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LOSING INSURANCE AND PSYCHIATRIC HOSPITALIZATIONS

Johanna Catherine Maclean
Sebastian Tello-Trillo
Douglas Webber

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ABSTRACT

We study the effect of losing insurance on psychiatric – mental health disorder (MHD) and substance use disorder (SUD) – hospital-based care. Psychiatric disorders cost the U.S. over $1T each year and hospitalizations provide important and valuable care for patients with these disorders. We use variation in public insurance coverage (Medicaid) eligibility offered by a large-scale and unexpected disenrollment in the state of Tennessee in 2005 that lead to 190,000 individuals losing their insurance. Medicaid enrollees are at elevated risk for psychiatric disorders. Following the disenrollment, hospitalizations for psychiatric disorders declined: 7.3% for MHD and 16.5% for SUD. The financing of care received also changed, MHD hospitalization financing was partially shifted to private insurance while SUD financing was transferred entirely to patients. In an extension, we provide suggestive evidence that psychiatric health declined post-disenrollment.

Johanna Catherine Maclean
Department of Economics
Temple University
Ritter Annex 869
Philadelphia, PA 19122
and NBER
catherine.maclean@temple.edu

Sebastian Tello-Trillo
Batten School of Leadership and Public Policy
University of Virginia
235 McCormick Road
Charlottesville, VA 22904
and NBER
sebastian.tello@virginia.edu

Douglas Webber
Department of Economics
Temple University
Ritter Annex 877, 1301 Cecil B. Moore Ave
Philadelphia, PA 19122
douglas.webber@temple.edu

1 Introduction

In this study we provide the first causal evidence on the effect of losing insurance on psychiatric disorder hospitalizations. Psychiatric disorders − mental health disorders (MHD) and substance use disorders (SUD) − are important to consider as these conditions are common and costly, but are also effectively treated. Each year these disorders cost the United States over $1T (Insel, 2008; Caulkins et al., 2014) and 47.6M and 20.3M Americans have a MHD and SUD respectively (Substance Abuse and Mental Health Services Administration, 2021), with millions more experiencing poor mental health and problematic patterns of substance use and misuse. As a specific example, the U.S. is currently in the middle of an opioid epidemic that has claimed well over 500,000 lives since 1999 (Centers for Disease Control and Prevention, 2022a).

We exploit exogenous variation in public insurance coverage eligibility generated by one of the largest disenrollments in the history of the Medicaid program: an August 2005 disenrollment in the state of Tennessee. Medicaid is a public insurance program for low-income people in the U.S. that covers approximately one in five Americans (Kaiser Family Foundation, 2022) and Medicaid enrollees have elevated rates of psychiatric disorders, leading to Medicaid being the single largest payer for associated services in the country (Medicaid and CHIP Payment and Access Commission, 2015). The disenrollment we study resulted in 190,000 enrollees – 10% of those enrolled in Medicaid in the state of Tennessee and 3% of the total state population (Chang and Steinberg, 2009) – unexpectedly losing Medicaid (referred to as 'TennCare'). The disenrollees were predominantly nondisabled, nonelderly, and childless adults. 24% of this population had serious psychological distress and 12% had an SUD in 2004 (the year prior to the disenrollment). Many more disenrollees likely had less severe psychiatric conditions that could benefit from treatment previously available through TennCare coverage.[1]

[1] Authors' analysis of the public use 2004 National Survey on Drug Use and Health. We calculated the share of adult Medicaid enrollees ages 21 to 64 years of age with no children who (i.e., those likely disenrolled) had serious psychological distress or an SUD in Tenneessee. We expect that this estimate

TennCare generously covers a wide range of efficacious psychiatric healthcare services including hospitalizations, medications, counseling services, and standalone inpatient and outpatient treatment. Additionally, access to primary care, also covered by TennCare, can have important and positive spillover benefits for psychiatric disorders (Maclean et al., 2018) [2] and primary care providers deliver substantial psychiatric care, one recent study found that that over the period 2016-2018, primary care physicians provided most of the care for depression, anxiety, and any mental illness in the U.S. (Jetty et al., 2021) and, for some patients, primary care providers can treat psychiatric health as well as specialists (Gaynes et al., 2009). The disenrollment reduced access to affordable treatment for many low-income individuals who had limited access to other forms of insurance (Farrar et al., 2007). We examine administrative data on psychiatric hospitalizations coupled with difference-in-differences methods to study TennCare effects.

Findings from the TennCare experience are useful to both economists and policymakers. Demand theory predicts that insurance, by reducing the out-of-pocket price faced by consumers, should increase the quantity of healthcare demanded (Grossman, 1972). To date, the literature has explored the effect of *gaining* insurance on psychiatric healthcare use due to available sources of experimental and quasi-experimental variation (Golberstein and Gonzales, 2015; Wen et al., 2015; Baicker et al., 2017; Wen et al., 2017; Maclean et al., 2018; Meinhofer and Witman, 2018; Grooms and Ortega, 2019; Maclean and Saloner, 2019). While there are exceptions, public insurance expansions appear to increase psychiatric healthcare use and shift financing away from patients and to-

understates the actual number disenrolled individuals who could benefit from the psychiatric healthcare services offered by TennCare coverage as we consider only serious conditions. For instance, 92% had some level of psychological distress and 20% reported past year illicit drug use (illicit drug use tends to be under-reported in survey settings, suggesting that this is a lower bound on such use). Further, the financial strain and general shock associated with unexpectedly losing insurance (and therefore access to treatment and providers) could potentially exacerbate psychiatric disorders (Maclean et al., 2015), pushing a less serious condition to a serious one.

[2]Medicaid enrollees have high rates of both physical health conditions and psychiatric disorders. Treating physical health conditions (e.g., diabetes, heart disease) can improve psychiatric disorders through reduced stress and simply improved health overall.

wards insurance.[3] No study has estimated the impact of *losing* insurance on psychiatric healthcare or health and this is the contribution of our study.

The effects of insurance gains and losses need not be symmetric. Previous work has noted this possibility within the context of physical health and healthcare (Ghosh and Simon, 2015; Tello-Trillo, 2021). For instance, a person who loses insurance can retain accumulated 'patient education,' which includes information on one's health stock, how to manage chronic conditions, how to interact with the healthcare system, and so forth. This education may allow a patient to continue to maintain health after a coverage loss more effectively than a patient with no insurance experience.

The nature of psychiatric disorders, patients who receive care, healthcare professionals who deliver care, and the structure of the U.S. healthcare delivery system generally suggests additional reasons to suspect asymmetry. First, a substantial fraction of psychiatric care is provided for free and/or at a heavy discount, with insurance playing a relatively modest role in the financing of such treatment; this is particularly true for SUD care (Buck, 2011). Charity care may act as a substitute for paid care, thereby muting the effect of any insurance loss. Second, many U.S. healthcare professionals will not accept public insurance patients − in particular Medicaid which offers low reimbursement rates relative to other payers (Decker, 2012), and this practice is particularly common within psychiatric care (Wen et al., 2019).[4] Losing insurance that cannot be used to pay for treatment may not lead to substantial reductions in use or shifts in payment source. Finally, there are established psychiatric provider shortages in the U.S. (Buck, 2011;

[3]We note that Golberstein and Gonzales (2015) document no change in MHD treatment use following a Medicaid expansion. The authors rely on a simulated instrument approach while other studies cited here enter Medicaid policies directly into the regression. This difference in methodology may lead to discordant findings. See Hamersma and Kim (2013) for a thoughtful discussion of alternative approaches to modelling Medicaid generosity. Further, many studies in this literature examine the effects of expansions to non-traditional populations (e.g., low-income childless and non-disabled adults) while Golberstein and Gonzales (2015) examine increases in income generosity for traditional populations (e.g., the disabled and low-income adults with children, often mothers). Differences across studies may be driven by differences in the marginal enrollee who gains coverage following an expansion.

[4]Nearly 50% of standalone SUD treatment providers did not accept Medicaid in 2004 (authors' calculations based on the 2004 National Survey of Substance Abuse Treatment Services).

Bishop et al., 2014); e.g., 77% of U.S. counties do not have a sufficient mental healthcare workforce to meet local patient demand. If losing insurance curtails a patient's access to their provider, the patient may be unable to locate alternative care.

We have several findings. Psychiatric hospitalizations declined post-disenrollment in Tennessee relative to a comparison group of geographically similar U.S. states, with some suggestive evidence of heterogeneity in effect size across disorders. MHD hospitalizations declined by 7.3% and SUD hospitalizations declined by 16.5%. The financing of care was also altered, with the probability that Medicaid was used to pay for treatment declining 25.7% for MHD and 30.0% for SUD hospitalizations post-disenrollment. MHD patients were to some extent able to substitute lost Medicaid coverage with private coverage, but patients of both types bore a substantial share of the costs themselves. We did not observe any substitution to Medicare, another form of public insurance. In an extension to the main analysis, we offer suggestive evidence that the severity of psychiatric disorders may have worsened post-disenrollment, potentially through both reduced care and increased financial burden associated with (self-financed) care received.

