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LOSING INSURANCE AND BEHAVIORAL HEALTH INPATIENT CARE: EVIDENCE FROM A LARGE-SCALE MEDICAID DISENROLLMENT

Johanna Catherine Maclean
Sebastian Tello-Trillo
Douglas Webber

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ABSTRACT

We study the effects of losing insurance on behavioral health – defined as mental health and substance use disorder (SUD) – on community hospitalizations. We leverage variation in public insurance coverage eligibility offered by a large-scale and unexpected Medicaid disenrollment in Tennessee. Losing insurance did not influence behavioral healthcare hospitalizations. Mental illness hospitalization financing was partially shifted to other forms of insurance while SUD treatment financing shifted entirely to patients. Combining our findings with previous work on public insurance gains suggests that demand for behavioral healthcare services is asymmetric: service use increases following a gain but does not decline after a loss. We are the first to document this finding. We also investigate the implications of reliance on data that is not representative at the level of treatment and propose a possible solution.

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

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

Sebastian Tello-Trillo
Frank Batten School of Leadership and Public Polic
University of Virginia
Charlotesville, VA 22903
sebastian.tello@virginia.edu

1. Introduction

In this study, we provide the first evidence on the effect of losing insurance on behavioral healthcare hospitalizations – defined as mental illness and substance use disorder (SUD) services received in community hospitals. We exploit exogenous variation in public insurance coverage eligibility generated by one of the largest disenrollments in the history of the Medicaid program: a 2005 disenrollment in the state of Tennessee. This disenrollment resulted in 190,000 enrollees, 10% of those enrolled in Medicaid in Tennessee and 3% of the total state population (Chang and Steinberg 2014), losing Medicaid (also referred to as 'TennCare'). A conservative estimate suggests that 31% of TennCare disenrollees – approximately 59,000 individuals – had a serious behavioral health condition in 2004.[1] TennCare generously covered a wide range of efficacious behavioral healthcare services including medications, counseling services, and specialty inpatient treatment. Thus, the disenrollment plausibly reduced access to affordable and valuable treatment. We examine administrative data on behavioral health-related hospitalizations coupled with differences-in-differences methods to study TennCare effects.

Evidence gleaned from the TennCare disenrollment can offer insight into the effects of public insurance on behavioral health more broadly within the U.S. The population that lost TennCare coverage shares similar demographics with the population that gained Medicaid eligibility under the Affordable Care Act (ACA) of 2010: low-income childless and non-disabled adults (Garthwaite, Gross, and Notowidigdo 2014). This population has elevated prevalence of

[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 had serious psychological distress or an SUD. 24% of this population had serious psychological distress and 12% had an SUD, leading to 31% of this sample either condition. We consider this estimate to understate the number disenrolled individuals who could benefit from the behavioral healthcare services offered by TennCare coverage as we consider only serious conditions. For instance, 92% of this population had some level of psychological distress. Further, the financial strain and general shock associated with unexpectedly losing insurance could potentially exacerbate behavioral health conditions, translating a less serious condition into a serious one.

mental illness and SUDs relative to groups traditionally Medicaid eligible and the privately insured (Garfield et al. 2011, Busch et al. 2013), and may therefore value TennCare coverage.

Understanding the effects of losing public insurance generally, and coverage for behavioral health conditions specifically, is important given that the future of the ACA Medicaid expansion and the Medicaid program itself is not secure. There have been multiple recent Congressional attempts to repeal Medicaid expansion and required coverage of behavioral healthcare services (e.g., 115 Congress of the United States (2017)).[2] Healthcare scholars note that losses from such government actions will be disproportionately borne by those will mental illness and SUDs (Frank and Glied 2017). There are also calls from policymakers to convert Medicaid from an entitlement to a block grant program. Such a change in program structure could lead to large-scale coverage losses (Goodman-Bacon and Nikpay 2017). Further, 27 states have an 1115 Medicaid Waiver pending or approved that compels some Medicaid enrollees to work, seek employment, or perform other pro-social activities to remain eligible (Kaiser Commission on Medicaid and the Uninsured 2019). Simulation analyses imply that these waivers, if applied nationally, will cause up to 4M of the 23.5M currently eligible enrollees to lose coverage (Kaiser Commission on Medicaid and the Uninsured 2018).

Demand theory predicts that insurance, by reducing the out-of-pocket price faced by consumers, should increase the quantity of healthcare demanded (Grossman 1972). Further, if ambulatory care and hospitalizations are substitutes, a loss of insurance may lead patients to substitute to emergency room treatment as federal law requires hospitals to stabilize patients

[2] In addition, see for example, https://www.politico.com/story/2019/01/11/trump-bypass-congress-medicaid-plan-1078885 (last accessed February 16th, 2020).

regardless of ability to pay.[3] Numerous studies that rely on quasi-experimental methods document behavioral healthcare service use increased and service financing shifted to Medicaid following a Medicaid expansion (Maclean and Saloner 2019; Grooms and Ortega 2019; Maclean et al. 2018; Meinhofer and Witman 2018; Wen, Hockenberry, and Cummings 2017; Wen, Druss, and Cummings 2015; Wen et al. 2017; Golberstein and Gonzales 2015).

A contribution of our study is that we are able to test the effect of *losing*, as opposed to *gaining*, insurance. We are the first to study this change within the context of behavioral healthcare service use and financing. The literature has focused on the effect of insurance *gains* due to available sources of quasi-experimental variation, but the effects of insurance gains and losses are not likely symmetric. For instance, an individual who loses insurance can retain accumulated 'patient education,' which includes information on one's health stock, how to manage chronic conditions, the importance of a healthy lifestyle, 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.

Several studies have used the TennCare experience to investigate the question of insurance elasticity asymmetry in the context of general health and healthcare (see Section 2.3). However, there are numerous reasons to suspect that the noted asymmetry in insurance gains/losses differs for general vs. behavioral health and service use, and thus offers premise for a separate study of behavioral health. First, a substantial fraction of SUD and mental illness care has historically been provided for free and/or at a heavy discount, with insurance playing a relatively modest role in the financing of behavioral healthcare (this is particularly true for SUD

[3] The extent to which emergency department care is an empirical substitute for ambulatory care is unclear, however. In particular, following a public insurance gain, Medicaid enrollees appear to use more emergency care and other forms of care, thus use of all services increases. See, for example, Nikpay et al. (2017) and Finkelstein et al. (2012).

care). Charity care may act as a substitute for paid care, thereby muting the effect of an insurance loss on service use. Relatedly, and distinct from much of general healthcare, federal policy in the U.S. has limited the ability to use Medicaid to pay for treatment in important settings, in particular 'Institutions of Mental Disease (IMDs)' that offer inpatient treatment.[4] Further, many healthcare professionals will not accept Medicaid patients, and this practice is particularly common within behavioral healthcare (Wen et al. 2019).[5] More specifically, losing insurance that cannot be used to pay for treatment may not lead to substantial reductions in use or shifts in payment source. Second, the risk of a drug overdose is elevated after prolonged periods of abstinence among those with SUDs (Merrall et al. 2010). An abrupt termination in access to effective treatment could be especially relevant for those in this population. Third, there are severe behavioral healthcare provider shortages in the U.S. (Bishop et al. 2014; Buck 2011); e.g., 77% of counties are classified as having a mental healthcare provider shortage. If losing insurance curtails a patient's access to his/her provider, the patient may be unable to find alternative care. Fourth, patient education may be uniquely important for behavioral health outcomes; e.g., forming relationships with non-substance users, avoiding situations in which substances are used and/or that present triggers for anxiety or depression, and cognitive behavioral techniques to minimize anxiety and/or substance use.

We have several findings. First, we observe no change in mental illness and SUD community hospitalizations in Tennessee post-disenrollment, which mirrors findings for general hospitalizations (Ghosh and Simon 2015). Second, while overall service use was unchanged, the

[4] IMDs are healthcare facilities that offer inpatient treatment for behavioral health conditions with 16 or more beds allocated to behavioral healthcare.
[5] Nearly 50% of specialty SUD treatment providers did not accept Medicaid insurance in 2004 (authors' calculations based on the 2004 National Survey of Substance Abuse Treatment Services, full details available on request).

financing of this care was substantially altered, with the probability that Medicaid was used to pay for treatment declining 25% to 30% post-disenrollment. Mental illness patients were able to substitute lost Medicaid coverage with private and Medicare, but SUD patients financed care themselves. In an extension, we observe no evidence that use of other common modalities of behavioral healthcare -- prescriptions for medications used to treat behavioral health conditions in outpatient settings and treatment in specialized behavioral health facilities -- changed. Thus, our findings stand in contrast to previous work that examines changes in behavioral healthcare service use following an insurance *gain* attributable to a Medicaid expansion and imply that there is asymmetry in insurance effects for behavioral health. In particular, demand may be elastic when there is a gain and inelastic when there is a loss.

We also investigate the use of data that is not representative at the level of treatment, in particular, the implications of using regionally representative data to study a state-level policy. While survey administrators often discourage this practice, it is common in economics.[6] Taking TennCare as a case study, we document using the National Inpatient Sample (NIS) that, due to year-to-year sampling variability, a regionally representative dataset may produce inaccurate estimates at the state-level which can lead to erroneous estimates of treatment effects. We first establish this phenomenon with a Monte Carlo simulation and then document its practical existence by comparing Tennessee data in the NIS with the universe of hospitalizations in Tennessee. Second, to address this issue empirically, we propose a combination of NIS and

[6] For instance, many studies -- including studies that we ourselves have written -- utilize data that is representative at the national or regional level to study state-level treatments. We note that data at the level of treatment is often not available, but nonetheless this study limitation, based on our understanding, is often overlooked, or at least not mentioned, by researchers. We simply note that researchers, when faced with this empirical challenge, could more carefully note this study limitation. See Currie and Gruber (1996), Schmeiser (2009), Kahn (2010), Kaestner and Yarnoff (2011), Kolstad and Kowalski (2012), Miller (2012), Hamersma and Kim (2013), Maclean (2013), Maclean (2014), Anderson, Hansen, and Rees (2015), Maclean (2015), Pacula et al. (2015), Tello-Trillo (2016), Wherry and Miller (2016), DeLeire (2018), and Nicholas and Maclean (2019).

administrative data. Our methods can be applied in other analyses that present this challenge. At minimum, our findings suggest that researchers should be cautious in interpreting findings from data that is not representative at the level of treatment.

