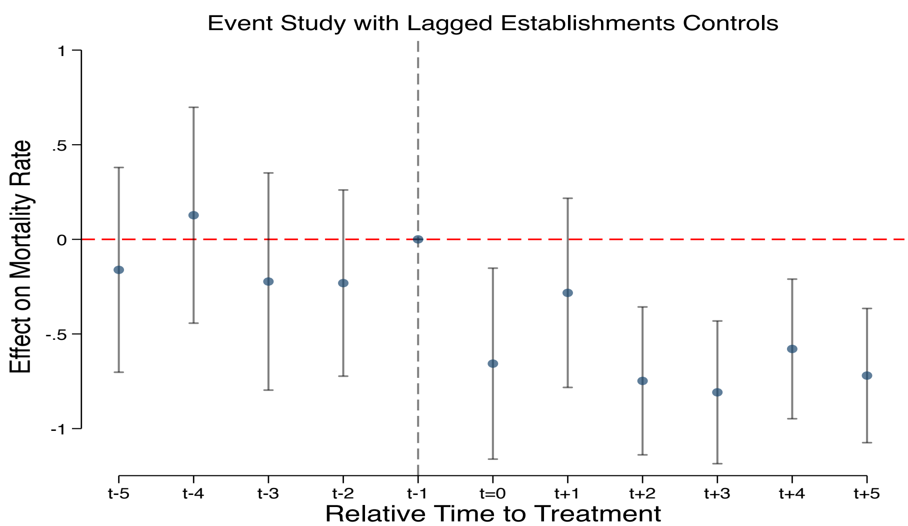
(b) Event Study: Contemporaneous Treatment Effects

Notes: The estimates are from Equation 5 specification where the outcome variable is the mortality rate related to mental and behavioral health disorders (MBD) per 100,000 county residents. Panel A1a examines the lagged effects of treatment, showing an overall treatment effect of -0.600 (representing a 23.5% change from pre-treatment mean). Panel A1b investigates contemporaneous effects, with an overall treatment effect of -0.504 (18% change from baseline). Both specifications include county and year fixed-effects, and state-by-year fixed effects. The observations are weighted by county-level demographic characteristics from 1999. Additional controls include demographic composition, economic conditions, healthcare infrastructure, and other county-level characteristics. The standard errors are clustered at the county level. The data combines County Business Patterns (CBP) and Vital Statistics mortality data for the period 1999-2016. The figures display point estimates and 95% confidence intervals, with dashed vertical lines indicating the timing of treatment and horizontal lines at zero serving as reference points.

Figure A2: Robustness Checks: Event Studies with Alternative Controls



(a) Event Study with Lagged Outcome Controls



(b) Event Study with Lagged Establishments Controls

Notes: These figures present robustness checks for our main event study analysis. Panel (a) augments our baseline specification by including two lags of the outcome variable (mortality rate) as additional controls. Panel (b) includes two lags of mental health establishments as controls. Both specifications maintain the core controls from our main analysis: county and year fixed-effects (Panel a) or county, year, and state-by-year fixed effects (Panel b), demographic characteristics, and economic conditions. All observations are weighted by 1999 county-level demographic characteristics, with standard errors clustered at the county level. The data combines County Business Patterns (CBP) and Vital Statistics mortality data for the period 1999-2016. The vertical dashed lines indicate the timing of treatment, while horizontal lines at zero provide reference points. Point estimates and 95% confidence intervals are displayed. These robustness checks help address potential concerns about pre-existing trends in either mortality rates or mental health establishment counts affecting our main results.