The paper is structured as follows. Section 2 provides background details on psychiatric disorders and associated care, the TennCare disenrollment we exploit, and related literature. Data and methods are described in Section 3. We present our main results in Section 4 and report robustness checking in Section 5. Finally, Section 6 offers a discussion and conclusion.

2 Background and prior research

2.1 Psychiatric disorders and associated healthcare

The American Psychiatric Association (APA) defines MHDs as '. . . conditions involving changes in thinking, emotion, or behavior (or a combination of these)' (American Psychiatric Association, 2018). Further, the APA defines SUDs as conditions that occur

'. . . when the recurrent use of alcohol and/or drugs causes clinically and functionally significant impairment, such as health problems, disability, and failure to meet major responsibilities at work, school, or home' (American Psychiatric Association, 2013). These conditions impose substantial burden on affected individuals, families, and communities.

Psychiatric disorders are common. In the U.S. 19.1% (47.6M) and 7.4% (20.3M) of adults met diagnostic criteria for a MHD and an SUD in 2020 (Substance Abuse and Mental Health Services Administration, 2021). The U.S. is in the midst of an unprecedented fatal drug overdose epidemic, largely related to opioids, with 93,398 fatal drug overdoses in 2020 (Ahmad et al., 2021). There are over 207 fatal opioid overdoses each day (Centers for Disease Control and Prevention, 2021b) and deaths related to stimulants such as cocaine are rising rapidly (Maclean et al., 2021). In 2020, 45,979 U.S. residents died by suicide (Centers for Disease Control and Prevention, 2022b) and the misuse of alcohol is associated with over 88,000 deaths annually (Centers for Disease Control and Prevention, 2021a). In 2021, MHDs and SUDs cost the U.S. over $1T in healthcare expenditures, disability payments, crime and violence, a less productive work force, and so forth (Insel, 2008; Caulkins et al., 2014).[5] While disadvantaged populations (e.g., those with lower income) are at elevated risk for psychiatric disorders (Substance Abuse and Mental Health Services Administration, 2021), no population is immune to these disorders and society as a whole pays the associated costs (financial and otherwise).

While they are costly, there are numerous effective treatment options for psychiatric disorders, both care provided by specialists and primary care providers (Lu and McGuire, 2002; American Psychiatric Association, 2006; Hunot et al., 2007; Scott et al., 2007; Gaynes et al., 2009; Cuijpers et al., 2011; Popovici and French, 2013; Murphy and Polsky, 2016; Olfson, 2016; Kisely et al., 2017; Krebs et al., 2018; National Institute on Drug Abuse, 2018). For example, individuals with a psychiatric disorder can be prescribed medications or receive therapy from primary care physicians or psychia-

[5]The original estimates are inflated by the authors to 2021 dollars using the Consumer Price Index.

trists. Patients can obtain treatment in standalone outpatient and residential facilities, or hospital (community or psychiatric) settings from psychologists, psychiatrists, social workers, counsellors, and other healthcare professionals.

Despite effective treatment options, many individuals do not receive psychiatric care – any care or adequate care, where adequate care is care that is of reasonable duration and is matched to patient need (National Institute on Drug Abuse, 2018). In 2020, less than half of U.S. adults who could benefit from mental healthcare did not receive any treatment while approximately one in ten adults meeting diagnostic criteria for an SUD received any care (Substance Abuse and Mental Health Services Administration, 2021).

Commonly reported barriers to treatment receipt are inability to pay and lack of insurance coverage (Rowan et al., 2013; Substance Abuse and Mental Health Services Administration, 2021). For example, among adults who needed, but did not receive mental healthcare, in 2020 the most commonly stated reason for failure to receive care was inability to pay (44.9%). Treatment is likely unaffordable for many low-income and uninsured individuals. The reimbursement rates for a single in-network session with a psychiatrist can cost up to \$77 (CPT code 99213) to \$106 (CPT code 99214) and such treatment typically involves a series of visits (Mark et al., 2018). Food and Drug Administration-approved medications used to treat opioid use disorder (buprenorphine, methadone, and naltrexone) cost up to \$16,470 per year (National Institute on Drug Abuse, 2021).[6] For comparison, in 2021 the median maximum income at which a single adult was eligible for Medicaid in the U.S. was \$17,774 (Kaiser Family Foundation, 2022). Finally, there is evidence that delays in receiving care, which could occur following an insurance loss, can have negative effects on psychiatric health (Penttilä et al., 2014; Reichert and Jacobs, 2018). In particular, insurance loss-induced treatment discontinuation can be fatal for those with an SUD (Sordo et al., 2017; Connery and Weiss, 2020; Krawczyk et al., 2020).

[6] All cost estimates reported in this paragraph inflated by the authors to 2021 dollars using the CPI.

One policy approach to addressing unmet need (quantity and/or quality) for psychiatric healthcare services is the provision of affordable insurance that covers a range of treatment options. TennCare provided such insurance to low-income and uninsurable Tennessee residents. Thus, removing this coverage from 190,000 people with elevated risk for a psychiatric disorders could have lead to a substantial reduction in access to valuable care for chronic conditions. We study the effects of losing TennCare on hospital-based psychiatric treatment.

While hospitalizations represent a single modality, they are an important one to consider for several reasons. First, in the U.S., hospitalizations comprise 18% of overall psychiatric healthcare service expenditures and 25% of total payments to providers and are there form important from a cost perspective (Substance Abuse and Mental Health Services Administration, 2014). In 2004 (the year prior to the TennCare disenrollment), one in four community adult hospitalizations (or 7.6M hospitalizations) involved a psychiatric disorder (Owens et al., 2007). Thus, due to their costs and use by patients, hospitalizations are central in discussions related to containing overall expenditures on healthcare. Second, and perhaps more practically, despite growth in ambulatory facilities and primary care for psychiatric treatment, community hospitals remain a critical facet of treatment for the thousands of Americans with psychiatric disorders (Stensland et al., 2012). Community hospitals provide patient stabilization services, complex drug therapies, coordinated psychotherapy, short-term detoxification, intense observation, and crisis care to psychiatric patients each year. Third, and related to the previous point, hospitalizations are important components of evidence-based psychiatric care: this modality is included in the Addiction Medicine Society of America's continuum of care and is used to treat patients with relatively severe episodes (Mee-Lee et al., 2013). Fourth, hospitalizations are often an entry point to the healthcare system for individuals with a psychiatric disorder and can lead patients to receipt of a broader set of services (O'Toole et al., 2002; Houry et al., 2018). Finally, through the federal The Emergency

Medical Treatment and Labor Act (EMTALA), in the U.S. all emergency departments must accept patients regardless of ability to pay, suggesting that hospitals may be particularly exposed to patients needing care following an insurance loss.

2.2 A brief overview of TennCare

Tennessee originally offered a fee-for-service Medicaid program. Due to high costs, the state transitioned to a managed care program in 1994, making Tennessee the first state in the U.S. to adopt managed care within Medicaid.[7] State legislators anticipated that the transition would reduce overall program costs. The expected savings were allocated to support a large-scale increase in Medicaid eligibility to low-income, non-disabled childless adults and uninsurable adults, defined as adults with pre-existing conditions that lead to prohibitively high premiums (Farrar et al., 2007). This population has historically had limited access to insurance in the U.S. The program was popular and TennCare covered 22% of the state's population by 2004. The TennCare program, which used a psychiatric healthcare carve out[8] throughout our study period, generously covered a wide range of efficacious psychiatric services (e.g., medications, assessment and evaluation services, and counseling) at low cost-sharing with limited application of utilization management; e.g., prior authorization (Farrar et al., 2007; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021). TennCare coverage for physical health conditions was similarly generous and, through positive spillovers attributable to well-managed co-morbidities (e.g, diabetes, heart disease), pychiatric care delivered by primary care providers (Gaynes et al., 2009; Jetty et al., 2021), and overall improvements in well-being, likely enhanced psychiatric health among enrollees (Maclean et al., 2018).

[7] Managed care is a common organizational structure for healthcare provision. Broadly, in managed care systems, patients visit certain healthcare professionals and hospitals which contract with a managing company that oversees and monitors costs. The goal of managed care is to minimize overuse of services without harming patient outcomes, leading to reduced costs to the insurer.

[8] The term 'carve out' generally is used to describe a specific set of services that is not covered by the primary insurance plan and instead are managed by another company, typically a company that specializes in the specific services 'carved out' of the main plan.

TennCare eventually became financially unsustainable for Tennessee (Bennett, 2014). By 2004 the program accounted for one-third of the state's budget (Farrar et al., 2007). Between August 2005 and July 2006 Medicaid eligibility was curtailed along several margins, with changes announced in November 2004. Eligibility for childless non-disabled and uninsurable adults was terminated. 190,000 enrollees or 10% of the total Medicaid population lost TennCare coverage (Bureau of TennCare, 2005; Chang and Steinberg, 2009).[9] Importantly for our design, the disenrollment was essentially unexpected by disenrollees (Farrar et al., 2007).

