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

Olanrewaju Yusuff*

Georgia State University

October, 2025

Please click here for the Latest Version

Abstract

Do mental health treatment facilities save lives? Using County Business Patterns data (1999-2016) and within-county variation, I provide the first causal evidence that mental health infrastructure reduces mortality broadly. Each additional facility prevents 1.56 deaths per 100,000 residents from all causes annually, with mental and behavioral disorder (MBD) mortality declining by 0.079%. A 10% increase in facilities lowers overall mortality by 0.5% and MBD mortality by 2%. Three key findings emerge: (1) facility closures increase mortality ten times more than openings reduce it, revealing asymmetries with welfare implications; (2) Medicaid expansion amplifies facility effectiveness by 26% in high-uninsurance counties, demonstrating that insurance and infrastructure are complements, not substitutes; (3) facilities operate through multiple mechanisms beyond direct treatment, serving as gateways to disability programs and enabling pharmaceutical access. Effects concentrate among elderly and less-educated populations who face the highest access barriers. Event studies using the Sun and Abraham (2021) estimator show immediate, persistent effects with no pre-trends. The benefit-cost ratio exceeds 4-to-1, with each facility generating $11.7 million in annual net benefits. Results indicate that neither insurance expansion nor infrastructure investment alone maximizes health benefits; coordinated policies addressing both dimensions are essential for reducing mortality.

JEL Classifications: H51, I10, I12, I13, I18, J24, R12; ***Keywords:*** Mental Health, Healthcare Access, Treatment Facilities, Mortality, Medicaid Expansion, Insurance Coverage, Healthcare Infrastructure, Asymmetric Effects.

*I am thankful to my advisors, James Marton, Lauren Hoehn-Velasco, Keith Teltser, and Ann DiGirolamo. Special thanks to Claudia Persico, Tejendra Singh, and Alberto Ortega for their invaluable feedback and guidance. I thank Anne Piehl, Sam Mann, Angelo Orane Hutchinson, Ben Harrell, Grace McCormack, Monica Deza, Isaac Swensen, Bocar A Ba, Ashley Bradford, Tamara Beetham, Shannon Self-Brown, Bradyn Churchill, and Anne M. Burton for helpful comments and suggestions. This paper benefited from presentations at the 2025 American Economic Association Annual Meeting and the AEA Mentoring Program, the 2024 and 2025 ASHEcon Conferences, the 2024 SEA Conference, and the 2025 Georgia State University Graduate Conference for Research, Scholarship, and Creative Activity. Special thanks to participants in all seminars for their constructive feedback. I am grateful for support from the Center for the Economic Analysis of Risk (CEAR) Fellowship at Georgia State University Robinson College of Business, and Institute for Research on Poverty, University of Wisconsin-Madison. Previous version of this paper was circulated under the title "Health Effects of Local and Geographic Access to Mental Health Treatment Facilities". All remaining errors are my own.

Job Market Paper: Contact: oyusuff4@student.gsu.edu, Department of Economics, Georgia State University.

1 Introduction

Does local access to mental health treatment save lives? Despite mental health disorders affecting one in five Americans and imposing costs exceeding 4 percent of GDP, we lack causal evidence on whether treatment infrastructure reduces mortality. This paper provides the first evidence that mental health facilities prevent deaths across multiple causes, with each additional facility reducing overall mortality by 1.56 deaths per 100,000 residents annually. The effects extend far beyond mental health-specific causes, revealing that mental health treatment generates broad health benefits previously unrecognized in the literature.

The 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.

Deaths from mental and behavioral disorders (MBD) increased fivefold between 1999 and 2016, from 30,000 to over 120,000 annually, making it one of the fastest-growing mortality categories. Figure 1, and 2 shows this crisis starkly: while overall mortality grew 15 percent, MBD deaths surged 300 percent. This divergence occurred despite a 50 percent expansion in mental health facilities, raising questions about whether infrastructure investments can address the crisis. My results show they can, but effectiveness depends critically on complementary insurance coverage and maintaining existing capacity.

Using establishment-level data from County Business Patterns (1999-2016) matched with mortality records, I exploit within-county variation in mental health facilities to identify causal effects. The baseline difference-in-differences specification with county and state-by-year fixed effects shows that each facility prevents 1.56 deaths per 100,000 residents from all causes. For mental and behavioral disorders specifically, facilities reduce mortality by 0.079 percent. A 10 percent increase in facilities lowers overall mortality by 0.5 percent and MBD mortality by 2 percent.

This paper makes four contributions to the health economics literature. First, I provide the first causal evidence that mental health infrastructure reduces overall mortality, extending the healthcare access literature beyond physical health facilities, 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). While Bailey and Goodman-Bacon (2015) showed that Community Health Centers reduced age-adjusted mortality by 2 percent over 10 years, and Buchmueller et al. (2006) found that hospital closures increased deaths among infants and the elderly, no prior work examined mental health facilities' mortality effects. My findings that mental health facilities reduce all-cause mortality by 0.5 percent annually place them alongside hospitals and primary care as essential health infrastructure. This builds on recent work showing that healthcare access improvements generate mortality benefits across diverse settings (Currie et al., 2023; Alexander and Richards, 2023; Bailey and Goodman-Bacon, 2015; Miller et al., 2021).

Second, I document asymmetry in facility effects: closures increase mortality ten times more than openings reduce it. In the full specification, closures raise mortality by 0.124 deaths per 100,000 while openings reduce it by only 0.013. This extends Corredor-Waldron and Currie (2022)'s findings on hospital closures to mental health, revealing even larger asymmetries. The pattern reflects the irreversible disruption of patient-provider relationships and difficulty rebuilding trust elsewhere (Frank, 2006). This asymmetry, documented here for the first time in mental healthcare, suggests that preventing closures in vulnerable communities should take priority over geographic expansion.

Third, I establish that insurance and infrastructure are complements, not substitutes, in reducing mortality. Using Medicaid expansion under the ACA as a quasi-experimental variation, I implement the first triple-difference analysis of how insurance modifies mental health treatment facility effectiveness. In high-uninsurance counties, Medicaid expansion amplifies facility mortality reduction by 26 percent for MBD and even more for overall mortality. This complementarity advances the insurance literature (Finkelstein, 2007; Miller, 2012; Sommers et al., 2013) by showing that coverage without capacity yields limited benefits. It also extends infrastructure research (Swensen, 2015; Bondurant et al., 2018) by demonstrating that facilities without coverage cannot maximize health gains. Recent work has increasingly recognized these interactions (Finkelstein and Hendren, 2020; Bradford and Maclean, 2023; Ortega, 2023), but mine is the first to quantify mortality implications of mental health treatment facilities.

Fourth, I identify mechanisms beyond direct treatment that explain the broad mortality effects. Facilities serve as gateways to disability programs, increasing SSI participation by 1.4 percent and connecting vulnerable populations to income support and healthcare (Messel et al., 2023; Deshpande, 2016). With insurance, facilities enable pharmaceutical treatment, generating 280 additional antidepressant prescriptions per 100,000 residents. These pathways help explain spillover effects on non-mental-health mortality and align with evidence that mental health treatment improves management of chronic physical conditions (Walker et al., 2015; Druss et al., 2011).

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. I validate that facility counts represent real capacity by showing each facility increases mental health employment by 3 percent (8-10 workers), using imputed data from Eckert et al. (2020). Placebo tests on unrelated causes (transport accidents, surgical complications) show null effects, confirming mental health-specific impacts rather than general healthcare improvements.

The heterogeneous effects reveal important disparities. Elderly populations experience the largest benefits, consistent with higher baseline risk and mobility constraints (Currie et al., 2024). Less-educated individuals see twice the mortality reduction of college-educated, suggesting geographic proximity matters most for resource-constrained populations (Gupta et al., 2024; Deza et al., 2022a). These patterns extend evidence on healthcare proximity gradients (Currie et al., 2023; Fadlon et al., 2025) to mental health, showing even stronger distance decay than physical health services.

The welfare implications are substantial. Each facility generates \$15.1 million in annual mortality benefits against \$3.4 million in costs, yielding net benefits of \$11.7 million and benefit-cost ratios exceeding 4-to-1. These returns justify significant public investment, particularly given market failures in mental healthcare provision, including externalities, information asymmetries, and insurance imperfections (Frank and McGuire, 2000; Bloom et al., 2012).

This work contributes to multiple strands of the economics literature. It extends research on geography and healthcare utilization (Wennberg and Gittelsohn, 1973; Baicker and Chandra, 2006; Chandra and Staiger, 2007; Skinner, 2011; Finkelstein et al., 2016; Molitor, 2018) by showing that mental health exhibits even stronger proximity gradients than physical healthcare. It sheds more light on the employment effects of new health facilities (Acemoglu and Finkelstein, 2008; Banerjee et al., 2004; Chowdhury et al., 2003; Chandra and Staiger, 2007; Clemens and Gottlieb, 2014; Baicker and Chandra, 2006). It advances the literature on healthcare infrastructure (Acemoglu and Finkelstein, 2008; Chay et al., 2009) by documenting how facility closures create disruptions that new openings cannot offset. The findings inform work on insurance-provider interactions (Clemens and Gottlieb, 2014; Cabral et al., 2021; Gottlieb et al., 2018) by quantifying complementarities between coverage and capacity. By revealing spillover effects on overall mortality, this paper also connects mental health treatment to the broader determinants of population health (Chetty et al., 2016; Dwyer-Lindgren et al., 2017; Case and Deaton, 2015a,b), showing that mental healthcare infrastructure deserves consideration alongside traditional medical facilities in explaining geographic mortality variation.

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 3).[1]

Figure 2 provides crucial context for this crisis. While all-cause mortality increased modestly by 15 percent from 1999 to 2016, MBD deaths surged 300 percent, making it one of the fastest-growing mortality categories. This divergence suggests that standard healthcare improvements have failed to address mental health, highlighting the need to understand whether expanding treatment infrastructure can reverse these trends.

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 4a 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 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.

[1] 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).

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.[2]

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.

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).[3]

The industry's structure exhibits important features that influence service provision. Treatment facilities

[2] 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.

[3] 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.

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.

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

This section develops a framework for understanding how mental health facilities affect mortality through multiple pathways and why facility closures may have larger effects than openings in Figure 5.

3.1 Primary Pathway: Local Access to Treatment

Mental health facilities affect mortality primarily through providing local access to treatment. Geographic proximity reduces travel costs, time burdens, and logistical barriers that prevent individuals from receiving care. This local access effect operates independently of insurance status; even uninsured individuals benefit from nearby facilities through sliding scale fees, charity care, and crisis intervention services.

However, the effectiveness of local access varies with insurance coverage. Insurance amplifies the baseline access effect by removing financial barriers and enabling more intensive treatment. While facilities provide benefits to all residents through improved local access, those with insurance can utilize services more frequently and consistently. This suggests two distinct but related effects: a direct effect of geographic access and an additional complementary effect when access combines with insurance coverage.

3.2 Asymmetric Adjustment Costs

The framework incorporates asymmetric adjustment costs between facility entry and exit. When facilities open, individuals gain an additional treatment option but may continue with existing care arrangements or self-management strategies. The marginal benefit depends on the quality differential between the new facility and current alternatives.

When facilities close, however, all current patients face immediate disruption. Finding new providers involves search costs, waiting periods, and rebuilding therapeutic relationships. These adjustment costs are particularly high for individuals experiencing acute symptoms who may struggle with the cognitive and emotional demands of navigating care transitions. These frictions suggest closures should generate larger mortality effects than openings, though the magnitude remains an empirical question.

3.3 Multiple Mechanisms

Beyond direct treatment provision, facilities may affect mortality through several indirect channels. First, mental health providers serve as gateways to social support programs, supplying documentation necessary for disability applications and connecting patients to wraparound services. Second, facilities enable prescription access even for those with limited ability to pay, through pharmaceutical assistance programs and sample medications. Third, if facilities represent real treatment capacity rather than administrative entities, we should observe corresponding changes in local mental health employment. These mechanisms suggest facilities affect mortality through both direct treatment and broader community health infrastructure.

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 lag between IRS reporting and CBP publication, 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 Treatment Facilities 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.[4]

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.

4.3 Vital Statistics Mortality Data

My primary outcomes are mortality rates constructed from the Multiple Cause of Death data files from the National Center for Health Statistics (NCHS) for the period 1999 to 2016. These restricted access 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 three categories of mortality outcomes. First, I measure *overall mortality* from all causes of death to capture the comprehensive health effects of mental health facility access. This broad measure includes both direct effects on mental health related mortality and indirect effects through improved

[4] 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.

management of comorbid conditions, reduced substance abuse, and other pathways (Walker et al., 2015; Druss et al., 2011).

Second, I focus on *mental and behavioral disorder (MBD) mortality*, defined using ICD-10 Chapter V codes F00 through F99.[5] I examine deaths attributed to eleven distinct diagnostic categories: 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), intellectual disabilities (F70-F79), developmental disorders (F80-F89), childhood onset disorders (F90-F98), and unspecified mental disorders (F99). I construct an aggregate measure of total MBD mortality by summing deaths across all F00 to F99 codes, providing the overall effect on mental health related mortality while the diagnostic subcategories allow examination of heterogeneous effects across condition types.[6]

Third, I examine *component causes of mortality* to understand mechanisms and rule out alternative explanations. These include mental health related causes (intentional self harm via ICD-10 codes X60 to X84, and substance use disorders), external causes potentially affected by mental health (assault, transport accidents, and other accidental injuries), and placebo outcomes not expected to respond to mental health treatment (deaths from medical and surgical care complications, and other natural causes). This categorization allows me to test whether effects are specific to mental health related causes or reflect broader changes in mortality reporting or healthcare quality.

To construct my dependent variables, I aggregate death counts at the county year level for each cause category 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.[7]

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

[5]The ICD-10 classification system is documented at https://icd.who.int/browse10/2019/en?blockCode=V. Classification includes dementia in Alzheimer disease (F00) and dementia in other diseases classified elsewhere (F02), based on ICD-10 Chapter V: Mental and Behavioral Disorders (World Health Organization, 2019).

[6]Table A13 in the appendix provides the complete classification structure.

[7]For county year cells with zero deaths in a particular category, I assign a mortality rate of zero. The NCHS suppresses county level data when death counts are small (typically fewer than 10 deaths) to protect privacy; I treat suppressed values as missing. Data suppression is minimal for overall mortality and aggregate MBD mortality due to aggregation across multiple cause categories, but more common for specific diagnostic subcategories and rare causes of death, particularly in small rural counties.

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 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 Social Security Disability Data

To examine whether mental health facilities affect disability program participation, I obtain county-level data on Supplemental Security Income (SSI) recipients from the Social Security Administration for 2009–2016.[8] The data provide counts of individuals receiving SSI disability payments, which require documented medical conditions that prevent substantial gainful activity.[9]

I merge the SSA disability data with my main county-year panel by FIPS code, restricting the analysis to 2009–2016 to match the SSA data availability.[10] I normalize disability recipients by county population to create a rate per 100,000 residents. This shorter panel (2009–2016) yields approximately 25,000 county-year observations for the mechanism analysis, compared to the full mortality panel (1999–2016) with 56,000 observations.

[8]SSA publishes annual county-level counts of SSI recipients by age group. I use recipients aged 18–64, the working-age population eligible for disability benefits based on mental health conditions. SSA county-level data are available at https://www.ssa.gov/policy/docs/statcomps/ssi_sc/

[9]SSI provides cash assistance to disabled individuals with limited income and resources. Unlike SSDI, SSI does not require prior work history, making it particularly relevant for individuals with severe mental illness who may have limited labor force attachment.

[10]The SSA data end in 2016. I process the raw Excel files to extract county-level recipient counts, handling suppressed values (coded as missing when counts are below disclosure thresholds) by setting them to zero. See the data appendix for details on the cleaning procedure.

4.6 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.

4.7 Analytical Sample Construction

My analysis employs two complementary samples to balance statistical power with clean identification. The full TWFE sample maximizes observations for detecting average treatment effects, while the event study sample provides cleaner identification of dynamic treatment patterns.

Full TWFE Sample. The baseline analysis includes all U.S. counties (excluding Alaska and Hawaii) with consistent identifiers from 1999 to 2016. I measure treatment using counts of mental health facilities identified through NAICS codes 621112 (offices of physicians, mental health specialists) and 621330 (offices of mental health practitioners except physicians). After excluding counties that never report facilities during the sample period, the full sample contains 53,498 county-year observations across 2,972 counties.

Event Study Sample. Following Messel et al. (2023), the event study analysis restricts attention to counties with clear treatment timing. This sample includes: (1) treatment counties experiencing exactly one facility increase with no subsequent decreases (758 counties), and (2) control counties maintaining zero facilities throughout the period (565 counties). Counties with multiple facility changes are excluded from event studies as they lack clean treatment timing. This sample restriction reduces observations to 26,455 county years but provides unambiguous identification of treatment dynamics.[11]

Figure 4 illustrates the spatial distribution of both samples. Panel (a) shows the full TWFE sample, with counties colored by whether they experienced increases (blue), decreases (red), or no change (yellow) in facilities between 1999 and 2016. Panel (b) displays the event study sample classification, distinguishing event counties (orange) from no event counties (light blue) and excluded multiple change counties (gray). The geographic dispersion of treated and control counties across all regions helps alleviate concerns about regional confounding.

For heterogeneity analyses examining insurance interactions, I classify counties by 2013 baseline uninsurance rates from SAHIE, using within-state medians to define high and low coverage groups. This yields balanced subsamples for examining how insurance environments moderate facility effects. Mechanism analyses using SSI disability data (2009 to 2016) and Medicare Part D prescriptions (2013 to 2016) employ corresponding restricted panels matched to data availability.

The dual sample approach allows me to present robust average effects from the full sample while providing credible dynamic evidence from the restricted event study sample. Small differences between TWFE and event study estimates reflect compositional differences, with event study counties representing more stable rural areas without existing mental health infrastructure.

[11] Table A1 in the appendix presents detailed summary statistics for the event study sample. Treatment and control counties are well balanced in terms of demographic characteristics and baseline mortality rates. However, treatment counties are somewhat larger and more urban, consistent with facilities locating in areas with sufficient demand to support operations.

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).[12] 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:

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

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.[13] 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:

[12] 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.

[13] 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.[14]

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).[15] 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.[16]

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

[14] 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.

[15] 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.

[16] 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.[17]

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 five years before and after changes in facility

[17] 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.[18]

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.[19] 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

[18] 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.

[19] 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.[20]

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. These fixed effects flexibly absorb any state-specific shocks or policy changes that could confound my relationship of interest at the county level.

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.

[20]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 2 presents estimates examining the relationship between facility counts and mental health employment using the specification described in Section 5.4.

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.[21]

6.2 Overall Mortality Effects

Mental health facilities generate substantial reductions in overall mortality. Table 3 presents estimates of facility effects on all-cause mortality across specifications. The baseline specification (Column 1) shows that an additional mental health facility reduces overall mortality by 1.73 deaths per 100,000 population. This effect remains stable and precisely estimated as controls are added: 1.56 deaths per 100,000 with state-by-year fixed effects (Column 2), maintaining similar magnitude with demographic controls (Column 3), and 1.55 deaths per 100,000 in the full specification (Column 4).

[21] 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.

The magnitude of these effects is economically significant. At the sample mean of 917 deaths per 100,000, the preferred estimate represents a 0.17 percent reduction in overall mortality. For the average county with 97,000 residents, each facility saves approximately 1.5 lives annually. This effect size is comparable to other major healthcare interventions: Miller et al. (2021) finds that Medicaid expansion reduces mortality by 0.13 percent annually, while Bailey and Goodman-Bacon (2015) documents a 2 percent reduction from community health centers.

Figure 7 examines the dynamic evolution of these effects using the Sun and Abraham (2021) heterogeneity robust estimator. Panel (a) reveals no differential pre-trends, with coefficients near zero and statistically insignificant for $t < 0$. Following facility entry, mortality reductions emerge immediately and grow over time, reaching 3.4 deaths per 100,000 by year five. The log specification in Panel (b) confirms these patterns, showing a 0.62 percent reduction that persists throughout the post-treatment period. The absence of pre-trends supports the identifying assumption, while the persistence of effects indicates sustained benefits rather than temporary responses.

6.3 From Overall Mortality to Mental and Behavioral Disorder (MBD) Mortality

While the overall mortality reduction demonstrates the comprehensive health value of mental health facilities, a detailed examination of mental and behavioral disorder (MBD) mortality is essential for understanding treatment effectiveness and designing targeted policy responses.

Figure 2 reveals why MBD mortality demands specific attention. Panel (a) shows that while all-cause deaths increased modestly from 2.3 to 2.65 million (15 percent growth), MBD deaths exploded from 40,000 to over 120,000. Panel (b) makes this divergence explicit: MBD mortality grew nearly 300 percent over 1999-2016, representing one of the fastest-growing mortality categories in the United States. This dramatic growth occurred despite substantial expansion in treatment infrastructure, suggesting a crisis that standard healthcare improvements have failed to address.

I focus detailed analysis on MBD mortality for four reasons. First, the 300 percent growth makes it an urgent policy priority requiring targeted intervention. Second, MBD provides the cleanest identification of facility effects, as these deaths result from conditions explicitly treated in mental health settings. Third, examining MBD allows precise estimation of treatment mechanisms and heterogeneity where the causal chain from treatment to outcome is most direct. Fourth, no prior economic study has examined MBD as a primary outcome despite its growing importance for population health.

The remainder of my analysis, therefore, examines MBD mortality in detail, exploring heterogeneous effects, asymmetric responses, and mechanisms, while using the overall mortality effects for welfare calculations. This approach provides both the broad health impacts needed for cost-benefit analysis and the specific mental health insights essential for policy design.

6.4 Mental and Behavioral Disorder Mortality: Detailed Analysis

Table 4 examines effects on MBD mortality across diagnostic categories. Column 1 shows that an additional facility reduces overall MBD mortality by 0.066 percent, with effects concentrated in organic mental disorders (F00-F09) and schizophrenia/psychotic disorders (F20-F29). These conditions require consistent medication management and therapeutic support, explaining their responsiveness to improved facility access.

Table 5 demonstrates robustness across specifications. The baseline TWFE model yields a 0.066 percent reduction, increasing slightly to 0.079 percent in the full specification with all controls. At the sample mean of 30.9 MBD deaths per 100,000, this implies each facility prevents 0.024 deaths per 100,000 residents annually.

Figure 8 presents dynamic effects using the Sun and Abraham (2021) estimator. Panel (a) shows lagged treatment effects, with mortality declining by 1.29 deaths per 100,000 by year five, representing a 50.5 percent reduction from baseline. Panel (b) examines contemporaneous timing, revealing immediate effects of 0.52 deaths per 100,000. The larger lagged effects align with clinical evidence that mental health treatment requires time to stabilize conditions and prevent mortality.

The discrepancy between TWFE estimates (0.024 deaths per 100,000) and Sun Abraham estimates (1.29 deaths per 100,000) reflects the heterogeneity bias identified by Goodman-Bacon (2021). The TWFE estimator underweights periods with large treatment effects when treatment timing varies, while the Sun Abraham approach uses only clean comparisons between treated and not yet treated units. The true effect likely lies between these estimates, with the Sun Abraham results providing the more credible causal effect given the staggered treatment timing in my setting.

6.5 Robustness and Validation

I conduct extensive robustness checks to validate the causal interpretation of my findings. The main results prove remarkably stable across alternative specifications, sample restrictions, and estimation methods.

Progressive Specifications. Tables 3 and 5 demonstrate that effects remain stable as controls are added progressively. For overall mortality, the coefficient ranges from -1.74 to -1.56 deaths per 100,000 across specifications, with the full model including state-by-year fixed effects and all controls yielding -1.56 (SE = 0.26). The stability across specifications with increasingly rich controls suggests that selection on unobservables is unlikely to drive the results.

Alternative Event Study Specifications. Figure A4 addresses potential concerns about dynamic selection and pre-existing trends. Panel (a) includes lagged mortality rates as controls, while Panel (b) controls for lagged facility counts. Both specifications show no pre-trends and similar post-treatment dynamics to the main results, confirming that facilities are not endogenously locating in counties with improving or deteriorating mortality trends.

Component Cause Analysis. To verify that effects concentrate in mental health-related causes, I examine specific mortality categories. Table A8 shows significant reductions in deaths plausibly affected by mental health treatment: assault deaths decline by 0.28 percent, self-harm by 0.23 percent, and other external injuries by 0.26 percent. Figure 9 confirms these patterns dynamically, with Panels (a) through (c) showing persistent reductions following facility entry.

Conversely, Table A7 reports null effects on placebo outcomes unrelated to mental health. Transport accidents show no response (coefficient = -0.001, SE = 0.009), nor do deaths from medical/surgical complications (-0.001, SE = 0.001). The specificity of effects to mental health-related causes rules out spurious correlation with general mortality trends or healthcare quality improvements.

Healthcare Infrastructure Controls. A critical concern is whether mental health facilities proxy for broader healthcare expansion. Table A6 addresses this by controlling for hospital establishments. The MBD mortality effect remains virtually unchanged at -0.079 percent (SE = 0.030), confirming that mental health facilities have distinct impacts beyond general healthcare access.

Additional Robustness Checks. Appendix Section C.6 reports extensive additional analyses. Inverse probability weighting following Fischer et al. (2024) yields similar estimates after balancing observable characteristics between treated and control counties. The Sun and Abraham (2021) estimator, which addresses potential bias from staggered treatment timing, produces comparable results to the main TWFE specifications. Sample restrictions excluding small rural counties or large urban areas do not meaningfully alter conclusions.

The consistency of results across specifications, the absence of pre-trends, the specificity to mental health-related causes, and the robustness to alternative estimators provide strong evidence for a causal interpretation. Mental health facilities reduce mortality through targeted treatment of mental health conditions rather than through general healthcare improvements or spurious correlation with local trends.

6.6 Heterogeneous Effects

The average treatment effects mask important heterogeneity across population subgroups and facility types. Understanding this variation helps identify vulnerable populations and inform targeted policy interventions.

Facility Type. Table 6 reveals that outpatient facilities generate larger mortality reductions than residential facilities. An additional outpatient facility reduces MBD mortality by 0.126 deaths per 100,000 (0.4 percent), while residential facilities show smaller effects of 0.090 deaths per 100,000. Figure 10 confirms these patterns dynamically, with outpatient facilities showing immediate and persistent effects while residential facilities exhibit more gradual responses. The greater impact of outpatient care likely reflects lower barriers to access and better integration with patients' daily routines.

Age Heterogeneity. Effects vary substantially across the age distribution (Table 7). The largest impacts appear among elderly populations, with facilities reducing MBD mortality by 0.27 percent for those over 65. Figure 11 reveals interesting dynamics: while elderly populations show immediate mortality reductions, working age adults (35 to 64) experience gradually increasing benefits over time. Youth under 19 show minimal effects, possibly reflecting lower baseline mortality or different treatment needs. The pronounced elderly response aligns with greater vulnerability to untreated mental health conditions and higher barriers to accessing distant care.

Education. Table 8 documents stark differences by educational attainment. Facilities reduce MBD mortality by 0.43 percent among those with a high school education or less, compared to insignificant effects for those with some college. The event studies in Figure 12 show persistent benefits for less educated populations emerging immediately after facility entry, while college-educated populations show no clear pattern. This gradient suggests geographic access particularly constrains less educated individuals who may face transportation barriers or limited awareness of alternative treatment options.