Appendix Tables

Table A1: Summary Statistics: Treatment and Control Counties

	Full Sample		Control		Treatment		
	Mean	(SD)	Mean	(SD)	Mean	(SD)	p-value
Panel A: Mental Health Treatment Facilities							
Total facilities	0.69	(0.95)	0.00	(0.00)	0.92	(1.00)	0.000***
Facilities per 100,000	3.03	(4.84)	0.00	(0.00)	4.04	(5.21)	0.000***
Outpatient facilities	0.52	(0.78)	0.00	(0.03)	0.70	(0.83)	0.000***
Outpatient per 100,000	2.34	(4.14)	0.00	(0.18)	3.11	(4.52)	0.000***
Inpatient facilities	0.17	(0.50)	0.00	(0.03)	0.23	(0.56)	0.000***
Inpatient per 100,000	0.72	(2.46)	0.00	(0.15)	0.95	(2.79)	0.000***
Annual openings (%)	0.03	(0.17)	0.00	(0.00)	0.04	(0.19)	0.000***
Annual closings (%)	0.04	(0.20)	0.00	(0.00)	0.06	(0.23)	0.000***
Panel B: Mental and Behavioral Disorder Deaths (per 100,000)							
All ages	30.82	(27.52)	30.40	(31.51)	30.96	(26.06)	0.554
Age $<$ 19	0.03	(0.39)	0.02	(0.47)	0.03	(0.36)	0.017**
Ages 20–34	0.20	(1.15)	0.20	(1.45)	0.20	(1.02)	0.955
Ages 35–49	0.79	(2.42)	0.83	(3.15)	0.78	(2.13)	0.331
Ages 50–64	1.56	(3.46)	1.57	(4.40)	1.56	(3.08)	0.794
Ages 65+	28.23	(26.55)	27.77	(30.42)	28.39	(25.13)	0.512
Panel C: MBD Deaths by Race (per 100,000)							
White	28.43	(26.61)	27.27	(30.26)	28.82	(25.26)	0.106
Black	2.15	(5.51)	2.82	(6.85)	1.92	(4.97)	0.002***
Other races	0.24	(1.96)	0.30	(2.75)	0.22	(1.62)	0.207
Panel D: MBD Deaths by Gender (per 100,000)							
Male	11.10	(11.94)	11.00	(14.05)	11.13	(11.14)	0.701
Female	19.72	(19.56)	19.40	(22.93)	19.83	(18.29)	0.522
Panel E: County Characteristics							
Population (100,000s)	0.28	(0.20)	0.17	(0.13)	0.31	(0.20)	0.000***
Employment-population ratio	0.47	(0.13)	0.46	(0.15)	0.47	(0.12)	0.772
Earnings per capita	17.54	(5.98)	17.19	(7.04)	17.66	(5.58)	0.203
Transfers per capita	6.48	(2.33)	6.53	(2.34)	6.46	(2.33)	0.395
Population growth (%)	0.32	(1.40)	0.19	(1.66)	0.36	(1.30)	0.015**
Population density	50.62	(49.53)	31.32	(28.52)	57.01	(53.21)	0.000***
Urban county	0.19	(0.39)	0.15	(0.35)	0.21	(0.41)	0.051*
Population share under 19 (%)	27.13	(3.43)	27.24	(3.92)	27.09	(3.26)	0.473
Population share 20–34 (%)	17.57	(3.15)	17.18	(3.55)	17.69	(2.99)	0.021**
Population share 35–49 (%)	20.50	(2.46)	20.25	(2.53)	20.58	(2.42)	0.008***
Population share 50–64 (%)	18.98	(3.08)	19.01	(3.30)	18.97	(3.00)	0.761
Population share 65+ (%)	15.83	(3.72)	16.31	(4.29)	15.67	(3.50)	0.011**
Counties	1,323		565		758		
County-year observations	26,455		11,295		15,160		

Notes: This table presents summary statistics for counties included in the event study analysis. Treatment counties are those that experience a single mental health facility opening during the sample period with no pre-treatment changes. Control counties never receive a mental health facility. All statistics are weighted by county population. Mental and Behavioral Disorder (MBD) deaths correspond to ICD-10 codes F10–F99. The p-value column reports the significance of the difference in means between treatment and control groups, calculated from regressions with standard errors clustered at the county level. Urban counties are those with Rural-Urban Continuum Codes 1–3. *** p$<$0.01, ** p$<$0.05, * p$<$0.10.