2.3 TennCare disenrollment literature

There is a small literature examining the health insurance, service use, and outcome effects of the TennCare disenrollment using quasi-experimental methods. To date, the literature has focused on general populations and physical health. No studies have examined psychiatric health or healthcare outcomes or insurance among patients with psychiatric disorders. Examining these outcomes is our contribution to this literature.

We contend that separate consideration of psychiatric disorders is warranted, which motivates our study. In addition to features of psychiatric disorders and associated care noted in Section, 1, important differences between psychiatric and physical health and healthcare have been highlighted by economists for decades (Frank and McGuire, 2000). As noted by Frank and McGuire (2000) in the context of mental vs. physical healthcare: 'Uncertainty and variation in treatments are greater; the assumption of patient self-interested behavior is more dubious; response to financial incentives such as insurance is exacerbated; the social consequences and external costs of illness are formidable.' Further, the risk of an overdose is elevated after periods of abstinence among those with SUDs (Merrall et al., 2010). An abrupt termination in access to treatment or the

[9] We emphasize disenrollment effects in our study. We acknowledge that coverage generosity was curtailed to some extent among continuing Medicaid enrollees. Nonetheless, coverage remained relatively generous and, in line with the broader TennCare literature (reviewed in Section 2.3), we assume that the effects of insurance losses dwarfed the effects of other changes.

associated loss of financial resources conferred by insurance (Maclean et al., 2015) could be especially relevant for patients with SUDs.

2.3.1 Coverage effects

The TennCare disenrollment reduced Medicaid and overall insurance coverage with some private insurance substitution (Garthwaite et al., 2014; Tarazi et al., 2017; DeLeire, 2019; Tello-Trillo, 2021). For instance, using the Current Population Survey, Garthwaite et al. (2014) find that, post-disenrollment, the probability of having Medicaid declined by 33% among low-income, childless, and non-disabled adults.[10]

2.3.2 Healthcare service use and health outcome effects

Several studies have examined the effect of the disenrollment on healthcare and health outcomes. Findings from the TennCare literature on physical healthcare suggest that losing insurance reduced service use, increased unmet need, and increased patient financial burden and hospital provision of uncompensated care, although there is some heterogeneity in estimated effects across studies.

Tello-Trillo (2021) leverages survey data from the National Health Interview Survey and Behavioral Risk Factor Surveillance Survey (BRFSS). The author finds that the reform lead to a 4% – 5% reduction in mammograms and breast exams, and an increase of 20% in number of days with limited by one's health and no strong evidence of changes in emergency department visits. Tarazi et al. (2017) use the BRFSS and show that the disenrollment increased cost-related barriers to seeing a doctor but did not change the probability of having a personal doctor. DeLeire (2019) uses the Survey of Income and Program Participation and finds reports of unmet healthcare need and reliance on charity care increased and doctor visits and self-reported health declined post-disenrollment.

[10] There is also work on labor market effects (Garthwaite et al., 2014; Ham and Ueda, 2017).

Garthwaite et al. (2018) use American Hospital Association data and document that uncompensated care increased in Tennessee post-disenrollment. Finally, in a working paper, Ghosh and Simon (2015) use the National Inpatient Sample (NIS) and show that, post disenrollment, the share of total non-elderly adult hospitalizations reimbursed by Medicaid decreased by 21% and uninsured hospitalizations increased in Tennessee relative to a comparison group. There was no change in the number of hospitalizations.

3 Data and methods

3.1 Hospitalization data

Our primary dataset is the NIS, an administrative database compiled by the Healthcare Cost and Utilization Project (HCUP). These data allow us to study hospitalizations and are the largest publicly available U.S. all-payer inpatient healthcare database. The NIS are regularly used by economists to study psychiatric healthcare (Antwi et al., 2015; Golberstein et al., 2015). The sample reflects a 20% stratified sample of U.S. hospitals, with five to eight million hospitalizations occurring at over 1,000 hospitals each year. Hospitals are sampled on region, ownership status, and bed size. In 2007 (the last year of our study) the weighted NIS sample covered 90% of the universe of hospitalizations and 78% of all hospitals (Barrett et al., 2010). The American Hospital Association defines hospitals as 'all nonfederal, short-term general, and other special hospitals' (American Hospital Association, 2018). The NIS does not include psychiatric hospitals. We focus on hospitals that have positive hospitalizations for patients 21 to 64 years of age.[11]

Our study period is January 2002 to December 2007. We choose these years to avoid the early 2000s recession (2001) and the Great Recession (2008-2010). In particular,

[11] We considered using elderly adults as a within-state comparison group in a triple difference estimator. The elderly have very different trends in psychiatric outcomes than the non-elderly. For example, 8% of adults 18 yers and older met diagnostic criteria for an SUD while the share was 2% for elderly adults in 2020 (Substance Abuse and Mental Health Services Administration, 2021).

recessions are linked with insurance (Cawley and Simon, 2005; Cawley et al., 2015), psychiatric disorders (Ruhm, 2015; Carpenter et al., 2017; Hollingsworth et al., 2017), and psychiatric healthcare use (Bradford and Lastrapes, 2014; Maclean et al., 2020).[12]

The NIS is not designed to be state representative. Instead these data (over our study period) are designed to be representative at the level of the region.[13] We are concerned that using the NIS data for Tennessee, which is a small state with 5.9M residents (2% of the total U.S. population) in 2004 (University of Kentucky Center for Poverty Research, 2020), could lead to reliance on an unrepresentative sample of hospitals.[14]

Given the structure of the NIS and our focus on a policy occurring in Tennessee, we propose an alternative empirical approach. We use state-representative data for Tennessee (from administrative sources) instead of the Tennessee observations included in the NIS, and then use the other Southern states (i.e., the comparison group) from NIS. Since we are combining data sets, we perform a simulation to test if our proposed strategy will allow us to estimate more accurate disenrollment effects. The results from this exercise are included in the Data Appendix (Section 8). Our analysis suggests that combining data in this manner allows us to more accurately estimate treatment effects. We also report results using NIS for Tennessee as a robustness check (see Section 5).

We analyze two sets of outcomes to study disenrollment effects. First, we consider the quarterly number of MHD and SUD hospitalizations per hospital (technically, we measure hospital *discharges*, but we refer to them as hospitalizations for simplicity). We separately classify MHD and SUD hospitalizations based on ICD-9 codes available on the discharge record (Stranges et al., 2011; Heslin et al., 2015). Second, we examine indicators for expected payment source: Medicaid, any insurance, private insurance, Medicare, and

[12] Further, there was a major re-certification of all Medicaid enrollees in Tennessee in 2002 (Division of TennCare, ND) and we do not want to confound effects by including data before and after this event.

[13] In more recent years, the NIS is representative at the level of the nation.

[14] We are less concerned with this issue in our comparison group as the NIS is designed to be representative at the regional level over our study period and our comparison group covers all other states in the South region. We have confirmed this assumption with an economist at the Agency for Healthcare Quality and Research, the agency that administers the HCUP. Further, we establish this point in a Monte Carlo simulation. Details available on request.

self-pay (which plausibly includes uninsured patients). We have information on up to two expected payers per hospitalization listed by the hospital and code these variables one if the payer is listed as primary or secondary payer, and zero otherwise.

3.2 Empirical model

We estimate the difference-in-differences (DID) model outlined in Equation 1:

$$Y_{h,s,q,t} = \beta_0 + \beta_1 DID_{s,q,t} + \alpha_h + \alpha_q + \alpha_t + \epsilon_{h,s,q,t} \tag{1}$$

where $Y_{h,s,q,t}$ represents a hospitalization or insurance outcome for hospital h in state s and in quarter q in year t. $DID_{s,q,t}$ is an indicator variable that takes on a value of one in Tennessee after the disenrollment and zero otherwise. α_h is a vector of hospital fixed-effects (which subsume state fixed-effects), and α_q and α_t are vectors of quarter and year fixed-effects respectively. $\epsilon_{h,s,q,t}$ is the error term. We apply NIS weights to the (non-Tennessee) NIS data and weight the Tennessee data equally. We follow Garthwaite et al. (2014) and apply a modified block-bootstrap procedure to calculate standard errors.[15]

We follow, as closely as possible given the states that appear in the NIS, Garthwaite et al. (2014) and use other Southern states as a comparison group: Arkansas (2004-2007), Florida (2002-2007), Georgia (2002-2007), Kentucky (2002-2007), Maryland (2002-2007), North Carolina (2002-2007), Oklahoma (2005-2007), South Carolina (2002-2007), Texas (2002-2007), Virginia (2002 to 2004 and 2006-2007), and West Virginia (2002-2007). The logic of using this comparison group is that other Southern states are subject to similar economic, social, and political shocks as Tennessee, and therefore offer a suitable counterfactual. As we show in Section 5.3, we observe no evidence of spatial spillovers that could suggest a violation of the stable unit treatment value assumption (STUVA)

[15] In our main specifications, we do not include time-varying covariates as recent work suggests that estimation of a DID method using two-way fixed-effects, as we do here, with time-varying controls can lead to inaccurate estimates of average treatment effects on the treated (Caetano et al., 2022). However, we report results based on regressions that do control for time-varying covariates in a robustness check.

which is required for identification in DID specifications. The NIS is an unbalanced panel at both the hospital and state level, hence the hospitals and states that appear in the comparison group vary across years. However, all comparison states are observed before and after the TennCare disenrollment. The Tennessee data are the universe, thus changing composition is not likely a concern for our treatment group.