2. Background, conceptual framework, and prior research

2.1 Behavioral health and healthcare

The American Psychiatric Association (APA) defines mental illnesses as '…health conditions involving changes in thinking, emotion, or behavior (or a combination of these)' (2015). 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). Mental illnesses and SUDs impose substantial internal costs on the affected individual in terms of morbidity/mortality, healthcare costs, employment problems, and relationship difficulties.

These conditions are common. In the U.S. 19.1% (47.6M) and 7.4% (20.3M) of adults met diagnostic criteria for a mental illness and an SUD respectively in 2018 (Center for Behavioral Health Statistics and Quality 2019). Moreover, the U.S. is in the midst of an alarming and unprecedented fatal drug overdose epidemic, largely attributed to opioids. Indeed, there are 130 fatal opioid overdoses each day (Centers for Disease Control and Prevention 2018). In 2017, over 47,000 U.S. residents died by suicide (Centers for Disease Control and Prevention 2018) and the misuse of alcohol is associated with over 88,000 deaths each year (Centers for Disease Control and Prevention 2013). Annually, mental illness and SUDs cost the U.S.

economy over $1 trillion in healthcare expenditures, disability payments, a less productive work force, and so forth (Insel 2008; Caulkins, Kasunic, and Lee 2014).[7]

There are numerous effective treatment options for mental illness and SUDs (Olfson 2016; Popovici and French 2013; Cuijpers et al. 2011; Hunot et al. 2006; American Psychiatric Association 2006; Scott, Colom, and Vieta 2007; Murphy and Polsky 2016; Lu and McGuire 2002; National Institute on Drug Abuse 2018). For instance, individuals with mental illness can be prescribed psychotropic medications or receive counseling services from primary care providers. Patients can obtain specialized treatment in outpatient, residential, or hospital settings from psychologists, psychiatrists, counsellors, and other healthcare professionals. Comparable modalities of care are available for individuals with SUDs. The majority of inpatient behavioral healthcare in the U.S. is received in community hospitals (Substance Abuse and Mental Health Services Administration 2013), which is the setting that we measure in our data.

Despite the availability of effective treatment options, many individuals with mental illness and SUDs do not receive care or may have substantial delay in receiving care. In 2018, 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 care (Center for Behavioral Health Statistics and Quality 2019). Commonly reported barriers to treatment receipt are inability to pay and lack of insurance coverage (Rowan, McAlpine, and Blewett 2013; Center for Behavioral Health Statistics and Quality 2019). Treatment is likely unaffordable for many low-income and uninsured individuals. For instance, reimbursement rates for a psychiatrist range from $74 to $136 per visit and treatment typically involves a series of

[7] The original estimates are inflated by the authors to 2020 dollars using the Consumer Price Index (CPI)

visits (Mark et al. 2018).[8] Medications used to treat opioid use disorder (i.e., methadone, buprenorphine, and naltrexone) cost $6,359 to $15,008 per year (National Institute on Drug Abuse 2018).[9] Finally, there is evidence that delays in receiving care, which could plausibly occur following an insurance loss, can have negative effects on behavioral health (Reichert and Jacobs 2018; Penttilä et al. 2014).

Behavioral healthcare specialists argue that, for care to be effective, treatment must be appropriate to the patient's needs and be of sufficient duration to stabilize and manage the condition(s) (National Institute on Drug Abuse 2018). One policy approach to addressing underuse (quantity and/or quality) of behavioral healthcare services is the provision of affordable insurance that covers a range of treatment options that allow care to match patient needs. TennCare provided such insurance to low-income and uninsurable Tennessee residents.

2.2 An overview of TennCare and the 2005 disenrollment

Tennessee originally offered a fee-for-service Medicaid program. Due to high costs, the state transitioned to a managed care program in 1994. State legislators anticipated that the transition would reduce program overall 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). The expansion was popular: TennCare covered 22% of the state's population in 2004 (Farrar et al. 2007). TennCare, which used a behavioral healthcare carve out in throughout our study period, generously covered a wide range of efficacious behavioral healthcare services (e.g., medications, assessment and evaluation services, and counseling) at

[8] Authors inflated the original estimates, derived from commercial claims, to 2020 dollars using the CPI.
[9] Estimates inflated by the authors to 2020 dollars using the CPI.

low cost-sharing with limited application of utilization management; e.g., prior authorization (Farrar et al. 2007; Kaiser Family Foundation 2020; Chang and Steinberg 2014).

Due to its popularity and generosity, enrollment surged and TennCare became financially unsustainable for the state (Bennett 2014). In 2004 TennCare accounted for one-third of the state 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 2014).[10] Indeed, as discussed in Section 2.3, several studies document substantial declines in Medicaid coverage, primarily among childless adults, following the dis-enrollment.

2.3 TennCare disenrollment literature

The TennCare disenrollment reduced Medicaid coverage and overall insurance coverage with some private insurance substitution (Tarazi, Green, and Sabik 2017; Garthwaite, Gross, and Notowidigdo 2014; Tello-Trillo 2016; DeLeire 2018). For instance, Garthwaite, Gross, and

[10] 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, we assume that the effects of insurance losses dwarfed the effects of other changes. Moreover, we note that most large-scale insurance policies (e.g., ACA, Massachusetts healthcare reform) include various coverage changes. However, three features of the disenrollment are important to consider. First, continuing enrollees were limited to four prescriptions per month and 20 days of inpatient care per year. All enrollees were treated which complicates the use of a within-state comparison group in a triple difference model (e.g., non-elderly adults with children). Second, the state developed a Health Care Safety Net program, funded with $193M (2020 dollars; inflated by the authors from the original estimate using the CPI), to provide care and assistance to disenrollees. This program included the Mental Health Safety Net (MHSN). There was no such program for SUDs. Reports indicate that registration with the MHSN by disenrollees with a serious mental health disorder was 65%. Disenrollees who registered with MHSN were eligible for some mental healthcare services. The safety net program may have provided a buffer for those who lost insurance. However, this program was financed through a single allotment of state funds which translates to $971 per disenrollee in 2020 dollars. At best, the program was able to provide temporary assistance to disenrollees. Third, community health centers and faith-based organizations were able to absorb some demand from the newly uninsured, but these organizations likely could not offer a full continuum of care. Interviews with disenrollees suggest that many had substantial difficulty accessing needed healthcare services after TennCare was terminated (Farrar et al. 2007). In sum, the available literature clearly shows that the disenrollment had a substantial negative effect on Medicaid enrollment and coverage overall.

Notowidigdo (2014) find that, post-disenrollment, the probability of having Medicaid declined by 33% among low-income, childless, and non-disabled adults. DeLeire (2018) documents a similar decline in Medicaid coverage: 31%.

Five studies have examined the effect of the disenrollment on health and healthcare outcomes using quasi-experimental methods, though none have examined behavioral health outcomes. Given the unique role that insurance has played within the behavior healthcare delivery system, and the characteristics of behavioral healthcare providers and patients, the findings based on general samples of patients and providers are difficult to extrapolate to behavioral health. Our contribution to this literature is to offer a careful study of TennCare on behavioral healthcare use and financing. Further, we consider a wide range of treatment settings to rule out treatment substitution by patients who have lost Medicaid coverage. To the best of our knowledge, we are the first to examine these questions.

Ghosh and Simon (2015) use the NIS and show that, post disenrollment, the share of 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 post-disenrollment. Garthwaite, Gross, and Notowidigdo (2018) use American Hospital Association data and confirm that uncompensated care increased in Tennessee post-disenrollment. Tello-Trillo (2016) leverages survey data from the National Health Interview Survey (NHIS) and Behavioral Risk Factor Surveillance Survey (BRFSS), and finds that post-disenrollment, primary care visits declined and reported physical health problems increased in Tennessee. There were no changes in days in poor mental health or use of inpatient services. Tarazi, Green, and Sabik (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 (2018) uses the Survey of Income and Program Participation and finds that self-assessed health and several forms of healthcare declined post-disenrollment while reports of unmet healthcare need and reliance on charity care increased.

3. Data, variables, and methods

3.1 Community 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 community hospitalizations and are the largest publicly-available U.S. all-payer inpatient healthcare database.[11] The sample reflects a 20% stratified sample of U.S. community hospitals, with five to eight million hospitalizations occurring at over 1,000 hospitals each year. Community hospitals are sampled on region, ownership status, and bed size. In 2007 (the last year of our study period) the weighted NIS sample covered 90% of the universe of discharges and 78% of all community hospitals (Barret, Wilson, and Whalen 2010). The American Hospital Association defines community 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. We aggregate the data to the hospital-quarter level and have 15,799 hospital-quarter observations.[12]

[11] Due to the IMD exclusion, Medicaid could be used to pay for treatment received in some hospitals during our study period. Based on our review, there were possibly five IMDs in operation in Tennessee during our study period, suggesting that the influence of these facilities did not likely biasing our results. Further, we have reviewed state budgets for mental health and SUD treatment services in Tennessee over the disenrollment period and we do not observe any substantial changes in these expenditures. Details available on request.

[12] We considered using elderly adults as a within-state comparison group in a triple difference estimator. The elderly have very different trends in behavioral healthcare service use and financing than the non-elderly. We suspect that elderly adults are different from non-elderly adults in terms of behavioral health; e.g., 7.4% of adults 18 years and older met diagnostic criteria for an SUD while the share was just 1.9% for elderly adults in 2018 (Center for Behavioral Health Statistics and Quality 2019).

In our main analysis, we study the effects of TennCare on behavioral health outcomes treated in inpatient settings within the general healthcare delivery system, in particular in community hospitals. Hospitalizations, including community hospitalizations we study, themselves are an important healthcare service to study as, while relatively rare, they are costly and an essential target in any attempt to contain overall healthcare costs. The median hospitalization cost is $12,497[13] and hospitalizations account for one-third of all civilian healthcare costs (Mirel and Carper 2013; Agency for Healthcare Research and Quality 2019). Hospitalizations may be avoidable through effective, and generally less costly, outpatient care (Akosa Antwi, Moriya, and Simon 2015); outpatient care is a modality that patients may no longer be able to easily access following an insurance loss. Moreover, the majority of psychiatric inpatient admissions in the U.S. occur in community hospitals that are captured by the NIS (Substance Abuse and Mental Health Services Administration 2013). Although we focus on a single modality in our main analysis, this modality is both common and relevant.