Table A2: First Stage: Mental Health Facilities and Sectoral Employment

	(1) Basic FE	(2) State×Year FE	(3) Add Demographics	(4) Full Controls
Number of MH Facilities	0.03351***	0.03351***	0.02941***	0.02903***
	(0.00778)	(0.00778)	(0.00829)	(0.00825)
	[3.35%]	[3.35%]	[2.94%]	[2.90%]
Fixed Effects:				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State × Year	No	Yes	Yes	Yes
Controls:				
Demographics	No	No	Yes	Yes
Economic	No	No	No	Yes
Observations	43,904	43,904	43,904	43,886
Counties	2,440	2,440	2,440	2,439
Adjusted R^2	0.642	0.642	0.642	0.642
Mean of Dep. Var.		5.307		

Notes: This table presents first-stage estimates validating that mental health (MH) treatment facilities represent real increases in mental healthcare resources. The dependent variable is the natural log of mental health employment per 100,000 county residents, constructed from County Business Patterns data for NAICS codes 621112 (offices of physicians, mental health specialists) and 621330 (offices of mental health practitioners except physicians). All specifications include county and year fixed effects. Column (1) presents the baseline specification. Column (2) adds state-by-year fixed effects to account for state-specific trends and policies. Column (3) adds demographic controls (share of population under 19). Column (4) adds economic controls (employment-to-population ratio). Standard errors clustered at the county level are in parentheses. Numbers in brackets show the percentage increase in employment from one additional facility (coefficient × 100 for log models). Sample period is 1999-2016. Counties with zero employment are included with ln(0+1) transformation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Asymmetric Effects of Mental Health Facilities on Disability Claims

	(1)	(2)	(3)	(4)
Panel A: Effect of Facility Openings				
Facilities Opened	1.87502	1.87502	7.90303***	8.09271***
	(2.03998)	(2.04198)	(1.99865)	(1.95310)
	[0.30%]	[0.30%]	[1.25%]	[1.28%]
Panel B: Effect of Facility Closings				
Facilities Closed	-5.88172**	-5.88172**	-3.65638	-3.32336
	(2.91666)	(2.91952)	(2.92752)	(2.89561)
	[-0.93%]	[-0.93%]	[-0.58%]	[-0.53%]
Asymmetry Test				
H_0: Opening effect = -Closing effect	p-value = 0.182			
Fixed Effects:				
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State × Year FE	No	Yes	Yes	Yes
Controls:				
Demographics	No	No	Yes	Yes
Economic	No	No	No	Yes
Pre-2014 Mean	633.0			
Observations	25,535	25,535	23,792	23,784
Counties	2,973			
Adjusted R^2	0.642			

Notes: This table presents asymmetric effects of mental health facility openings versus closings on disability claims using SSA county-level data (2009-2016). The dependent variable is SSI disability recipients aged 18-64 per 100,000 population. Panel A shows the effect of facility openings (increases in the number of facilities), while Panel B shows the effect of facility closings (decreases in the number of facilities). The asymmetry test examines whether the magnitude of opening effects equals the negative of closing effects. A significant p-value indicates asymmetric effects, suggesting that preventing closures may be more important than facilitating openings for disability prevention. Demographic controls include share under 19. Economic controls include employment-population ratio. Standard errors clustered at the county level in parentheses. Percentage changes relative to pre-2014 mean in square brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects of Treatment Facilities on Different MBD Outcome and Sub-category: Full Specification