A necessary assumption for canonical DID models to recover causal estimates is that the treatment and comparison group would have followed the same trends in outcomes had the treatment group not received treatment (i.e., 'parallel trends'). The assumption is untestable as the treatment group is treated in the post-period. We provide suggestive evidence on parallel trends through estimation of an event-study.

Quarterly hospital-level summary statistics using data from the pre-disenrollment period in Tennessee and other Southern states are reported in Table 1. Unadjusted trends in MHD and SUD hospitalizations and payment sources for the treatment and comparison groups are reported in Figure 1. While there are some level differences across the two groups of states, trends in outcomes (pre-disenrollment) appear to move in parallel, post-disenrollment there are some differences in trends.

4 Results

4.1 DID analysis of hospitalizations and payment sources

Our main DID results for hospitalizations are reported in Table 2. Following the disenrollment, quarterly MHD and SUD hospitalizations declined by 8.3 and 6.2 per hospital operating in Tennessee. Comparing these coefficient estimates to the means in Tennessee pre-disenrollment, our findings suggest a 7.3% reduction in MHD hospitalization (baseline mean = 114.7) and 16.5% in SUD hospitalizations (baseline mean = 37.7). Thus, the disenrollment arguably lead to meaningful reductions in hospitalization care for psychiatric disorders among Tennessee Medicaid enrollees.

In Tables 3 and 4 we report the estimated impacts on payments for MHD and SUD hospitalizations. We note that we interpret these findings cautiously as they are based on samples of patients receiving hospital care for psychiatric conditions, which appear to be impacted by the policy (see Table 2), and hence findings are potentially subject to conditional-on-positive bias. With this caveat in mind, we show that the use of Medicaid to pay for psychiatric treatment declined by 8.9 percentage points ('ppts') and 11.7 ppts for MHD and SUD hospitalizations. Compared to the proportions of hospitalizations financed by Medicaid in Tennessee pre-disenrollment (34.6% for MHD and 39.0% for SUD), these coefficient estimates imply that Medicaid financing was reduced by 25.7% for MHD hospitalizations and 30.0% for SUD hospitalizations. The use of any insurance to pay for treatment declined more modestly for MHD hospitalizations (3.6 ppts or 3.8%). The decline in the use of any insurance to pay for SUD hospitalizations was nearly as large as the Medicaid decline (10.9 ppts or 12.7%). MHD patients were able to partially offset the insurance loss with private coverage (which increased by 1.9 ppts or 6.6%), but SUD patients were not able to substitute in this matter. Self-financing increased for both MHD and SUD: 2.2 ppts and 8.8 ppts respectively, which correspond to 55.0% and 65.2% rises. We observe no statistically significant evidence that either MHD or SUD patients substituted lost Medicaid coverage with Medicare.

Thus, while the reductions in use of Medicaid to pay for care were similar for MHD and SUD patients, the 'substitute' payment forms were potentially somewhat different, with SUD patients shouldering the costs of care to a larger extent than MHD patients. Given that the average charge for a community hospitalization for psychiatric conditions ranged from $6,432 to $26,986 for an uninsured patient in 2006 (Stensland et al., 2012), this shift in financing from Medicaid to patients (in particular SUD patients) was arguably non-trivial. Further, many expected self-pay hospitalizations result in the facility absorbing the cost as patients, ultimately, are not able to (at least fully) pay for treatment (Garthwaite et al., 2018).

4.2 Internal validity

We estimate an event study to provide suggestive evidence as to whether our treatment and comparison groups would have followed parallel trends in psychiatric hospitalizations and payment sources post-disenrollment after adjusting for fixed-effects. More specifically, we decompose $DID_{s,q,t}$ in Equation 1 into a series of interactions between an indicator for Tennessee and time leads and lags reflecting periods around the disenrollment. To smooth the data, we use six-month bins to define periods. The omitted category is the six-month period prior to the disenrollment. Event study results are reported graphically in Figures 2 (hospitalizations) and 3 (payment source).

There are two key findings from the event studies. First, we do not observe substantial evidence of differential pre-trends in our outcomes between Tennessee and comparison states. Coefficient estimates are small and not statistically distinguishable from zero for the policy lead indicators. Second, examination of the policy lag indicators largely supports our DID findings. That is, we observe declines in psychiatric hospitalizations, declines in the use of Medicaid and any insurance to pay for care, and increases in private coverage and self-pay (increases in self-pay are only observable for MHD hospitalizations) post-policy. However, the event study reveals some evidence in dynamics for hospitalizations (but less so for payment sources). That is, the declines in psychiatric hospitalizations may moderate as time passes. While we lack the data to explore why effects may dissipate, we can offer potential hypotheses. Patients may delay hospitalizations as long as possible, either through self-treatment or reliance on forms of (non-hospital) charity care, but eventually seek hospital care when their condition can no longer be effectively treated through these alternative channels.

4.3 DID analysis of psychiatric health

Next, we explore the impact of the disenrollment on MHD and SUD proxies: deaths by suicide, and fatal alcohol poisoning and drug overdoses. We use the Centers for

Disease Control and Prevention's National Vital Statistics System (NVSS) Underlying Cause of Death public use files. These data record the universe of deaths in the U.S. and classify deaths by cause. We select all related deaths for adults 21 to 64 in each quarter 2002 to 2007 for Tennessee and other Southern states. We report results based on all states but results based on only state/year pairs in the NIS data are available on request and are similar. Deaths are expressed as a quarterly rate per 100,000 adults 21 to 64 and weighted by the state non-elderly adult population.[16] We modify Equation 1 to account for the fact that the NVSS data are at the state rather than hospital level, in particular hospital fixed-effects are replaced with state fixed-effects.

Results are reported in Table 5. Rates of deaths by suicides declined by 0.321 per 100,000 state residents or 7.4% relative to the mean in Tennessee pre-disenrollment. Rates of fatal alcohol and drug poisonings increased by 0.635 or 19.9%. These findings suggest that losing insurance, through reduced service use or increased financial burden associated with healthcare, may lead to worse psychiatric health.[17] Effects appear to be larger for alcohol poisonings and drug overdoses. This finding is in line with previous research suggests that unexpected treatment discontinuation can be fatal for those with an SUD (Sordo et al., 2017; Connery and Weiss, 2020; Krawczyk et al., 2020).

5 Robustness checks

We report a serious of robustness checks. Reassuringly, our findings are stable. For brevity, we report robustness checking for hospitalization outcomes. Results for payment sources are similarly stable and are available on request.

[16] All state-month cells in the public use NVSS with less than ten suicides are suppressed for confidentiality reasons. We impute these cells with a value of five. Results are not sensitive to imputing a value of zero (the smallest possible value) or nine (the largest possible value).

[17] As noted by Black et al. (2019), we could be under-powered to detect effects. To speak to this issue, we have attempted to assess statistical power in our study. In unreported analyses, we conducted a *post-hoc* power analysis. Results, available on request, suggest that we are able to detect effect sizes of the magnitudes that we estimate with approximately 80% power.

5.1 Alternative approaches to statistical inference

In our main analysis, we apply a block-bootstrap approach to calculate our standard errors. This is a method proposed by Garthwaite et al. (2014) in their analysis of TennCare insurance and labor market effects. We next show that the precision of our estimates is not markedly different if we instead apply other approaches: classical standard errors that assume homoscedasticity, robust standard errors, and clustering standard errors at the state-level.

Results − reported in Table 6 − are broadly similar across the different methods to inference. However, we note that for MHD hospitalizations inference using standard errors clustered at the level of the state suggests that this coefficient estimate is not statistically different from zero. Given that we have just 15 clusters in our data, a number considered too small for clustering in this manner by econometricians (Cameron and Miller, 2015), we do not place substantial weight on this finding.

5.2 Alternative specifications, samples, and periods

We re-estimate Equation 1 using alternative time periods, comparison groups, and specifications. More specifically, we: (i) include time-varying state-level covariates (see Table 1, demographics from the CPS (Flood et al., 2021) and population from the Census);[18] (ii) aggregate to the state-year level; (iii) estimate unweighted regression; (iv) use the NIS data for Tennessee;[19] (v) exclude Texas and Georgia from the comparison group – we exclude these states as their Medicaid programs appear, based on available evidence, to potentially cover psychiatric healthcare services less generously than Tennessee over our study period (Kaiser Family Foundation, 2018); (vi) exclude the year of

[18] In earlier versions of this manuscript, we included time-varying covariates in our main specifications, reporting regressions without these controls as a robustness check. We have elected to change our presentation to emphasize the more parsimonious specifications (i.e., not including the time-varying state-level covariates) based on recent research suggesting that DID regressions are vulnerable to bias from such controls. See Caetano et al. (2022) for a helpful discussion of this issue.