Our study period is January 2000 to December 2007. Following Garthwaite, Gross, and Notowidigdo (2014), we close the study period in 2007 to avoid contamination from the large recession of 2008 to 2010. Recessions are linked with insurance (Cawley, Moriya, and Simon 2015; Cawley and Simon 2005), behavioral health (Hollingsworth, Ruhm, and Simon 2017; Carpenter, McClellan, and Rees 2017; Ruhm 2015), and behavioral healthcare use (Bradford and Lastrapes 2013; Maclean, Cantor, and Horn 2019). However, as we show in robustness checking, our results are insensitive to incorporating this time period. Of note, our study period overlaps with the escalation in misuse of prescription opioid medications (e.g., Oxycontin), which may have fueled the current opioid epidemic (Alpert, Powell, and Pacula 2018).

[13] Inflated by the authors to 2020 dollars using the CPI from the original estimate.

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.[14] We study a subset of the population (ages 21 to 64) and specific types of hospitalizations (mental illness and SUD). There are important differences across hospitals that provide different service lines (Horwitz 2005). For instance, behavioral healthcare is a low profit service line, and for-profit hospitals are less likely to offer this line. We are concerned that using the NIS data for Tennessee could lead to reliance on an unrepresentative sample of hospitals.[15] 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 first 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 2000 to 2007.[16] 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 AHRQ administrators to select

[14] 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 February 16th, 2020).
[15] 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 our Monte Carlo simulation. Details available on request.
[16] We use the six digit North American Industry Classification System code 622110.

hospitals for inclusion in the NIS; we note that our simulation does not *exactly* replicate the NIS sampling method. Second, we generate an outcome variable where the data generating process emulates a standard DD functional form.[17] 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 behavioral healthcare and that treat non-elderly adult patients;[18] 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 (see Section 3.3) for hospitals that provide behavioral 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 DD specification in each sampling scheme across 1,000 simulated populations. Full simulation details are available on request.

The simulation results are reported in Figure 1, 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 2). However, the sampling framework employed has consequential implications for the likelihood that the estimated DD parameter will be significantly over- or under-estimated. The difference between region- and state-representativeness matters in a DD context, particularly one in which only a single state is

[17] We generated a variable Y that is determined by a DD estimate (Tennessee interacted with a post-disenrollment period indicator), state fixed effects, year fixed effects, and a random error term. We used Southern states that appear in the NIS (see Section 3.3) to form the comparison group.
[18] 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 behavioral health hospitalizations among non-elderly adults in our main analysis.

treated. In a regionally-representative dataset such as the 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, we see that the distribution of betas 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. However, 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 is what NIS administrators state will occur when the NIS is used for state-level analyses, but researchers often ignore this caution.

A high-variance estimator, like the one arising from the typical state-level analysis NIS 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, see Gelman and Carlin (2014) for a comprehensive discussion of this issue. 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).[19] 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. We note that combining datasets in this manner is not uncommon in economic research (Farber et al. 2018; Schwandt and von Wachter 2020; Altonji, Kahn, and Speer 2016; Webber 2016).[20]

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 mental illness and SUD hospitalizations (Figures 2 and 3) 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 (Figure 4). 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

[19] Of note, the Tennessee NIS data is drawn from the DOH data. Thus, the measures are standardized across the two datasets. However, 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.
[20] 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 February 16th, 2020).

hospitals sampled for the NIS, which further underscores our concern that reliance on the NIS for a single-state analysis may be problematic. The correlation between the DOH and NIS time series are 0.74 (mental illness), 0.76 (SUD), and 0.52 (total). Thus, while the 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.

Tables 1 and 2 report the shares of mental illness 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 mental illness or SUD hospitalizations in at least one quarter during our study period in our calculations.[21] 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; see for example Clemens and Hunt (2017).

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

[21] Some hospitals have zero discharges 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 mental illness 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.

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.

3.2 Outcome variables

First, we consider the number of mental illness and SUD hospitalizations. We separately classify mental illness and SUD hospitalizations based on ICD-9 codes available on the discharge record (specific codes available on request).[22] Second, we consider indicators for expected payment source: Medicaid, any insurance, private insurance, Medicare, and self-pay (which plausibly includes uninsured patients). We have information on up to two expected payers listed by the hospital and code these variables one if the payer is listed as primary or secondary payer, and zero otherwise. We also examine total hospitalizations and payments.

3.3 Empirical model

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

$$BH_{i,s,q,t} = \alpha_0 + \alpha_1 DD_{s,q,t} + X_{s,t}\alpha_2 + \vartheta_q + \tau_t + \delta_i + \varepsilon_{i,s,q,t} \quad (1)$$

$BH_{i,s,q,t}$ is a behavioral healthcare outcome for hospital *i* in state *s* in quarter *q* in year *t*. $DD_{s,q,t}$ is an interaction between the treatment state (Tennessee) and the post-disenrollment period (August 2005 to December 2007). $X_{s,t}$ is a vector of state-level characteristics: demographic information (age, sex, race/ethnicity, and education) from the monthly Current Population Survey (Flood et al. 2020) and the poverty rate from the University of Kentucky Center for Poverty Research (2020). ϑ_q and τ_t are vectors of quarter and year fixed effects. δ_i is

[22] We classify these conditions using reports from Agency for Healthcare Quality and Research (https://www.hcup-us.ahrq.gov/reports/statbriefs/sb117.pdf and https://www.hcup-us.ahrq.gov/reports/statbriefs/sb191-Hospitalization-Mental-Substance-Use-Disorders-2012.pdf; last accessed February 16th, 2020).

a vector of hospital fixed effects which incorporate state fixed effects. We do not control for patient-level variables as the disenrollment plausibly influences them. $\varepsilon_{i,s,q,t}$ is the error term.[23]

We estimate Equation (1) with least squares (LS). We apply NIS weights to the (non-Tennessee) NIS data and weight the DOH data equally. We follow Garthwaite, Gross, and Notowidigdo (2014), and Tello-Trillo (2016) and apply a modified block-bootstrap procedure to calculate standard errors in our main analysis.[24]

We follow, as closely as possible given the states that appear in the NIS, the TennCare literature and use other Southern states as our comparison group (Tello-Trillo 2016; Garthwaite, Gross, and Notowidigdo 2014): Arkansas, Florida, Georgia, Kentucky, Maryland, North Carolina, Oklahoma, South Carolina, Texas, Virginia, and West Virginia.[25] 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.[26]

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[23] We have also estimated a dynamic model in which we divide the post-period into two sub-periods: 'during' the disenrollment (2005; Q3-2006; Q2) and 'after' the disenrollment (2006; Q3-2007; Q4). The dynamic model allows disenrollment effects to vary across the post-period. However, we observe limited evidence of dynamic effects, that is the coefficient estimates on the 'during' and 'after' variables are very similar in sign, magnitude, and statistical significance. Full results available on request.

[24] The standard approach in a DD specification is typically to cluster standard errors at the state-level, see for example the well-known study by Bertrand, Duflo, and Mullainathan (2004). However, our context provides additional empirical challenges to the standard case. In particular, (1) there are only 12 clusters in the data (i.e., a small number of clusters) and (2) only one of the 12 clusters is treated (i.e., the share of the clusters treated is small). Clustering when faced with these two empirical realities can lead to inaccurate estimates of precision. To date the economics literature has not reached consensus on the appropriate inference approach in this context (e.g., the wild bootstrap is the usual suggestion for a small number of clusters, but this approach is not recommended when the percentage of treated clusters is small). Hence, as in several previous TennCare papers, we follow a method that addresses these two issues and has been shown in simulations to have appropriate rejection rates: a modified version of block-bootstrap (Garthwaite, Gross, and Notowidigdo 2014; Tello-Trillo 2016). In addition, we report results using alternative approaches to inference in robustness checking (see Appendix Tables 1A and 1B).

[25] In particular we observe Arkansas 2004 to 2007; Florida 2000 to 2007; Georgia 2000 to 2007; Kentucky 2000 to 2007; Maryland 2000 to 2007; North Carolina 2000 to 2007; Oklahoma 2005 to 2007; South Carolina 2000 to 2007; Tennessee 2000 to 2007; Texas 2000 to 2007; Virginia 2000 to 2005 and 2006 to 2007; and West Virginia 2000 to 2007. We note that some studies within the TennCare literature use within-county variation in Tennessee only, see for example a recent study by Argys et al. (2017).

[26] We considered using synthetic control methods (SCM) (Abadie and Gardeazabal 2003; Abadie, Diamond, and Hainmueller 2010). We do not have a sufficiently long pre-period as required for SCM because ICD codes, which we use to select behavioral health hospitalizations, were updated between 1998 and 1999. There is no method to

A necessary assumption for canonical DD 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').[27] The assumption is untestable as the treatment group is treated in the post-period and hence counterfactual trends are not observed. We attempt to provide suggestive evidence on the ability of our hospitalization data to satisfy this version of the parallel trends assumption. We conduct an event study following Autor (2003) to explore the extent to which our data can potentially satisfy parallel trends.

4. Results

4.1 Summary statistics

Quarterly hospital-level summary statistics using data from the pre-disenrollment period in Tennessee and other Southern states are reported in Table 3. The average numbers of community hospitalizations per quarter for mental illness and SUDs were 107 and 36 in Tennessee hospitals, and 111 and 37 in other Southern hospitals. Total hospitalizations were 671 per quarter in Tennessee hospitals and 927 in other Southern hospitals. Medicaid was the expected payer for 35%, 40%, and 25% of mental illness, SUD, and total hospitalizations in Tennessee. The Medicaid payment shares in other Southern states were: 26 %, 22%, and 25%. The relatively substantial use of Medicaid payment for hospital care within Tennessee vs. other Southern states is in line with the documented generosity of TennCare (see Section 2.2).

4.2 Differences-in-differences analysis of hospitalizations

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crosswalk across the two sets of codes for SUD outcomes. Therefore, we have just five pre-treatment years to establish trends which is not sufficient.

[27] We note that our regression model is a 'reverse' DD model. In the canonical DD treatment is 'turned off' in the pre-period and then 'turned on' in the post-period. Our treatment was turned on in the pre-period and turned off in the post-period. However, as we document in an event study reported later in the manuscript, the comparison states, in the treated state, appear to provide a suitable counterfactual for Tennessee post-disenollment.

Table 4 contains results from the basic DD model outlined in Equation (1). We observe no statistically significance evidence that behavioral healthcare hospitalizations changed following the disenrollment. Moreover, the coefficient estimates are small relative to the baseline means. Further, we do not observe any change in total hospitalizations and the coefficient estimate is, again, very small relative to the baseline mean. We have also explored the effect of the disenrollment on non-behavioral health hospitalizations. We define these as hospitalizations that do not have any code flagging a mental illness or SUD on the entry record. The coefficient estimate is -9.79 and the block-boot-strapped standard error estimate is 19.90. Thus, we observe no evidence that non-behavioral health hospitalizations were altered.