	All MBD-Deaths	F00-F09	F10-F19	F20-F29	F30-F39	F40-F48	F50-F59	F60-F69	F70-F79
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Facilities	-0.07898***	-0.07747***	-0.00047	0.00022	-0.00028	-0.00038	-0.00057	0.00002	-0.00027
	(0.02974)	(0.02841)	(0.00385)	(0.00068)	(0.00087)	(0.00028)	(0.00048)	(0.00003)	(0.00057)
Ratio									
Adj. R^2	0.529	0.545	0.106	0.024	0.025	0.013	0.000	-0.003	0.085
N	53,480	53,480	53,480	53,480	53,480	53,480	53,480	53,480	53,480
Fixed Effects									
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls									
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 2 using our preferred specification that includes all fixed effects and controls. Heteroskedasticity robust standard errors clustered by county in parentheses (* p<.10 ** p<.05 *** p<.01). The ratio of point estimate and mean is in square brackets. Each column represents a separate regression. All specifications include county and year fixed effects, state-by-year fixed effects, and demographic and economic controls.

Table A5: Sun and Abraham (2021) Estimates of Mental Health Treatment Facility Effects

	(1)	(2)	(3)	(4)
Number of Facilities	-1.800***	-1.474***	-1.308***	-1.287***
	(0.170)	(0.169)	(0.164)	(0.163)
	[-70.6%]	[-57.8%]	[-51.3%]	[-50.5%]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	No	Yes	Yes	Yes
Controls				
Demographic	No	No	Yes	Yes
Economic	No	No	No	Yes
Adj. R^2	0.760	0.792	0.735	0.735
Observations	27,338	27,238	26,395	26,395
Number of Counties	1,368	1,363	1,320	1,320
Number of Treated Counties	870	868	840	840
Number of Control Counties	649	645	626	626

Notes: This table reports Sun and Abraham (2021) interaction-weighted estimates of the effect of mental health treatment facilities on mortality rates from mental and behavioral disorders (MBD). Each column represents a separate model specification. The dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses ($^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. Model (1) includes only county and year fixed effects. Model (2) adds state-by-year fixed effects. Model (3) introduces demographic controls. Model (4) adds economic controls. See Section 4 for more details on the construction of the variables and data sources. The sample period is 1999-2016.

Table A6: Dynamic Effects of Mental Health Treatment Facilities on External Cause Mortality: Sun and Abraham (2021) Estimates

Panel A: Dynamic Treatment Effects	
t = -5	0.151
	(0.285)
t = -4	0.435
	(0.301)
t = -3	-0.029
	(0.282)
t = -2	-0.233
	(0.260)
t = 0	-0.409
	(0.274)
t = 1	-1.114***
	(0.189)
t = 2	-1.049***
	(0.193)
t = 3	-1.110***
	(0.190)
t = 4	-0.796***
	(0.193)
t = 5	-0.999***
	(0.190)
Panel B: Sample Information	
Number of Treated Counties	783
Number of Control Counties	585
Total Counties	1,319
Observations	23,742
Pre-treatment Mean	2.55
Panel C: Specification	
County FE	Yes
Year FE	Yes
State $\times$ Year FE	Yes
Demographic Controls	Yes
Economic Controls	Yes

Notes: This table presents dynamic treatment effect estimates of mental health treatment facilities on external cause mortality rates using the methodology developed by Sun and Abraham (2021). The estimates account for treatment effect heterogeneity in the presence of staggered treatment timing and multiple treatment cohorts. Panel A reports event-study coefficients for periods t = -5 to t = 5 relative to treatment timing, with t = -1 as the omitted reference period. Estimates are interaction-weighted averages across all treatment cohorts. Standard errors (in parentheses) are clustered at the county level. Treatment counties are defined as those that experience exactly one increase in mental health facilities during the sample period, with no pre-treatment changes. Control counties never experience changes in facility numbers. The sample spans 1999-2016 and includes demographic and economic controls of age, employment-to-population ratio, earnings per capita, transfer payments per capita, hospital presence, population density, rural-urban classification. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Effects of Treatment Facilities on Different MBD Outcome and Sub-category: Robustness Check with Hospital Controls