[19] We apply the NIS-provided weights to both Tennessee and other Southern States in this regression.

the policy change (2005); (vii) include a separate linear time trend for Tennessee; and (viii) use a longer study period (2000-2010). Results are reported in Figure 4.

Overall, our findings − while not identical across all specifications − appear to be broadly stable. Findings are less precise when we include time-varying covariates, this change may be attributable to the vulnerabilities of two-way fixed-effects DID regressions with such controls included (Caetano et al., 2022).

5.3 Program-induced migration

An empirical concern in policy analysis is that the policy under study may have induced individuals to migrate away from or towards the affected locality leading to biased estimates of regression coefficients due to violation of STUVA (Moffitt, 1992). To explore this possibility, we draw micro-level data from the Annual and Social Economic Supplement (ASEC) to the CPS between 2003 and 2008 and model past-year across-state migration among respondents ages 21 to 64 years as a function of the disenrollment using a modified version of Equation 1. ASEC data over the period 2003 to 2008 pertains to migration 2002 to 2007. We exclude those respondents with family income $>$ 400% FPL as such respondents are unlikely to be eligible for Medicaid coverage in any state in our analysis sample. Next, we aggregate the micro-data to the state-year level, we include all Southern states but results based on only state/year pairs that appear in the NIS data are very similar. Data are weighted by the state non-elderly adult population. We estimate an augmented version of Equation 1 as outlined in Section 4.3, although due to the structure of the ASEC data, we have annual not quarterly data and thus we cannot include quarter fixed-effects in the regression.

Migration results are reported in Table 7. We observe no evidence that the disenrollment induced people to move across state lines. These null findings are perhaps not suprising as Medicaid programs other than TennCare were not overly generous and those who lost coverage likely did not have other options in other states.

6 Discussion

We provide the first evidence on the effect of losing public insurance on psychiatric hospitalizations. Our findings are relevant from both an economic and a policy perspective. First, we extend the economic literature that has estimated the insurance-elasticity of demand for psychiatric healthcare by leveraging plausibly exogenous variation offered by a large and unexpected Medicaid disenrollment. We are the first study to document this elasticity. Second, many countries grapple with providing quality healthcare to individuals and curtailing high healthcare costs to governments, which are in turn borne by taxpayers. For example, in the United States there have been recent policy debates regarding repealing or re-designing the Affordable Care Act (ACA) – a massive transformation of the U.S. healthcare system which substantially increased both public and private coverage and required insurers to cover psychiatric healthcare services. These findings speak to the insurance elasticity of demand for psychiatric healthcare services and can inform policy decisions how best to provide coverage for such care.

Our findings suggest that the disenrollment reduced MHD hospitalizations by 7.3% and SUD hospitalizations by 16.5%. In additional, the financing of psychiatric care changed, MHD hospitalization financing was partially shifted to private insurance while SUD financing was transferred entirely to patients. These findings suggest that losing insurance reduces access to valuable psychiatric care and likely imposes financial burden on patients. Given that self-payments by patients often translates into bad debt to hospitals (Garthwaite et al., 2018), this shift in financing may also spillover to healthcare providers who treat patients with psychiatric disorders. Further, while both MHD and SUD patients were arguably negatively impacted by the disenrollment, effects were disproportionately larger for those with SUDs.

We can compare our findings to studies that have examined the effect of pre- and post-ACA state Medicaid expansions to 'non-traditional' populations similar to the population impacted by the TennCare disenrollment (Wen et al., 2015, 2017; Meinhofer and

Witman, 2018; Maclean et al., 2018; Cher et al., 2019; Ghosh et al., 2019; Grooms and Ortega, 2019; Maclean and Saloner, 2019; Saloner and Maclean, 2020) and the Oregon Medicaid experiment (Baicker et al., 2017). Non-traditional populations are low-income non-disabled childless adults that historically been categorically ineligible for Medicaid coverage. To date, this literature has examined the effect of insurance gains attributable to Medicaid expansions. We examine insurance losses follow the TennCare disenrollment. While there are numerous reasons to expect asymmetry in the effects of insurance gains and losses on psychiatric healthcare, we do not find that to be the case. We observe suggestive evidence that psychiatric health may worsen following an insurance loss but there is less of improvements in this health metric following an insurance gain (Abouk et al., 2019; Averett et al., 2019), although Wettstein (2019) shows that private insurance gains among young adults appear to improve psychiatric health.

Our findings depart from the TennCare literature on all-cause hospitalizations. Ghosh and Simon (2015) show that there was no change in the number of total hospitalizations post-disenrollment. These differing findings may imply differences in the insurance-elasticity of demand across services. Previous work demonstrates differences in the price-elasticity of demand for healthcare services (Ellis et al., 2017). However, findings for shifts in the financing of hospitalizations post-disenrollment across total and psychiatric hospitalizations: for example Ghosh and Simon (2015) find a 21% reduction in the use of Medicaid to pay for hospitalizations while we document a 6.6% reduction.

In sum, we provide the first evidence on the impact of losing insurance on psychiatric hospitalizations and financing, and measures of psychiatric health. Given the ongoing opioid and mental illness crisis in the U.S. (Maclean et al., 2021), alongside an emerging stimulant crisis, understanding how insurance impacts these outcomes is critical. Establishing and understanding differences in responsiveness to policy changes across services is critical to optimal insurance design. Our findings shed light on these questions.

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7 Tables and figures

Table 1: Summary statistics: Pre-disenrollment

Sample:	Tennessee	Other Southern States
MHD hospitalizations	115.018	118.703
SUD hospitalizations	37.483	38.395
Age (years)	36.317	35.696
Female	0.515	0.512
Black	0.167	0.167
Other race	0.025	0.044
Hispanic	0.043	0.162
High school	0.267	0.240
Some college	0.191	0.195
College	0.158	0.166
Population 21-64	3,564,215	7,272,9032
Observations	2172	5712
Hospitals	142	911

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in quarter in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights.

Table 2: Effect of TennCare disenrollment on psychiatric hospitalizations among adults 21-64 years per hospital-quarter: Hospitalization data 2002-2007

Outcome:	MHD hospitalizations	SUD hospitalizations
TN × post	-8.345***	-6.199***
	(2.179)	(0.951)
Observations	11,894	11,894
TN mean, pre-policy	114.72	37.65

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in quarter in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects. Standard errors are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported in parentheses. ***, **, & * = statistically different from zero at the 1%, 5%, and 10% level of confidence.

Table 3: Effect of the TennCare disenrollment on source of payment for MHD hospitalizations among adults 21-64 years per hospital-quarter: Hospitalization data 2002-2007

Payment source:	Medicaid	Any insurance	Private	Medicare	Self-pay
TN × post	-0.089***	-0.036***	0.019***	0.012	0.022***
	(0.007)	(0.005)	(0.006)	(0.007)	(0.004)
Observations	11871	11871	11871	11871	11871
TN mean, pre-policy	0.346	0.958	0.287	0.325	0.040

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in quarter in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects. Standard errors are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported in parentheses. ***, **, & * = statistically different from zero at the 1%, 5%, and 10% level of confidence.

Table 4: Effect of the TennCare disenrollment on source of payment for SUD hospitalizations among adults 21-64 years per hospital-quarter: Hospitalization data 2002-2007

Payment source:	Medicaid	Any insurance	Private	Medicare	Self-pay
TN × post	-0.117***	-0.109***	0.002	-0.004	0.088***
	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	11664	11664	11664	11664	11664
TN mean, pre-policy	0.390	0.860	0.224	0.246	0.135

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in quarter in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects. Standard errors are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported in parentheses. ***, **, & * = statistically different from zero at the 1%, 5%, and 10% level of confidence.

Table 5: Effect of the TennCare disenrollment on rates of suicides and fatal alcohol poisonings and drug overdoses among adults 21-64 years per quarter: NVSS 2002-2007

Cause of death:	Death by suicide	Alcohol poisoning or drug overdose
TN $\times$ post	0.321***	0.635***
	(0.119)	(0.159)
Observations	408	408
TN mean, pre-policy	4.353	3.195

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a state in a quarter in a year. Data are weighted by the state non-elderly adult population. Regressions are estimated with least squares and control for state, quarter, and year fixed-effects. Standard errors are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported in parentheses. ***, **, & * = statistically different from zero at the 1%, 5%, and 10% level of confidence.