4.3 Internal validity

We estimate an event study in the spirit of Autor (2003) to explore whether our treatment and comparison groups followed parallel trends after adjusting for covariates. More specifically, we include interactions between an indicator for Tennessee and leads and lags reflecting periods around the disenrollment. To smooth out noise in the data, we use six-month period bins to define periods in our event study. The omitted category is the six-month period prior to the TennCare disenrollment (i.e., 2005; Q1-Q2).

Event study estimates (Figures 5 to 7) do not reveal evidence of policy endogeneity or anticipatory behavior by enrollees (e.g., increasing service use prior to losing insurance): coefficient estimates on the lead indicators are small and imprecise, and change signs in a manner that does not suggest a clear trend. We interpret these results to provide suggestive evidence that our hospitalization data can satisfy the above-noted modified version of parallel trends. Examination of the lags confirm our DD estimates: we observe no change in mental illness- or SUD-related hospitalizations post-disenrollment.

4.4 Differences-in-differences analysis of hospitalization payments

We next document the effect of the TennCare disenrollment on the financing of community hospital care (Table 5). Several findings emerge from this analysis. First, in line with previous work, we document a substantial decline in the use of both Medicaid and any insurance to pay for hospitalization care, this pattern is observed across mental illness, SUD, and total hospitalizations although the magnitude for the reduction in any insurance varies to some extent. In particular, we observe a 9 percentage point ('ppt') or 26% (comparing the coefficient estimate with the proportion in Tennessee prior to the disenrollment), 12 ppt (30%), and 7 ppt (28%) reduction in the probability that Medicaid was used to pay for mental illness, SUD, and total hospitalization care. Thus, our findings of Medicaid losses are similar to those documented in the general healthcare literature (see Section 2.3). In terms of any insurance, the declines were as follows: 4 ppts (4%) for mental illness, 10 ppts (11%) for SUD, and 4 ppts (5%) for total hospitalizations. One interpretation of these findings is that SUD patients experienced larger declines in the use of any insurance to pay for treatment than mental illness or all patients. However, confidence intervals overlap and we do not wish to overstate heterogeneity, instead we simply note this possibility. Further, because we do not observe changes along the extensive margin (i.e., the number of hospitalizations), we do not believe that compositional shift in patients receiving treatment can fully explain our findings.[28]

We next explore how patients financed care following the disenrollment, and the ensuing loss of Medicaid, by examining other insurance forms and self-pay. Put differently, were patients able to 'fill the Medicaid gap?' Mental illness patients replaced lost Medicaid coverage

[28] Of course, we acknowledge that we cannot rule out the possibility that there were identical increases and decreases in the types of patients in treatment, leaving the net number unchanged.

with private coverage (2 ppts or 7%) and Medicare (2 ppts or 6%). SUD patients instead used self-payments to offset lost Medicaid (9 ppts or 69%). Among all patients, Medicaid losses were replaced with Medicare only (2 ppts or 13%). These findings offer suggestive evidence that different types of patients potentially had heterogeneous responses to losing Medicaid coverage. Mental illness patients and patients overall were able to, at least partially, fill the Medicaid gap with other insurance forms (a mixture of private coverage and Medicare for the former and Medicare for the latter), while SUD patients relied on their own finances (self-pay). Given that self-payments often translate into uncompensated care, hospitals that delivered SUD treatment in Tennessee may have also borne some of the financial burden of lost Medicaid coverage.

4.5 Comparison of the universe of community hospitals with NIS data for Tennessee

We next consider the effect of the disenrollment on mental illness, SUD, and total hospital hospitalizations and payments using the NIS data only; our treatment group is now defined using the NIS data and our comparison group is unchanged (Tables 6 and 7). Our findings based on the NIS depart from our main results in several non-trivial ways.

First, the baseline means and proportions in the NIS and DOH data differ; this pattern was foreshadowed in Section 3.1. For instance, the number of mental illness, SUD, and total hospitalizations in Tennessee prior to the disenrollment was 92, 29, and 764, respectively (Table 6) vs. 107, 36, and 671 in the DOH data (Table 3). Thus, Tennessee community hospitals appearing in the NIS are smaller in terms of quarterly discharges than the average community hospital in this state. Second, in terms of payments, following the disenrollment we observe declines in Medicaid as a source of payments for mental illness, SUD, and total hospitalizations but the relative effect sizes were more modest: 19% vs. 26%, 22% vs. 30%, and 17% vs. 28%, respectively. The absolute effect sizes are more comparable across datasets, but the baseline payment proportions are quite different. For instance, pre-disenrollment in the NIS Medicaid coverage was 52%, 45%, and 47% for mental illness, SUD, and total hospitalizations while in the DOH the comparable coverage rates were 35%, 40%, and 25%. Thus, the NIS Tennessee community hospitals were substantially more likely to accept Medicaid than the average community hospital within the state, which implies that relative effect sizes are much smaller. Interestingly, when using the NIS data to form the treatment group, we find no statistically significant evidence that patients for any type of service were able to find alternative sources of coverage: the coefficient estimates for private and Medicare coverage are small and statistically indistinguishable from zero. Thus, using the NIS data to form the comparison group appear to *over-estimate* the extent to which many patients bore the financial hospitalization costs attributable to the disenrollment.

4.6 Additional treatment settings and behavioral health outcomes

Thus far we have focused our attention on community hospitalizations only. While this is an important modality (see Section 1), we acknowledge that there are other settings that are also valuable to patients. Further, other modalities may be substitutes for hospitalizations. Thus, we next use additional datasets that capture different treatment modalities that are commonly used within the U.S. (Center for Behavioral Health Statistics and Quality 2019).

First, we consider prescriptions for mental illnesses and SUDs prescribed in outpatient settings using the Medicaid State Drug Utilization Database (SDUD). These data are comprised of all filled outpatient prescriptions purchased at online or retail pharmacies and covered under the Medicaid Drug Rebate Program financed by Medicaid (U.S. Department of Health and Human Services 2012). Medicaid programs collect these data to bill pharmaceutical manufacturers for rebates, and states pass this information to the Centers for Medicare and

Medicaid Services (CMS). The SDUD have been used to study Medicaid expansion effects on behavioral health prescription fills (Maclean and Saloner 2019; Maclean et al. 2018; Cher, Morden, and Meara 2019; Meinhofer and Witman 2018).[29]

We follow coding schemes developed by Maclean et al. (2018), and Maclean and Saloner (2019) to classify medications likely to be used to treat mental illness and SUDs in outpatient settings, we note that medications are often used to treat multiple conditions; e.g., bupropion is used to for both smoking cessation and depression (Maclean, Pesko, and Hill 2019). We aggregate the SDUD to the state-year-quarter level and convert prescription counts to the rate per 100,000 non-elderly adults in each state.

Second, we draw data from the Treatment Episode Data Set (TEDS), a federally mandated database for all specialty SUD treatment providers that accept public funding or are otherwise subject to state regulation. These data are maintained by the Substance Abuse and Mental Health Services Administration (SAMHSA) and capture approximately two-thirds of specialty SUD treatment in the U.S. and disproportionately measure facilities that receive public funding (Dave and Mukerjee 2011), thus TEDS plausibly includes facilities in which Medicaid enrollees and the uninsured may receive specialty treatment. Specialty care is treatment received in a hospital,[30] residential facility, or outpatient facility with a specific program for SUD treatment. Further, TEDS are regularly used by economists to study SUD treatment (Maclean and Saloner 2019; Meinhofer and Witman 2018; Grooms and Ortega 2019; Saloner et al. 2018;

[29] Over our study period the SDUD included prescriptions reimbursed by fee-for-service (FFS) Medicaid programs only. However, managed care Medicaid, such as TennCare, generally carved behavioral healthcare delivery from the managed care program and used FFS to cover associated services. Thus, we expect that the medications for TennCare, which did use a carve out plan for behavioral health, will appear in the SDUD.

[30] Hospitals captured in TEDS are not likely community hospitals as TEDS captures specialty SUD providers and are therefore more likely to be psychiatric hospitals.

Popovici et al. 2018; Dave and Mukerjee 2011; Grecu, Dave, and Saffer 2019; Powell, Pacula, and Jacobson 2018). We consider two outcomes: the total number of admissions and the number of admissions for patients with a co-occurring mental illness.[31] Unfortunately, we do not have access to a comparable data set for mental healthcare treatment, thus our second measure acts as a proxy (albeit imperfect) for specialty mental illness treatment receipt. We convert our admissions to the annual rate per 100,000 non-elderly adults using data on age-shares from the CPS and population from the U.S. Census (Flood et al. 2020; University of Kentucky Center for Poverty Research 2020). The TEDS does not include admission date, thus we cannot use a finer time period than the year.

For comparability with our hospitalization analysis, we use only state-year pairs in the South region (i.e., our comparison group) that are recorded in the NIS data (as outlined in Section 3.3) although results are not appreciably different if we use all Southern states to form the comparison group, these results are available on request from the authors. Similar to our main hospitalization analysis, we observe no change in either medications or specialty care admissions (Tables 8 and 9). Broadly, we conclude that losing Medicaid coverage did not restrict access to behavioral healthcare, at least across the modalities that we are able to consider.

We next examine TennCare effects on behavioral health outcomes: (i) suicides, and (ii) unintentional fatal alcohol poisonings and drug overdoses. The purpose of this exercise is allow us to examine if losing TennCare influenced behavioral health. While we show that there was no

[31] We note that TEDS includes both inpatient and outpatient SUD treatment. Thus, not all entries in the TEDS reflect a patient being admitted to treatment. We use the term admissions for brevity and to be in line with language used in previous TEDS studies; e.g., Maclean and Saloner (2019). We have also estimated similar regressions using the National Survey of Substance Abuse Treatment Services (N-SSATS). The N-SSATS is also maintained by SAMHSA but has a different survey frame than the TEDS. Results are comparable. We choose to emphasize the TEDS in our study as this data set allows us to better proxy treatment for mental illness than N-SSATS.

change in treatment receipt, i.e. the extensive margin of treatment, we have not explored the possibility that *quality* of treatment changed following the disenrollment. For example, uninsured patients may have had shorter stays and/or lower quality treatment more broadly (e.g., less time spent with healthcare professionals). Further, we show changes in how hospitalizations were financed post-disenrollment, in particular, SUD patients appeared to shoulder the burden of treatment post-disenrollment and treatment is costly (see Section 1). Relatedly, Argys et al. (2017) establish that losing public insurance reduced financial security and financial strain has been linked with behavioral health outcomes (Maclean, Webber, and French 2015).