	All MBD-Deaths	F00-F09	F10-F19	F20-F29	F30-F39	F40-F48	F50-F59	F60-F69	F70-F79
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Facilities	-0.07928***	-0.07979***	0.00025	0.00053	0.00033	-0.00029	-0.00052	0.00003	-0.00009
	(0.02760)	(0.02666)	(0.00422)	(0.00075)	(0.00096)	(0.00031)	(0.00053)	(0.00004)	(0.00063)
Ratio									
Adj. R^2	0.503	0.526	0.097	0.025	0.024	0.013	-0.001	-0.002	0.089
N	50,512	50,512	50,512	50,512	50,512	50,512	50,512	50,512	50,512
Fixed Effects									
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls									
Hospital Establishments	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 2 with additional controls for hospital establishments. Heteroskedasticity robust standard errors clustered by county in parentheses (* p<.10 ** p<.05 *** p<.01). The ratio of point estimate and mean is in square brackets. Each column represents a separate regression. All specifications include county and year fixed effects, state-by-year fixed effects, demographic and economic controls, and controls for the number of hospital establishments in each county.

Table A8: Effects of Treatment Facilities on Other Mortality Outcomes

	Other Deaths	Transport Accidents	Medical/Surgical Care Deaths
	(1)	(2)	(3)
Number of Facilities	0.00290	-0.00112	-0.00091
	(0.00310)	(0.00943)	(0.00125)
	[0.82]	[-0.01]	[-0.08]
Fixed Effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes
Controls			
Demographic	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Adj. R^2	0.290	0.275	0.022
N	53,480	53,480	53,480

Notes: This table reports the effects of mental health treatment facilities on other mortality rates unrelated to mental and behavioral disorders (MBD). Each coefficient represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for other unclassified deaths, column (2) for deaths from transport accidents, and column (3) for deaths related to medical/surgical care. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1998-2016.

Table A9: Robustness Check: Effects of Mental Health Treatment Facilities on MBD Mortality Pre-ACA (1999-2013)

	(1)	(2)	(3)	(4)
Dependent Variable: MBD Mortality Rate (per 100,000)				
Number of Facilities	-0.0301	-0.0409	-0.0535*	-0.0535*
	(0.0328)	(0.0255)	(0.0307)	(0.0308)
	[-0.11%]	[-0.15%]	[-0.19%]	[-0.19%]
Fixed Effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
State-by-Year	No	Yes	Yes	Yes
Controls				
Demographic	No	No	Yes	Yes
Economic	No	No	No	Yes
Adj. R^2	0.505	0.523	0.524	0.524
Observations	47,552	47,552	47,552	47,536

Notes: This table reports the robustness check of mental health treatment facilities' effects on mortality rates from mental and behavioral disorders (MBD), restricting the sample to pre-Affordable Care Act years (1999-2013). Each column represents a separate estimation of Equation 2, where the dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. Column (1) presents the baseline specification with county and year fixed effects. Column (2) adds state-by-year fixed effects. Column (3) introduces demographic controls . Column (4) adds economic controls. This robustness check confirms that the main results are not driven by the post-ACA period implementation.

Table A10: Effects of Treatment Facilities on Similar Deaths to MBD

	Assault Deaths (1)	Self-Harm Deaths (2)	Other External Injuries (3)
Number of Facilities	-0.01075**	-0.03083***	-0.07288***
	(0.00502)	(0.00732)	(0.01668)
	[-0.28]	[-0.23]	[-0.26]
Fixed Effects			
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
State-by-Year	Yes	Yes	Yes
Controls			
Demographic	Yes	Yes	Yes
Economic	Yes	Yes	Yes
Adj. R^2	0.270	0.174	0.280
N	53,480	53,480	53,480