Table 6: Effect of TennCare disenrollment on psychiatric hospitalizations among adults 21-64 years per hospital-quarter using alternative approaches to inference: Hospitalization data 2002-2007

Outcome:	MHD hospitalizations	SUD hospitalizations
Method: Homoskedastic		
Standard error	2.179	0.951
p-value	0.0001	0.0000
Method: Robust		
Standard error	2.179	0.951
p-value	0.0001	0.0000
Method: Cluster by state		
Standard error	6.824	2.591
p-value	0.2469	0.0357

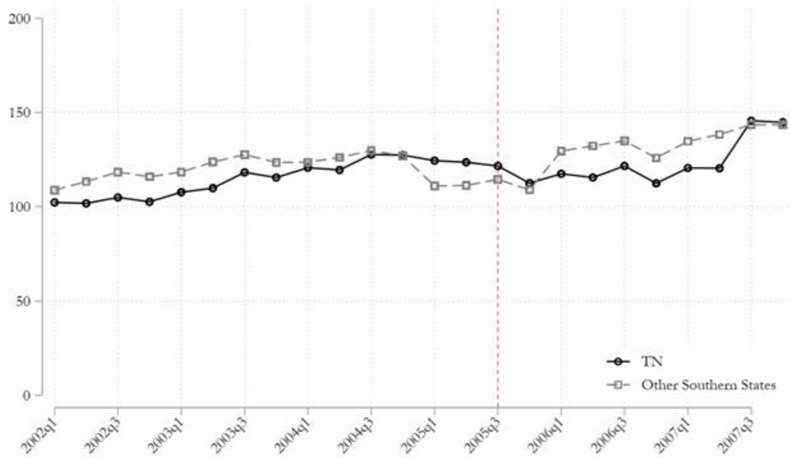
Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a state in a quarter in a year. Data are weighted by the state non-elderly adult population. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects.

Table 7: Effect of the TennCare disenrollment on migration among adults 21-64 years per quarter: ASEC-CPS 2002-2007

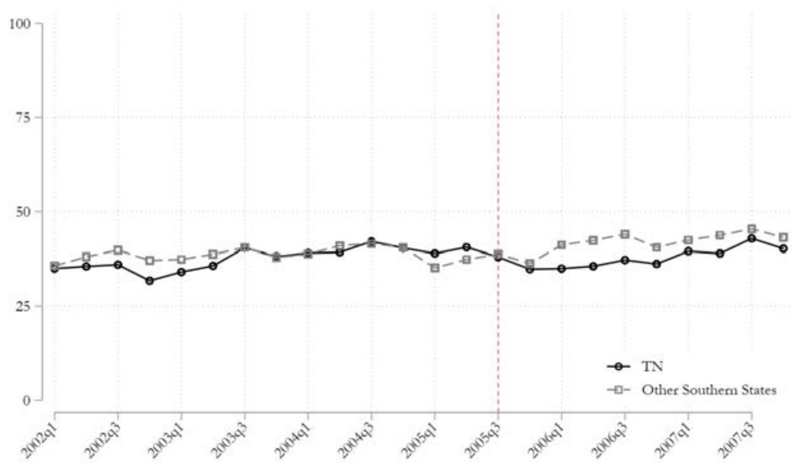
Outcome:	Move across state lines in the past year
TN × post	-0.003
	(0.003)
Observations	102
TN mean, pre-policy	0.040

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a state in a year. Data are weighted by the state non-elderly adult population. Regressions are estimated with least squares and control for state and year fixed-effects. Standard errors are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported in parentheses. ***, **, & * = statistically different from zero at the 1%, 5%, and 10% level of confidence.

Figure 1: Trends in psychiatric hospitalizations among adults 21-64 years per hospital-quarter: Hospitalization data 2002-2007



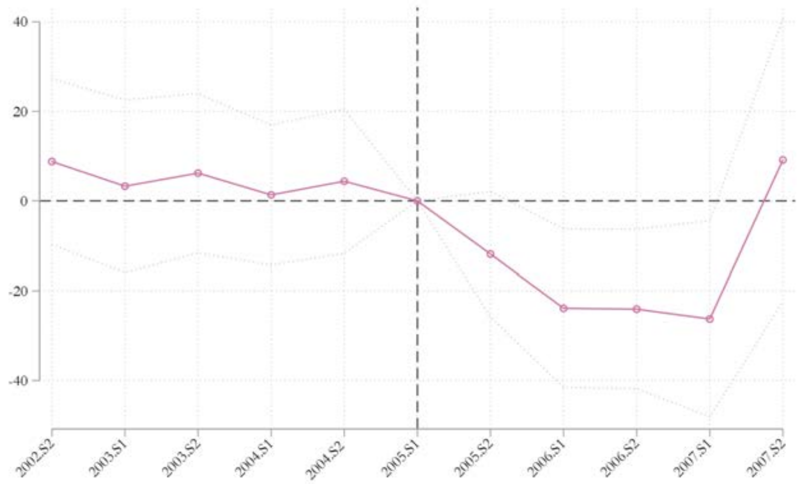
MHD hospitalizations



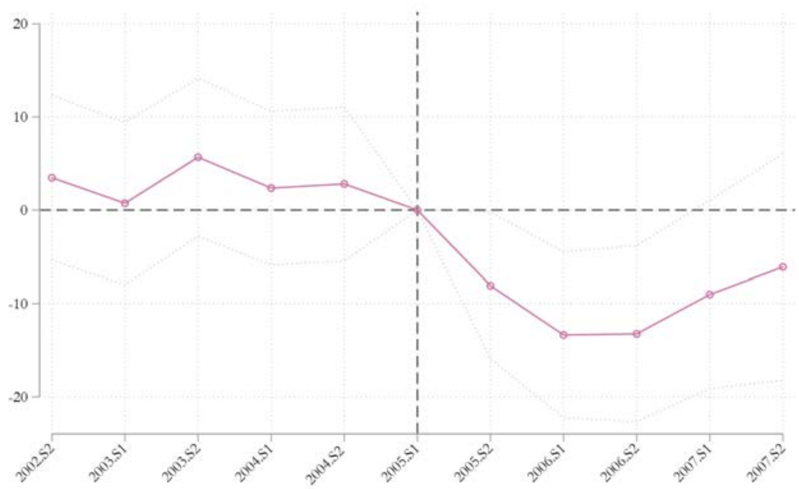
SUD hospitalizations

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. Data are aggregated to the treatment-time period level.

Figure 2: Effect of TennCare disenrollment on psychiatric hospitalizations among adults 21-64 years per hospital-quarter using an event study: Hospitalization data 2002-2007.



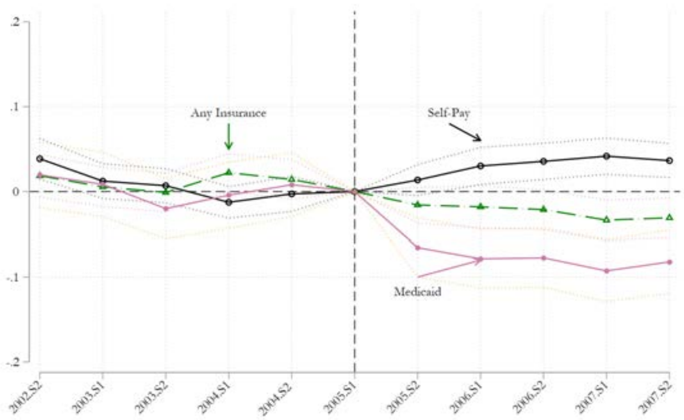
MHD hospitalizations



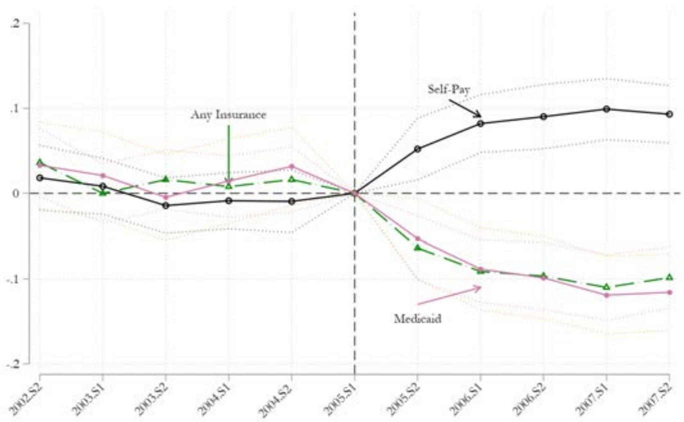
SUD hospitalizations

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects. 95% confidence intervals are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported with vertical lines.

Figure 3: Effect of TennCare disenrollment on psychiatric hospitalization payment sources among adults 21-64 years per hospital-quarter using an event study: Hospitalization data 2002-2007.