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, and are used by economists to study behavioral health (Lang 2013; Ruhm 2018). We select all related deaths for adults 21 to 64 in each quarter 2000 to 2007 for Tennessee and other Southern states that appear in the NIS data. Deaths are expressed as a quarterly rate per 100,000 adults 21 to 64 and weighted by the state non-elderly adult population.[32] Results are reported in Table 10. We observe no change in suicides post-disenrollment, which is in line with the null findings of Tello-Trillo (2016) using survey data on days in bad mental health, but fatal alcohol poisonings and drug overdoses increased by 0.97 deaths per 100,000 non-elderly adults (36%).[33]

5. Robustness checks

[32] 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). More details available on request

[33] Recent work raises the concerns related to statistical power in estimating the effects of insurance policies on mortality because this outcome is rare (Black et al. 2019). In unreported analyses, we conduct a post-hoc power analysis. Results, available on request, suggest that we are able to detect effect sizes of the magnitudes that we estimate for (i) suicides, and (ii) fatal alcohol poisonings and drug overdose deaths with approximately 80% power.

We report a serious of robustness checks. Reassuringly, are findings are generally stable. For brevity, when examining our hospitalization data, we report results for behavioral health treatment only. Results for total hospitalizations are available on request.

5.1 Alternative approach to statistical inference

In our main analysis, we apply a block-bootstrap approach to calculate our standard errors. However, we next show that the precision of our estimates is not markedly different if we instead apply other approaches: estimate classical standard errors that assume homoscedasticity, clustering standard errors at the state-level (Ghosh and Simon, 2015), or applying randomization inference. In randomization inference, we sequentially treat each Southern state that appears in the NIS data as the treated unit and re-estimate Equation (1), then observing where our main coefficient estimate (i.e., correctly treating Tennessee as the state that experienced a major Medicaid disenrollment) falls within this distribution. Results from these additional analyses are reported in Appendix Tables 1A and 1B. We note that assuming homoscedasticity leads to smaller estimated standard errors.

5.2 Alternative comparison groups, specifications, and time periods

We re-estimate Equation (1) using alternative time periods, comparison groups, and specifications. We: (i) exclude 2005 (the year of the disenrollment), (ii) exclude the 3rd and 4th quarters of 2007 (as we observe, in unadjusted trends available on request, an uptick in hospitalizations for mental illness in that time period in Tennessee), (iii) include the 2008 to 2010 recession period, (iv) drop Texas and Georgia from our comparison group -- we exclude these states as their Medicaid programs appear, based on available evidence, to cover behavioral healthcare services less generously than Tennessee over our study period (Kaiser Family Foundation 2020), (v) estimate unweighted LS regressions, (iv) include a separate linear trend for Tennessee and all other Southern states in the NIS, (vii) exclude time-varying controls, and (viii) aggregate to the state-time level. Results are reported in Appendix Tables 2A, 2B, and 2C. While there are some changes in the coefficient estimates and their precision, overall our findings on SUD are broadly robust to these various checks.

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 (Moffitt 1992). To explore this possibility, we draw micro-level data from the Annual and Social Economic Supplement (ASEC) to the CPS between 2001 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 2001 to 2008 pertains to migration 2000 to 2007. We exclude those respondents with family income > 400% FPL as such respondents are not likely to be eligible for Medicaid in any state in our analysis sample. We apply ASEC sample weights. Results are reported in Appendix Table 3. We observe no statistically significant evidence that the disenrollment altered migration propensities.

6. Discussion

We provide new evidence on the effect of losing public insurance on behavioral health community hospitalizations and related outcomes. 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 behavioral healthcare by leveraging plausibly exogenous variation offered by a large and unexpected Medicaid disenrollment. To the best of our knowledge, we are the first study to document this elasticity. Second, the source of variation in our empirical models, TennCare disenrollment – one of the largest disenrollments in the history of the Medicaid program, allows us to provide evidence that can inform the current policy debate surrounding proposed changes to the Affordable Care Act (ACA) and Medicaid generally. In particular, we can shed light on the possible behavioral health implications from repealing ACA Medicaid expansions, converting Medicaid to a block grant program, and imposing work and other pro-social activity requirements on enrollees, all of which could reduce Medicaid enrollment and have been proposed by policy makers (Goodman-Bacon and Nikpay 2017). These findings are potentially in non-U.S. settings as well as they speak to the insurance elasticity of demand for behavioral healthcare services and can inform policy decisions regarding curtailing coverage for lower-income populations.

We note that a series of studies have estimated TennCare effects on general healthcare and health outcomes. Our unique contribution is to provide the first evidence on how this major disenrollment influenced behavioral healthcare, coverage among those with behavioral health conditions, and behavior health. There are stark differences in terms of patients, insurance, and providers across behavioral and general health, thus separate study of behavior health is necessary to fully understand the impact of losing Medicaid.

We find no evidence that mental illness- or SUD-related community hospitalizations decline following an insurance loss. Further, we do not observe changes in other common modalities of care (i.e., treatment received in specialized behavioral health facilities or primary care). Therefore, and distinct from studies that examine the effects of gaining public coverage on these outcomes, we find that demand for these services is inelastic. While there is no change in service use post-disenrollment, there is a non-trivial shift in treatment financing, with heterogeneity across patients with behavioral health conditions. In particular, and similar to previous work on general healthcare, the use of Medicaid and any insurance to pay for behavioral healthcare declined post-disenrollment by 25% to 30%, which is in line with findings based on general populations. Mental illness patients are able to partially substitute other insurance, but SUD patients fully finance treatment post-disenrollment. We suspect that the deeper penetration of insurance payments within the mental healthcare delivery system explains this heterogeneity, although we note that there are potentially other factors such as differences in patients who receive these two types of care. Shouldering the costs of SUD treatment, which include chronic conditions and multiple treatment episodes for most individuals, potentially implies a non-trivial increase in medical financial burden for disenrolled Medicaid patients.

We can compare our findings to studies that have examined the effect of pre- and post-ACA state Medicaid expansions (Wen, Hockenberry, and Cummings 2017; Wen, Druss, and Cummings 2015; Meinhofer and Witman 2018; Maclean et al. 2018; Ghosh, Simon, and Sommers 2019; Cher, Morden, and Meara 2019; Grooms and Ortega 2019) and the Oregon Medicaid experiment (Baicker et al. 2017). Broadly studies that rely on quasi-experimental methods show that gaining public insurance increases service use, with effect sizes as large as a more than 100% increase (Meinhofer and Witman 2018). In contrast, we find no change in hospitalizations, prescription medications obtained in outpatient settings, or specialty care following an insurance loss. Our null findings for SUD treatment are similar to results based on experimental data from the Oregon Medicaid experience (Baicker et al. 2017).[34] However, we do observe a comparable decline in the use of Medicaid as a source of payments, our effect sizes are similar in size but – as expected – opposite in sign. Thus, as we hypothesized, the insurance-demand for behavioral healthcare is asymmetric: service use increased following a gain but did

[34] The authors find no difference in the use of medications used to treat opioid use disorder between low-income adults randomized to the treatment group and the control group (Baicker et al. 2017).

not decline following a loss. This finding suggests that, instead of foregoing treatment, the financial burden shifted from Medicaid to other payers.

Finally, our case study of Tennessee suggests that researchers should be cautious when using regionally representative datasets to study state-level interventions. This caution plausibly extends to a broader set of studies in which the selected dataset is not representative at the level of treatment; we encourage more work on this understudied question.

In summary, we offer the first evidence of the effect of losing insurance on behavioral healthcare and financing. These findings may be useful for policymakers considering changes to Medicaid. Finally, we highlight that researchers must take particular care in the estimation of single-state treatments. While previous work has documented the importance of carefully selecting a comparison group (Abadie, Diamond, and Hainmueller 2010, Angrist and Pischke 2010), we add to this discussion by showing that the data used to study such treatments must provide the researcher with accurate representation at the treatment state-level.

Table 1. Share of all hospitalizations captured by NIS: Hospitals with discharges among patients ages 21-64 years

Year	Share of all Tennessee hospitals with >0 behavioral health hospitalizations appearing in NIS
2000	24.31
2001	27.91
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 mental illness and SUD hospitalizations are measured separately.

Table 2. Share of all hospitalizations captured by NIS: Hospitals with discharges among patients ages 21-64 years

Year	Share of all Tennessee hospitalizations appearing in NIS
2000	22.25
2001	23.99
2002	29.61
2003	34.79
2004	38.20
2005	31.71
2006	32.91
2007	20.20

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.

Table 3. Quarterly Hospital-level summary statistics in Tennessee and other Southern states in the pre-TennCare disenrollment period among adults 21 to 64 years: Hospitalization data 2000-2005 Q2

Sample:	**Tennessee**	**Other Southern states┼**
Hospitalizations:(Average per hospital per quarter)		
Mental illness	107.01	110.50
SUD	36.21	37.17
Total	670.82	927.32
Expected primary payer mental illness hospitalizations		
Medicaid	0.35	0.26
Any insurance	0.96	0.76
Private insurance	0.29	0.34
Medicare	0.32	0.25
Self-pay	0.04	0.13
Expected payer SUD hospitalizations		
Medicaid	0.40	0.22
Any insurance	0.87	0.55
Private insurance	0.23	0.22
Medicare	0.24	0.16
Self-pay	0.13	0.22
Expected payer total hospitalizations		
Medicaid	0.25	0.25
Any insurance	0.74	0.82
Private insurance	0.34	0.45
Medicare	0.15	0.19
Self-pay	0.04	0.16
State level demographics		
Age	36.04	35.67
% male	48.9	48.8
% female	51.1	51.2
% white	80.8	79.1
% African American	17.0	17.0
% other race	2.2	3.9
% Hispanic	4.7	16.0
% less than high school	39.09	40.01
% high school	26.39	24.19
% some college	19.06	19.36
% college or more	15.46	16.44
% poverty	14.55	13.69
Population 21-64 years	3,529,292	7,164,659
Observations (Hospitals x time)	3,195	8,440
Observations (Hospitals)	143	1,059

Notes: The unit of observation is the hospital-state-quarter. The data are equally weighted in the Tennessee Department of Health data and weighted by NIS weights for the comparison group.
┼We include other Southern states that appear in the NIS (see Section 3.3).