Race and Gender. Racial heterogeneity analysis (Table 9) shows significant effects for White populations (0.35 percent reduction) with similar magnitude but imprecise estimates for Black populations. Figure 13 reveals comparable dynamic patterns across racial groups, with the precision differences reflecting sample composition. White individuals comprise 90 percent of observations in the data (Table 1). The imprecision for minority populations reflects limited statistical power rather than differential treatment effectiveness. Gender effects (Table 10), and Figure 14 are remarkably similar, with facilities reducing male and female MBD mortality by 0.26 and 0.25 percent, respectively, suggesting geographic access equally constrains both genders despite documented differences in help-seeking behavior.

Asymmetric Responses. Table 11 documents an important asymmetry: facility closures increase mortality by 0.124 deaths per 100,000, while openings reduce mortality by only 0.013 deaths per 100,000 in the full specification. Figure 15 confirms this pattern, with closures showing immediate and growing mortality impacts while openings have modest effects. This tenfold asymmetry suggests substantial adjustment frictions; established patients face immediate disruption when facilities close, while new facilities compete with existing treatment options. The asymmetry implies that preventing closures may generate larger welfare gains than expanding capacity in already served areas.

These heterogeneous effects highlight that mental health facility benefits concentrate among vulnerable populations: the elderly, less educated, and those losing existing access. The patterns suggest targeting expansion in areas with older, less educated populations while prioritizing the prevention of closures in underserved communities.

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 16, by 2016, 31 states and the District of Columbia had expanded Medicaid, while 19 states had not.[22,23]

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.[24]

[22] Table A14 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)

[23] 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.

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

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 pre-trends, 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.[25]

The pre-treatment coefficients ($k < 0$) provide a test of the identifying assumption that the mortality ef-

[25] 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.

fects 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 Amplifies Facility Effects

Table 12 presents triple-difference estimates examining how Medicaid expansion affects the mortality-reducing impact of mental health facilities. The results reveal substantial complementarities between insurance coverage and treatment infrastructure.

For MBD mortality, Column 3 shows the key triple interaction coefficient of -0.081 ($p < 0.01$), indicating that facilities in high-uninsurance counties within expansion states prevent an additional 0.081 deaths per 100,000 residents after Medicaid implementation. This represents a 26 percent amplification of the baseline facility effect.

Unreported results for overall mortality show even larger complementarities. The triple interaction yields a reduction of 0.31 deaths per 100,000 for all causes ($p < 0.05$), nearly four times the MBD effect. This pattern, larger effects for overall than MBD mortality, mirrors our main results and suggests insurance amplifies facility effects across multiple mortality pathways, not just direct mental health deaths.

Figure 17 presents dynamic evidence from event study specifications. Both panels show no differential pre-trends, with coefficients near zero and statistically insignificant for years -5 through -1. Following Medicaid expansion in 2014, the complementarity emerges immediately. Panel (a) reveals that facilities in expansion states reduce overall mortality by an additional 0.32 deaths per 100,000 by year 1 post-expansion. Panel (b) shows the corresponding MBD effect of 0.08 deaths per 100,000. The immediate response suggests pent-up demand, as individuals who could not afford treatment at existing facilities gain access when financial barriers fall.

8 Mechanisms

The large mortality reductions documented above, particularly the spillover effects beyond direct mental health causes, raise questions about underlying pathways. This section examines two mechanisms through which facilities affect mortality: connecting individuals to social safety nets and enabling pharmaceutical treatment when combined with insurance coverage.

8.1 Gateway to Disability Benefits

Mental health facilities may reduce mortality by serving as gateways to disability programs that provide both income support and healthcare coverage. For individuals with severe mental illness, SSI/SSDI benefits can prevent homelessness and ensure treatment continuity, both critical for survival (Shinn et al., 2007; Silverman et al., 2017).

I estimate the effect of facilities on disability claims using SSA county-level data on SSI recipients aged 18–64 for 2009–2016:

$$\text{Disability}_{ct} = \sum_{k=-5}^{1} \beta_k \mathbf{1}[\text{EventTime}_{ct} = k] + \alpha_c + \gamma_t + \delta_{st} + X'_{ct}\theta + \varepsilon_{ct} \tag{10}$$

where Disability_{ct} is SSI recipients per 100,000 population in county c and year t, EventTime_{ct} measures years relative to the first facility opening, α_c are county fixed effects, γ_t are year fixed effects, δ_{st} are state-by-year fixed effects, and X_{ct} includes demographic and economic controls. Standard errors are clustered at the county level.

Figure 18 presents event study estimates of facility effects on SSI disability claims. Panel (a) shows that facility openings increase the number of disability recipients by 8 to 9 per 100,000 population, with effects emerging immediately and persisting through the post-treatment period. The log specification in Panel (b) confirms a 1.4 percent increase that stabilizes after facility entry. Table 13 provides corresponding regression estimates across specifications.

This increase in disability claims represents improved access to existing benefits rather than deteriorating mental health. Mental health providers supply the diagnostic documentation and longitudinal treatment records essential for successful disability applications (Messel et al., 2023). Without provider documentation, individuals with severe mental illness often cannot navigate the complex application process despite qualifying conditions. The immediate response suggests pent-up demand, as individuals with existing conditions gain access to benefits they previously could not obtain.

The mortality implications are substantial. SSI recipients gain Medicaid coverage in most states, ensuring continued access to mental health treatment and medications. The income support (averaging $600 monthly) provides housing stability, reducing exposure to violence, substance abuse, and untreated medical conditions associated with homelessness. This gateway function may explain part of the spillover mortality effects documented earlier.

8.2 Prescription Access and Insurance Complementarity

A second mechanism operates through prescription drug access, particularly when facilities combine with insurance coverage.

I examine whether mental health facilities combined with Medicaid expansion increase antidepressant utilization, using Medicare Part D prescriber data aggregated to the state level for 2013–2016. The triple-difference specification compares facility effects in Medicaid expansion versus non-expansion states:

$$\text{Prescriptions}_{st} = \sum_{k=-1}^{2} \beta_k^{DDD}(\text{Facilities}_{st} \times \text{Expansion}_s \times \mathbf{1}[\text{EventTime}_{st} = k]) + \alpha_s + \gamma_t + Z_{st}'\theta + \varepsilon_{st} \quad (11)$$

where $\text{Prescriptions}_{st}$ is antidepressant claims per 100,000 population in state s and year t, Facilities_{st} is the count of mental health facilities, Expansion_s indicates Medicaid expansion status, EventTime_{st} measures years relative to 2014 when expansion began, α_s are state fixed effects, γ_t are year fixed effects, and Z_{st} includes controls. Standard errors are clustered at the state level.

Figure 19 presents triple difference event studies examining how Medicaid expansion affects the relationship between facilities and antidepressant prescriptions.

Panel (a) reveals striking complementarity: facilities in expansion states generate 200 to 280 additional antidepressant claims per 100,000 population post-expansion, compared to minimal effects in non-expansion states. The effect emerges immediately in 2014 and grows over time, consistent with gradual Medicaid enrollment. Panel (b) confirms this pattern in logs, showing a 3 to 5 percent increase in prescriptions. Table 14 reports the triple difference coefficient of 217.9 ($p < 0.01$), indicating that insurance amplifies facility effects on pharmaceutical treatment by over 200 percent.

This complementarity shows why insurance expansion magnifies mortality reductions. Facilities can prescribe medications, but uninsured patients often cannot afford them. Antidepressants cost $50to200$ monthly without insurance, which is prohibitive for many individuals with mental illness who have limited employment. Medicaid coverage reduces copayments to $1to3$, transforming prescription access.

The mortality consequences are direct: antidepressant treatment reduces suicide risk by 20 to 30 percent (Craig Nelson, 2018) and improves management of comorbid conditions through better sleep, reduced inflammation, and enhanced treatment adherence. The immediate prescription response following Medicaid expansion, combined with the gradual mortality improvements documented in Section 7, traces a clear causal pathway from insurance to prescriptions to reduced mortality.

8.3 Implications for Understanding Treatment Effects

These mechanisms reveal that mental health facilities operate as multidimensional interventions rather than simple treatment providers. They connect vulnerable populations to social insurance programs, enable pharmaceutical treatment when financial barriers fall, and create cascading benefits through improved economic and health stability.

The mechanisms also explain the heterogeneous effects documented earlier. Elderly populations show larger mortality reductions partly because they qualify for Medicare Part D, ensuring prescription access regardless of Medicaid expansion. Less educated populations benefit more because they face higher barriers to navigating disability applications without provider assistance. The asymmetric effects of closures versus openings reflect the disruption of established provider relationships crucial for maintaining disability benefits and prescription regimens.

Most importantly, these mechanisms validate the complementarity between supply-side and demand-side interventions. Facilities without insurance enable some benefits through disability connections, while insurance without facilities provides coverage but limited access. The combination of facilities with insurance generates the full mortality reductions documented in this paper, underscoring that comprehensive mental health policy requires coordinated investments in both infrastructure and coverage.

9 Welfare Analysis

The mortality reductions documented in this paper have substantial welfare implications. In this section, I quantify the net social benefits of mental health treatment facilities by comparing the value of lives saved against facility operating and capital costs. I employ standard welfare analysis methods used in health economics (Cutler and Richardson, 1998; Murphy and Topel, 2006), valuing mortality reductions using the Value of Statistical Life (VSL) approach commonly applied by regulatory agencies and in the academic literature (Viscusi and Aldy, 2003; Viscusi, 2018; Finkelstein and Hendren, 2020).

9.1 Framework

The welfare gain per facility can be expressed as:

$$W = \theta \times \text{VSL} - C \tag{12}$$

where θ represents lives saved per facility per year, VSL denotes the value of statistical life, and C captures total annual costs (operating plus annualized capital expenditures). From the mortality estimates in Table 4, Column 4, each additional mental health facility reduces deaths by 1.559 per 100,000 residents (SE = 0.255). Given the average county population of 97,051 in my sample, this translates to 1.51 lives saved per facility annually.

I value mortality reductions using a baseline VSL of $10 million, consistent with the EPA's 2014 estimate (Agency, 2010) and widely used in benefit-cost analyses (Ashenfelter, 2006; Kniesner et al., 2012). For robustness, I also consider a range from $7 million to $13 million. Annual facility costs include operating expenses of $3 million per year and annualized capital costs. Drawing on data from the Montana Legislative HJR 16 Study (2014),[26] I use construction costs of $4.5 to $7.6 million for a 16-bed facility, annualized over a 20-year facility lifetime at a 3 percent discount rate (Viscusi, 2006). This yields total annual costs of $3.30 to $3.51 million per facility.

9.2 Main Results

Table 15 presents the cost-benefit analysis. Under baseline assumptions (VSL = $10 million, midpoint costs), each mental health facility generates annual benefits of $15.1 million from mortality reductions

[26]Montana Legislative Children, Families, Health, and Human Services Interim Committee, "HJR 16 Study: State-Operated Institutions Building and Operating a 16-Bed Inpatient Facility" (May 2014).
Available at: `https://archive.legmt.gov/content/Committees/Interim/2013-2014/Children-Family/Committee-Topics/HJR16/hjr16-building-operating-16-bed-facilities-may2014.pdf`.

alone. Against total annual costs of $3.4 million, this implies net benefits of $11.7 million per facility per year, yielding a benefit-cost ratio of 4.44. Figure 20 illustrates these benefit-cost ratios across all nine combinations of VSL and cost assumptions, with all ratios substantially exceeding the break-even threshold of 1.0. The lower bound estimate, using the 95 percent confidence interval for mortality effects and low facility costs, still delivers substantial net benefits of $11.8 million annually (benefit-cost ratio of 4.58). Even the upper bound scenario, combining the confidence interval upper limit with high costs, generates net benefits of $11.6 million (benefit-cost ratio of 4.31).

These estimates are conservative for several reasons. First, I measure only mortality benefits, excluding substantial morbidity reductions and quality-of-life improvements from mental health treatment (Chisholm et al., 2016; Bloom et al., 2012). Second, the analysis focuses on overall mortality without separately valuing the particularly high toll of suicide and overdose deaths, which disproportionately affect younger individuals with longer remaining life expectancies (Zeckhauser and Shepard, 1980; Aldy and Viscusi, 2008). Third, I do not account for reduced healthcare utilization, criminal justice costs, or productivity gains associated with improved mental health (Kessler, 2011) Fourth, the mortality effects likely understate the true impact, as my difference-in-differences design captures only local treatment effects and may miss broader spillovers to neighboring areas or untreated populations (Goodman-Bacon, 2021).

9.3 Sensitivity Analysis

Table A11 reports net benefits under nine combinations of VSL and cost assumptions, with all scenarios yielding positive net benefits ranging from $7.1 million to $16.4 million annually per facility. Figure A8 in the appendix visualizes this pattern, showing that results are more responsive to VSL assumptions than to cost variation, consistent with findings in the broader VSL literature (Robinson and Hammitt, 2019). Moving from the conservative $7 million VSL to the upper bound $13 million VSL more than doubles net benefits, while cost uncertainty produces relatively modest variation.

As an alternative approach, I calculate benefits using Value of Statistical Life-Year (VSLY) estimates, which may better capture the age distribution of prevented deaths (Aldy and Viscusi, 2008; Murphy and Topel, 2006). Assuming 25 years of remaining life expectancy at the average age of mental health-related mortality and applying VSLY estimates ranging from $100,000 to $400,000 per life-year,[27] I find present values of $2.6 to $10.5 million per facility (discounted at 3 percent annually). The midpoint VSLY estimate of $250,000 yields net benefits of $3.2 million per facility per year, reinforcing the finding of positive welfare effects even under more conservative valuation approaches.

[27] These VSLY values correspond to VSL estimates of $2-10 million divided by remaining life expectancy, consistent with the approach in Murphy and Topel (2006) and Aldy and Viscusi (2008).

9.4 Aggregate National Effects

Scaling these facility-level estimates to the national level reveals substantial aggregate welfare gains. Table A12 aggregates across the 268,699 mental health facilities in my sample spanning 3,199 counties. At baseline parameters, these facilities collectively save approximately 406,000 lives annually, generating total benefits of $4.06 trillion against costs of $915 billion. Net annual benefits amount to $3.15 trillion, equivalent to roughly $9,840 per capita for the US population. These aggregate calculations provide a lower bound for national welfare effects, as my sample does not include all US counties and facilities.[28] Moreover, the estimates exclude the substantial benefits from reduced morbidity, improved quality of life, and other positive externalities of mental health treatment (Cuijpers et al., 2013).

9.5 Interpretation

The welfare analysis delivers a clear message: mental health treatment facilities generate large positive net social benefits through mortality reductions alone. With benefit-cost ratios consistently exceeding 4 to 1 across all specifications, each dollar invested in mental health facilities yields more than four dollars in mortality-related benefits. These findings inform ongoing policy debates about mental health infrastructure investment (Frank, 2006) and suggest that expanding access to mental health treatment may be welfare-enhancing even before accounting for the full range of benefits beyond mortality reduction.

The results also speak to the underinvestment in mental health services documented in prior research (Frank and McGuire, 2000). If markets functioned efficiently, we would expect investment to continue until marginal benefits equal marginal costs. The substantial net benefits I document suggest we remain far from this margin, consistent with significant market failures in mental health care provision, including externalities, information asymmetries, and insurance market imperfections (Arrow, 1978; Frank, 2006). Policies that increase access to mental health treatment facilities appear to address these market failures while generating significant social returns.

10 Discussion

This study provides the first causal evidence that mental health treatment facilities reduce mortality broadly. Each additional facility prevents 1.56 deaths per 100,000 residents annually from all causes. For mental and behavioral disorders specifically, facilities reduce mortality by 0.079 percent. These effects extend far beyond mental health deaths, showing that mental healthcare improves overall population

[28] The sample covers counties with available data from both County Business Patterns and Vital Statistics for the period 1999-2016. Counties with missing or suppressed data are excluded from the analysis.

health.

Three findings stand out. First, the spillover effects are large. Overall mortality reductions are three times bigger than MBD effects alone. This places mental health facilities alongside hospitals as essential healthcare infrastructure. While previous work showed that geographic access affects utilization (Buchmueller et al., 2006; Currie and Stabile, 2006), and that treatment reduces suicide (Currie, 2025; Ortega, 2023), no prior study demonstrated that mental health facilities reduce overall mortality.

Second, facility closures cause mortality increases ten times larger than the reductions from openings. This asymmetry extends findings from Corredor-Waldron and Currie (2022) on hospital closures to mental health settings. When facilities close, established patient-provider relationships are severed, and rebuilding trust elsewhere proves difficult (Frank, 2006). This suggests that protecting existing facilities may matter more than opening new ones.

Third, insurance and infrastructure work together. Medicaid expansion amplifies facility effectiveness by 26 percent in high-uninsurance counties. This complementarity advances work by Sommers et al. (2016) and Maclean and Saloner (2019), showing that coverage without facilities or facilities without coverage both fall short. States that expanded Medicaid should prioritize building facilities, while non-expansion states may see limited gains from new facilities without addressing coverage gaps.

The welfare benefits are substantial. Each facility generates \$15.1 million annually in mortality benefits against \$3.4 million in costs, yielding net benefits of \$11.7 million per year, a benefit-cost ratio exceeding 4 to 1. Beyond mortality, facilities increase mental health employment by 3 percent, creating 8-10 jobs, including psychiatrists and support staff (Eckert et al., 2020). These employment effects validate that new facilities represent real treatment capacity, not just reorganization.

The mechanisms extend beyond direct treatment. Facilities connect people to disability benefits, increasing SSI participation by 1.4 percent (Messel et al., 2023). With insurance, facilities enable medication access, generating 280 additional antidepressant prescriptions per 100,000 residents. These pathways explain why elderly and less-educated populations benefit most; they face the highest barriers to navigating healthcare alone, or driving to far facilities when they are not available locally (Gupta et al., 2024).

References

Acemoglu, Daron and Amy Finkelstein, "Input and technology choices in regulated industries: Evidence from the health care sector," *Journal of Political Economy*, 2008, *116* (5), 837–880.

Agency, US Environmental Protection, "Valuing mortality risk reductions for environmental policy: a white paper," 2010.

Aldy, Joseph E and W Kip Viscusi, "Adjusting the value of a statistical life for age and cohort effects," *The Review of Economics and Statistics*, 2008, *90* (3), 573–581.

Alexander, Diane and Michael R. Richards, "Economic consequences of hospital closures," *Journal of Public Economics*, 2023, *221*, 104821.

Ameel, Maria, Raija Kontio, and Maritta Välimäki, "Interventions delivered by nurses in adult outpatient psychiatric care: An integrative review," *Journal of Psychiatric and Mental Health Nursing*, 2019, *26* (9-10), 301–322.

Andrilla, C Holly A, Davis G Patterson, Lisa A Garberson, Cynthia Coulthard, and Eric H Larson, "Geographic variation in the supply of selected behavioral health providers," *American journal of preventive medicine*, 2018, *54* (6), S199–S207.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2009.

Arrow, Kenneth J, "Uncertainty and the welfare economics of medical care," in "Uncertainty in economics," Elsevier, 1978, pp. 345–375.

Ashenfelter, Orley, "Measuring the value of a statistical life: problems and prospects," *The Economic Journal*, 2006, *116* (510), C10–C23.

Autor, David H, William R Kerr, and Adriana D Kugler, "Does employment protection reduce productivity? Evidence from US states," *The Economic Journal*, 2007, *117* (521), F189–F217.

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman, "The impact of Medicaid on labor market activity and program participation: evidence from the Oregon Health Insurance Experiment," *American Economic Review*, 2014, *104* (5), 322–328.

— **and Amitabh Chandra**, "The labor market effects of rising health insurance premiums," *Journal of Labor Economics*, 2006, *24* (3), 609–634.

Bailey, Martha J. and Andrew Goodman-Bacon, "The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans," *American Economic Review*, March 2015, *105* (3), 1067–1104.

Banerjee, Abhijit, Angus Deaton, and Esther Duflo, "Health, health care, and economic development: Wealth, health, and health services in rural Rajasthan," *The American economic review*, 2004, *94* (2), 326.

Beronio, Kirsten, Sherry Glied, and Richard Frank, "How the Affordable Care Act and Mental Health Parity and Addiction Equity Act greatly expand coverage of behavioral health care," *The journal of behavioral health services & research*, 2014, *41* (4), 410–428.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly journal of economics*, 2004, *119* (1), 249–275.

Bloom, David E, Elizabeth Cafiero, Eva Jané-Llopis, Shafika Abrahams-Gessel, Lakshmi Reddy Bloom, Sana Fathima, Andrea B Feigl, Tom Gaziano, Ali Hamandi, Mona Mowafi et al., "The global economic burden of noncommunicable diseases," Technical Report, Program on the Global Demography of Aging 2012.

Bondurant, Samuel R., Jason M. Lindo, and Isaac D. Swensen, "Substance abuse treatment centers and local crime," *Journal of Urban Economics*, 2018, *104*, 124–133.

Bradford, Ashley C. and Johanna Catherine Maclean, "Evictions and psychiatric treatment," *Journal of Policy Analysis and Management*, 2023, *n/a* (n/a).

Buchmueller, Thomas C., Mireille Jacobson, and Cheryl Wold, "How far to the hospital?: The effect of hospital closures on access to care," *Journal of Health Economics*, 2006, *25* (4), 740–761.

Bureau of Economic Analysis, "Regional Economic Information System (REIS)," BEA. Accessed: 2023-11-06.

Cabral, Marika, Colleen Carey, and Sarah Miller, "The impact of provider payments on health care utilization of low-income individuals: Evidence from Medicare and Medicaid," Technical Report, National Bureau of Economic Research 2021.

Callaway, Brantly and Pedro H.C. Sant'Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230. Themed Issue: Treatment Effect 1.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller, "Bootstrap-based improvements for inference with clustered errors," *The review of economics and statistics*, 2008, *90* (3), 414–427.

Carey, Colleen M., Sarah Miller, and Laura R. Wherry, "The Impact of Insurance Expansions on the Already Insured: The Affordable Care Act and Medicare," *American Economic Journal: Applied Economics*, October 2020, *12* (4), 288–318.

Case, Anne and Angus Deaton, "Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century," *Proceedings of the National Academy of Sciences*, 2015, *112* (49), 15078–15083.

— **and** — , "Suicide, age, and well-being: An empirical investigation," in "Insights in the Economics of Aging," University of Chicago Press, 2015, pp. 307–334.

Centers for Medicare & Medicaid Services, "Medicare Part D Prescriber PUF Methodology," Technical Report, U.S. Department of Health and Human Services, Centers for Medicare & Medicaid Services 2023. Accessed on August 12, 2025.

Chandra, Amitabh and Douglas O Staiger, “Productivity spillovers in health care: evidence from the treatment of heart attacks,” *Journal of political Economy*, 2007, *115* (1), 103–140.

Chay, Kenneth Y, Jonathan Guryan, and Bhashkar Mazumder, “Birth cohort and the black-white achievement gap: The roles of access and health soon after birth,” Technical Report, National Bureau of Economic Research 2009.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler, “The association between income and life expectancy in the United States, 2001-2014,” *Jama*, 2016, *315* (16), 1750–1766.

Chisholm, Dan, Kim Sweeny, Peter Sheehan, Bruce Rasmussen, Filip Smit, Pim Cuijpers, and Shekhar Saxena, “Scaling-up treatment of depression and anxiety: a global return on investment analysis,” *The Lancet Psychiatry*, 2016, *3* (5), 415–424.

Chowdhury, N, J Hammer, M Kremer, K Muralidharan, and H Rogers, “Teachers and health care providers' absenteeism: a multi-country study (Mimeo of Development Research Group),” *Washington: World Bank*, 2003.

Cipriani, Andrea, Toshi A Furukawa, Georgia Salanti, Anna Chaimani, Lauren Z Atkinson, Yusuke Ogawa, Stefan Leucht, Henricus G Ruhe, Erick H Turner, Julian PT Higgins et al., “Comparative efficacy and acceptability of 21 antidepressant drugs for the acute treatment of adults with major depressive disorder: a systematic review and network meta-analysis,” *The Lancet*, 2018, *391* (10128), 1357–1366.

Clemens, Jeffrey and Joshua D. Gottlieb, “Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?,” *American Economic Review*, April 2014, *104* (4), 1320–49.

Colton, Patricia A and Gary Rodin, “Eating disorders and depression in women with diabetes,” in “Diabetes in Women: Pathophysiology and Therapy,” Springer, 2009, pp. 127–143.

Corredor-Waldron, Adriana and Janet Currie, ““Tackling the Substance Use Disorder Crisis: The Role of Access to Treatment Facilities”,” *Journal of Health Economics*, 2022, *81*, 102579.

Courtemanche, Charles, James Marton, Benjamin Ukert, Aaron Yelowitz, and Daniela Zapata, “Early Impacts of the Affordable Care Act on Health Insurance Coverage in Medicaid Expansion and Non-Expansion States,” *Journal of Policy Analysis and Management*, 2017, *36* (1), 178–210.

Cuijpers, Pim, Marcus Huibers, David Daniel Ebert, Sander L Koole, and Gerhard Andersson, “How much psychotherapy is needed to treat depression? A metaregression analysis,” *Journal of affective disorders*, 2013, *149* (1-3), 1–13.

Cummings, Janet R., Lindsay Allen, Julie Clennon, Xu Ji, and Benjamin G. Druss, “Geographic Access to Specialty Mental Health Care Across High- and Low-Income US Communities,” *JAMA Psychiatry*, 05 2017, *74* (5), 476–484.

Currie, Janet, “Presidential Address: Investing in Children to Address the Child Mental Health Crisis,” *American Economic Review*, 2025, *115* (5), 1369–1399.

— **, Anastasia Karpova, and Dan Zeltzer**, "Do urgent care centers reduce Medicare spending?," *Journal of health economics*, 2023, *89*, 102753.

— **and Mark Stabile**, "Child mental health and human capital accumulation: the case of ADHD," *Journal of health economics*, 2006, *25* (6), 1094–1118.

— **, N Meltem Daysal, Mette Gørtz, and Jonas Cuzulan Hirani**, "Child Disability and Effects on Sibling Mental Health," Technical Report, National Bureau of Economic Research 2024.

Cutler, David M and Elizabeth Richardson, "The value of health: 1970-1990," *The American economic review*, 1998, *88* (2), 97–100.

Cutler, David, Winnie Fung, Michael Kremer, Monica Singhal, and Tom Vogl, "Early-Life Malaria Exposure and Adult Outcomes: Evidence from Malaria Eradication in India," *American Economic Journal: Applied Economics*, April 2010, *2* (2), 72–94.

Dave, Dhaval, Monica Deza, and Brady Horn, "Prescription drug monitoring programs, opioid abuse, and crime," *Southern Economic Journal*, 2021, *87* (3), 808–848.

de Chaisemartin, Clément and Xavier D'Haultfoeuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, September 2020, *110* (9), 2964–96.

Deshpande, Manasi, "Does welfare inhibit success? The long-term effects of removing low-income youth from the disability rolls," *American Economic Review*, 2016, *106* (11), 3300–3330.

Deza, Monica, Johanna Catherine Maclean, and Keisha Solomon, "Local access to mental healthcare and crime," *Journal of Urban Economics*, 2022, *129*, 103410.

— **, Thanh Lu, and Johanna Catherine Maclean**, "Office-based mental healthcare and juvenile arrests," *Health Economics*, 2022, *31* (S2), 69–91.

Drake, Robert E, Howard H Goldman, H Stephen Leff, Anthony F Lehman, Lisa Dixon, Kim T Mueser, and William C Torrey, "Implementing evidence-based practices in routine mental health service settings," *Psychiatric services*, 2001, *52* (2), 179–182.