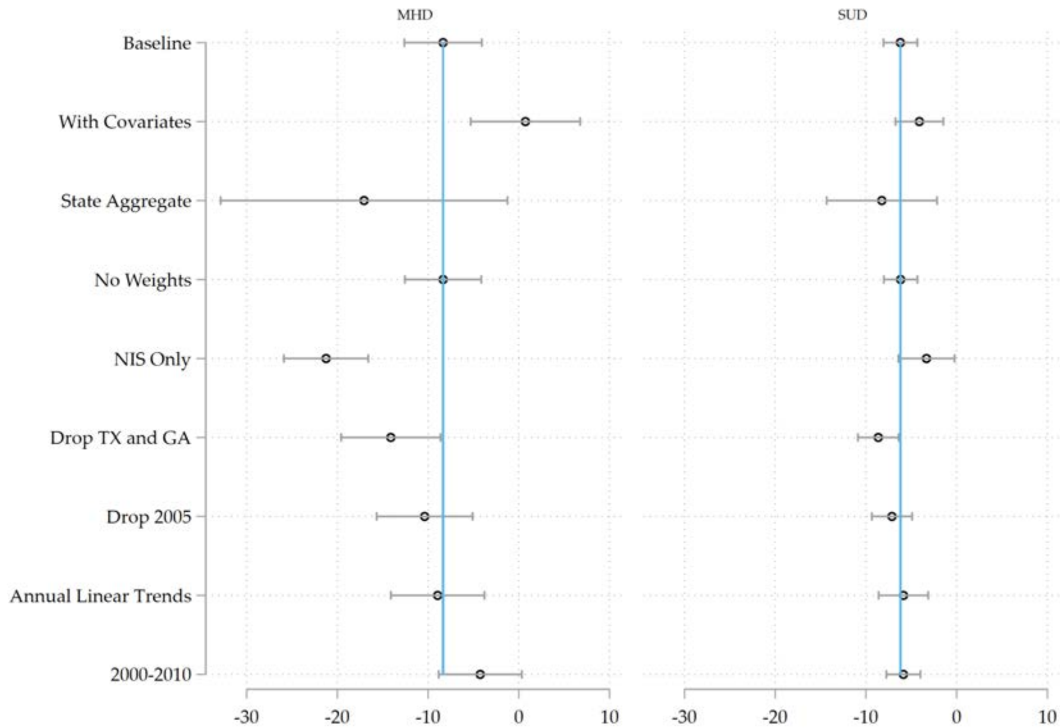
MHD hospitalizations



SUD hospitalizations

Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in a year. TN observations are unweighted and non-TN observations are weighted by NIS sample weights. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects. 95% confidence intervals are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported with vertical lines.

Figure 4: Effect of TennCare disenrollment on psychiatric hospitalizations among adults 21-64 years per hospital-quarter using alternative samples, specifications, and time periods: Hospitalization data 2002-2007



Notes: Other Southern states include AK, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, and WV. The unit of observation is a hospital in a state in a year unless otherwise noted. TN observations are unweighted and non-TN observations are weighted by NIS sample weights unless otherwise noted. Regressions are estimated with least squares and control for hospital, quarter, and year fixed-effects unless otherwise noted. 95% confidence intervals are estimated with a modified block-bootstrap procedure following Garthwaite et al. (2014) and are reported with vertical lines.

8 Data appendix

The NIS is not designed to be state representative. Instead, the dataset is representative at the national and regional level over our study period. HCUP administrators strongly advise researchers against using the NIS for single-state estimates.[20] We study a subset of the population (ages 21 to 64) and specific types of hospitalizations (i.e, psychiatric). There are important differences across hospitals that provide different service lines. For instance, psychiatric healthcare is a low profit service line, and for-profit hospitals are less likely to offer this type of care. We are concerned that using the NIS data for Tennessee could lead to reliance on an unrepresentative sample of hospitals. We propose an alternative empirical approach, in which we use a state-representative data for Tennessee (from administrative sources) instead of the Tennessee included in the NIS and then use the other southern states (i.e., the comparison group) from NIS. Since we are combining data, we perform a simulation to test if our proposed strategy will allow us to estimate more accurate disenrollment effects. We conduct this analysis for MHD and SUD hospitalizations (which are the focus of our study) and, for completeness, we report results for total hospitalizations.

We initially provide suggestive evidence on the implications of relying on a regionally representative dataset to study TennCare through a Monto Carlo simulation. First, we use data from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW) database to determine the total number of community hospitals in each Southern state in each year over the period 2002 to 2007 (we use the six digit North American Industry Classification System code 622110). This information provides us with the universe of community hospitals. We construct variables that take on three values (1, 2, and 3) for (i) ownership and (ii) bed size, to mimic the variables used by

[20] See: '...strongly advises researchers against using the NIS to estimate state-specific statistics. ... However, these NIS samples were not designed to yield a representative sample of hospitals at the State level': `https://www.hcup-us.ahrq.gov/db/nation/nis/nis_statelevelestimates.jsp` (last accessed September 8th, 2021).

AHRQ administrators to select hospitals for inclusion in the NIS; we note that our simulation does not exactly replicate the NIS sampling method, but our approach is very similar. Second, we generate an outcome variable where the data generating process emulates a standard DID functional form. In particular, we generate a variable Y that is determined by a DID estimate (Tennessee interacted with a post-disenrollment period indicator), hospital fixed-effects, year fixed-effects, and a random error term. We used Southern states that appear in the NIS to form the comparison group. Third, we perform various draws from the universe of hospitals: (1) a 100% sample; (2) a 20% sample by year, ownership, and bed size and retaining only hospitals that provide psychiatric healthcare and that treat non-elderly adult patients;[21] and (3) a 100% sample in Tennessee and a 20% sample by year, ownership, and bed size in other Southern states that are included in the NIS data set for hospitals that provide psychiatric healthcare and that treat non-elderly adult patients. We select the data in this manner to reflect the universe of hospitals (1), the NIS sample after making exclusions necessary for our research question (2), and the value of our proposed combination of NIS and other administrative data which we describe in more detail later (3). We then estimate a DID specification in each sampling scheme across 1,000 simulated populations. Full details are available on request.

The simulation results are reported in Data Appendix Figure A1, and the implications of reliance on the NIS are immediately apparent. First, all distributions of beta hat are centered on the true parameter value (constructed to have a value of two). However, the sampling framework employed has consequential implications for the likelihood that the estimated DID parameter will be significantly over- or under-estimated. The difference between region- and state-representativeness matters in a DID context, particularly one in which only a single state is treated. In a regionally representative dataset such as the

[21] We constructed these variables to have different distributions in Tennessee and other Southern states included in the NIS data set and they are designed to mimic, albeit imperfectly, our focus on psychiatric hospitalizations among non-elderly adults in our main analysis.

NIS, a state like Tennessee may contribute a very small number of observations within any given conditional cell (e.g., ownership, bed size, and year). Intuitively, when the identifying variation is small number of observations which by design are not necessarily representative of the treatment group, the variability in coefficient estimates increases substantially.

Using the 100% sample, the distribution of beta hats is tightly centered around the true value, as we would expect. The 20% sample with exclusions required to form our analysis sample produces a very wide distribution of estimates, with many estimates differing substantially from the true treatment effect. Using a combination of the universe of Tennessee hospitals and a 20% sample of hospitals in other Southern states, while not fully alleviating the increase in distribution spread, substantially tightens the distribution of beta hats and nearly offsets the increase in the width of the distribution induced by sampling. In sum, this simulation exercise implies that sampling used to construct the NIS, while not leading to bias, substantially increases the chance that the researcher will have an unrepresentative sample which can lead to inaccurate estimates of treatment effects. This outcome is what NIS administrators state will occur when the NIS is used for state-level analyses, but researchers (including ourselves in previous work) often ignore this caution.

A high-variance estimator, like the one arising from the typical state-level analysis administrators warn researchers against applying when using the NIS data, is underpowered to detect small and modest effect sizes. When using an underpowered estimator, the distribution of statistically significant coefficient estimates will be biased away from zero. This situation illustrates the real danger of using such estimators: researchers who find statistically significant evidence are potentially overstating the true effect size.