Table 4. Effect of TennCare disenrollment on hospitalizations by adults 21-64 years per hospital-quarter: Hospitalizations data 2000-2007

Outcome:	Mental illness hospitalizations	SUD hospitalizations	Total hospitalizations
Mean in TN adults 21-64 years, pre-disenrollment	107.01	36.21	670.82
DD	0.49	-2.67	-10.55
	(10.33)	(4.70)	(26.09)
Observations	15,554	15,554	15,799

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted in the Tennessee Department of Health data and weighted by NIS weights for the comparison group. We note that sample sizes are modestly smaller in the mental illness and SUD hospitalization samples than in the total hospitalization sample. The difference is attributable to 245 observations that lack ICD-9 information that we use to classify mental illness and SUD hospitalizations.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Table 5. Effect of TennCare disenrollment on expected payer source among adults 21-64 years: Hospitalization data 2000-2007

Outcome:	Medicaid	Any insurance	Private	Medicare	Self-Pay
Mental illness hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.35	0.96	0.29	0.32	0.04
Baseline model					
DD	-0.09***	-0.04**	0.02*	0.02*	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	15,522	15,522	15,522	15,522	15,522
SUD hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.40	0.87	0.23	0.24	0.13
Baseline model					
DD	-0.12***	-0.10***	0.00	0.01	0.09***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Observations	15,276	15,276	15,276	15,276	15,276
Total hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.25	0.74	0.34	0.15	0.04
Baseline model					
DD	-0.07***	-0.04**	-0.00	0.02***	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	15,799	15,799	15,799	15,799	15,799

Notes: The unit of observation is the discharge-hospital-state-quarter. All models estimated with LPM and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted in the Tennessee Department of Health data and weighted by NIS weights for the comparison group. We note that sample sizes are modestly smaller in the mental illness and SUD hospitalization samples that in the total hospitalization sample. The difference is attributable to 245 observations that lack ICD-9 information that we use to classify mental illness and SUD hospitalizations. Further, we have some missing information on payment, leading to differences in the payment samples vs. the hospitalization samples. ***,**, *= statistically different from zero at the 1%,5%,10% level.

Table 6. Effect of TennCare disenrollment on hospitalizations among adults 21-64 years using NIS data for Tennessee: NIS only data 2000-2007

Outcome:	**Mental illness hospitalizations**	**SUD hospitalizations**	**Total hospitalizations**
Mean in TN adults 21-64 years, pre-disenrollment	91.59	28.99	764.01
Baseline model			
DD	-11.25 (9.30)	-0.05 (4.22)	-26.22 (25.85)
Observations	12,580	12,580	12,580

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are weighted by NIS weights.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Table 7. Effect of TennCare disenrollment on expected payer source among adults 21-64 years using NIS data for Tennessee: NIS only data 2000-2007

Outcome:	**Medicaid**	**Any insurance**	**Private**	**Medicare**	**Self-Pay**
Mental illness hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.52	0.84	0.26	0.30	0.07
Baseline model					
DD	-0.10*** (0.02)	-0.06*** (0.01)	0.02 (0.01)	0.01 (0.01)	0.04*** (0.01)
Observations	12,580	12,580	12,580	12,580	12,580
SUD hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.45	0.67	0.17	0.19	0.13
Baseline model					
DD	-0.10*** (0.02)	-0.09*** (0.02)	-0.01 (0.01)	0.02 (0.01)	0.08*** (0.02)
Observations	12,580	12,580	12,580	12,580	12,580
Total hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.47	0.90	0.38	0.23	0.09
Baseline model					
DD	-0.08*** (0.01)	-0.07*** (0.01)	0.00 (0.01)	0.00 (0.01)	0.05*** (0.01)
Observations	12,580	12,580	12,580	12,580	12,580

Notes: The unit of observation is the discharge-hospital-state-quarter. All models estimated with LPM and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted by NIS weights for the comparison group.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Table 8. The effect of the TennCare disenrollment on Medicaid-financed prescriptions per 100,000 non-elderly adults for behavioral health medications prescribed in outpatient settings: SDUD 2000-2007

Outcome:	Mental health medications	SUD medications
Mean in TN adults 21-64 years, pre-disenrollment	1,139,167	6,895
DD	215,379	3,987
	(98,193)	(5,801)
Observations	352	350

Notes: The unit of observation is the state-year-quarter. All models estimated with LS and control for state demographics, and state, year, and quarter fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are weighted by the state population ages 21-64 years.
***,**,*= statistically different from zero at the 1%,5%,10% level.

Table 9. The effect of the TennCare disenrollment on admissions to specialty behavioral healthcare treatment per 100,000 non-elderly adults: TEDS 2000-2007

Outcome:	All admissions	Admissions for patients with co-occurring mental illness
Mean in TN adults 21-64 years, pre-disenrollment	251.8	18.05
Panel B:		
DD	161.09	67.77
	(111.79)	(46.16)
Observations	85	85

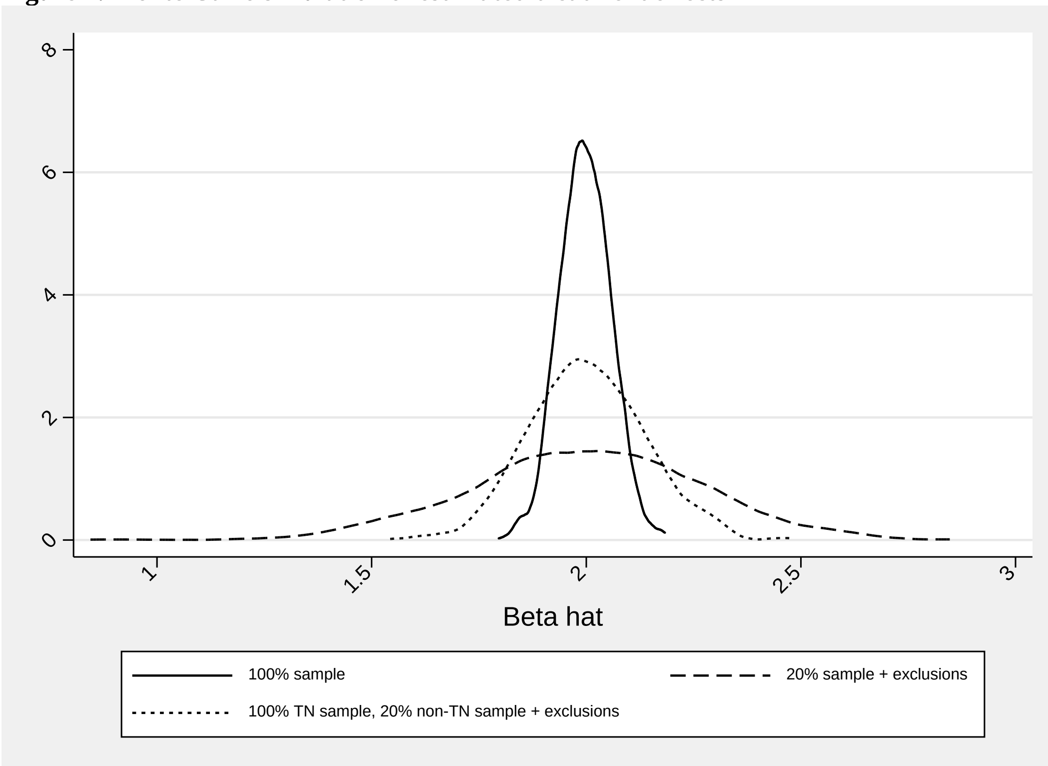
Notes: The unit of observation is the state-year-quarter. All models estimated with LS and control for state demographics, and state, year, and quarter fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are weighted by the state population ages 21-64 years.
***,**,*= statistically different from zero at the 1%,5%,10% level.

Table 10. Effect of TennCare disenrollment on suicide rates, and fatal alcohol poisonings and drug overdoses among adults ages 21-64 years: NVSS 2000-2007

Outcome:	**Suicides per 100,000**	**Fatal alcohol poisonings and drug overdoses per 100,000**
Mean in TN adults 21-64 years, pre-disenrollment	4.25	2.72
Baseline model		
DD	0.36	0.97***
	(0.18)	(0.29)
Observations	544	544

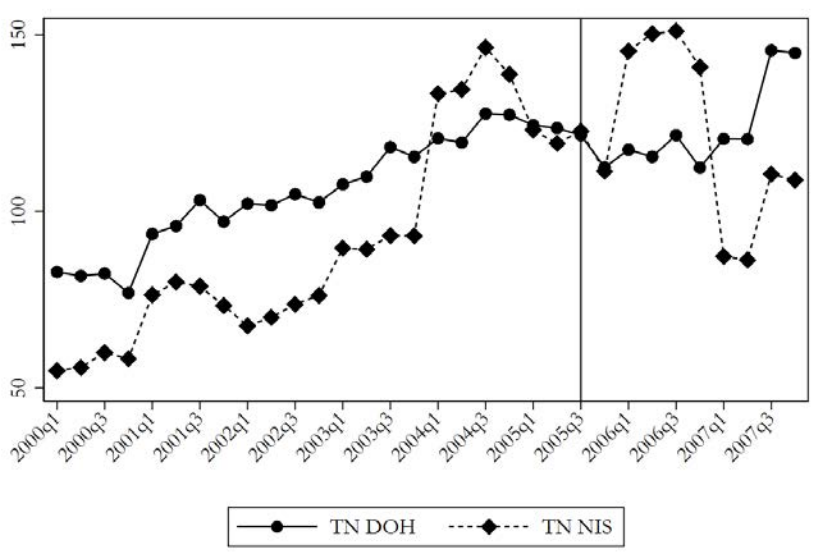
Notes: The unit of observation is the state-year-quarter. All models estimated with LS and control for state demographics, and state, year, and quarter fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are weighted by the state population ages 21-64 years.
***,**,*= statistically different from zero at the 1%,5%,10% level.