Druss, Benjamin G, Liping Zhao, Silke Von Esenwein, Elaine H Morrato, and Steven C Marcus, "Understanding excess mortality in persons with mental illness: 17-year follow up of a nationally representative US survey," *Medical care*, 2011, *49* (6), 599–604.

Dwyer-Lindgren, Laura, Amelia Bertozzi-Villa, Rebecca W Stubbs, Chloe Morozoff, Johan P Mackenbach, Frank J Van Lenthe, Ali H Mokdad, and Christopher JL Murray, "Inequalities in life expectancy among US counties, 1980 to 2014: temporal trends and key drivers," *JAMA internal medicine*, 2017, *177* (7), 1003–1011.

Eckert, Fabian, Teresa C Fort, Peter K Schott, and Natalie J Yang, "Imputing Missing Values in the US Census Bureau's County Business Patterns," Working Paper 26632, National Bureau of Economic Research January 2020.

Ettner, Susan L, Richard G Frank, and Ronald C Kessler, "The impact of psychiatric disorders on labor market outcomes," *ILR Review*, 1997, *51* (1), 64–81.

Fadlon, Itzik, Astrid Sophie Fugleholm, and Torben Heien Nielsen, "Survivors' Mental Health and the Protective Role of Income Stability," Technical Report, National Bureau of Economic Research 2025.

Finkelstein, Amy, "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare*," *The Quarterly Journal of Economics*, 02 2007, *122* (1), 1–37.

— **and Nathaniel Hendren**, "Welfare analysis meets causal inference," *Journal of Economic Perspectives*, 2020, *34* (4), 146–167.

— **, Matthew Gentzkow, and Heidi Williams**, "Sources of Geographic Variation in Health Care: Evidence From Patient Migration*," *The Quarterly Journal of Economics*, 07 2016, *131* (4), 1681–1726.

Fischer, Stefanie, Heather Royer, and Corey White, "Health Care Centralization: The Health Impacts of Obstetric Unit Closures in the United States," *American Economic Journal: Applied Economics*, 2024, *16* (3), 113–141.

Frank, Richard G, *Better but not well: Mental health policy in the United States since 1950*, JHU Press, 2006.

— **and Thomas G McGuire**, "Economics and mental health," *Handbook of health economics*, 2000, *1*, 893–954.

Glied, Sherry and Richard G Frank, "Economics and the transformation of the mental health system," *Journal of health politics, policy and law*, 2016, *41* (4), 541–558.

Goodman-Bacon, Andrew, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277. Themed Issue: Treatment Effect 1.

Gottlieb, Joshua D, Adam Hale Shapiro, and Abe Dunn, "The complexity of billing and paying for physician care," *Health Affairs*, 2018, *37* (4), 619–626.

Grooms, Jevay and Alberto Ortega, "Examining Medicaid expansion and the treatment of substance use disorders," in "AEA Papers and Proceedings," Vol. 109 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 2019, pp. 187–191.

Grossman, Michael, "On the concept of health capital and the demand for health," *Journal of Political economy*, 1972, *80* (2), 223–255.

Gujral, Kritee and Anirban Basu, "Impact of rural and urban hospital closures on inpatient mortality," Technical Report, National Bureau of Economic Research 2019.

Guo, Shenyang, David E Biegel, Jeffrey A Johnsen, and Hayne Dyches, "Assessing the impact of community-based mobile crisis services on preventing hospitalization," *Psychiatric Services*, 2001, *52* (2), 223–228.

Gupta, Sumedha, Dario Salcedo, and Kosali I Simon, "School Closures and Parental Mental Health," Technical Report, National Bureau of Economic Research 2024.

Guth, Madeline, Rachel Garfield, Robin Rudowitz et al., "The effects of Medicaid expansion under the ACA: updated findings from a literature review," *Kaiser Family Foundation*, 2020, *37* (6), 944–950.

Heisler, Michele, Adrienne Lapidos, Edith Kieffer, James Henderson, Rebeca Guzman, Jasmina Cunmulaj, Jason Wolfe, Trish Meyer, and John Z Ayanian, "Impact on health care utilization and costs of a Medicaid community health worker program in Detroit, 2018–2020: a randomized program evaluation," *American Journal of Public Health*, 2022, *112* (5), 766–775.

Hill, Nicole, "Wilderness therapy as a treatment modality for at-risk youth: A primer for mental health counselors," *Journal of Mental Health Counseling*, 2007, *29* (4), 338–349.

Hofmann, Stefan G, Anu Asnaani, Imke JJ Vonk, Alice T Sawyer, and Angela Fang, "The efficacy of cognitive behavioral therapy: A review of meta-analyses," *Cognitive therapy and research*, 2012, *36* (5), 427–440.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan, "Earnings losses of displaced workers," *The American economic review*, 1993, pp. 685–709.

Kessler, Ronald C, "The costs of depression," *The psychiatric Clinics of north America*, 2011, *35* (1), 1.

Kniesner, Thomas J, W Kip Viscusi, Christopher Woock, and James P Ziliak, "The value of a statistical life: Evidence from panel data," *Review of Economics and Statistics*, 2012, *94* (1), 74–87.

Kupfer, David J, Ellen Frank, and Mary L Phillips, "Major depressive disorder: new clinical, neurobiological, and treatment perspectives," *The Lancet*, 2012, *379* (9820), 1045–1055.

Lang, Matthew, "The impact of mental health insurance laws on state suicide rates," *Health economics*, 2013, *22* (1), 73–88.

Lindrooth, Richard C, Anthony T Lo Sasso, and Ithai Z Lurie, "The effect of distance to provider on employee response to changes in mental health benefits," *Health economics*, 2006, *15* (10), 1133–1141.

Linehan, Marsha, *Cognitive-behavioral treatment of borderline personality disorder*, Guilford press, 1993.

Maclean, Johanna Catherine and Brendan Saloner, "The effect of public insurance expansions on substance use disorder treatment: evidence from the Affordable Care Act," *Journal of Policy Analysis and Management*, 2019, *38* (2), 366–393.

Malani, Anup and Julian Reif, "Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform," *Journal of Public Economics*, 2015, *124*, 1–17.

Mann, J John, Alan Apter, Jose Bertolote, Annette Beautrais, Dianne Currier, Ann Haas, Ulrich Hegerl, Jouko Lonnqvist, Kevin Malone, Andrej Marusic et al., "Suicide prevention strategies: a systematic review," *Jama*, 2005, *294* (16), 2064–2074.

Marmot, Michael, "Social determinants of health inequalities," *The lancet*, 2005, *365* (9464), 1099–1104.

Messel, Matt, Isaac Swensen, and Carly Urban, “The effects of expanding access to mental health services on SS (D) I applications and awards,” *Labour Economics*, 2023, *81*, 102339.

Miller, Sarah, “The effect of insurance on emergency room visits: An analysis of the 2006 Massachusetts health reform,” *Journal of Public Economics*, 2012, *96* (11), 893–908. Fiscal Federalism.

— **and Laura R Wherry**, “Health and access to care during the first 2 years of the ACA Medicaid expansions,” *New England Journal of Medicine*, 2017, *376* (10), 947–956.

— **, Norman Johnson, and Laura R Wherry**, “Medicaid and mortality: new evidence from linked survey and administrative data,” *The Quarterly Journal of Economics*, 2021, *136* (3), 1783–1829.

Molitor, David, “The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration,” *American Economic Journal: Economic Policy*, February 2018, *10* (1), 326–56.

Murphy, Kevin M and Robert H Topel, “The value of health and longevity,” *Journal of political Economy*, 2006, *114* (5), 871–904.

Nelson, J Craig, “Management of late-life depression,” in “Antidepressants: From Biogenic Amines to New Mechanisms of Action,” Springer, 2018, pp. 389–413.

Norcross, John C and Christie P Karpiak, “Our best selves: Defining and actualizing expertise in psychotherapy,” *The Counseling Psychologist*, 2017, *45* (1), 66–75.

Olfson, Mark, Carlos Blanco, Shuai Wang, Gonzalo Laje, and Christoph U Correll, “National trends in the mental health care of children, adolescents, and adults by office-based physicians,” *JAMA psychiatry*, 2014, *71* (1), 81–90.

Ortega, Alberto, “Medicaid Expansion and mental health treatment: Evidence from the Affordable Care Act,” *Health Economics*, 2023, *32* (4), 755–806.

Phoenix, Bethany J, “The current psychiatric mental health registered nurse workforce,” *Journal of the American Psychiatric Nurses Association*, 2019, *25* (1), 38–48.

Popovici, Ioana, Johanna Catherine Maclean, and Michael T French, *The effects of health insurance parity laws for substance use disorder treatment on traffic fatalities: evidence of unintended benefits*, National Bureau of Economic Research, 2017.

Robinson, Lisa A and James K Hammitt, “Benefit-Cost Analysis,” *Global Health Priority-Setting: Beyond Cost-Effectiveness*, 2019, p. 0.

Schmitt, Susan K, Ciaran S Phibbs, and John D Piette, “The influence of distance on utilization of outpatient mental health aftercare following inpatient substance abuse treatment,” *Addictive behaviors*, 2003, *28* (6), 1183–1192.

Shannon, Gary W, Rashid L Bashshur, and Joseph E Lovett, “Distance and the use of mental health services,” *The Milbank Quarterly*, 1986, pp. 302–330.

Shinn, Marybeth, Jamie Gottlieb, Jessica L Wett, Ajay Bahl, Arnold Cohen, and Deborah Baron Ellis, "Predictors of homelessness among older adults in New York City: Disability, economic, human and social capital and stressful events," *Journal of Health Psychology*, 2007, *12* (5), 696–708.

Silverman, Arielle M, Ivan R Molton, Amanda E Smith, Mark P Jensen, and Geoffrey L Cohen, "Solace in solidarity: Disability friendship networks buffer well-being.," *Rehabilitation Psychology*, 2017, *62* (4), 525.

Skinner, Jonathan, "Chapter Two - Causes and Consequences of Regional Variations in Health Care," in Mark V. Pauly, Thomas G. Mcguire, and Pedro P. Barros, eds., *Handbook of Health Economics*, Vol. 2 of Handbook of Health Economics, Elsevier, 2011, pp. 45–93.

Sommers, Benjamin D, Robert J Blendon, E John Orav, and Arnold M Epstein, "Changes in utilization and health among low-income adults after Medicaid expansion or expanded private insurance," *JAMA internal medicine*, 2016, *176* (10), 1501–1509.

— **, Thomas Buchmueller, Sandra L Decker, Colleen Carey, and Richard Kronick**, "The Affordable Care Act has led to significant gains in health insurance and access to care for young adults," *Health affairs*, 2013, *32* (1), 165–174.

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199. Themed Issue: Treatment Effect 1.

Surveillance, Epidemiology, and End Results (SEER) Program, "Surveillance, Epidemiology, and End Results (SEER) Program," SEER. Accessed: 2023-11-06.

Swensen, Isaac D., "Substance-abuse treatment and mortality," *Journal of Public Economics*, 2015, *122*, 13–30.

U.S. Bureau of Labor Statistics, "Medical and Health Services Managers," in "Occupational Outlook Handbook," U.S. Bureau of Labor Statistics, 2022. Data from the 2022-32 projections. Accessed on August 13, 2025.

U.S. Census Bureau, "Small Area Health Insurance Estimates (SAHIE) Program," Official Website 2021. Data for reference year 2020. Accessed on August 13, 2025.

Viscusi, W, *Pricing lives: Guideposts for a safer society*, Princeton University Press, 2018.

Viscusi, W Kip, "Rational discounting for regulatory analysis," 2006.

— **and Joseph E Aldy**, "The value of a statistical life: a critical review of market estimates throughout the world," *Journal of risk and uncertainty*, 2003, *27*, 5–76.

Walker, Elizabeth Reisinger, Robin E McGee, and Benjamin G Druss, "Mortality in mental disorders and global disease burden implications: a systematic review and meta-analysis," *JAMA psychiatry*, 2015, *72* (4), 334–341.

Wennberg, John and Alan Gittelsohn, "Small area variations in health care delivery: a population-based health information system can guide planning and regulatory decision-making.," *Science*, 1973, *182* (4117), 1102–1108.

Wherry, Laura R and Sarah Miller, "Early coverage, access, utilization, and health effects associated with the Affordable Care Act Medicaid expansions: a quasi-experimental study," *Annals of internal medicine*, 2016, *164* (12), 795–803.

— , — , Robert Kaestner, and Bruce D Meyer, "Childhood Medicaid coverage and later-life health care utilization," *Review of Economics and Statistics*, 2018, *100* (2), 287–302.

WHO, World Health Organization, "WHO global air quality guidelines: particulate matter (PM2. 5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide," https://iris.who.int/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1 2021. Accessed: 2023-12-23.

World Health Organization, "International Statistical Classification of Diseases and Related Health Problems (ICD-10)," 2019. Accessed: 2024-01-14.

Zalsman, Gil, Keith Hawton, Danuta Wasserman, Kees van Heeringen, Ella Arensman, Marco Sarchiapone, Vladimir Carli, Cyril Höschl, Ran Barzilay, Judit Balazs et al., "Suicide prevention strategies revisited: 10-year systematic review," *The Lancet Psychiatry*, 2016, *3* (7), 646–659.

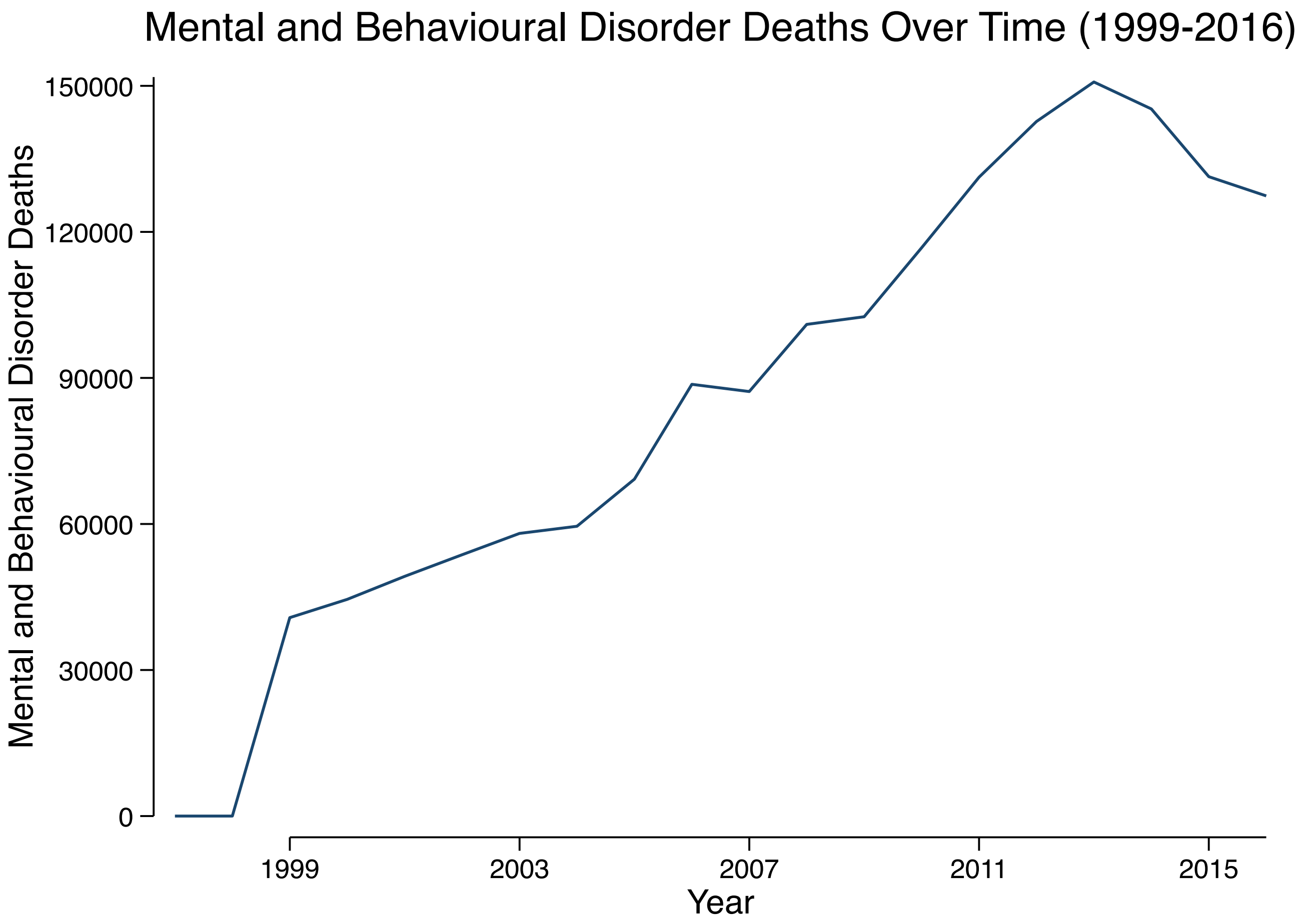
Zeckhauser, Richard J and Donald S Shepard, "The Choice of Health Policies with Heterogeneous Populations," 1980.

Ziguras, Stephen J and Geoffrey W Stuart, "A meta-analysis of the effectiveness of mental health case management over 20 years," *Psychiatric services*, 2000, *51* (11), 1410–1421.

Zuccarini, Michelle M and Cate Stiller, "The effect of peer support on treatment engagement for opioid use disorder," *Journal of the American Psychiatric Nurses Association*, 2024, *30* (3), 709–715.

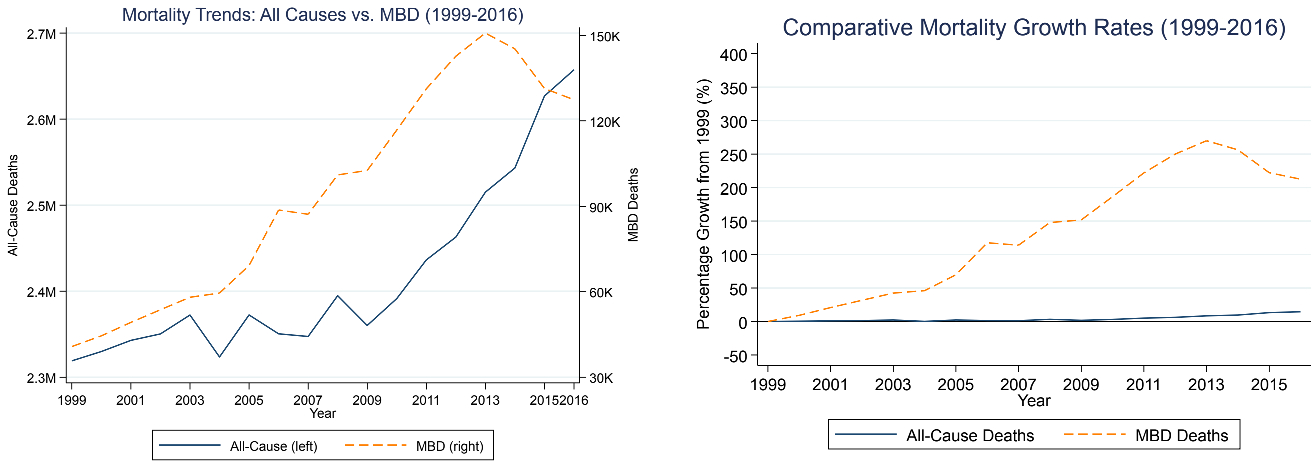
Figures

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: Divergent Mortality Trends: The Mental Health Crisis

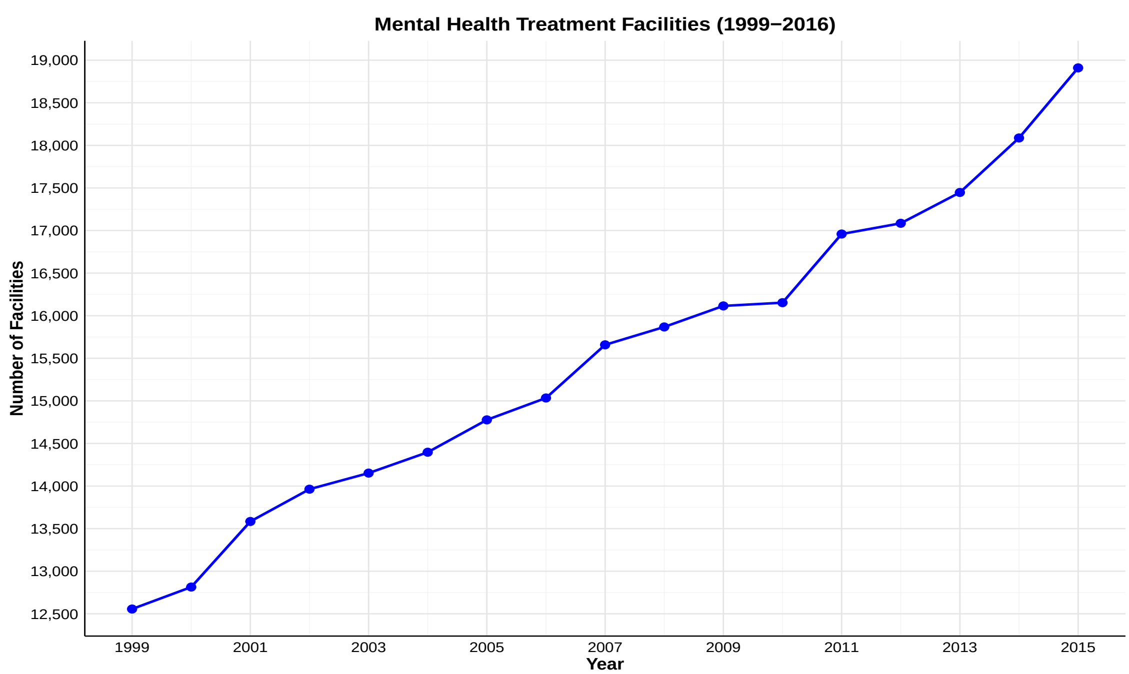


(a) Levels

(b) Growth Rates

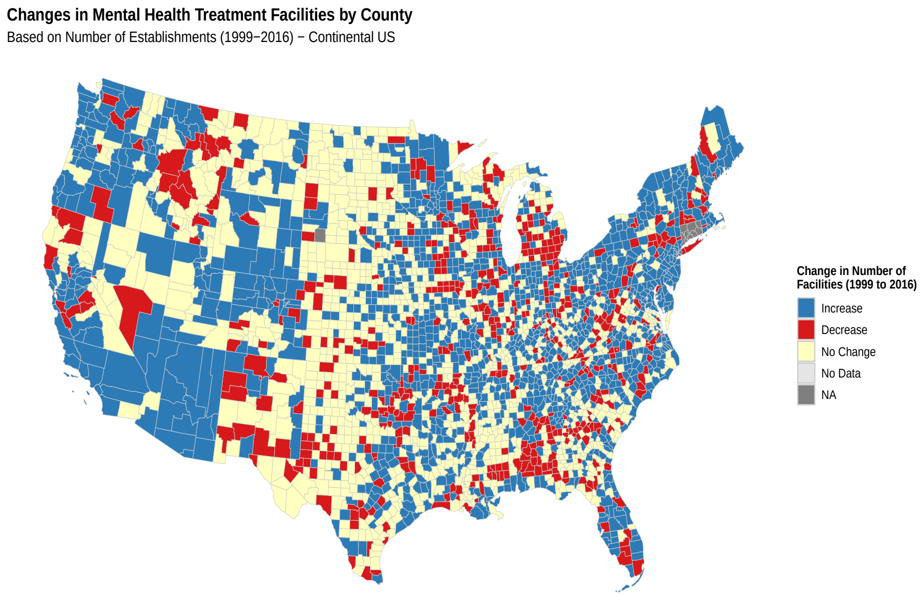
Notes: Panel (a) shows total deaths from all causes (left axis) and mental and behavioral disorder (MBD) deaths (right axis) from 1999-2016. Panel (b) shows the percentage growth from the 1999 baseline. While all-cause mortality increased modestly by 15 percent over this period, MBD deaths surged nearly 300 percent from 40,000 to over 120,000 annually. Data from restricted-access Multiple Cause of Death files. MBD deaths are defined as ICD-10 codes F00-F79.

Figure 3: Temporal Variation of Mental Health Treatment Facilities

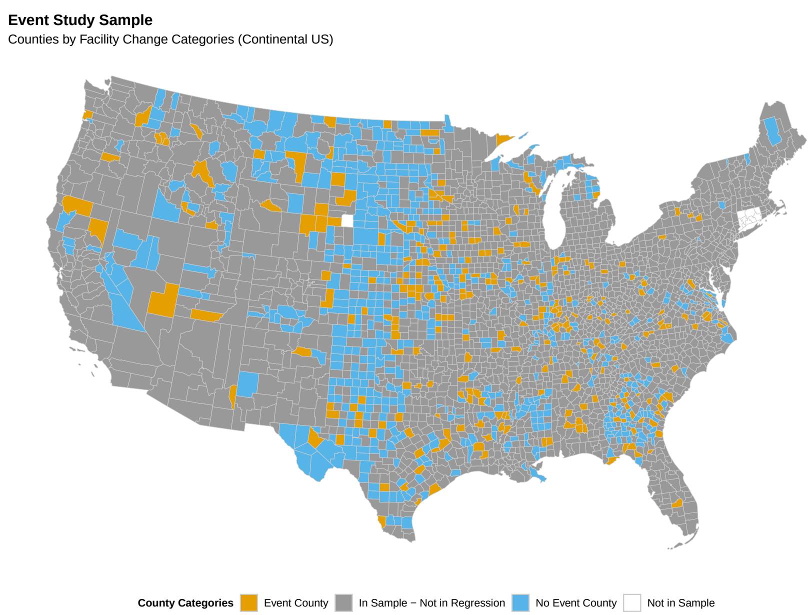


Note: Data on the county's mental health facility treatment comes from the County Business Patterns. A county is designated as having access to mental health services if it has any establishment that provides these services at a given year. The sample is restricted to 1999-2016. The figure presents mean 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 4: Spatial Variation in Access to Mental Health Treatment Facilities



(a) Spatial Variation in Mental Health Treatment Facilities

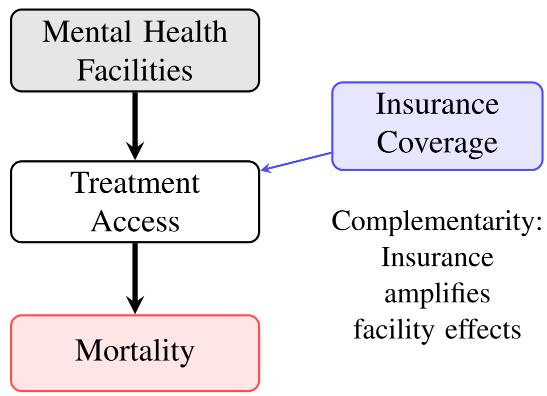


(b) Spatial Variation in Mental Health Treatment Facilities: Event Study Sample

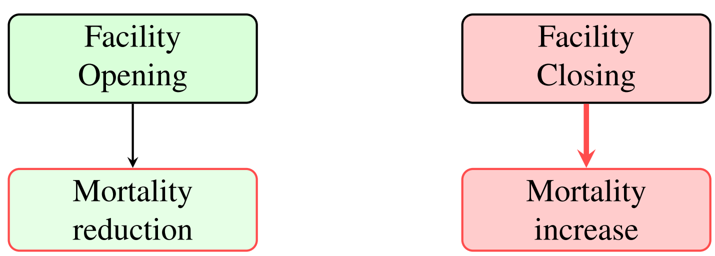
Note: Data on mental health treatment facilities comes from the County Business Patterns. The top panel (a) displays the spatial distribution of changes in mental health treatment facilities across U.S. counties between 1999 and 2016. Section 4.1 presents more information on these data. Counties are 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 5: Conceptual Framework. Panel A illustrates how mental health facilities affect mortality through treatment access, with insurance coverage potentially acting as a complementary input. Panel B depicts potential asymmetry in facility changes, where closures may generate larger mortality effects than openings due to disruption costs and adjustment frictions. Panel C shows three hypothesized mechanisms: facilities as gateways to disability programs, enablers of prescription access, and sources of mental health employment.