Notes: This table reports the effects of mental health treatment facilities on mortality rates from causes similar to mental and behavioral disorders (MBD). Each coefficient represents a separate estimation of Equation **??**, where the dependent variable is deaths per 100,000 county residents. The main explanatory variable is the number of treatment facilities in a county. Heteroskedasticity-robust standard errors clustered at the county level are reported in parentheses (* p<.10 ** p<.05 *** p<.01). Numbers in square brackets represent the percentage change relative to the pre-treatment mean of the dependent variable. All specifications include county, year, and state-by-year fixed effects, as well as demographic and economic controls. Column (1) presents estimates for deaths due to assault, column (2) for intentional self-harm deaths, and column (3) for other external injury deaths. See Section 4 for more details on the construction of the variables and data sources. The sample is restricted to 1998-2016.

Table A11: Classification of Mental and Behavioral Disorders Related Mortality

Category Code	Description	Classification Group
F00-F09	Organic Mental Disorders[a]	Primary Disorders
F10-F19	Mental and Behavioral Disorders due to Psychoactive Substance Use	Substance-Related
F20-F29	Schizophrenia, Schizotypal and Delusional Disorders	Psychotic Disorders
F30-F39	Mood [Affective] Disorders	Affective Disorders
F40-F48	Neurotic, Stress-related and Somatoform Disorders	Anxiety-Related
F50-F59	Behavioral Syndromes Associated with Physiological Disturbances	Physiological
F60-F69	Disorders of Adult Personality and Behavior	Personality
F70-F79	Mental Retardation	Developmental
F80-F89	Disorders of Psychological Development	Developmental
F90-F98	Behavioral and Emotional Disorders with Childhood Onset	Early-Onset
F99	Unspecified Mental Disorder	Other

[a] Including dementia in Alzheimer's disease (F00*) and other diseases classified elsewhere (F02*)
Note: Classification based on ICD-10 Chapter V: Mental and Behavioral Disorders (World Health Organization, 2019). Asterisk (*) categories indicate special coding for certain conditions.
Mental and Behavioural Disorders (ICD-10 Section V)

Table A12: State Medicaid Expansion Status and Timing Under the ACA

State	Expansion Status	Implementation Date
Arizona	Expansion	January 2014
Arkansas	Expansion	January 2014
California	Expansion	January 2014
Colorado	Expansion	January 2014
Connecticut	Early Expansion	January 2014[a]
Delaware	Early Expansion	January 2014[a]
Hawaii	Expansion	January 2014
Illinois	Expansion	January 2014
Iowa	Expansion	January 2014
Kentucky	Expansion	January 2014
Maryland	Expansion	January 2014
Massachusetts	Early Expansion	January 2014[a]
Michigan	Expansion	January 2014
Minnesota	Expansion	January 2014
Nevada	Expansion	January 2014
New Hampshire	Expansion	January 2014
New Jersey	Expansion	January 2014
New Mexico	Expansion	January 2014
New York	Early Expansion	January 2014[a]
North Dakota	Expansion	January 2014
Ohio	Expansion	January 2014
Oregon	Expansion	January 2014
Rhode Island	Expansion	January 2014
Vermont	Early Expansion	January 2014[a]
Washington	Expansion	January 2014
West Virginia	Expansion	January 2014
Indiana	Expansion	February 2015
New Hampshire	Expansion	August 2015
Pennsylvania	Expansion	January 2015
Louisiana	Expansion	July 2016
Montana	Expansion	January 2016

[a] These states implemented early expansion under Section 1115 waivers prior to 2014.

Notes: This table shows the timing of Medicaid expansion adoption under the Affordable Care Act. Early expansion states implemented expansion through Section 1115 waivers prior to 2014. Large expansion states (California, Iowa, Minnesota, Hawaii, Indiana, Maryland, Connecticut, Wisconsin) experienced particularly large increases in Medicaid enrollment following expansion. Data sources: Medicaid expansion dates from Kaiser Family Foundation and state websites. Early expansion classification follows NEJM appendix Miller and Wherry (2017). Large expansion states identified following Carey et al. (2020).