Figure 1. Monte Carlo simulation of estimated treatment effects



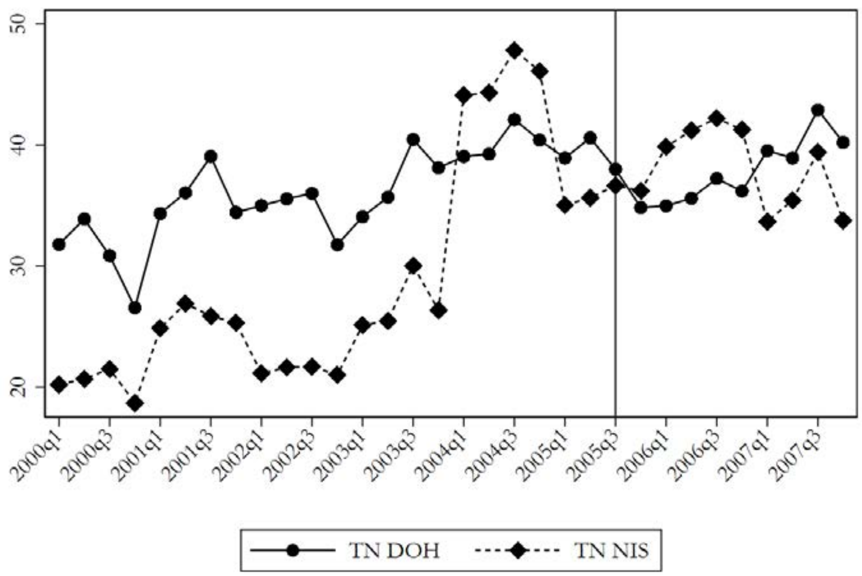
Notes: Each of the four simulations are conducted using 1,000 repetitions. Data is generated such that the true value of the treatment effect is 2. See text for full details.

Figure 2. Trends in mental illness hospitalizations: NIS vs. DOH administrative data



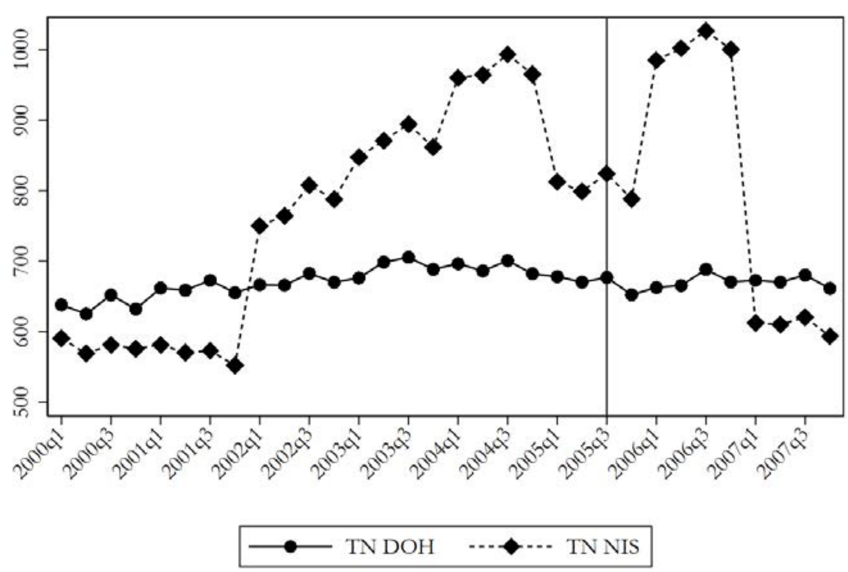
Notes: Outcomes are quarterly averages of hospitalizations among patients 21 to 64 years. DOH = Tennessee Department of Health data.

Figure 3. Trends in SUD hospitalizations per hospital-quarter: NIS vs. DOH administrative data



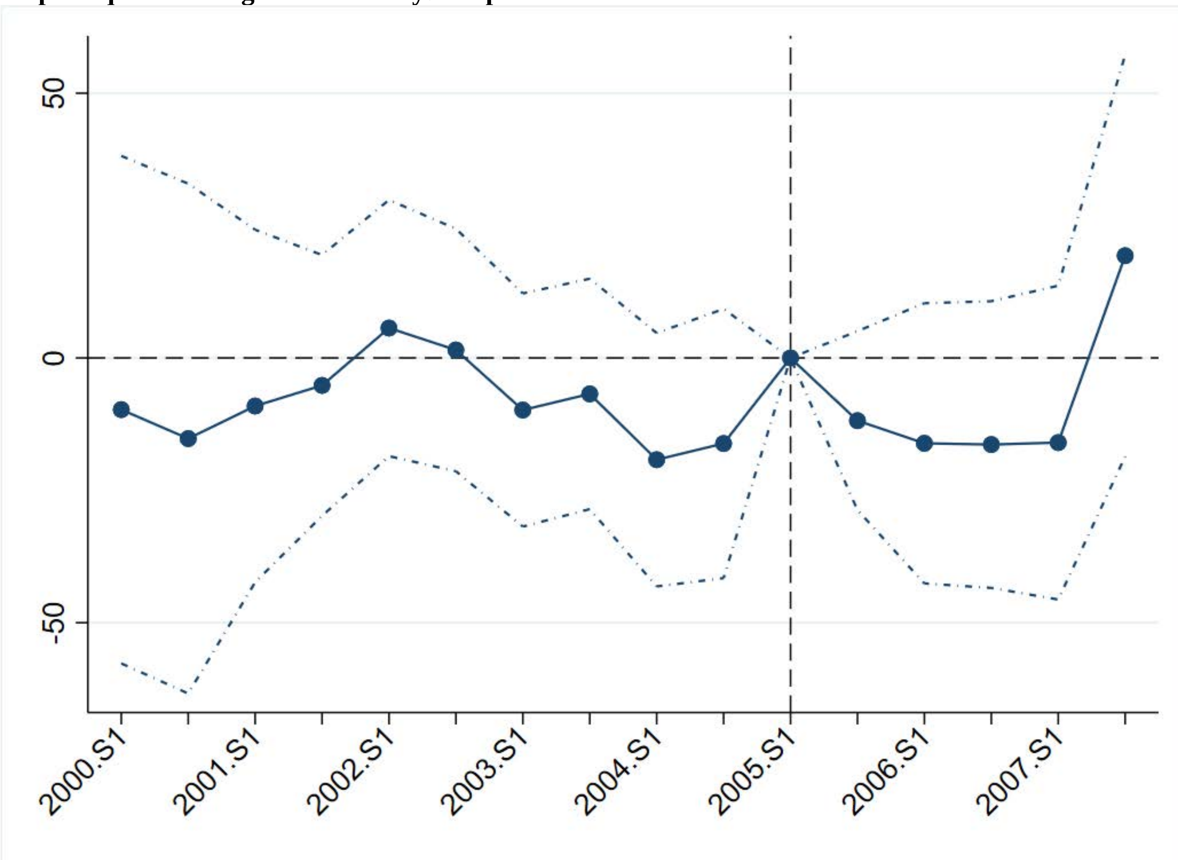
Notes: Outcomes are quarterly averages of hospitalizations among patients 21 to 64 years. DOH = Tennessee Department of Health data. NIS = National Inpatient Sample.

Figure 4. Trends in Total hospitalizations per hospital-quarter: NIS vs. DOH administrative data



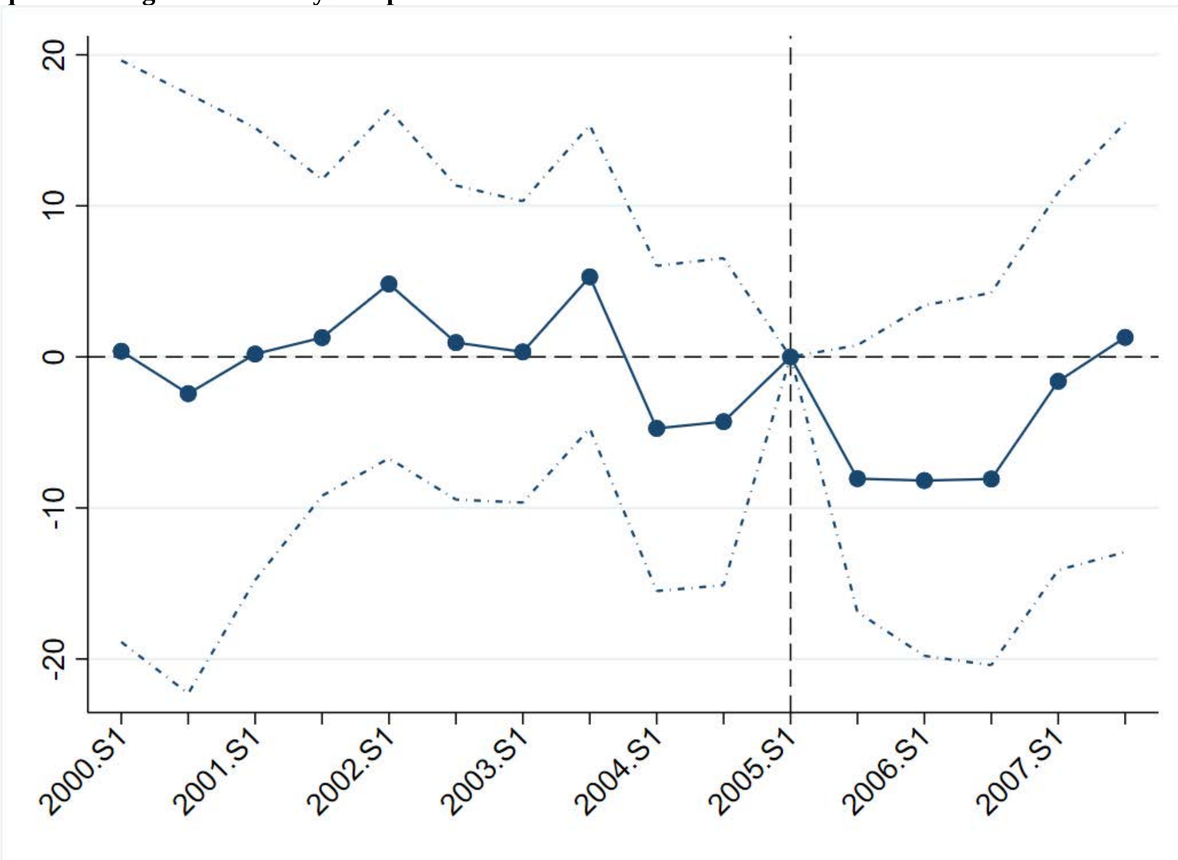
Notes: Outcomes are quarterly averages of hospitalizations among patients 21 to 64 years. DOH = Tennessee Department of Health data. NIS = National Inpatient Sample.