Panel A: How Mental Health Facilities Affect Mortality



Panel B: Asymmetric Effects



Panel C: Mechanisms

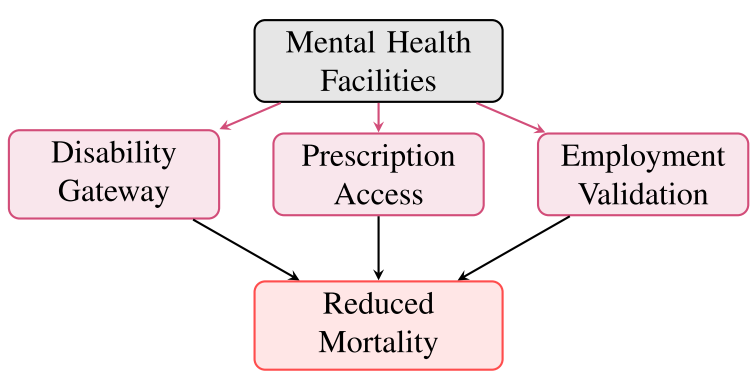
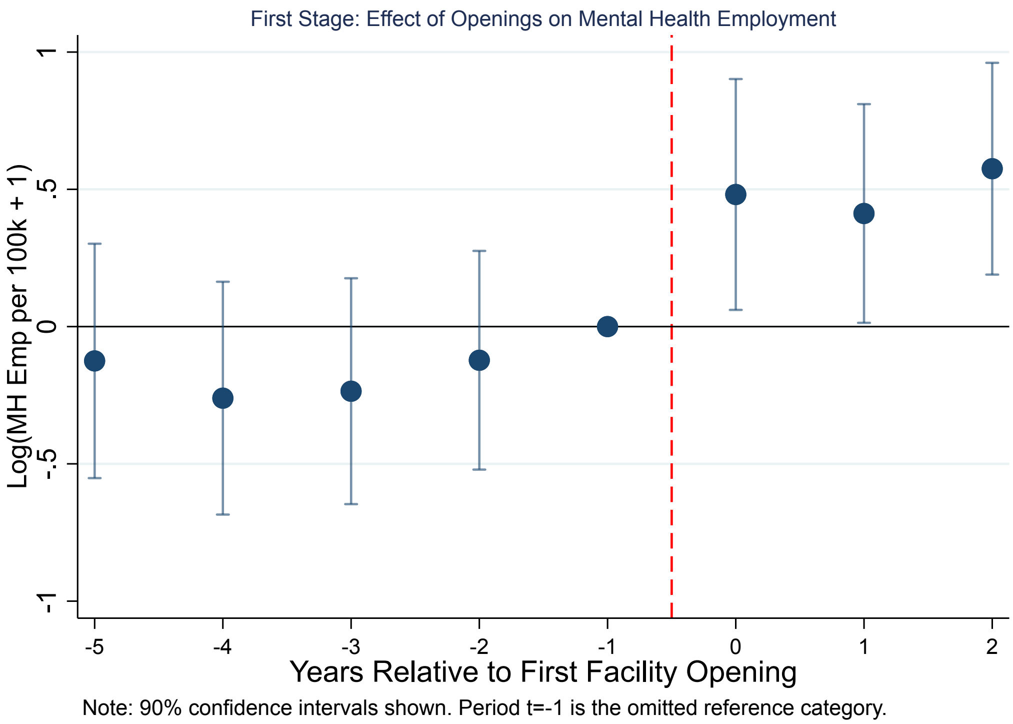
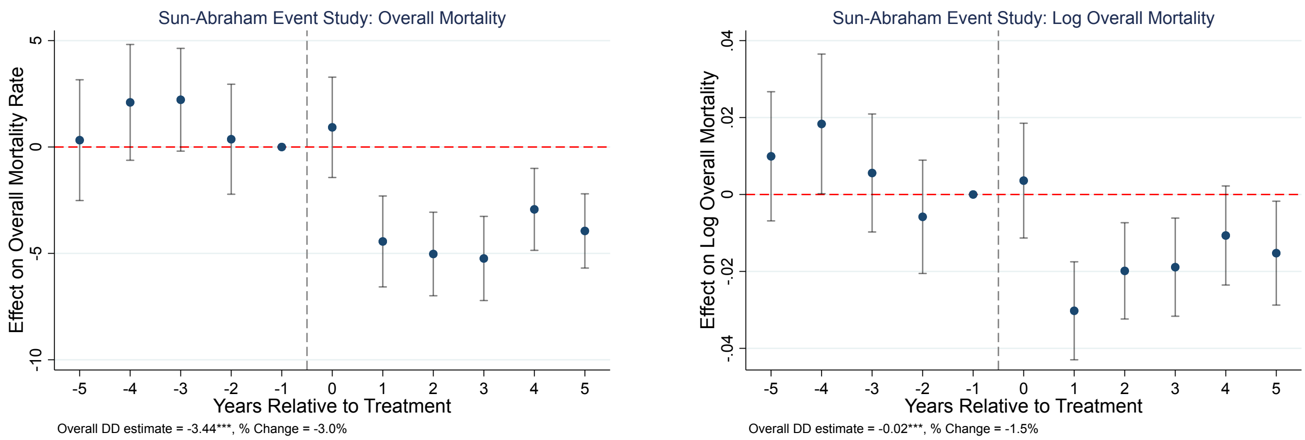


Figure 6: First Stage: Effect of Facility Openings on Mental Health Employment



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 Mental Health Treatment Facilities on Overall Mortality: Sun-Abraham Estimates

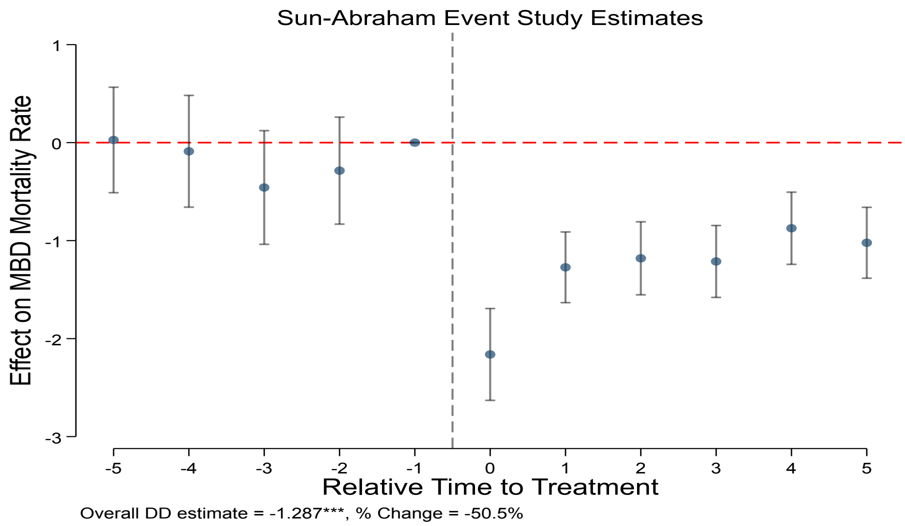


(a) Main Event Study

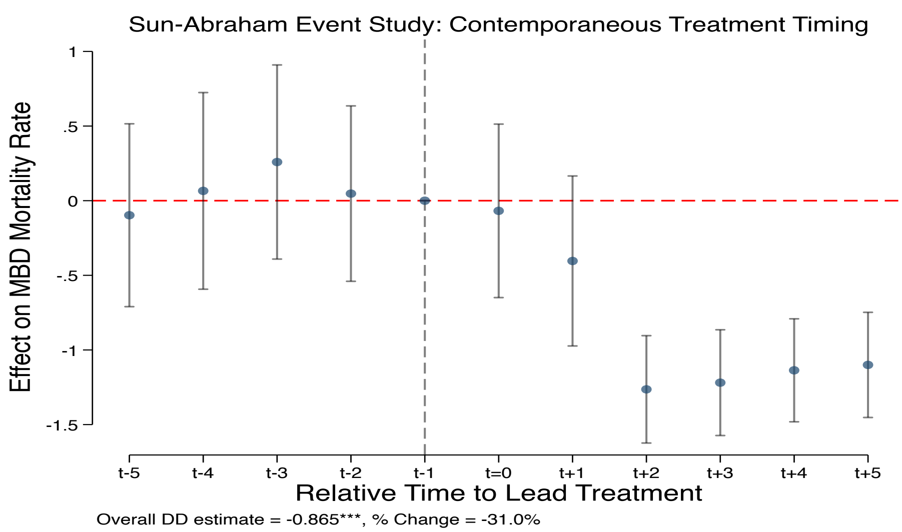
(b) Log Specification

Notes: The estimates implement the Sun and Abraham (2021) heterogeneity-robust event study estimator where the outcome variable is the mortality rate from all causes of death per 100,000 county residents. Panel (a) examines the lagged effects of treatment. Panel (b) displays the log specification. 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 estimates and 95% confidence intervals, with 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 Local Access to MHT Treatment Facilities on Mental and Behavioral Health Disorder Mortality: Sun-Abraham Estimates



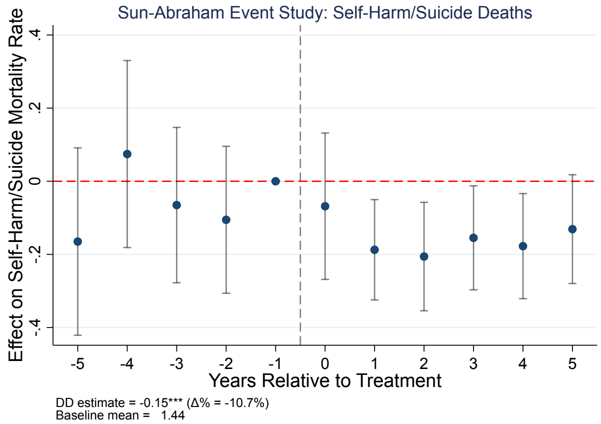
(a) Main Event Study: Lagged Treatment Effects (Sun-Abraham)



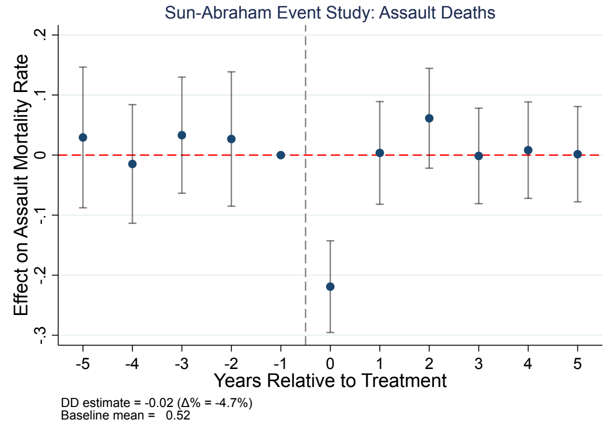
(b) Event Study: Contemporaneous Treatment Timing (Sun-Abraham)

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 8a examines the lagged effects of treatment, showing an overall treatment effect of -1.29 (representing a 50.5% change from pre-treatment mean). Panel 8b 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.

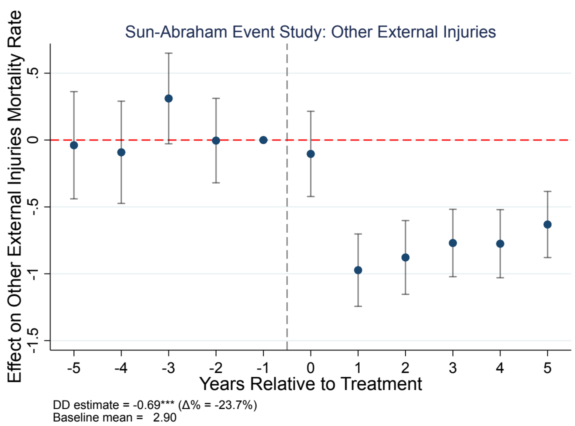
Figure 9: Sun-Abraham Event Study Estimates for Component Causes of Mortality



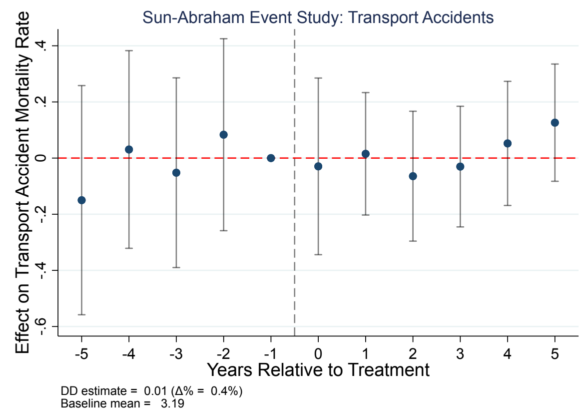
(a) Self-Harm/Suicide Deaths



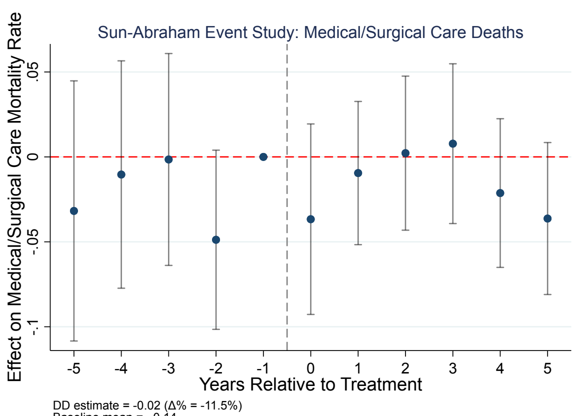
(b) Assault Deaths



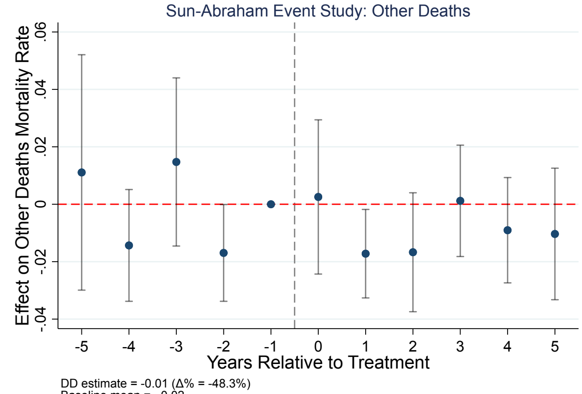
(c) Other External Injuries



(d) Transport Accidents



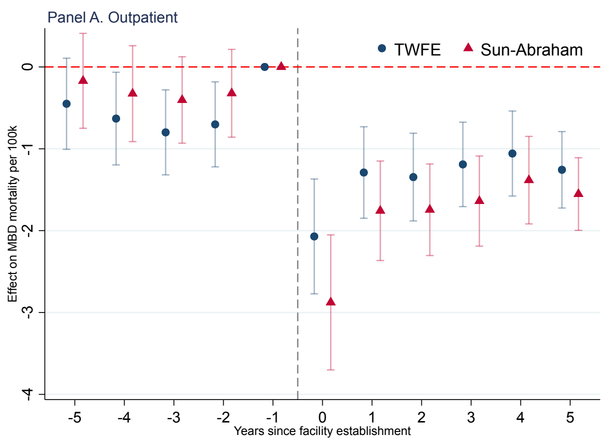
(e) Medical/Surgical Care Deaths



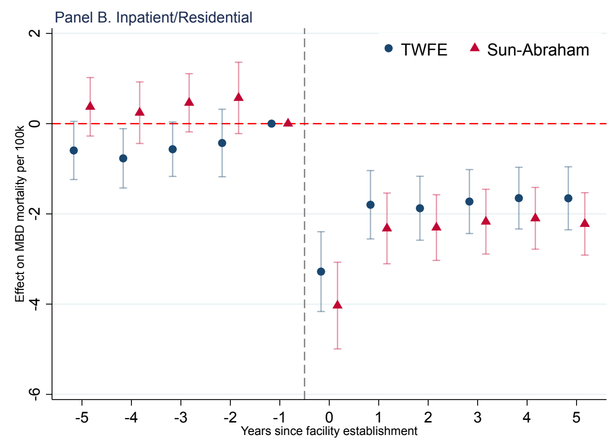
(f) Other Deaths

Notes: This figure presents event study estimates using the Sun and Abraham (2021) interaction-weighted estimator for component causes of mortality. Each panel shows point estimates and 95% confidence intervals for the effect of mental health treatment facility openings on cause-specific mortality rates. The horizontal axis measures years relative to the first facility opening in a county, with $t = -1$ (one year before treatment) as the omitted reference period indicated by the vertical dashed line. The outcome variables are deaths per 100,000 county residents from each specific cause. The sample is restricted to counties with a single facility opening and no pre-treatment changes in facility counts, plus never-treated counties as the control group. All specifications include county fixed effects, year fixed effects, state-by-year fixed effects, demographics and controls controls. Standard errors are clustered at the county level. The average treatment effect shown in each panel note is calculated as the mean of coefficients from $t = 0$ to $t = 5$. Panel (c) is Other external causes of accidental injury, and panel (f) is Other (skin, blood, residual codes). See Table A8, and A7 for coefficient estimates and baseline means.

Figure 10: Effect of Outpatient versus Inpatient Facility Establishment on Mortality



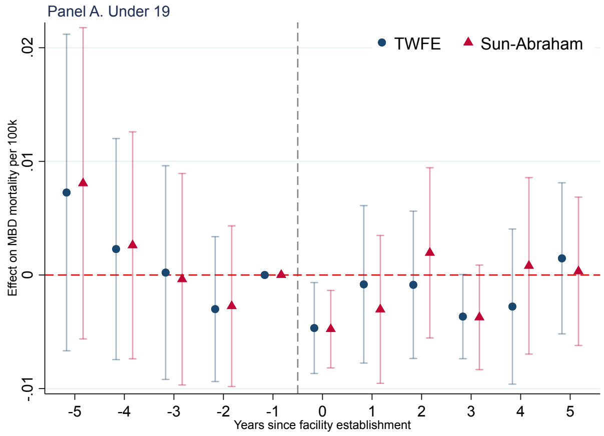
(a) Outpatient Facilities (NAICS 621420)



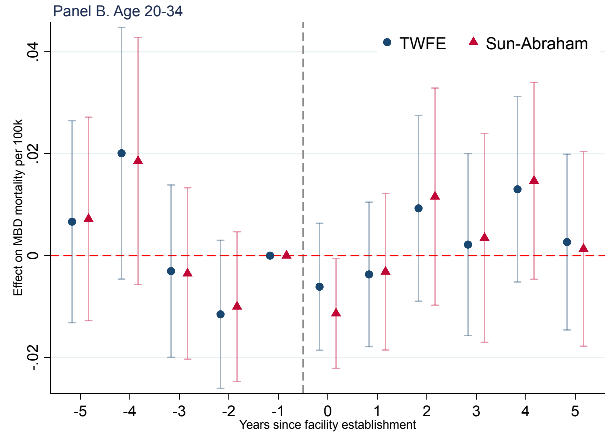
(b) Inpatient/Residential Facilities (NAICS 623220)

Notes: These figures plot event study coefficients from equation (3) for the effect of different facility types on MBD mortality rates. Circles represent two-way fixed effects (TWFE) estimates; triangles represent Sun and Abraham (2020) estimates. The vertical line at $t = -1$ denotes the year before facility establishment (normalized to zero). Bars represent 95 percent confidence intervals. The TWFE average represents the mean effect over periods 0–5 relative to period -1. The Sun-Abraham average represents the weighted average of cohort-specific treatment effects. Standard errors clustered at the county level in parentheses. See Table 6 for full regression results.

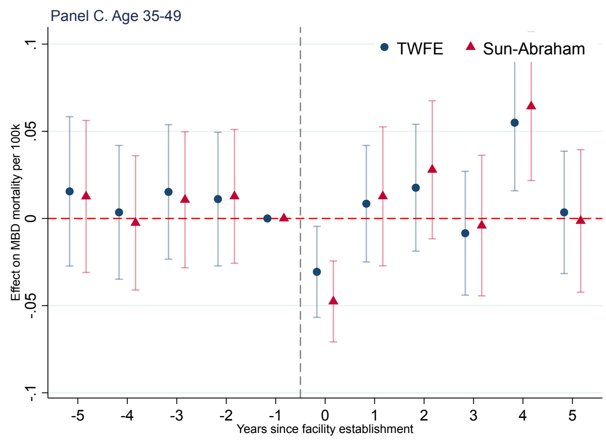
Figure 11: Effect of Mental Health Facility Establishment on Age-Specific Mortality



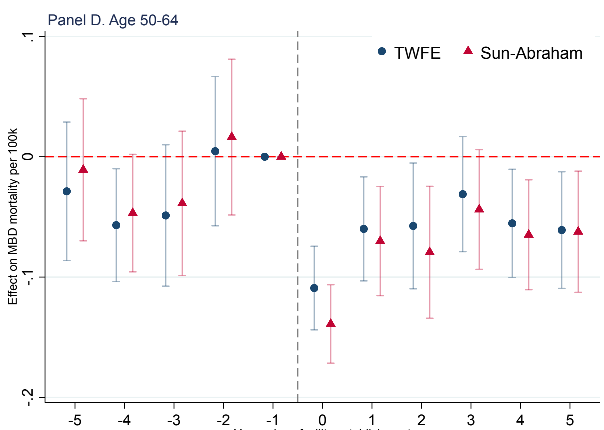
(a) Under 19



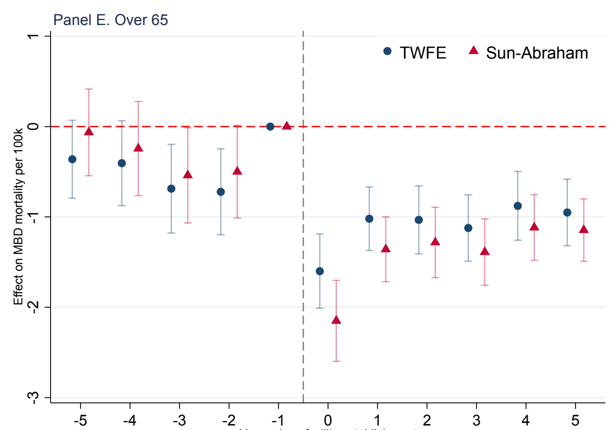
(b) Age 20–34



(c) Age 35–45



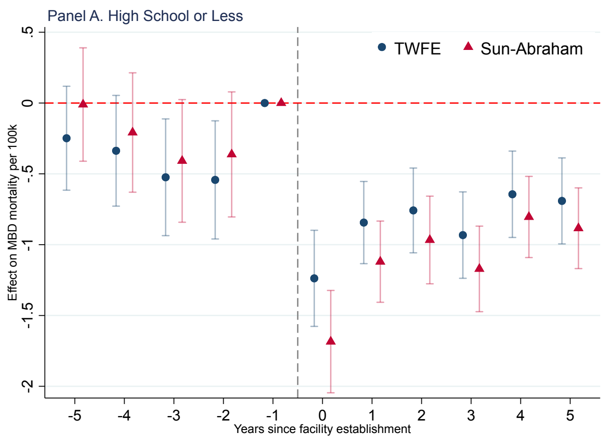
(d) Age 50–64



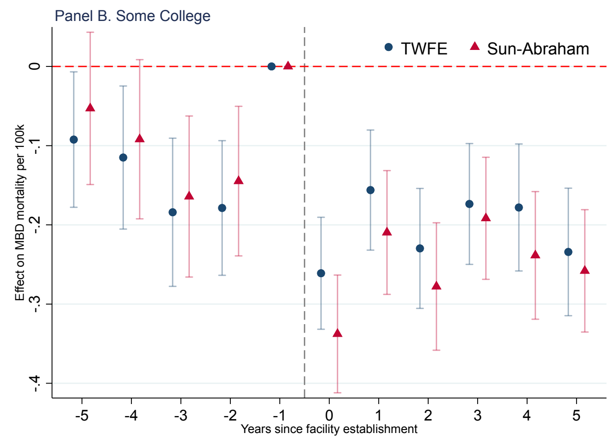
(e) Over 65

Notes: These figures plot event study coefficients from equation (3) for age-specific MBD mortality rates. Circles represent two-way fixed effects (TWFE) estimates; triangles represent Sun and Abraham (2020) estimates. The vertical line at $t = -1$ denotes the year before facility establishment (normalized to zero). Bars represent 95 percent confidence intervals. The TWFE average represents the mean effect over periods 0–5 relative to period -1. The Sun-Abraham average represents the weighted average of cohort-specific treatment effects. Standard errors clustered at the county level in parentheses. See Table 7 for full regression results.

Figure 12: Effect of Mental Health Facility Establishment on Mortality by Education Level



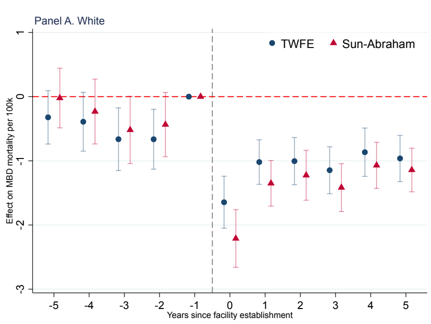
(a) High School or Less



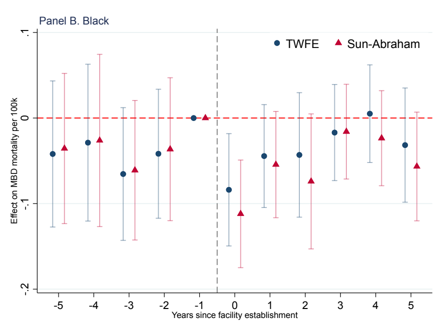
(b) Some College

Notes: These figures plot event study coefficients from equation (3) for education-specific MBD mortality rates. Circles represent two-way fixed effects (TWFE) estimates; triangles represent Sun and Abraham (2020) estimates. The vertical line at $t = -1$ denotes the year before facility establishment (normalized to zero). Bars represent 95 percent confidence intervals. The TWFE average represents the mean effect over periods 0–5 relative to period -1. The Sun-Abraham average represents the weighted average of cohort-specific treatment effects. Standard errors clustered at the county level in parentheses. See Table 8 for full regression results.