Using the simulation evidence above to help us identify the best possible estimation strategy, we propose a combination of the NIS and administrative data for Tennessee. We replace the NIS Tennessee observations with the universe of hospitalizations at community hospitals for this state that we obtained from the Tennessee Department of Health ('DOH' data).[22] Of note, the NIS Tennessee is drawn from the DOH data that we use, thus the datasets are entirely compatible. Put differently, we are not introducing bias into the analysis attributable to using different data sources as the NIS uses a sub-set of the DOH data to form the Tennessee sample. This combination mimics (3) in our simulation and, we hypothesize, will allow more accurate estimates of treatment effects than reliance on the NIS data alone.[23]

We further investigate the value of our combined dataset by comparing NIS and DOH data for Tennessee over our study period. We exclude non-community hospitals from the DOH data to match the NIS sample frame; we confirmed our definition of community hospitals with administrators at the Tennessee DOH (details available on request). We plot trends in the average number of hospitalizations among non-elderly adults per hospital in each quarter of our study period in Tennessee in the NIS and the DOH data. Trends in MHD, SUD, and total hospitalizations (Data Appendix Figure A2) display more period-to-period variation in the NIS data than the DOH data, and the variation in the NIS occurs around the disenrollment period. Differences in trend between NIS hospitals and the universe of hospitals in the DOH are arguably more pronounced for total hospitalizations. Of note, based on our analysis of the data, review of Tennessee DOH hospital directories, and discussions with DOH staff, the deviations apparent in the NIS data for Tennessee do indeed reflect the unrepresentative nature of the hospitals sampled for the NIS, which further underscores our concern that reliance on the NIS for a single-state analysis may be problematic. The correlations between the DOH and NIS time series are 0.46 (MHD), 0.56 (SUD), and 0.39 (total). Thus, while the

[22]Because the Tennessee NIS data is drawn from the DOH data the measures, we use in our analysis are standardized across the two datasets (i.e., NIS Tennessee sample and DOH). However, we note that the parameters of our data use agreement with the Tennessee Department of Health do not permit us to link data in the DOH to the Tennessee NIS data to compare hospitals. Full details available on request.

[23]The State Inpatient Database or the State Emergency Department Database for Tennessee are not available to the public (`https://www.hcup-us.ahrq.gov/db/availability_public.jsp`; last accessed September 8th, 2021).

DOH and NIS time series generally follow similar trends, there are clear and non-trivial differences, in particular at pivotal periods relative to the TennCare disenrollment.

Data Appendix Tables A1 and A2 report the shares of MHD and SUD hospitalizations, and total hospitalizations respectively that appear in the NIS in each year of our study period. We include only hospitals that have positive MHD or SUD hospitalizations in at least one quarter during our study period in our calculations.[24] There are substantial differences across the DOH and the NIS data suggesting that the NIS data are not representative of all community hospitals in Tennessee, which is perhaps not unexpected based on our simulation exercise and cautions from NIS administrators. For instance, in 2000 22% of all community hospitals in Tennessee appeared in the NIS while in 2004 the share had increased to 38%. In 2005 this share declined to 32%, and by 2007 the share fell to 20%. Changes in sample that are concurrent with the policy under study can lead to inaccurate estimates.

We refer to the combined NIS (for non-Tennessee states) and DOH (for Tennessee) dataset as the 'hospitalizations dataset.' We view our large sample size for Tennessee, we have the universe of community hospitals, as an advantage over previous TennCare studies that have relied on smaller, non-state representative datasets for Tennessee. Other studies seeking to use NIS, or other datasets, to investigate single-state treatments may consider such a combination. Or, if data are not available, the potential limitation could be noted in the study.

[24]Some hospitals have zero hospitalizations in a given year-quarter. When creating a percentage measure, we could not divide by zero as this value is undefined. Thus, to avoid losing these observations, we added a value of one to each hospital in our sample. The minimum for year-quarters is therefore one as opposed to zero. This change shifts the distribution but does not affect the coefficient estimates. We test whether the disenrollment influenced the probability that a hospital has any MHD or SUD hospitalizations using the empirical model outlined in Equation (1). The coefficient estimate and associated standard error for are -0.004 and 0.008. Thus, we observe no statistically significant evidence that the disenrollment influenced this probability.

Table A1: Share of all hospitalizations captured by NIS: Hospitals with hospitalizations patients ages 21−64 years

Year	Share of TN hospitals with > 0 psychiatric hospitalizations appearing in NIS
2002	25.56
2003	27.56
2004	27.11
2005	26.33
2006	21.99
2007	22.26

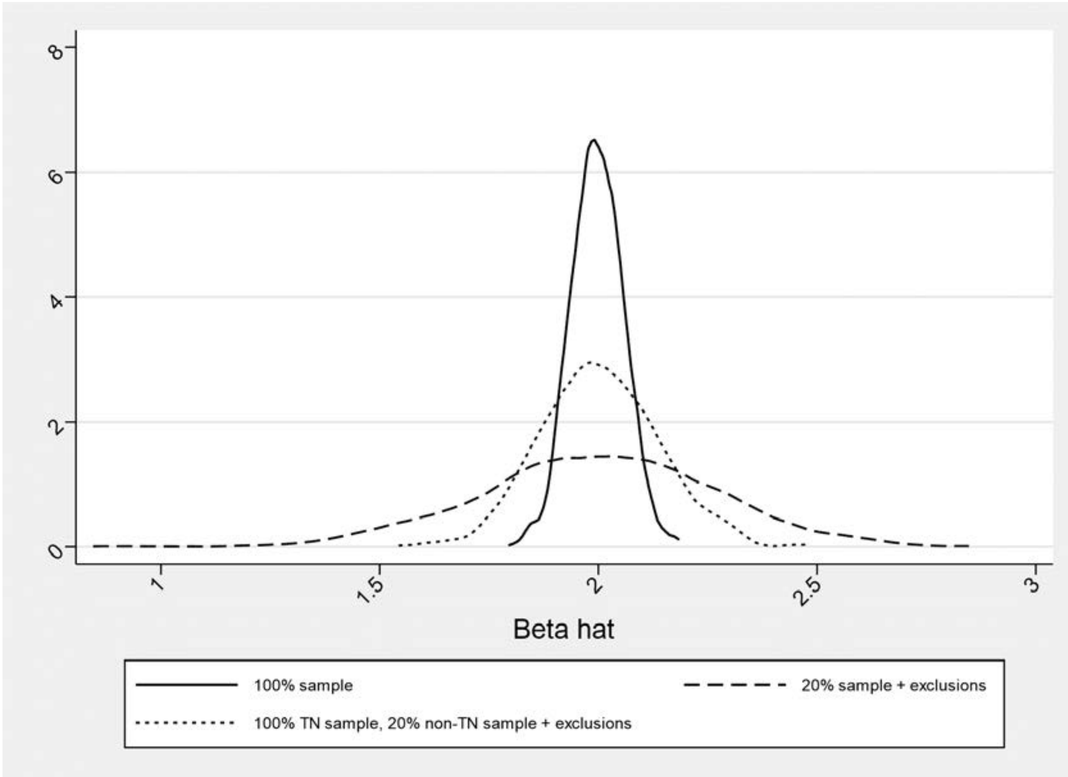
Notes: Denominator is the number of community hospitalizations in the Tennessee Department of Health data. Numerator is the number of community hospitalizations in the NIS. The numbers are very similar when MHD and SUD hospitalizations are measured separately.

Table A2: Share of all hospitalizations captured by NIS: Hospitals with hospitalizations among patients ages 21−64 years

Year	Share of all TN hospitalizations appearing in NIS
2002	29.61
2003	34.79
2004	38.20
2005	31.71
2006	32.91
2007	20.20

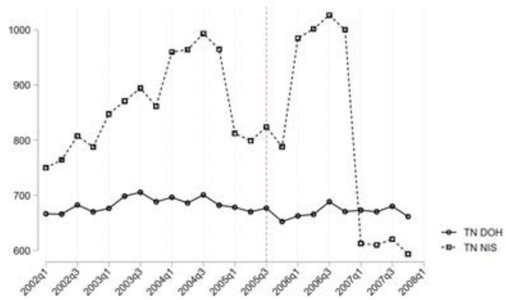
Notes: The denominator is the number of community hospitalizations in the Tennessee Department of Health data. The numerator is the number of community hospitalizations in the NIS.

Figure A1: Monte Carlo simulation of estimated treatment effects

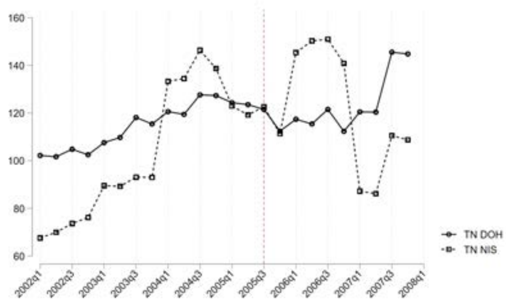


Notes: Each of the four simulations are conducted using 1,000 repetitions. Data is generated such that the true value of the treatment effect is two. See text for full details.

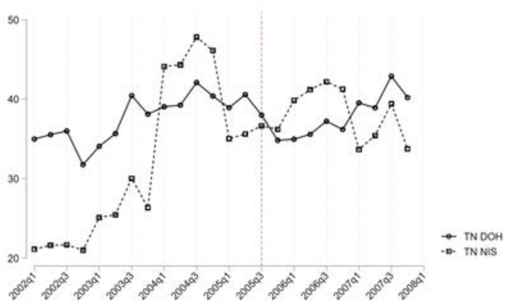
Figure A2: Effect of TennCare disenrollment on psychiatric hospitalization payment sources among adults 21-64 years per hospital-quarter using an event study: Hospitalization data 2002-2007.



Total hospitalizations



MHD hospitalizations



SUD hospitalizations

Notes: Outcomes are quarterly averages of hospitalizations among patients 21 to 64 years. DOH = Tennessee Department of Health data.