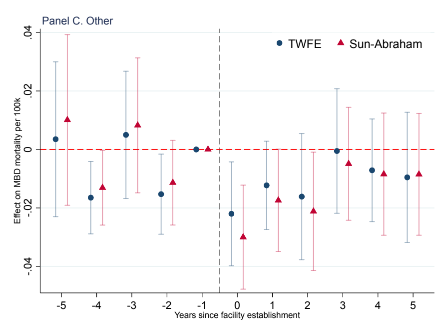
Figure 13: Effect of Mental Health Facility Establishment on Mortality by Race



(a) White



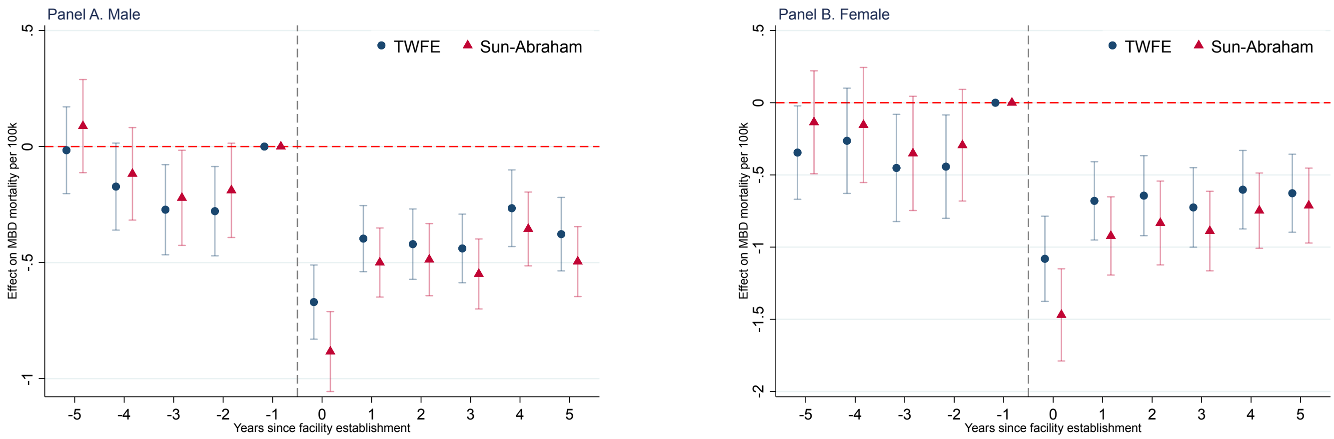
(b) Black



(c) Other

Notes: These figures plot event study coefficients from equation (3) for race-specific MBD mortality rates. Circles represent two-way fixed effects (TWFE) estimates; triangles represent Sun and Abraham (2020) estimates. The vertical line at $t = -1$ denotes the year before facility establishment (normalized to zero). Bars represent 95 percent confidence intervals. The TWFE average represents the mean effect over periods 0–5 relative to period -1. The Sun-Abraham average represents the weighted average of cohort-specific treatment effects. Standard errors clustered at the county level in parentheses. See Table 9 for full regression results.

Figure 14: Effect of Mental Health Facility Establishment on Mortality by Gender

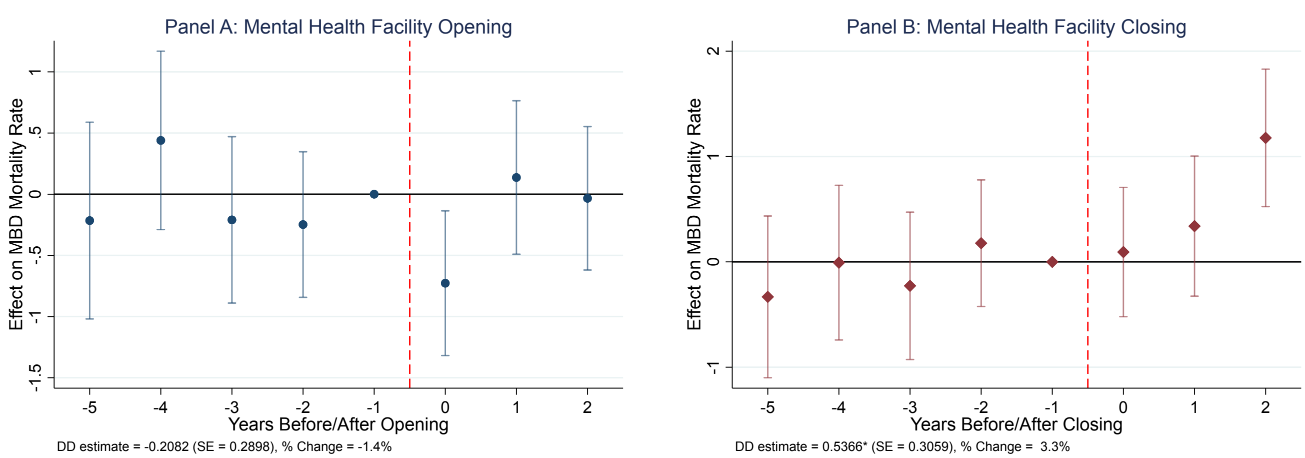


(a) Male

(b) Female

Notes: These figures plot event study coefficients from equation (3) for gender-specific MBD mortality rates. Circles represent two-way fixed effects (TWFE) estimates; triangles represent Sun and Abraham (2020) estimates. The vertical line at $t = -1$ denotes the year before facility establishment (normalized to zero). Bars represent 95 percent confidence intervals. The TWFE average represents the mean effect over periods 0–5 relative to period -1. The Sun-Abraham average represents the weighted average of cohort-specific treatment effects. Standard errors clustered at the county level in parentheses. See Table 10 for full regression results.

Figure 15: Dynamic Effects of Facility Openings and Closings on MBD Mortality: Sun and Abraham (2021) Estimates

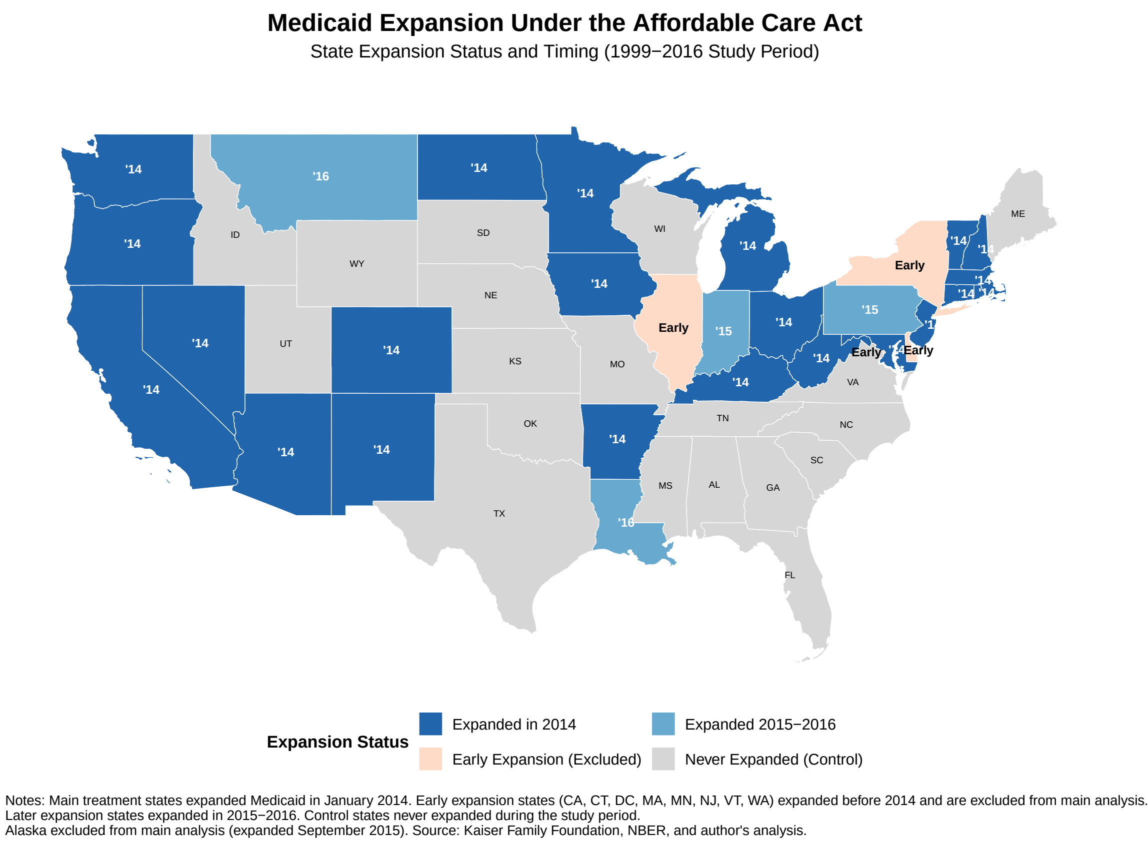


(a) Mental Health Facility Opening

(b) Mental Health Facility Closing

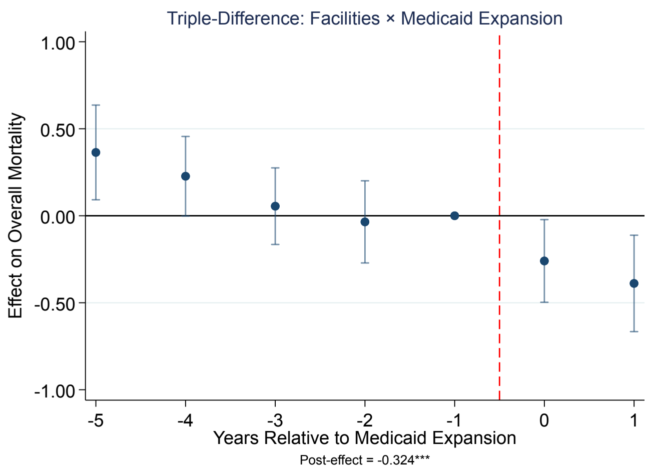
Notes: This figure plots event study estimates from the Sun and Abraham (2021) heterogeneity-robust estimator. The outcome variable in both panels is the mortality rate related to mental and behavioral disorders (MBD) per 100,000 county residents. Panel (a) shows the dynamic effect of the first opening 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 16: Medicaid Expansion Status and Timing Under the ACA

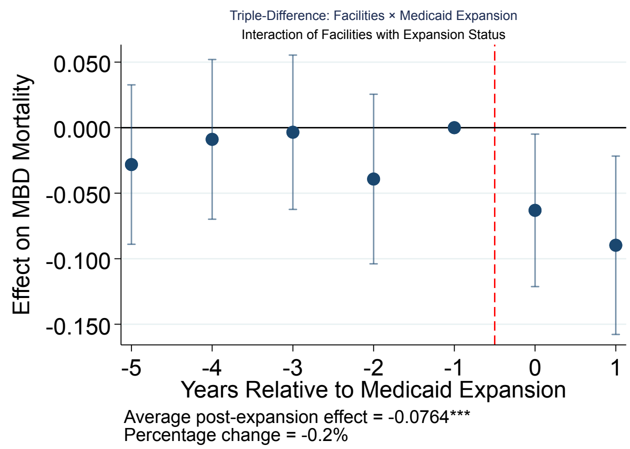


Notes: This figure illustrates the state-level timing of Medicaid expansion under the Affordable Care Act (ACA). States are categorized based on their expansion status and timing. The main treatment group consists of states that expanded in 2014. "Early Expansion" states adopted Medicaid expansion prior 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 17: Triple-Difference Event Studies: Mental Health Facilities and Medicaid Expansion



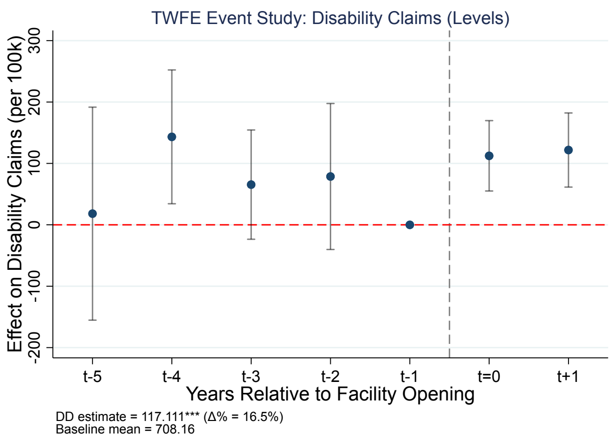
(a) Overall Mortality



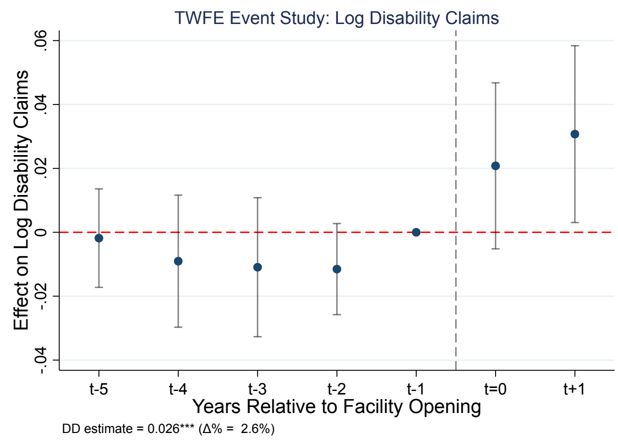
(b) MBD Mortality

Notes: These figures present triple-difference (DDD) event study estimates examining how Medicaid expansion affects the relationship between mental health facilities and mortality. The coefficients represent the differential effect of facilities in expansion versus non-expansion states for each year relative to 2013 (t = -1, the omitted reference period). Panel (a) shows effects on overall mortality from all causes. Panel (b) shows effects on mental and behavioral disorder (MBD) mortality. The vertical dashed line indicates 2014, when most states implemented expansion. Both 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 post-expansion coefficients reveal that facilities in expansion states generate additional mortality reductions beyond their baseline effects, with overall mortality showing larger absolute effects (-0.324 deaths per 100,000) than MBD mortality (-0.076 deaths per 100,000), consistent with spillover benefits when insurance barriers are removed. Data: County Business Patterns and Vital Statistics, 2009-2015.

Figure 18: Mechanism: Dynamic Effects of Mental Health Treatment Facilities on Disability Claims



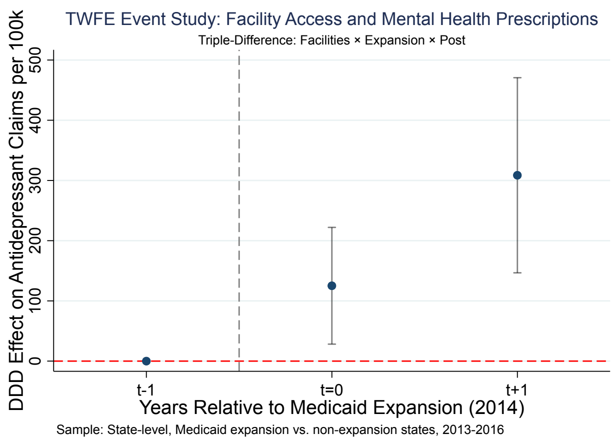
(a) Main Event Study



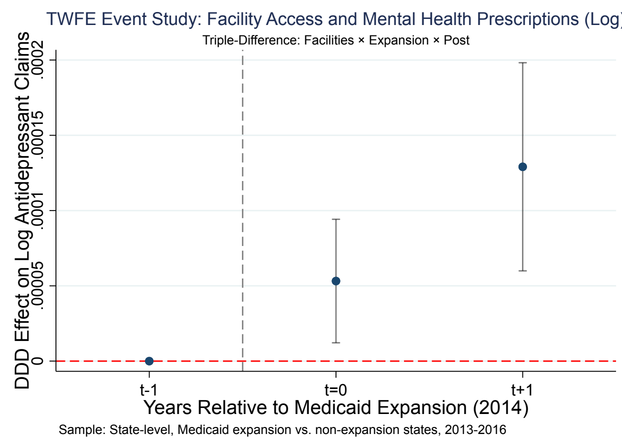
(b) Log Specification

Notes: The estimates implement a two-way fixed effects (TWFE) event study estimator where the outcome variable is SSI disability recipients aged 18–64 per 100,000 county residents obtained from Social Security Administration county-level data. Panel (a) examines the effects in levels. Panel (b) displays the log specification. Both specifications include county fixed effects, year fixed effects, and state-by-year fixed effects. The observations are weighted by inverse propensity score weights based on county-level demographic characteristics. Additional controls include demographic composition (share under 19) and labor market conditions (employment-to-population ratio). The standard errors are clustered at the county level. The data combines County Business Patterns (CBP) for mental health facility openings with SSA disability data for the period 2009–2016. The figures display coefficient estimates and 95% confidence intervals, with $t = -1$ as the omitted reference period. The vertical dashed line indicates the treatment period ($t = 0$). The sample is restricted to counties with a single facility opening and no pre-treatment changes in facility counts, plus never-treated counties as the control group. Negative coefficients indicate that mental health facilities reduce disability claims. The time window spans five pre-treatment periods ($t = -5$ to $t = -1$) and two post-treatment periods ($t = 0$ to $t = 1$), constrained by the availability of SSA disability data through 2016.

Figure 19: Mechanism: Dynamic Effects of Mental Health Facilities and Medicaid Expansion on Antidepressant Prescriptions



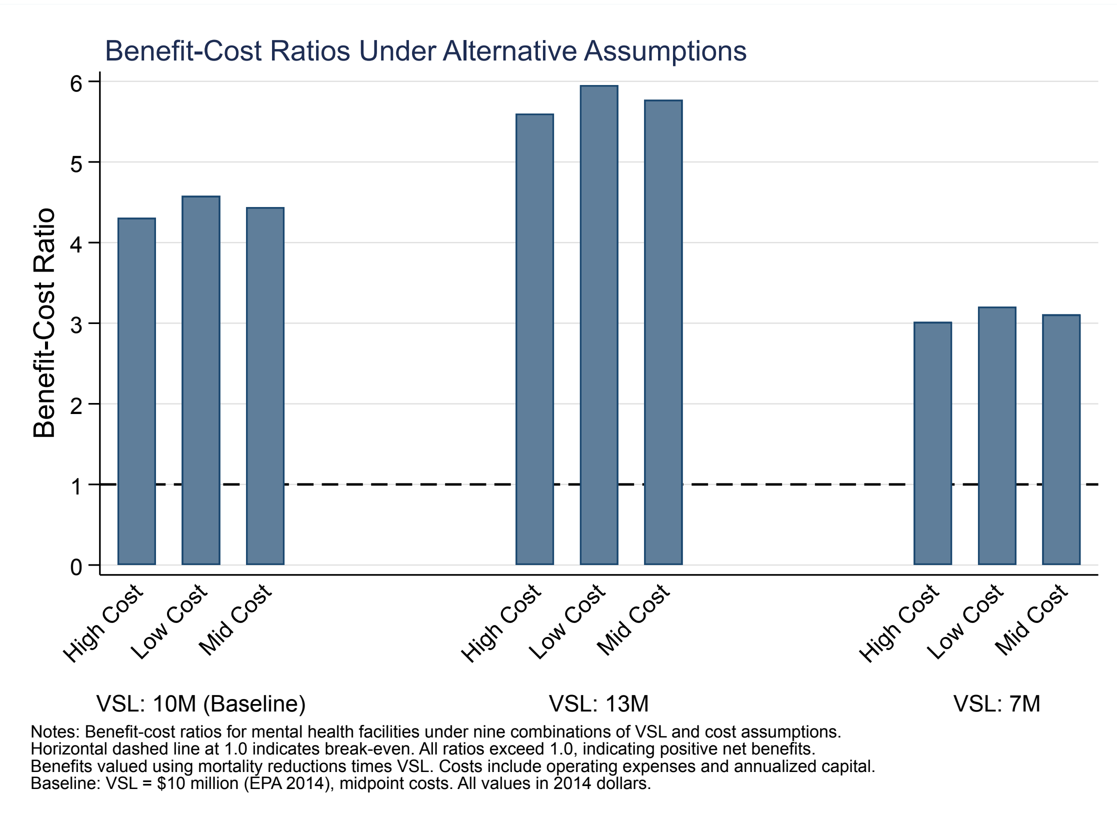
(a) Main Event Study



(b) Log Specification

Notes: The estimates implement a two-way fixed effects (TWFE) triple-difference event study estimator where the outcome variable is antidepressant claims per 100,000 population obtained from Medicare Part D prescriber data. The triple-difference specification compares the effect of mental health facilities in Medicaid expansion states versus non-expansion states, before and after expansion. Panel (a) examines the effects in levels. Panel (b) displays the log specification. Both specifications include state fixed effects and year fixed effects. Additional controls include demographic composition (share under 19) and labor market conditions (employment-to-population ratio). The standard errors are clustered at the state level. The data combines state-level aggregates of County Business Patterns (CBP) for mental health facilities with Medicare Part D geographic prescriber data for the period 2013–2016. The figures display triple-difference coefficient estimates and 95% confidence intervals, with $t = -1$ (2013) as the omitted reference period. The vertical dashed line indicates $t = 0$ (2014), when Medicaid expansion took effect in participating states. Medicaid expansion states are those that adopted expansion between 2014 and 2016. The antidepressant category includes commonly prescribed SSRIs, SNRIs, and tricyclic antidepressants (sertraline, escitalopram, trazodone, bupropion, fluoxetine, citalopram, duloxetine, venlafaxine, amitriptyline). The limited pre-period reflects data availability constraints; 2013 is the first year of Medicare Part D geographic prescriber data. The event study captures the dynamic complementarity between mental health facility access and insurance coverage expansion. Positive coefficients indicate that facility effects on prescription utilization are larger in expansion states post-expansion, consistent with increased demand for mental health services when insurance barriers are reduced.

Figure 20: Benefit-Cost Ratios Under Alternative Assumptions



Notes: This figure displays benefit-cost ratios for mental health facilities under nine combinations of Value of Statistical Life (VSL) and cost assumptions. The horizontal dashed line at 1.0 indicates break-even. All ratios exceed 1.0, indicating positive net benefits across all scenarios. Benefits are valued using mortality reductions times VSL. Costs include operating expenses and annualized capital expenditures. The baseline scenario uses VSL = $10 million (EPA 2014 estimate) and midpoint facility costs. All monetary values are in 2014 dollars.

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: 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 3: 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 4: Baseline Model - Main Effects of Access to Mental Health Treatment Facilities on Mortality Related to Mental Health and Behavioral Disorders

	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	-0.06647**	-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 5: 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 6: 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 7: Effects of Treatment Facilities by Age Groups

	All Ages (1)	Under 19 (2)	20-34 (3)	35-49 (4)	50-64 (5)	Over 65 (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 8: Effects of Treatment Facilities by Education Level

	All Levels (1)	High School or Less (2)	Some College (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 9: Effects of Treatment Facilities by Race

	All Races	White	Black	Other Races
	(1)	(2)	(3)	(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 10: Effects of Treatment Facilities by Gender

	All	Male	Female
	(1)	(2)	(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 11: 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 12: 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 13: Mechanism: Effect of Mental Health Facilities on Disability Claims: TWFE Esimates

	(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 14: Mechanism: Mental Health Facilities and Medicaid Expansion on Antidepressant Prescriptions: TWFE Estimates

	(1) Basic	(2) Year FE	(3) Demographics	(4) Full
MH Facilities × Post × Expansion	279.586	279.586	276.995	217.894
	(54.667)***	(54.667)***	(49.234)***	(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 15: Welfare Analysis: Cost-Benefit of Mental Health Facilities

	Scenario		
	Baseline	Lower Bound	Upper Bound
Panel A: Lives Saved and Benefits			
Lives saved per facility per year	1.51	2.00	1.03
Annual benefit (VSL = $10M)	$ 15125951	$ 19978864	$ 10273038
Panel B: Costs			
Annual operating cost	$3,000,000	$3,000,000	$3,000,000
Annualized capital cost	$ 406,655	$ 302,471	$ 510,839
Total annual cost	$3,406,655	$3,302,471	$3,510,839
Panel C: Net Benefits			
Net annual benefit	$ 11719296	$ 11823480	$ 11615111
Benefit-cost ratio	4.44	4.58	4.31

Notes: This table presents the welfare analysis of mental health treatment facilities based on the mortality effects estimated in Table 3, Column 4. The baseline scenario uses a Value of Statistical Life (VSL) of 10 million dollars (EPA 2014 estimate) and midpoint facility costs. The lower bound uses the 95% confidence interval lower bound for mortality effects and low facility costs; the upper bound uses the 95% CI upper bound and high facility costs. Lives saved per facility per year is calculated as absolute value of coefficient times (county population / 100,000), where coefficient = -1.559 (SE = 0.255) from Table 3, Column 4, and mean county population is 97,051. Annual benefits equal lives saved times VSL. Operating costs (3 million dollars per year) and capital costs (4.5M to 7.6M one-time) are from the Montana Legislative HJR 16 Study (May 2014). Capital costs are annualized over 20 years at a 3% discount rate. Net annual benefit equals annual benefit minus total annual cost. Benefit-cost ratio is annual benefit divided by total annual cost. All monetary values are in 2014 dollars.

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

Olanrewaju Yusuff [29]

Goergia State University

Supplementary Appendix

For Online Publication

[29]Department of Economics, Georgia State University: oyusuff4@student.gsu.edu

Appendix Contents:

A Mental Health Treatment Facilities: Context and Institutional Details

This section provides context on mental health treatment facilities in the United States, documenting trends in facility availability during the sample period and describing the services these facilities provide. Understanding the institutional details helps interpret the estimated treatment effects and welfare calculations.

A.1 Trends in Facility Availability (1999–2016)

Figure 3 displays the aggregate trend in mental health treatment facilities from 1999 to 2016. The total number of facilities increased substantially over this period, rising from approximately 10,500 facilities in 1999 to nearly 18,000 by 2016. This represents a 71 percent increase in aggregate facility availability, corresponding to an average annual growth rate of approximately 3.3 percent.

This aggregate expansion masks important heterogeneity in where facility growth occurred. The increase in facilities was concentrated primarily in counties that already had existing mental health infrastructure. Counties without any baseline mental health facilities were significantly less likely to gain access during the sample period. This pattern is consistent with market forces driving facility location decisions: providers locate where demand is established, reimbursement rates are favorable, and complementary healthcare infrastructure exists (Frank and McGuire, 2000).

The concentration of facility growth in areas with existing infrastructure has important implications for access disparities. Rural counties, which are less likely to have baseline mental health services, experienced slower growth in facility availability compared to urban and suburban counties. This geographic pattern contributes to persistent disparities in mental healthcare access documented in prior research (Cummings et al., 2017; Andrilla et al., 2018). My analysis exploits within county variation in facility openings and closings over time, treating the timing of these changes as plausibly exogenous conditional on county fixed effects, time fixed effects, and observable county characteristics.

The variation I exploit comes from discrete changes in facility counts: new facilities opening, existing facilities closing, or facilities changing their service offerings. These changes reflect a combination of market forces (demand growth, competition), policy changes (state licensing requirements, Medicaid reimbursement rates), and economic conditions (local labor markets, real estate costs). The event study analysis in Section 5.5 shows no evidence of differential pre trends between counties that experience facility changes and those that do not, supporting the parallel trends assumption underlying the difference in differences design.

A.2 Treatment Services Provided by Mental Health Facilities

Mental health treatment facilities in my sample include both outpatient and residential settings, identified using NAICS codes 621112 (offices of physicians, mental health specialists) and 621330 (offices of mental health practitioners except physicians). Understanding the services these facilities provide helps interpret the estimated mortality effects and clarifies the mechanisms through which facility access affects health outcomes.

Outpatient Services. The majority of facilities in my sample provide outpatient mental health services. Outpatient facilities offer several core treatment modalities:

- *Psychotherapy*: Individual, group, and family therapy addressing emotional and behavioral symptoms. Common therapeutic approaches include cognitive behavioral therapy (CBT), dialectical behavior therapy (DBT), and trauma informed therapies (Hofmann et al., 2012; Linehan, 1993).
- *Medication management*: Psychiatrists, nurse practitioners, and physician assistants prescribe and monitor psychotropic medications, including antidepressants, mood stabilizers, and antipsychotic medications. Medication management typically involves regular follow up appointments to assess treatment response and adjust dosing (Glied and Frank, 2016).
- *Crisis intervention*: Many outpatient facilities provide crisis services for individuals experiencing acute psychiatric symptoms, including suicidal ideation, severe anxiety, or psychotic episodes. Crisis intervention aims to stabilize patients and connect them with appropriate ongoing care (Guo et al., 2001).
- *Case management*: Coordination of care across providers and connection to community resources, including housing assistance, employment services, and social support programs (Ziguras and Stuart, 2000).

Table 6, Panel A shows that outpatient facilities have significant effects on mental health related mortality, with each additional outpatient facility reducing deaths by 0.126 per 100,000 residents (approximately 0.4 percent relative to baseline).

Residential Services. A smaller subset of facilities provide residential or inpatient mental health treatment. Residential facilities offer more intensive, structured care for individuals who require 24 hour supervision and support. Services at residential facilities include:

- *Structured daily programming*: Scheduled therapeutic activities, group sessions, and skills building exercises throughout the day.

- *Medication management*: Daily medication administration and close monitoring by clinical staff, particularly important for medication titration and managing side effects.

- *Skills development*: Training in coping strategies, stress management, social skills, and activities of daily living. These programs help individuals develop tools for managing symptoms after discharge (Drake et al., 2001).

- *Stabilization and safety*: Residential settings provide a safe, supervised environment for individuals at high risk of harm to themselves or others. This is particularly important for suicide prevention and crisis stabilization (Zalsman et al., 2016).

Table 6, Panel B shows that residential facilities also reduce mental health mortality, with effects of similar magnitude to outpatient facilities (coefficient of 0.090 per 100,000, approximately 0.3 percent relative to baseline).

Treatment Pathways and Mortality Reduction. The services provided by these facilities can reduce mortality through several pathways. First, effective treatment of depression, anxiety, bipolar disorder, and other mental health conditions directly reduces suicide risk (Mann et al., 2005). Second, mental health treatment may reduce mortality from substance use disorders through integrated treatment approaches and referrals to specialized substance abuse services (Drake et al., 2001). Third, improved mental health can lead to better self care and treatment adherence for co occurring physical health conditions, reducing mortality from cardiovascular disease and other chronic conditions (Kupfer et al., 2012). Fourth, case management and social support services connect individuals with housing, employment, and community resources that address social determinants of health (Marmot, 2005).

The welfare calculations in Section 9 value only the mortality reductions documented in this paper. These estimates exclude substantial additional benefits from improved quality of life, reduced morbidity, decreased healthcare utilization, and positive spillovers to family members and communities. The mortality effects I estimate therefore represent a lower bound on the total welfare gains from improved mental health facility access.

A.3 Facility Types and Treatment Intensity

Mental health treatment facilities vary substantially in treatment intensity, staffing levels, and patient populations served. This heterogeneity has important implications for interpreting the estimated effects.

Outpatient Facilities (NAICS 621420) typically serve patients who can safely live in the community while receiving treatment. Patients may attend therapy sessions weekly or biweekly, with additional appointments for medication management as needed. Treatment episodes can range from a few months for acute conditions to years for chronic mental health conditions requiring ongoing management. Outpatient facilities are the primary source of mental healthcare for most individuals, serving patients with depression, anxiety disorders, bipolar disorder, and less severe manifestations of schizophrenia and other psychotic disorders.

Residential Facilities (NAICS 623220) serve patients requiring more intensive, structured care. Length of stay typically ranges from 30 to 90 days, though some programs extend longer for chronic conditions. Residential facilities serve individuals with more severe symptoms, those who have not responded to outpatient treatment, or those requiring intensive stabilization following a crisis. After discharge, patients typically transition to outpatient care for ongoing management.

The similar magnitudes of estimated effects for outpatient and residential facilities (Table 6) suggest that both types of care contribute to mortality reduction. This is consistent with a treatment model where different facility types serve complementary roles: residential facilities provide intensive stabilization and initiate treatment, while outpatient facilities provide ongoing maintenance care and prevent relapse.

Geographic Distribution and Access Barriers. Access to mental health facilities varies substantially across geographic areas. Urban counties tend to have multiple facilities offering diverse treatment options, while rural counties often have limited or no local mental health services. Travel distance to the nearest facility represents a significant access barrier, particularly for individuals without reliable transportation (Cummings et al., 2017). The within county variation I exploit in the empirical analysis captures changes in local access, holding constant county specific factors that affect baseline mental health needs and healthcare infrastructure. The estimated effects therefore represent the impact of improving local access for individuals who previously faced travel barriers or had no proximate source of care.

B Data

This section provides detailed documentation of the data sources, variable construction, and sample selection criteria used in the analysis. All data processing follows standard practices in the literature and ensures consistency with previous studies on healthcare access and mortality outcomes.

B.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.[30] 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).

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

- NAICS 621112: Offices of physicians, mental health specialists
- NAICS 621330: Offices of mental health practitioners (except physicians)

Each establishment represents a single physical location where mental healthcare services are provided. Establishments can only be assigned one NAICS code, ensuring no double-counting of facilities. While these establishments primarily focus on mental healthcare, they may also provide substance use disorder (SUD) treatment services, allowing me to capture the full spectrum of mental health treatment facilities available in each county.

Timing and Lags. The CBP collects data during the payroll period including March 12th of each year. Following IRS processing and Census Bureau compilation, the data typically become available 18-24 months after collection. Consistent with previous studies (Swensen, 2015; Bondurant et al., 2018), I lag facility counts by one year in my regression analyses. This lag accounts for: (1) the time required for facility establishment and staffing, (2) patient awareness and access to new facilities, (3) the lag between IRS reporting and CBP publication, and (4) the time needed for potential improvements in mental health outcomes to materialize.

[30] The CBP provides comprehensive coverage of business establishments with paid employees, excluding most government entities, self-employed individuals, and agricultural production workers. Coverage includes approximately 98 percent of private non-farm employment.

Sample Coverage. My analytical sample includes 53,498 county-year observations spanning 1999 to 2016, covering 3,199 counties across all 50 states and the District of Columbia. This extensive temporal and geographic coverage enables me to examine how changes in local access to mental health treatment facilities affect health outcomes while controlling for time-invariant county characteristics and common temporal shocks.

B.2 Mental Health Employment Data

To establish that facility openings correspond to actual expansion in 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: the majority of county-industry cells have suppressed values to protect establishment confidentiality, particularly in small counties or industries with few establishments.

Imputation Methodology. Eckert et al. (2020) address these limitations through a linear programming method that exploits the hierarchical adding-up constraints implicit in the CBP data structure.[31] Their approach ensures that imputed values satisfy all disclosed totals and subtotals while minimizing deviations from observed patterns in the data.

Variable Construction. For my analysis, I extract employment data for mental health establishments using NAICS codes 621112 and 621330, consistent with my facility count measures. The 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. I construct two key measures:

1. *Mental health employment per 100,000 population*:

$$\text{MH Emp}_{ct} = \frac{\text{Total MH Employment}_{ct}}{\text{County Population}_{ct}} \times 100{,}000 \tag{13}$$

2. *Log mental health employment (plus one)*: $\ln(\text{MH Emp}_{ct} + 1)$ to account for counties with zero mental health employment

These employment measures serve as first-stage outcomes, verifying that facility openings translate into increased mental healthcare capacity rather than merely reflecting administrative changes or establishment reorganizations. For counties with suppressed employment values in the original CBP that could

[31] Eckert et al. (2020) develop a comprehensive imputation procedure that leverages the nested structure of industry classifications (2-digit through 6-digit NAICS codes) and geographic aggregations (national, state, county levels) in the CBP data. Their method ensures that imputed values satisfy all disclosed totals and subtotals while minimizing deviations from observed patterns. The authors make their imputed employment data publicly available at `https://www.fpeckert.me/cbp/`.

not be imputed, I assign zero employment, which represents a lower bound on actual mental health sector employment.

B.3 Vital Statistics Mortality Data

My primary outcome measures are mortality rates constructed from the Multiple Cause of Death (MCOD) data files from the National Center for Health Statistics (NCHS) for the period 1999 to 2016. These restricted access 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.

Data Structure and Coverage. The MCOD files contain one record for each death occurring in the United States, including information on the underlying cause of death (the disease or injury that initiated the chain of events leading directly to death) and up to 20 contributing causes. Each death record includes county of residence, allowing aggregation to the county level for analysis. The data cover all 50 states plus the District of Columbia and represent the complete census of deaths rather than a sample.

Mortality Classification System. Deaths are classified using the International Classification of Diseases, Tenth Revision (ICD-10), implemented in the United States in 1999 (World Health Organization, 2019). The ICD-10 system provides a hierarchical structure for categorizing diseases and causes of death, with alphanumeric codes ranging from broad categories (Chapter level) to specific diagnoses (four character subcategories). I use ICD-10 codes to identify deaths attributable to mental and behavioral disorders, as well as other specific causes of interest.

Mental and Behavioral Disorder Mortality. My primary outcome of interest is mortality from mental and behavioral disorders (MBD), defined using ICD-10 Chapter V codes F00 through F99. Table A13 provides the complete classification structure. I examine deaths attributed to eleven distinct diagnostic categories:

- F00-F09: Organic mental disorders, including dementia in Alzheimer disease (F00) and vascular dementia (F01)
- F10-F19: Mental and behavioral disorders due to psychoactive substance use
- F20-F29: Schizophrenia, schizotypal and delusional disorders
- F30-F39: Mood (affective) disorders, including depressive episodes and bipolar disorder
- F40-F48: Neurotic, stress related and somatoform disorders
- F50-F59: Behavioral syndromes associated with physiological disturbances

- F60-F69: Disorders of adult personality and behavior
- F70-F79: Mental retardation (intellectual disabilities)
- F80-F89: Disorders of psychological development
- F90-F98: Behavioral and emotional disorders with onset in childhood
- F99: Unspecified mental disorder

I construct an aggregate measure of total MBD mortality by summing deaths across all F00 to F99 codes. This provides the overall effect on mental health related mortality while the diagnostic subcategories allow examination of heterogeneous effects across condition types.

Overall Mortality. To capture broader health impacts beyond MBD specific causes, I also examine all cause mortality. This outcome includes deaths from all ICD-10 chapters and external causes, providing a comprehensive measure of population health. The all cause mortality measure captures both direct effects of mental health treatment (preventing MBD deaths) and indirect effects through improved management of comorbid physical health conditions, reduced substance abuse, and other pathways.

Component Causes of Mortality. To distinguish mental health related mortality effects from placebo outcomes and to understand mechanisms, I examine several specific causes of death:

Mental health related causes:

- Intentional self harm (suicide): ICD-10 codes X60 through X84
- Mental and behavioral disorders due to substance use: ICD-10 codes F10 through F19

External causes potentially related to mental health:

- Assault: ICD-10 codes X85 through Y09
- Transport accidents: ICD-10 codes V01 through V99
- Other external causes of accidental injury: ICD-10 codes W00 through X59

Placebo outcomes (not expected to respond to mental health treatment):

- Deaths from medical and surgical care complications: ICD-10 codes Y40 through Y84

- Other causes: Residual category including deaths from infectious disease, neoplasms, circulatory disease, and other natural causes not directly linked to mental health

This categorization allows me to test whether effects are specific to mental health related causes or reflect broader changes in mortality reporting or healthcare quality.

Variable Construction. For each cause of death category, I construct annual mortality rates at the county level. I first sum death counts across all relevant ICD-10 codes within each category for each county and year combination. I then normalize these counts by county population (expressed per 100,000 residents) using annual population estimates from the U.S. Census Bureau. This normalization ensures comparability across counties of different sizes and over time.

For county year cells with zero deaths in a particular category, I assign a mortality rate of zero. This approach is standard in mortality research and appropriate given that I examine aggregate county level outcomes rather than individual death records. For very small counties where mortality rates may be volatile due to small denominators, my estimates are less precise but remain unbiased under the parallel trends assumption.

Data Restrictions and Suppression. The NCHS suppresses county level data when death counts are small (typically fewer than 10 deaths) to protect privacy. Suppression is more common for rare causes of death and in small counties. For suppressed values, I cannot distinguish between zero deaths and small positive counts. Following standard practice, I treat suppressed values as missing rather than imputing values. This approach provides conservative estimates of mortality effects, as counties with suppressed data are excluded from the analysis for that particular cause and year.

For my main outcome (overall MBD mortality), data suppression is minimal due to the aggregation across all F00 to F99 codes. For specific diagnostic subcategories and component causes, suppression rates are higher, particularly in rural counties. The sample size varies across outcomes accordingly, as documented in the notes to each regression table.

Consistency Across Sample Period. The ICD-10 classification system remained stable throughout my sample period (1999 to 2016), ensuring consistent death classification over time. This stability is important for my identification strategy, as changes in coding practices could confound temporal variation in mortality rates with changes in facility availability. The NCHS made minor updates to coding rules during this period, but these changes were incremental and did not affect the major cause of death categories I examine.

B.4 Social Security Disability Data

To examine whether mental health facility access affects disability insurance enrollment, I obtain county-level data on Supplemental Security Income (SSI) recipients from the Social Security Administration's SSI State and County Data publication. These data provide annual counts of SSI recipients by county and age group, published in December of each year.

Data Structure and Processing. The SSA publishes disability data in Excel format with non-standard formatting that requires careful processing. The raw files contain multiple header rows and use special characters to indicate suppressed values. For each year from 2009 to 2016, I implement the following processing steps:

1. Import data starting from row 4 to skip header information
2. Extract three key columns: State name (Column A), County name (Column B), ANSI/FIPS Code (Column C), and Recipients aged 18-64 (Column H)
3. Clean FIPS codes by removing commas, spaces, and non-numeric characters
4. Clean recipient counts by removing commas and special characters (#, b, -)
5. Recode suppressed values (indicated by special characters or missing data) to zero, representing a lower bound on actual disability enrollment
6. Convert string variables to numeric format
7. Split 5-digit FIPS codes into 2-digit state codes and 3-digit county codes

Sample Restrictions. The SSA disability data are available from 2009 onwards, restricting this portion of my analysis to the period 2009-2016. I focus on recipients aged 18-64 as this working-age population is most directly affected by labor market conditions and mental health treatment availability. The final disability panel contains 25,592 county-year observations across 3,199 counties.

Suppressed Values. The SSA suppresses county-level data when recipient counts are small (typically fewer than 10 recipients) to protect individual privacy. Suppression is more common in rural counties with small populations. By coding suppressed values as zero, I obtain a lower bound on disability insurance enrollment. This conservative approach biases results toward zero, making it more difficult to detect treatment effects.

Outcome Measures. I construct two measures of disability insurance enrollment:

1. *SSI recipients per 100,000 population*: Raw count normalized by county population

2. *Log SSI recipients (plus one)*: $\ln(\text{SSI}_{ct}+1)$ to handle counties with zero reported recipients

B.5 Medicare Part D Data

To investigate whether mental health facility access affects medication treatment for mental health conditions, I obtain prescription drug data from the Centers for Medicare and Medicaid Services (CMS) Medicare Part D Prescribers by Geography and Drug dataset. These data provide aggregate information on prescription drug claims filled by Medicare Part D beneficiaries, broken down by prescriber geography and generic drug name.

Data Availability and Geographic Level. The Medicare Part D geographic data are publicly available beginning in 2013, limiting this analysis to 2013-2016. CMS provides these data at multiple geographic levels: national, state, and metropolitan statistical area. For consistency with my facility-level analysis, I aggregate prescriptions to the state level. State-level aggregation provides sufficient statistical power while avoiding the extensive data suppression that occurs at finer geographic levels.

Drug Selection. I focus on antidepressant medications, which represent the most commonly prescribed class of psychotropic medications and serve as a key treatment modality for depression and anxiety disorders. Following clinical practice guidelines () and previous economic research on mental health treatment (), I identify nine commonly prescribed antidepressants:

- Selective Serotonin Reuptake Inhibitors (SSRIs): Sertraline, Escitalopram, Fluoxetine, Citalopram
- Serotonin-Norepinephrine Reuptake Inhibitors (SNRIs): Duloxetine, Venlafaxine
- Atypical Antidepressants: Bupropion, Trazodone
- Tricyclic Antidepressants: Amitriptyline

These medications account for the vast majority of antidepressant prescriptions in the United States during the study period.

Variable Construction. For each state-year, I sum total prescription claims across all nine antidepressant medications. The key outcome variable is:

$$\text{Antidepressant Claims}_{st} = \sum_{d \in \text{Antidepressants}} \text{Total Claims}_{dst} \tag{14}$$

where s indexes states, t indexes years, and d indexes the nine antidepressant drugs. I also construct a per-capita measure by dividing total claims by state population to account for differences in state size.

Data Processing. The CMS data require several processing steps:

1. Import annual CSV files for years 2013-2016
2. Filter to state-level observations (excluding national and MSA aggregates)
3. Select observations where the generic drug name matches one of the nine antidepressants using case-insensitive string matching
4. Convert state FIPS codes from string to numeric format
5. Collapse to state-year level by summing prescription claims across all antidepressant types

Sample Coverage. The final Medicare Part D panel contains 204 state-year observations (51 states/DC × 4 years) covering 2013-2016. This state-level analysis complements the county-level facility analysis and provides evidence on treatment intensity margins.

Limitations. Several limitations should be noted. First, Medicare Part D covers only beneficiaries aged 65 and older plus some younger disabled individuals, not the full population. Second, the data capture only filled prescriptions, not prescriptions written but not filled. Third, state-level aggregation may mask heterogeneity in treatment patterns across counties within states. Despite these limitations, the Medicare Part D data provide valuable evidence on whether facility expansion affects pharmaceutical treatment of mental health conditions.

B.6 Additional Data Sources

Demographic and Economic Controls. I incorporate time-varying county-level controls from several sources to account for differences between counties that experience changes in mental health treatment facility access and those that do not. From the National Institute for Health Surveillance (SEER) (Surveillance, Epidemiology, and End Results , SEER), I obtain population counts by age group (under 18, 18-64, 65 and over), which are crucial for controlling for demographic factors that affect both mental health treatment needs and mortality patterns. From the Regional Economic Information System (REIS) (Bureau of Economic Analysis, BEA), I obtain measures of economic conditions including per capita net earnings, welfare receipts, and employment-to-population ratios.

Urban-Rural Classification. I use the 1993 rural-urban continuum codes from the U.S. Department of Agriculture to classify counties along the urban-rural spectrum.[32] This classification is time-invariant,

[32] The rural-urban continuum codes classify counties into nine categories based on population size and adjacency to metropolitan areas. I use the 1993 vintage to avoid endogenous reclassification during the sample period.

reflecting longstanding geographic characteristics that may influence both mental health facility location decisions and health outcomes. Access to mental health facilities may vary systematically with urbanization levels due to differences in population density, provider supply, and treatment-seeking behavior.

Health Insurance Coverage. To examine heterogeneous treatment effects by baseline 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 2013 baseline uninsurance rates to capture pre-Affordable Care Act variation in insurance coverage. This baseline measure reflects longstanding differences in healthcare access that predate both Medicaid expansion and the individual mandate.

Medicaid Expansion. To explore 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. As of 2016, 31 states plus the District of Columbia had expanded Medicaid eligibility to 138 percent of the federal poverty level, while 19 states had not expanded.[33] This policy variation allows me to explore whether mental health facility effects 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. I do not separately document these data sources in detail here, as their construction and use are standard in the health economics literature studying ACA impacts.

[33] See Table A14 for detailed information on expansion timing by state.

C Additional Details on Empirical Strategy

This section provides additional details on the identification strategy, estimation methods, and robustness checks employed in the main analysis.

C.1 Identification Strategy

The identification strategy exploits within-county variation in mental health treatment facility presence to estimate their effect on mortality outcomes. This approach builds on established research examining the health effects of treatment access (Swensen, 2015; Bondurant et al., 2018; Messel et al., 2023). The empirical strategy leverages temporal within-county variation from facility openings and closings while accounting for time-invariant county characteristics and aggregate shocks.

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

$$Y_{ct} = \alpha_c + \eta_t + \beta \,\text{Facilities}_{c,t-1} + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{15}$$

where Y_{ct} represents the mortality rate (per 100,000 residents) in county c in year t. The main explanatory variable, $\text{Facilities}_{c,t-1}$, measures the number of mental health treatment facilities in county c in year $t-1$, allowing for delayed mortality responses to changes in treatment access.[34] The model includes county fixed effects (α_c) to absorb time-invariant county characteristics that might correlate with both facility locations and mortality outcomes, and year fixed effects (η_t) to control for common temporal shocks. The vector $\mathbf{X}_{ct}$ includes demographic and economic controls. Standard errors are clustered at the county level to account for serial correlation in outcomes within counties over time.

Identification Assumptions. The TWFE estimator identifies the causal effect of mental health facilities under the parallel trends assumption: in the absence of facility changes, mortality trends would have evolved similarly across counties with different facility trajectories. This assumption is stronger than required for simple cross-sectional comparisons but weaker than assuming selection on observables, as county fixed effects absorb all time-invariant confounders. The inclusion of state-by-year fixed effects further relaxes this assumption by allowing for state-specific temporal shocks to mortality and mental health policy.

Threats to Identification. The primary threat to identification is that facility location decisions might re-

[34]The one-year lag structure follows Swensen (2015) and helps mitigate potential simultaneity bias between facility locations and current-period health outcomes. This specification also accounts for the lag between IRS reporting and CBP publication, as discussed in Appendix Section B.1.

spond to anticipated changes in local mortality patterns. Several features of my empirical design address this concern. First, the one-year lag between facility counts and outcomes reduces simultaneity bias. Second, mental health treatment facilities typically require substantial lead time for planning, construction, and staffing, making it unlikely that facility openings respond quickly to local mortality shocks. Third, I show in event study analyses (see below and Appendix Section C.2) that pre-treatment mortality trends are parallel between counties that do and do not experience facility changes, providing support for the parallel trends assumption.

C.2 Event Study Specifications

To examine the dynamic effects of mental health facility changes and test the parallel trends assumption, I estimate event study specifications that trace out mortality responses in the years before and after facility openings.

TWFE Event Study. The TWFE event study specification is:

$$Y_{ct} = \alpha_c + \eta_t + \gamma_{st} + \sum_{\substack{k=-5 \\ k\neq -1}}^{5} \beta_k \mathbf{1}(\text{RelTime}_{ct} = k) + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{16}$$

where $\text{RelTime}_{ct} = t - T_c^*$ measures years relative to the first treatment year T_c^* for county c. The coefficients β_k trace out the temporal path of mortality responses relative to the year before facility opening ($k = -1$), which serves as the baseline period. I include leads up to five years before treatment ($k = -5, \dots, -2$) to test for pre-treatment differences in trends, and lags up to five years after treatment ($k = 0, \dots, 5$) to examine treatment effect dynamics.

Sample Restrictions. Following Messel et al. (2023), I restrict the event study sample to ensure clean identification. Treatment counties experience exactly one increase in mental health establishments during the sample period, with no decreases before or after this increase. Control counties (never-treated) maintain constant establishment counts throughout. This restriction eliminates counties with multiple treatment episodes or reversals, which could confound the interpretation of dynamic effects.[35]

Contemporaneous Event Study. I also estimate a contemporaneous event study specification to examine anticipatory effects:

[35] Counties with multiple increases or any pre-treatment changes are excluded from the event study sample but retained in the main TWFE analysis, which uses all available variation. Approximately 85 percent of county-year observations are included in the event study sample.

$$Y_{ct} = \alpha_c + \eta_t + \gamma_{st} + \sum_{\substack{k=-5 \\ k\neq -1}}^{5} \beta_k \mathbf{1}(\text{RelTime}_{ct} = -k) + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{17}$$

The key difference is that the event time is reversed: negative values of k now correspond to post-treatment periods, while positive values correspond to pre-treatment periods. This specification tests for anticipatory responses to facility changes. Following Malani and Reif (2015) and Angrist and Pischke (2009), examining both lagged and contemporaneous effects provides a more complete picture of treatment dynamics.

C.3 Inverse Probability Weighting

To address potential selection bias from non-random facility location decisions, I implement inverse probability weighting (IPW) following Fischer et al. (2024). The IPW approach reweights observations to create balance between treated and control counties on observable characteristics, reducing bias from selection on observables.

Propensity Score Estimation. I estimate the propensity score, the probability of receiving treatment conditional on observables, using a probit model:

$$\Pr(\text{Treated}_c = 1 | \mathbf{Z}_c) = \Phi(\mathbf{Z}'_c \delta) \tag{18}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, and $\mathbf{Z}_c$ includes pre-treatment county characteristics that might influence facility location decisions: baseline population, age distribution, income levels, employment rates, urbanicity, and existing healthcare infrastructure. The propensity score $\hat{p}_c = \hat{\Phi}(\mathbf{Z}'_c \hat{\delta})$ captures the predicted probability that county c experiences a facility opening based on these observables.

IPW Estimation. I construct inverse probability weights as:

$$w_c = \frac{\text{Treated}_c}{\hat{p}_c} + \frac{1 - \text{Treated}_c}{1 - \hat{p}_c} \tag{19}$$

These weights upweight observations that are underrepresented in their treatment group given their characteristics. Counties that receive treatment despite having characteristics typical of control counties receive higher weight, and vice versa. The IPW-weighted regression is:

$$Y_{ct} = \alpha_c + \eta_t + \gamma_{st} + \beta\,\text{Facilities}_{c,t-1} + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{20}$$

weighted by w_c. Under the assumption of selection on observables, the IPW estimator recovers the average treatment effect on the treated (ATT).

Balance Diagnostics. I assess covariate balance by comparing standardized differences in pre-treatment characteristics between treated and control counties before and after weighting. The IPW procedure substantially improves balance: all standardized differences fall below 0.1 after weighting, compared to several exceeding 0.25 before weighting. This improved balance increases confidence that the IPW estimates reflect causal effects rather than selection bias.

C.4 Sun and Abraham (2021) Estimator

Recent econometric research has shown that two-way fixed effects estimators can produce biased estimates of treatment effects when treatment timing varies across units and treatment effects are heterogeneous (Goodman-Bacon, 2021; Sun and Abraham, 2021). The bias arises because TWFE uses already-treated units as controls for newly treated units, which can lead to negative weights on some treatment effects.

Sun-Abraham Methodology. I address this concern by implementing the interaction-weighted estimator proposed by Sun and Abraham (2021). This estimator separates treatment effects by cohort (defined by initial treatment timing) and estimates cohort-specific effects using only never-treated and not-yet-treated units as controls. The Sun-Abraham specification is:

$$Y_{ct} = \alpha_c + \eta_t + \sum_{g \in G} \sum_{\substack{k=-5 \\ k \neq -1}}^{5} \beta_{g,k} \mathbf{1}(G_c = g) \times \mathbf{1}(\text{RelTime}_{ct} = k) + \mathbf{X}'_{ct}\theta + \varepsilon_{ct} \tag{21}$$

where G is the set of treatment cohorts, G_c denotes county c

where $\omega_{g,k}$ are weights proportional to cohort size. This approach ensures that estimates are not contaminated by comparisons between already-treated and newly-treated units.

Implementation Details. I implement the Sun-Abraham estimator using the `eventstudyinteract` command in Stata (Sun and Abraham, 2021). Treatment cohorts are defined by the first year a county experiences a facility increase. Never-treated counties (those with constant facility counts throughout the sample period) serve as the primary control group. I estimate cohort-specific effects for relative times $k \in \{-5, \ldots, 5\}$, excluding $k = -1$ as the baseline period. Standard errors are clustered at the county level to account for serial correlation.

Comparison to TWFE. In practice, I find that Sun-Abraham estimates are very similar to TWFE estimates, suggesting limited heterogeneity in treatment effects across cohorts or that the timing of treatment is sufficiently dispersed that already-treated units do not heavily influence TWFE estimates. This similarity provides reassurance that the main TWFE results are not driven by the econometric issues identified by Goodman-Bacon (2021) and Sun and Abraham (2021).

C.5 Robustness Checks

I conduct several analyses to validate the causal interpretation of my main findings and assess the sensitivity of results to alternative specifications.

Progressive Specification Checks. As shown in Table 5, 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. Column 1 includes only county and year fixed effects, yielding a coefficient of -1.740 deaths per 100,000 (SE = 0.220). Column 2 adds state-by-year fixed effects to account for state-specific policy changes and economic trends, with the coefficient changing to -1.373 (SE = 0.224). Columns 3 and 4 sequentially add demographic controls (age distribution) and economic controls (employment rates, per capita earnings, transfer payments), with the full specification (Column 4) indicating a coefficient of -1.559 (SE = 0.255). The stability of estimates across these specifications suggests that observed time-varying characteristics do not heavily confound the facility-mortality relationship.

Event Studies with Additional Controls. The event study analysis in Figure A4 provides crucial robustness checks by testing for pre-existing trends. Panel A augments the baseline specification with lagged mortality rates to account for pre-existing trends in health outcomes. 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 (all pre-treatment coefficients are small and statistically insignificant), 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 and confirm that results are not driven by anticipatory effects or pre-existing divergent trends.

Controlling for General Healthcare Infrastructure. A key concern is that mental health facility locations might correlate with broader healthcare infrastructure expansion. To address this, Table A6 presents estimates that explicitly control for hospital establishments. The results remain stable: an additional mental health facility reduces MBD mortality by 0.079 percent (Column 1), nearly identical to my baseline estimates. This robustness extends to diagnostic subcategories, with particularly strong effects for organic mental disorders (F00-F09) and mood disorders (F30-F39). Importantly, controlling for general healthcare access does not meaningfully alter my conclusions, suggesting that mental health facilities have distinct effects beyond overall healthcare infrastructure and are not merely proxying for broader improvements in medical access.

Placebo Outcomes: Unrelated Mortality Causes. To rule out that my findings reflect broader local health trends or changes in mortality reporting practices, I examine causes of death that should be unrelated to mental health treatment access. Table A7 investigates three placebo outcomes: non-mental-health-related deaths, transport accidents, and deaths from medical/surgical care complications. The estimates are small in magnitude and statistically insignificant across all outcomes. For instance, the effect on non-MBD mortality is -0.029 (SE = 0.074, p = 0.69), and the effect on transport accidents is 0.004 (SE = 0.014, p = 0.77). These null effects on unrelated mortality measures provide strong evidence against the hypothesis that results are driven by spurious correlation with broader mortality trends, changes in death certificate coding, or general improvements in healthcare quality. The specificity of effects to mental health-related mortality, combined with the hospital control analysis and event studies, strongly supports a causal interpretation of the main results.

$$\beta_k = \sum_{g \in G} \omega_{g,k} \beta_{g,k} \tag{22}$$

where $\omega_{g,k}$ are weights proportional to cohort size. This approach ensures that estimates are not contaminated by comparisons between already-treated and newly-treated units.

Implementation Details. I implement the Sun-Abraham estimator using the `eventstudyinteract` command in Stata (Sun and Abraham, 2021). Treatment cohorts are defined by the first year a county experiences a facility increase. Never-treated counties (those with constant facility counts throughout the sample period) serve as the primary control group. I estimate cohort-specific effects for relative times $k \in \{-5, \ldots, 5\}$, excluding $k = -1$ as the baseline period. Standard errors are clustered at the county level to account for serial correlation.

Comparison to TWFE. In practice, I find that Sun-Abraham estimates are very similar to TWFE estimates, suggesting limited heterogeneity in treatment effects across cohorts or that the timing of treatment is sufficiently dispersed that already-treated units do not heavily influence TWFE estimates. This similarity provides reassurance that the main TWFE results are not driven by the econometric issues identified by Goodman-Bacon (2021) and Sun and Abraham (2021).

C.6 Robustness Checks

I conduct several analyses to validate the causal interpretation of my main findings and assess the sensitivity of results to alternative specifications.

Progressive Specification Checks. As shown in Table 5, 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. Column 1 includes only county and year fixed effects, yielding a coefficient of -1.740 deaths per 100,000 (SE = 0.220). Column 2 adds state-by-year fixed effects to account for state-specific policy changes and economic trends, with the coefficient changing to -1.373 (SE = 0.224). Columns 3 and 4 sequentially add demographic controls (age distribution) and economic controls (employment rates, per capita earnings, transfer payments), with the full specification (Column 4) indicating a coefficient of -1.559 (SE = 0.255). The stability of estimates across these specifications suggests that observed time-varying characteristics do not heavily confound the facility-mortality relationship.

Event Studies with Additional Controls. The event study analysis in Figure A4 provides crucial robustness checks by testing for pre-existing trends. Panel A augments the baseline specification with lagged mortality rates to account for pre-existing trends in health outcomes. 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 (all pre-treatment coefficients are small and statistically insignificant), 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 and confirm that results are not driven by anticipatory effects or pre-existing divergent trends.

Controlling for General Healthcare Infrastructure. A key concern is that mental health facility locations might correlate with broader healthcare infrastructure expansion. To address this, Table A6 presents estimates that explicitly control for hospital establishments. The results remain stable: an additional mental health facility reduces MBD mortality by 0.079 percent (Column 1), nearly identical to my baseline estimates. This robustness extends to diagnostic subcategories, with particularly strong effects for organic mental disorders (F00-F09) and mood disorders (F30-F39). Importantly, controlling for general healthcare access does not meaningfully alter my conclusions, suggesting that mental health facilities have distinct effects beyond overall healthcare infrastructure and are not merely proxying for broader improvements in medical access.

Placebo Outcomes: Unrelated Mortality Causes. To rule out that my findings reflect broader local health trends or changes in mortality reporting practices, I examine causes of death that should be unrelated to mental health treatment access. Table A7 investigates three placebo outcomes: non-mental-health-related deaths, transport accidents, and deaths from medical/surgical care complications. The estimates are small in magnitude and statistically insignificant across all outcomes. For instance, the effect on non-MBD mortality is -0.029 (SE = 0.074, p = 0.69), and the effect on transport accidents is 0.004 (SE = 0.014, p = 0.77). These null effects on unrelated mortality measures provide strong evidence against the hypothesis that results are driven by spurious correlation with broader mortality trends, changes in death certificate coding, or general improvements in healthcare quality. The specificity of effects to mental health-related mortality, combined with the hospital control analysis and event studies, strongly supports a causal interpretation of the main results.

D Additional Details on Welfare Analysis

This section provides additional technical details on the welfare analysis presented in Section 9, including the VSL methodology, cost data sources, alternative VSLY calculations, and sensitivity to discount rate assumptions.

D.1 Value of Statistical Life (VSL) Approach

The VSL represents the rate at which individuals are willing to trade wealth for reductions in mortality risk. It is derived from observed behavior in markets with mortality risk, such as labor markets where workers accept wage premiums for dangerous jobs, or consumer markets where individuals pay more for safety features. The VSL is not the value of a specific identified life, but rather the aggregated willingness to pay for small reductions in mortality risk across a population.

EPA Baseline Estimate. I use the Environmental Protection Agency's 2014 VSL estimate of $10 million as my baseline (Agency, 2010). This estimate is derived from a meta analysis of labor market studies examining compensating wage differentials for occupational mortality risk. The EPA regularly updates its VSL estimate for regulatory impact analyses, and the $10 million value (in 2014 dollars) represents the agency's central tendency estimate during my sample period.

Sensitivity Range. To account for uncertainty in VSL estimates, I consider a range from $7 million to $13 million. This range reflects the distribution of VSL estimates in the academic literature (Viscusi, 2018; Kniesner et al., 2012). The lower bound ($7 million) represents more conservative estimates from stated preference studies and some labor market analyses, while the upper bound ($13 million) captures higher estimates from recent hedonic wage studies and benefit transfer adjustments for income growth over time.

Application to Mortality Reductions. The welfare benefit of preventing θ deaths per facility per year is calculated as:

$$B = \theta \times \text{VSL} \tag{23}$$

From Table 3, Column 4, each mental health facility reduces deaths by 1.559 per 100,000 residents. Given the average county population of 97,051, this translates to:

$$\theta = \left|\hat{\beta}\right| \times \frac{\bar{P}}{100,000} = 1.559 \times \frac{97,051}{100,000} = 1.51 \text{ lives per facility per year} \tag{24}$$

At the baseline VSL of \$10 million, annual benefits per facility are:

$$B_{\text{baseline}} = 1.51 \times \$10,000,000 = \$15,100,000 \quad (25)$$

Limitations and Conservative Nature. Several factors suggest that VSL-based estimates may understate true welfare gains. First, VSL estimates are typically derived from working-age populations, while mental health-related mortality affects a broader age distribution. Second, VSL does not capture the value of reduced morbidity, improved quality of life, or positive externalities to family members and communities. Third, the VSL approach assumes that all prevented deaths have equal value, while deaths at younger ages (with more remaining life-years) may warrant higher valuations. Despite these limitations, the VSL approach provides a transparent, widely accepted framework for monetizing mortality reductions that facilitates comparison with other health interventions and policy analyses.

D.2 Facility Cost Data

Facility cost estimates are drawn from the Montana Legislative Children, Families, Health, and Human Services Interim Committee's "HJR 16 Study: State-Operated Institutions Building and Operating a 16-Bed Inpatient Facility" (May 2014).[36] This study provides detailed cost projections for constructing and operating a 16-bed mental health treatment facility, based on proposals from multiple architectural firms and operational data from existing facilities.

Capital Costs. The study reports construction cost estimates ranging from \$4.5 million to \$7.6 million for a 16-bed secure residential treatment facility. These costs include:

- Building construction and site work
- Specialized infrastructure (security systems, safety features)
- Furniture, fixtures, and equipment
- Architectural and engineering fees
- Contingency reserves (typically 10-15% of construction costs)

The range reflects variation in site characteristics, construction materials, and regulatory requirements. I use the midpoint estimate of \$6.05 million for baseline calculations and report results across the full range for robustness.

[36] Available at: https://archive.legmt.gov/content/Committees/Interim/2013-2014/Children-Family/Committee-Topics/HJR16/hjr16-building-operating-16-bed-facilities-may2014.pdf

Operating Costs. Annual operating costs are estimated at \$3.0 million per 16-bed facility, based on staffing models and operational data from comparable facilities. Major cost components include:

- Personnel (psychiatrists, nurses, counselors, administrative staff): \$2.1 million (70%)
- Pharmaceuticals and medical supplies: \$450,000 (15%)
- Facility maintenance and utilities: \$300,000 (10%)
- Other operating expenses (food, transportation, etc.): \$150,000 (5%)

These estimates are conservative in that they reflect secure residential treatment settings with higher staffing ratios and operational requirements than typical outpatient mental health facilities. Many facilities in my sample provide outpatient services with lower per-facility operating costs.

Annualization of Capital Costs. To compare one-time capital costs with annual operating costs and benefits, I annualize capital expenditures over the facility's expected lifetime. Following standard practice in infrastructure cost-benefit analysis, I assume a 20-year facility lifetime and a 3 percent real discount rate. The annuity factor is:

$$a_{T,r} = \frac{1-(1+r)^{-T}}{r} = \frac{1-(1.03)^{-20}}{0.03} = 14.88 \tag{26}$$

The annualized capital cost is then:

$$C_{\text{capital}}^{\text{annual}} = \frac{C_{\text{capital}}^{\text{total}}}{a_{T,r}} \tag{27}$$

For the midpoint capital cost of \$6.05 million, this yields an annual equivalent of \$407,000. Combined with the \$3.0 million annual operating cost, total annual costs are \$3.407 million per facility.

Applicability to Sample Facilities. The Montana cost data provide a reasonable benchmark for mental health treatment facilities in my sample. While facility sizes vary (the Montana study focuses on 16-bed facilities), cost estimates scale approximately linearly with capacity for facilities of similar type. Moreover, using these standardized cost estimates avoids endogeneity concerns that might arise from using actual facility-specific costs, which could correlate with local economic conditions or treatment effectiveness.

D.3 Value of Statistical Life-Year (VSLY) Alternative

As an alternative to the VSL approach, I calculate benefits using the Value of Statistical Life-Year (VSLY), which may better capture the age distribution of prevented deaths. The VSLY represents willingness to pay for an additional year of life expectancy and is particularly appropriate when comparing interventions with different age profiles of mortality reduction.

Methodology. The total value of preventing a death is:

$$V = \text{VSLY} \times \sum_{j=1}^{T} \left(\frac{1}{1+r}\right)^{j-1} \tag{28}$$

where T is remaining life expectancy at the average age of death, r is the discount rate, and the sum represents the present value of future life-years. For a remaining life expectancy of T years and discount rate r, this simplifies to:

$$V = \text{VSLY} \times \frac{1-(1+r)^{-T}}{r} \tag{29}$$

Parameter Assumptions. Mental health-related mortality in my sample affects individuals across a broad age range, with substantial mortality in middle age (45-65 years). For individuals dying at age 55, remaining life expectancy is approximately 25 years (based on actuarial tables). I use this as my baseline assumption, with sensitivity analysis considering 20 to 30 years.

For the VSLY, I consider three estimates:

- Conservative: \$100,000 per life-year
- Baseline: \$250,000 per life-year
- Upper bound: \$400,000 per life-year

These values are consistent with VSL estimates of \$2-10 million divided by remaining life expectancy of 25-40 years, as recommended by Murphy and Topel (2006) and applied in recent health economics research **?**.

Results. At the baseline VSLY of \$250,000 and 25 years remaining life expectancy, the present value (discounted at 3% annually) of preventing one death is:

$$V = \$250,000 \times \frac{1-(1.03)^{-25}}{0.03} = \$250,000 \times 17.41 = \$4,353,000 \tag{30}$$

For 1.51 lives saved per facility per year, total annual benefits are:

$$B_{\text{VSLY}} = 1.51 \times \$4,353,000 = \$6,573,000 \tag{31}$$

Against midpoint annual costs of $3.407 million, this yields net benefits of $3.166 million per facility per year. While lower than VSL-based estimates (reflecting the discounting of future life-years), the VSLY approach still indicates substantial positive net benefits.

Sensitivity to Life Expectancy. The VSLY-based benefits are sensitive to assumptions about remaining life expectancy:

- 20 years: Net benefits = $1.79 million per facility
- 25 years (baseline): Net benefits = $3.17 million per facility
- 30 years: Net benefits = $4.35 million per facility

All scenarios yield positive net benefits, confirming that results are robust to alternative assumptions about the age distribution of prevented deaths.

D.4 Sensitivity to Discount Rates

The choice of discount rate affects both the annualization of capital costs and the present value of future life-years in VSLY calculations. I examine sensitivity to discount rates ranging from 2 percent to 7 percent, spanning the range commonly used in regulatory cost benefit analyses.

Impact on Capital Costs. The discount rate directly affects the annuity factor used to convert one time capital expenditures into annual equivalents. At lower discount rates, the annuity factor is larger, reducing the annual equivalent cost of capital investments. At higher rates, annualized capital costs increase. Using the midpoint capital cost of $6.05 million from the Montana study:

Discount Rate	Annuity Factor	Annual Capital	Total Annual Cost
2%	16.35	$370,000	$3,370,000
3% (baseline)	14.88	$407,000	$3,407,000
5%	12.46	$486,000	$3,486,000
7%	10.59	$571,000	$3,571,000

where total annual cost includes $3.0 million in operating expenses plus the annualized capital cost. The variation in total annual costs is modest (6 percent range from lowest to highest), suggesting that discount rate uncertainty has limited impact on cost estimates. The baseline 3 percent discount rate used in Table 15 yields an annualized capital cost of $407,000, producing total annual costs of $3.407 million as reported in the main welfare analysis.

Impact on VSLY Calculations. The discount rate more substantially affects VSLY based benefit estimates, as higher discount rates reduce the present value of future life years. For baseline VSLY of $250,000 and 25 year life expectancy, the present value of preventing one death varies significantly with the discount rate:

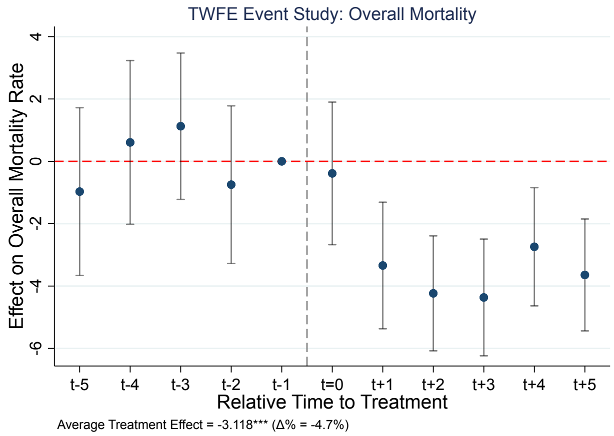
Discount Rate	PV Factor	Value per Life	Net Benefit per Facility
2%	19.52	$4,880,000	$4,000,000
3% (baseline)	17.41	$4,353,000	$3,166,000
5%	14.09	$3,523,000	$1,911,000
7%	11.65	$2,913,000	$831,000

where the present value factor equals $(1-(1+r)^{-T})/r$ for discount rate r and life expectancy $T = 25$ years. Net benefit per facility equals the value per life times 1.51 lives saved per facility (from Table 15) minus total annual costs of $3.407 million. While net benefits decline with higher discount rates (reflecting lower present value of future life years), all scenarios remain positive. Even at the conservative 7 percent discount rate, which is higher than typical rates used for long term health investments, mental health facilities generate net benefits exceeding $800,000 per facility per year.

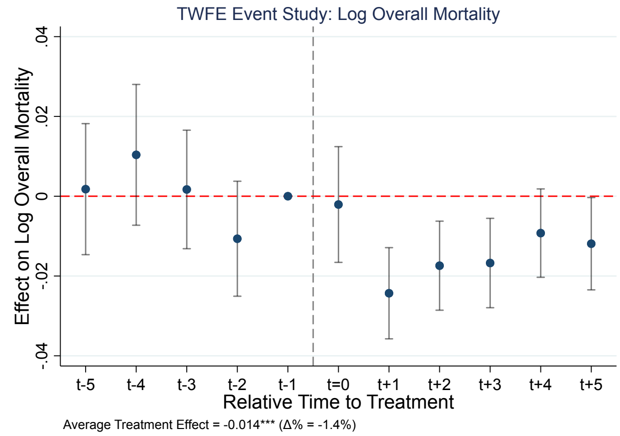
Comparison to VSL Approach. Importantly, the VSL approach used in the main analysis (Table 15) does not require explicit discounting of future mortality reductions, as VSL estimates already embed individuals' time preferences and mortality risk profiles. The VSLY approach requires explicit discounting and is therefore more sensitive to discount rate assumptions. The robustness of conclusions across both approaches and across different discount rates strengthens confidence in the finding of positive net social benefits from mental health facility access.

E Appendix Figures

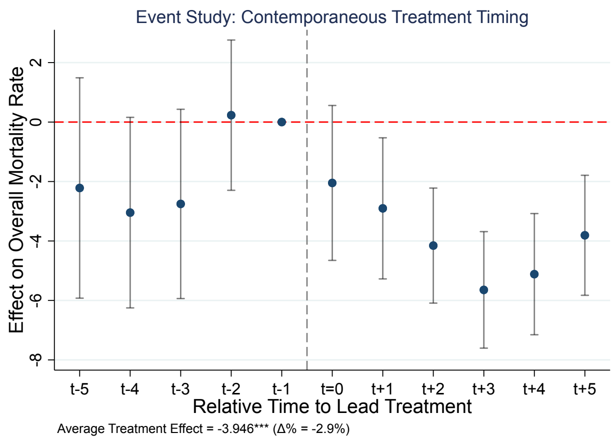
Figure A1: Robustness: Two-Way Fixed Effects Event Study Estimates for Overall Mortality



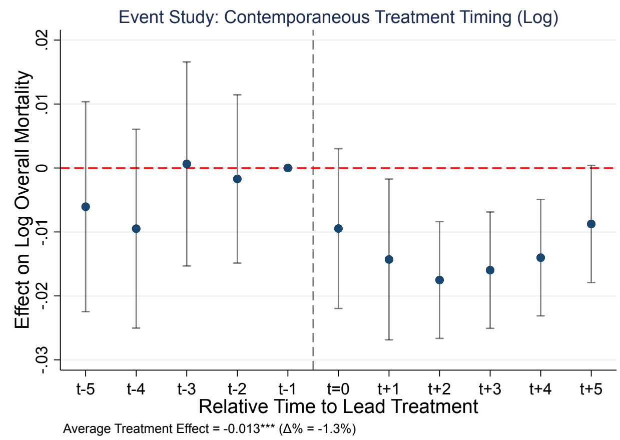
(a) Main Specification



(b) Log Specification



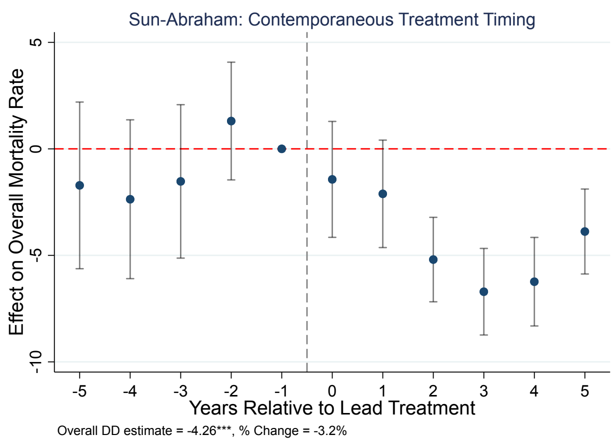
(c) Contemporaneous Treatment Timing



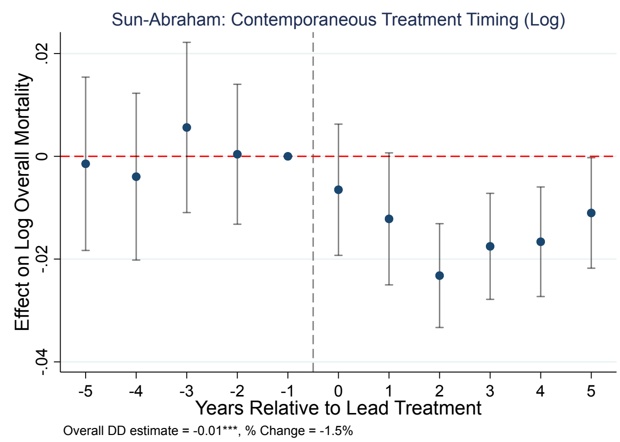
(d) Contemporaneous Treatment Timing (Log)

Notes: This figure presents two-way fixed effects (TWFE) event study estimates as a robustness check for the Sun-Abraham specifications shown in Figure 7. Panel (a) shows the main specification using the mortality rate from all causes per 100,000 county residents. Panel (b) presents the log specification. Panels (c) and (d) use contemporaneous treatment timing (lead specification) to test for anticipatory effects, where relative time is defined using the lead of facility openings. Points represent coefficient estimates for each period relative to $t = -1$ (the omitted reference category). All specifications include county fixed effects, year fixed effects, state-by-year fixed effects, demographic controls (share of population under 19), labor market controls (employment-to-population ratio), and additional county-level covariates including earnings per capita, transfer payments per capita, hospital availability, population density, rural status indicators, and age distribution. The sample is restricted to counties with a single facility opening and no pre-treatment changes in facility counts, plus never-treated counties as controls. Inverse probability weights are applied based on 1999 demographic characteristics. Standard errors are clustered at the county level. Data combine County Business Patterns and Vital Statistics mortality data for 1999–2016. The vertical dashed line indicates the treatment period.

Figure A2: Sun-Abraham Event Study: Contemporaneous Treatment Timing for Overall Mortality



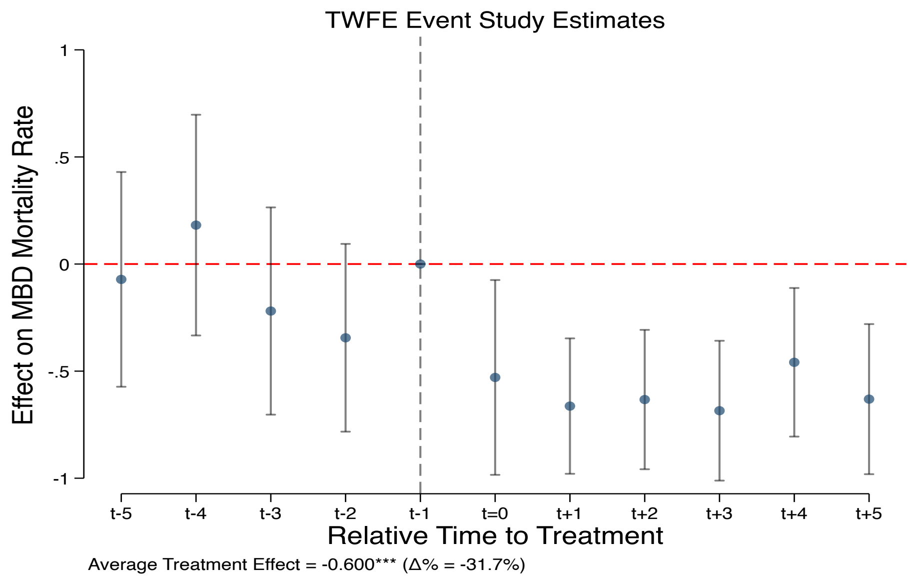
(a) Contemporaneous Treatment Timing



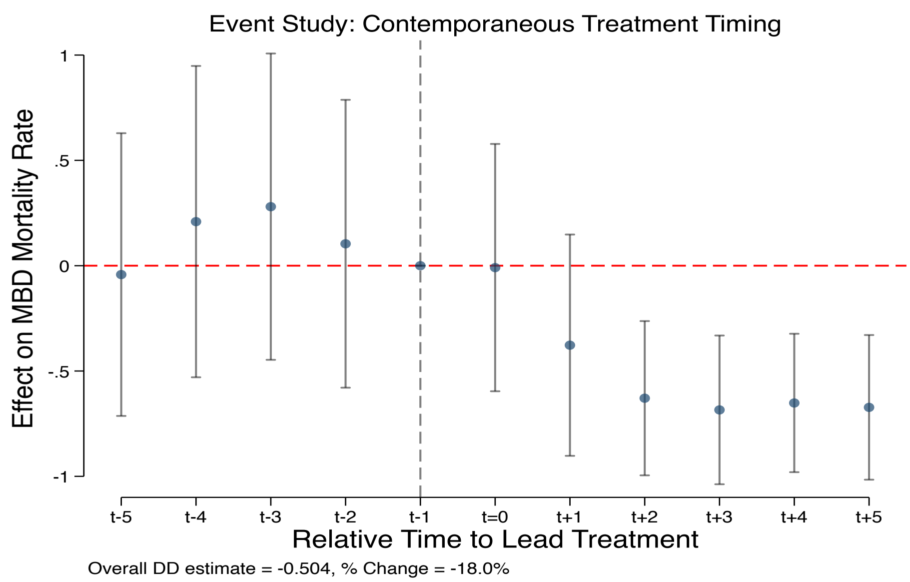
(b) Contemporaneous Treatment Timing (Log)

Notes: This figure presents Sun and Abraham (2021) event study estimates using contemporaneous treatment timing as an alternative specification to address potential anticipatory effects. The relative time is defined using the lead of facility openings, testing whether effects occur at the time of treatment rather than in anticipation. Panel (a) uses the mortality rate from all causes per 100,000 county residents. Panel (b) presents the log specification. The sample, controls, and estimation approach are identical to Figure 7, but the timing is shifted forward by one period. This specification helps distinguish between effects that occur contemporaneously with facility openings versus those that may reflect anticipatory behavioral changes. Points represent interaction-weighted estimates and 95% confidence intervals for each period relative to $t = -1$, with the vertical dashed line indicating the treatment period. Standard errors are clustered at the county level. Data: 1999–2016.

Figure A3: Dynamic Effects of Local Access to MHT Treatment Facilities on Mental and Behavioral Health Disorder Mortality



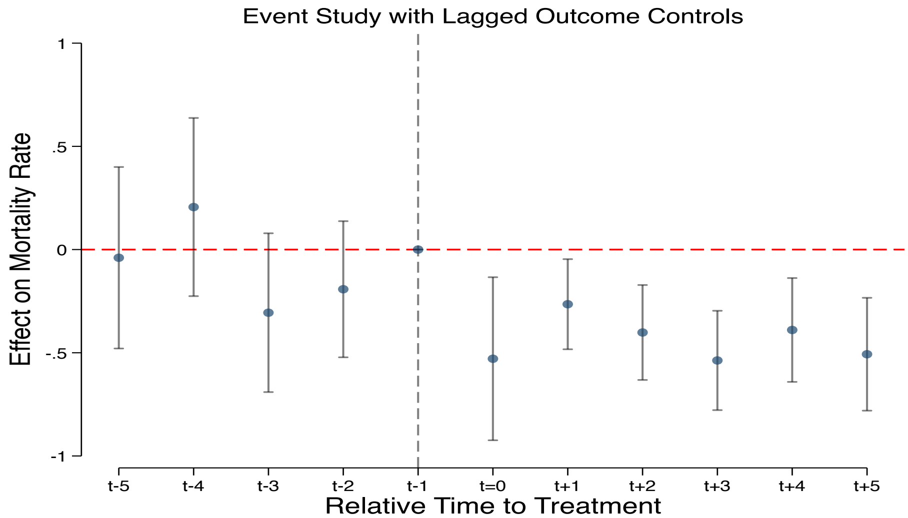
(a) Main Event Study: Lagged Treatment Effects



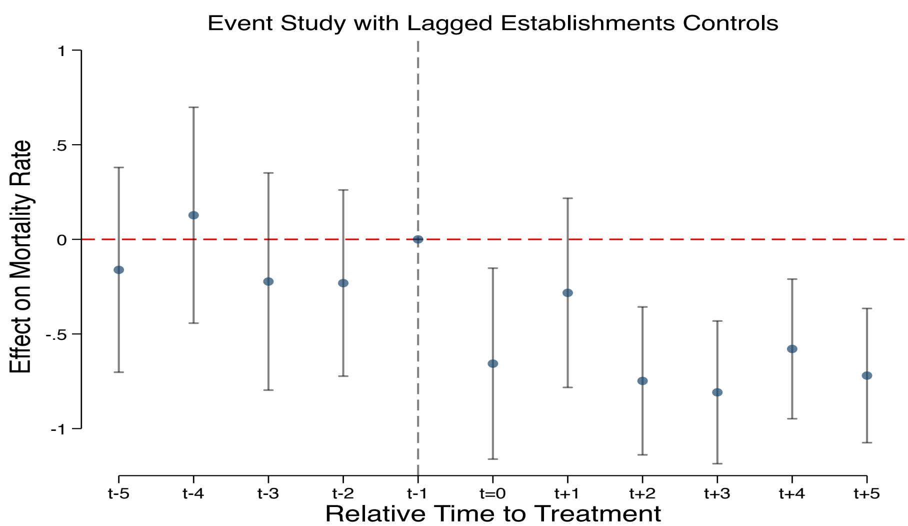
(b) Event Study: Contemporaneous Treatment Effects

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 A3a examines the lagged effects of treatment, showing an overall treatment effect of -0.600 (representing a 23.5% change from pre-treatment mean). Panel A3b 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 A4: Robustness Checks: Event Studies with Alternative Controls



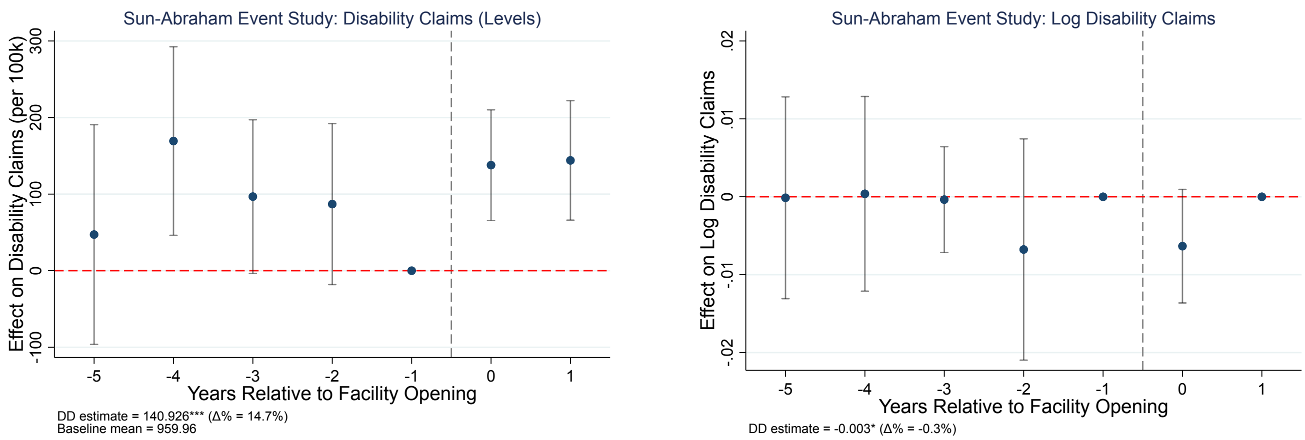
(a) Event Study with Lagged Outcome Controls



(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.

Figure A5: Dynamic Effects of Mental Health Treatment Facilities on Disability Claims: Sun-Abraham Estimates

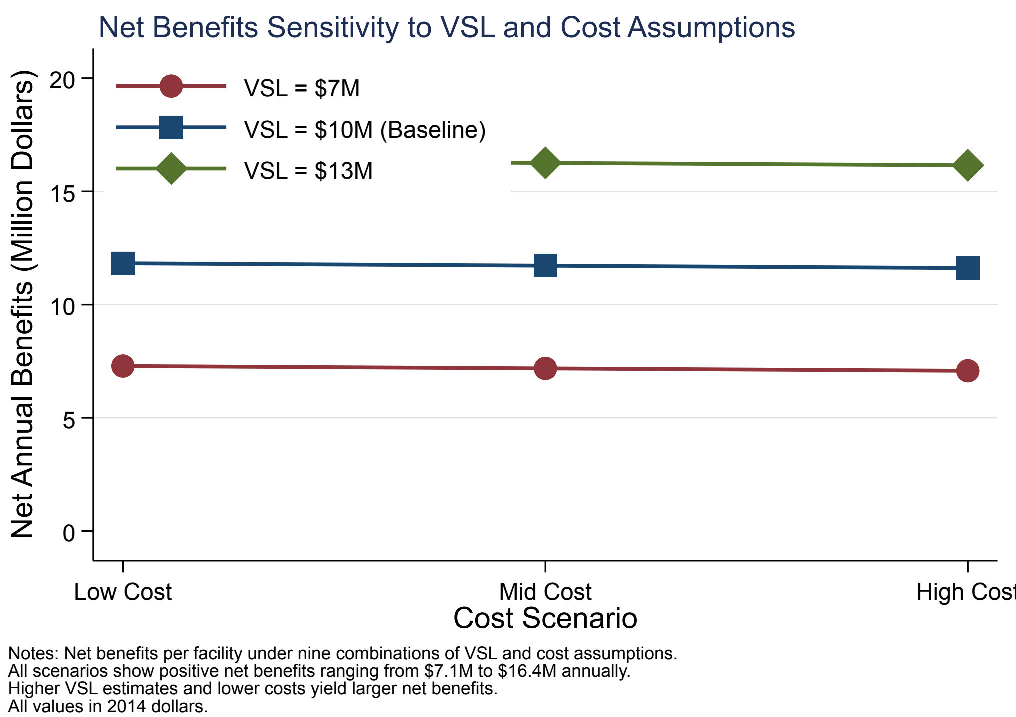


(a) Main Event Study

(b) Log Specification

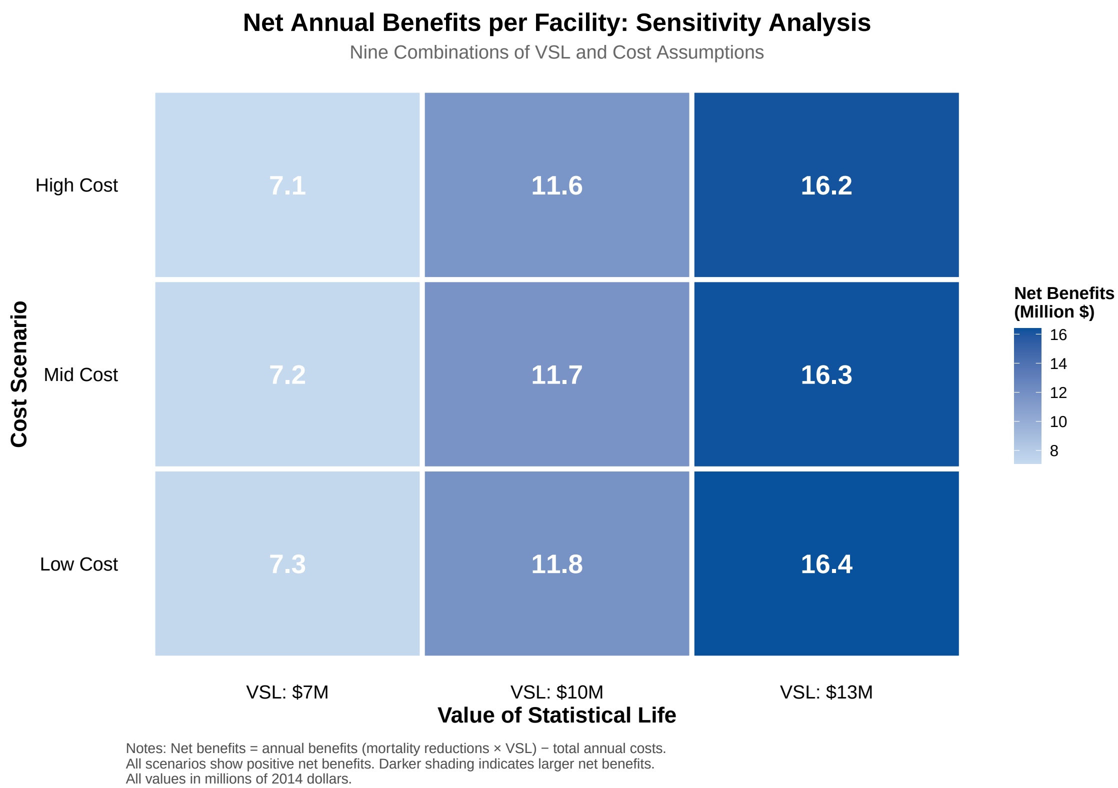
Notes: The estimates implement the Sun and Abraham (2021) heterogeneity-robust event study estimator where the outcome variable is SSI disability recipients aged 18–64 per 100,000 county residents obtained from Social Security Administration county-level data. Panel (a) examines the effects in levels. Panel (b) displays the log specification. Both specifications include county fixed effects, year fixed effects, and state-by-year fixed effects. The observations are weighted by inverse propensity score weights based on county-level demographic characteristics. Additional controls include demographic composition (share under 19) and labor market conditions (employment-to-population ratio). The standard errors are clustered at the county level. The data combines County Business Patterns (CBP) for mental health facility openings with SSA disability data for the period 2009–2016. The figures display interaction-weighted estimates and 95% confidence intervals, with $t = -1$ as the omitted reference period. The vertical dashed line indicates the treatment period ($t = 0$). The sample is restricted to counties with a single facility opening and no pre-treatment changes in facility counts, plus never-treated counties as the control group. These estimates account for potential heterogeneity in treatment effects across cohorts, addressing limitations of traditional two-way fixed effects models. The time window spans five pre-treatment periods ($t = -5$ to $t = -1$) and two post-treatment periods ($t = 0$ to $t = 1$), constrained by the availability of SSA disability data through 2016. In Panel (b), the coefficient for $t = 1$ is not estimated due to insufficient observations with positive disability rates after log transformation, reflecting the sparse nature of disability claims data at the county-year level.

Figure A6: Net Benefits Sensitivity to VSL and Cost Assumptions



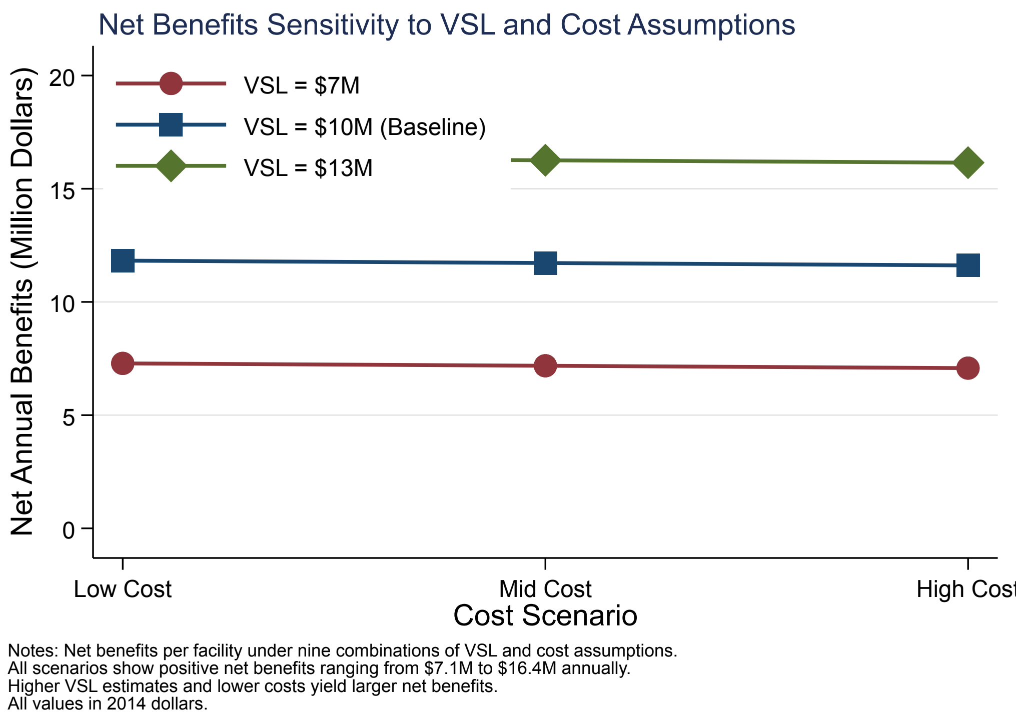
Notes: This figure shows net annual benefits per facility across nine combinations of VSL and cost assumptions. Each line represents a different VSL level: $7 million (conservative), $10 million (baseline), and $13 million (upper bound). All nine scenarios yield positive net benefits ranging from $7.1 million to $16.4 million annually. Results are more sensitive to VSL variation than to cost variation. All monetary values are in 2014 dollars.

Figure A7: Net Benefits Heatmap: VSL and Cost Combinations



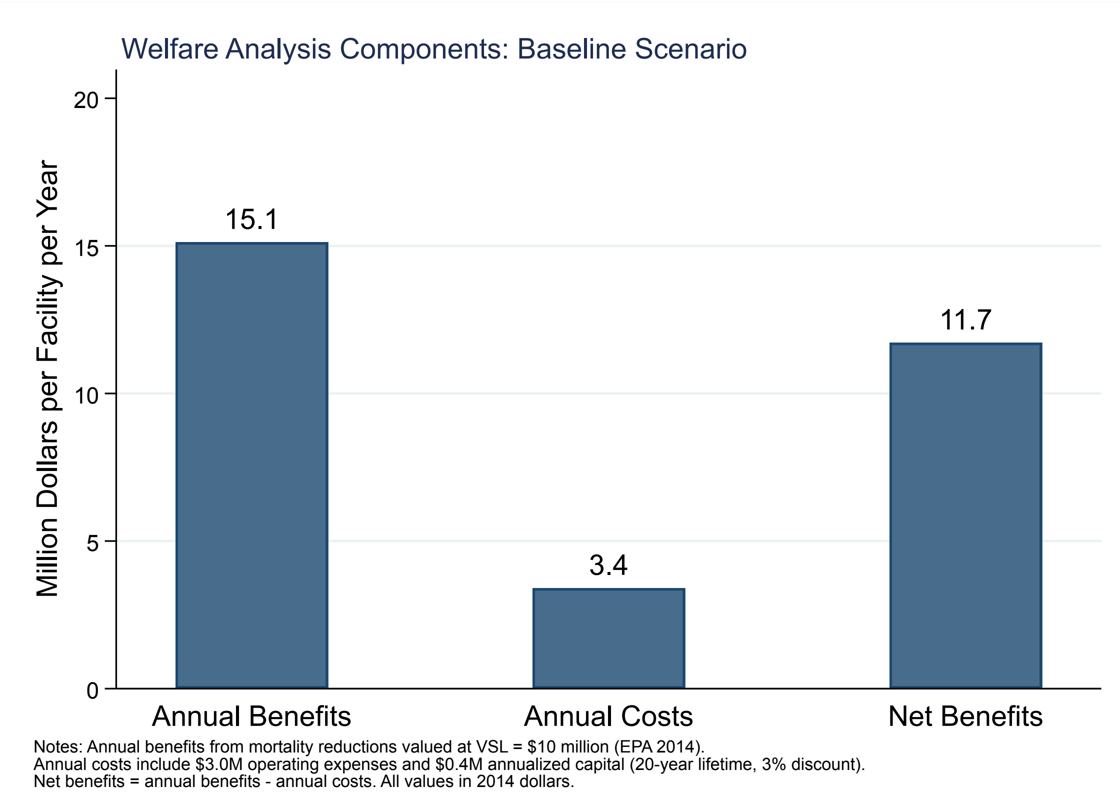
Notes: This heatmap visualizes net annual benefits per facility under nine combinations of VSL and cost assumptions. Darker shading indicates larger net benefits. All scenarios show positive net benefits, demonstrating robustness to alternative assumptions. Values range from \$7.1 million (VSL = \$7M, high cost) to \$16.4 million (VSL = \$13M, low cost) annually. All monetary values are in 2014 dollars.

Figure A8: Sensitivity of Net Benefits to VSL and Cost Assumptions



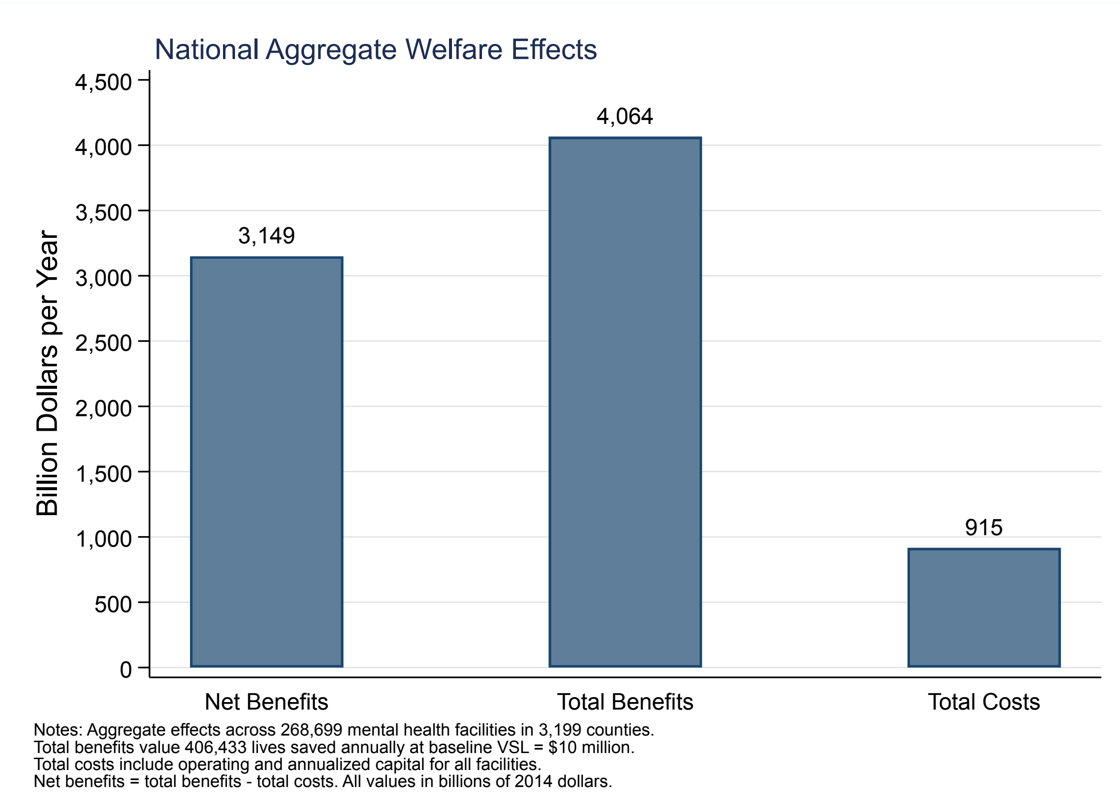
Notes: This figure displays net annual benefits per facility across nine combinations of Value of Statistical Life (VSL) and cost assumptions. Each line represents a different VSL level: $7 million (conservative), $10 million (baseline, EPA 2014), and $13 million (upper bound). The x-axis shows three cost scenarios: low ($3.30M per year), mid ($3.41M per year), and high ($3.51M per year), reflecting operating costs plus annualized capital expenditures. All nine scenarios yield positive net benefits ranging from $7.1 million to $16.4 million annually, demonstrating robustness to alternative assumptions. Results are more sensitive to VSL variation than to cost variation. All monetary values are in 2014 dollars.

Figure A9: Welfare Analysis Components: Baseline Scenario



Notes: This figure decomposes the welfare analysis into its constituent components under baseline assumptions. Annual benefits ($15.1 million) represent mortality reductions valued at VSL = $10 million (EPA 2014 estimate). Annual costs ($3.4 million) include $3.0 million in operating expenses and $0.4 million in annualized capital costs, based on construction costs of $4.5-7.6 million amortized over a 20-year facility lifetime at a 3 percent discount rate (Montana Legislative HJR 16 Study, May 2014). Net benefits equal annual benefits minus annual costs, yielding $11.7 million per facility per year. The figure illustrates that mortality-related benefits alone substantially exceed facility costs, with a benefit-cost ratio of 4.44. All monetary values are in 2014 dollars.

Figure A10: Aggregate National Welfare Effects of Mental Health Facilities



Notes: This figure aggregates facility-level welfare effects to the national level across 268,699 mental health facilities in 3,199 counties in the sample. Total annual benefits ($4,064 billion) value 406,433 lives saved per year at the baseline VSL of $10 million. Total annual costs ($915 billion) include operating expenses and annualized capital costs for all facilities. Net annual benefits ($3,149 billion) equal total benefits minus total costs, equivalent to approximately $9,840 per capita for the US population. These estimates represent a lower bound for national welfare effects, as the sample excludes some counties and does not account for morbidity reductions, quality-of-life improvements, reduced healthcare utilization, or other positive externalities of mental health treatment. The magnitude of these aggregate effects underscores the substantial returns to investments in mental health infrastructure. All monetary values are in billions of 2014 dollars.

F 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: 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 A3: 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 4 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 A4: 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 A5: 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 A6: 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 4 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 A7: 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 A8: 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 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 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 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: Decomposition of Overall Mortality Effects by Cause of Death

Cause of Death	Coefficient	Std. Error	Baseline Mean (per 100k)	Share of Baseline (%)	Contribution to Reduction (%)
Overall Mortality	-1.5586***	(0.2551)	927.41	100.00	–
MBD Deaths	-0.0790***	(0.0297)	31.56	3.40	5.07
Self-Harm/Suicide Deaths	-0.0308***	(0.0073)	13.23	1.43	1.98
Assault Deaths	-0.0107**	(0.0050)	3.80	0.41	0.69
Other External Injuries	-0.0729***	(0.0167)	27.52	2.97	4.68
Transport Accidents	-0.0011	(0.0094)	21.86	2.36	0.07
Medical/Surgical Care Deaths	-0.0009	(0.0012)	1.10	0.12	0.06
Other Deaths	0.0029	(0.0031)	0.36	0.04	-0.19

Notes: This table presents the decomposition of treatment effects on overall mortality by underlying cause of death. Column (1) shows the outcome variable. Column (2) reports point estimates from separate regressions where the dependent variable is deaths per 100,000 county residents from each cause. Column (3) reports heteroskedasticity-robust standard errors clustered at the county level. Column (4) shows the pre-treatment mean mortality rate for each cause. Column (5) reports each cause's share of total baseline mortality, calculated as the ratio of the cause-specific baseline mean to the overall baseline mortality rate. Column (6) shows each component cause's contribution to the overall mortality reduction, calculated as the ratio of the cause-specific coefficient to the overall mortality coefficient. All regressions include county fixed effects, year fixed effects, state-by-year fixed effects, and controls for economic and demographics.
(* p<.10 ** p<.05 *** p<.01)

Table A11: Sensitivity Analysis: Net Benefits Under Alternative Assumptions

	Cost Scenario		
VSL Assumption	Low Cost	Mid Cost	High Cost
$7 million	$ 7,285,695	$ 7,181,511	$ 7,077,326
$10 million (baseline)	$11,823,480	$11,719,296	$11,615,111
$13 million	$16,361,265	$16,257,081	$16,152,897

Notes: This table reports net annual benefits per facility under nine combinations of VSL and cost assumptions. Each cell shows annual benefit (lives saved times VSL) minus total annual cost (operating + annualized capital). Low cost: 3.30M per year (operating + annualized capital at lower bound). Mid cost: 3.41M per year (operating + annualized capital at midpoint). High cost: 3.51M per year (operating + annualized capital at upper bound). Lives saved per facility per year: 1.51 (point estimate from Table 3, Column 4). All nine scenarios show positive net benefits, indicating that mental health facilities generate welfare gains under conservative, baseline, and optimistic assumptions. All values in 2014 dollars.

Table A12: Aggregate National Welfare Effects of Mental Health Facilities

Effect	Annual Estimate
Lives saved per year	406,433
Total annual benefits (VSL = $10M)	$ 4064.33 billion
Total annual costs	$ 915.36 billion
Net annual benefits	$ 3148.96 billion

Notes: This table aggregates the facility-level welfare effects to the national level based on the total number of mental health facilities in the sample (268,699 facilities across 3,199 counties). Lives saved per year equals total facilities times lives saved per facility (1.51). Total annual benefits use baseline VSL of 10 million dollars. Total annual costs use midpoint cost estimates (3.41M per facility per year). Net annual benefits equal total benefits minus total costs. These estimates represent the aggregate welfare effects across the sample of counties and provide a lower bound for national effects, as the sample does not include all U.S. counties. All values in 2014 dollars.

Table A13: 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 A14: 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).