Figure 5. Effect of TennCare disenrollment on mental illness hospitalizations by adults ages 21-64 years per hospital-quarter using an event study: Hospitalization data 2000-2007



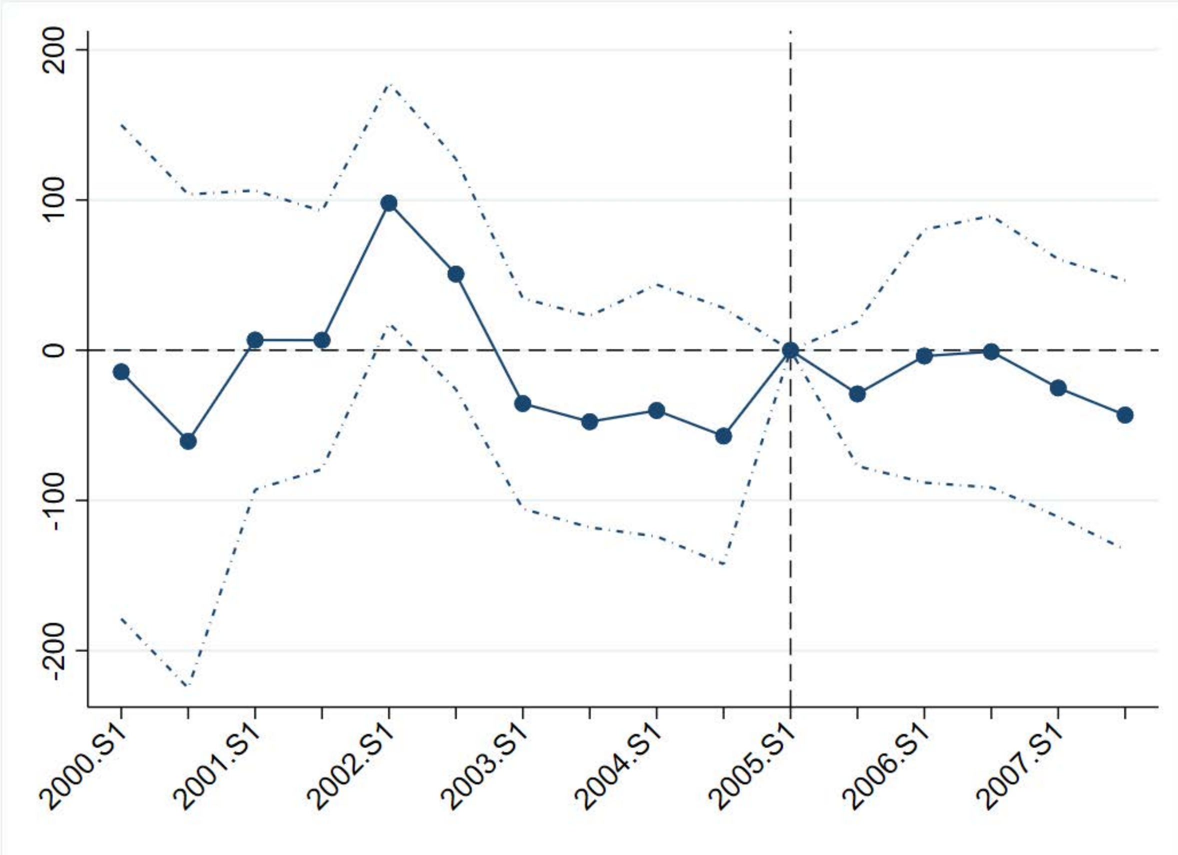
Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, six-month period fixed effects (rather than quarter fixed effects), year fixed effects, and hospital fixed effects. 95% confidence intervals reported with dashed lines and are calculated with a modified block-bootstrap procedure. 2005 Q1-Q2 is the omitted category. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data. S1 = Q1 to Q2.

Figure 6. Effect of TennCare disenrollment on SUD hospitalizations by adults ages 21-64 years per hospital-quarter using an event study: Hospitalization data 2000-2007



Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, six-month period fixed effects (rather than quarter fixed effects), year fixed effects, and hospital fixed effects. 95% confidence intervals reported with dashed lines and are calculated with a modified block-bootstrap procedure. 2005 Q1-Q2 is the omitted category. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data. S1 = Q1 to Q2.

Figure 7. Effect of TennCare disenrollment on total hospitalizations by adults ages 21-64 years per hospital-quarter using an event study: Hospitalization data 2000-2007



Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, six-month period fixed effects (rather than quarter fixed effects), year fixed effects, and hospital fixed effects. 95% confidence intervals reported with dashed lines and are calculated with a modified block-bootstrap procedure. 2005 Q1-Q2 is the omitted category. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data. S1 = Q1 to Q2.

Appendix Table 1A. Effect of TennCare disenrollment on hospitalizations among adults 21 to 64 years sample; alternative approaches to inference: Hospitalization data 2000-2007

Outcome:	**Mental illness hospitalizations**	**SUD hospitalizations**
Classical SE	0.89	0.03
Cluster SE by state	0.95	0.43
Randomization inference	3/10	4/10
Observations	15,554	15,554

Notes: *p*-values reported. The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.

Appendix Table 1B. Effect of TennCare disenrollment on expected payer source among adults 21-64 years sample; alternative approaches to inference: Hospitalization data 2000-2007

Outcome:	**Medicaid**	**Any insurance**	**Private**	**Medicare**	**Self-Pay**
Mental illness hospitalizations					
Classical SE	<0.001	<0.001	0.004	0.01	0.003
Cluster SE by state	<0.001	0.01	0.01	0.01	0.09
Randomization inference	10/10	10/10	2/10	2/10	1/10
Observations	15,522	15,522	15,522	15,522	15,522
SUD hospitalizations					
Classical SE	<0.001	<0.001	0.77	0.26	<0.001
Cluster SE by state	<0.001	<0.001	0.66	0.29	<0.001
Randomization inference	10/10	10/10	4/10	3/10	1/10
Observations	15,276	15,276	15,276	15,276	15,276

Notes: *p*-values reported. The unit of observation is the hospital-state-quarter. All models estimated with an LPM and control for state demographics, and quarter, year, and hospital fixed effects. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.

Appendix Table 2A. Effect of TennCare disenrollment on hospitalizations among adults 21-64 years using different time periods and samples: Hospitalizations data 2000-2007

Outcome:	**Mental illness hospitalizations**	**SUD hospitalizations**
Mean in TN adults 21-64 years, pre-disenrollment+	107.01	36.21
2000-2007 (drop 2005)	4.63	-2.63
	(13.67)	(6.49)
Observations	13,510	13,510
2000-2007q2	-6.11	-4.15
	(9.72)	(4.59)
Observations	14,531	14,531
2000-2010	-0.44	-2.91
	(9.92)	(4.51)
Observations	21,771	21,771
2000-2007 (drop TX & GA)	-1.20	-4.00
	(9.87)	(4.12)
Observations	10,761	10,761
2000-2007 (no weight adjustment)	-1.08	-3.20
	(7.62)	(3.42)
Observations	15,554	15,554
2000-2007 (separate trend for TN and other states)	-4.79	-3.36
	(14.03)	(5.05)
Observations	15,554	15,554
2000-2007 (drop time-varying controls)	-7.81	-5.97**
	(7.04)	(3.03)
Observations	15,554	15,554
2000-2007 (aggregate to the state-quarter- year level)	-10.60	-7.07
	(16.00)	(7.18)
Observations	344	344

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.
+We use the main sample means.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Appendix Table 2B. Effect of TennCare disenrollment on mental illness hospitalization expected payer source among adults 21-64 years using different time periods and samples: Hospitalizations data 2000-2007

Outcome:	Medicaid	Any insurance	Private	Medicare	Self-Pay
Mean in TN adults 21-64 years, pre-disenrollment+	0.347	0.956	0.290	0.319	0.042
2000-2007 (drop 2005)	-0.10***	-0.03	0.03	0.03	0.02
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	13,480	13,480	13,480	13,480	13,480
2000-2007q2	-0.09***	-0.03**	0.03**	0.02	0.02
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	14,499	14,499	14,499	14,499	14,499
2000-2010	-0.13***	-0.06***	0.00	0.04***	0.04***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Observations	21,733	21,733	21,733	21,733	21,733
2000-2007 (drop TX & GA)	-0.08***	-0.02	0.03***	0.03**	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	10,729	10,729	10,729	10,729	10,729
2000-2007 (no weight adjustment)	-0.09***	-0.03**	0.03**	0.02	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	15,522	15,522	15,522	15,522	15,522
2000-2007 (separate trend for TN and other states)	-0.04	-0.02	0.05***	0.00	0.04***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	15,522	15,522	15,522	15,522	15,522
2000-2007 (drop time-varying controls)	-0.10**	-0.04***	0.01	0.01	0.01
	(0.01)	(0.01)	(0.019)	(0.01)	(0.01)
Observations	15,522	15,522	15,522	15,522	15,522
2000-2007 (aggregate to the state-quarter- year level)	-0.10***	-0.02	0.05*	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Observations	344	344	344	344	344

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.
+We use the main sample means.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Appendix Table 2C. Effect of TennCare disenrollment on SUD hospitalization expected payer source among adults 21-64 years using different time periods and samples: Hospitalizations data 2000-2007

Outcome:	Medicaid	Any insurance	Private	Medicare	Self-Pay
Mean in TN adults 21-64 years, pre-disenrollment+	0.403	0.866	0.226	0.236	0.127
2000-2007 (drop 2005)	-0.14***	-0.10***	0.00	0.03	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Observations	13,275	13,275	13,275	13,275	13,275
2000-2007q2	-0.11***	-0.10***	0.00	0.00	0.08***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Observations	14,271	14,271	14,271	14,271	14,271
2000-2010	-0.16***	-0.13***	-0.00	0.02	0.12***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	21,395	21,395	21,395	21,395	21,395
2000-2007 (drop TX & GA)	-0.10***	-0.09***	0.01	0.01	0.07***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	10,483	10,483	10,483	10,483	10,483
2000-2007 (no weight adjustment)	-0.11***	-0.10***	0.00	0.00	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	15,276	15,276	15,276	15,276	15,276
2000-2007 (separate trend for TN and other states)	-0.06***	-0.09***	0.01	-0.03	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	15,276	15,276	15,276	15,276	15,276
2000-2007 (drop time-varying controls)	-0.14***	-0.12***	0.002	0.01	0.09***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	15,276	15,276	15,276	15,276	15,276
2000-2007 (aggregate to the state-quarter- year level)	-0.12***	-0.09***	0.01	0.02	0.08***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Observations	344	344	344	344	344

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state demographics, and quarter, year, and hospital fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.
+We use the main sample means.
***,**, *= statistically different from zero at the 1%,5%,10% level.

Appendix Table 3. Effect of TennCare disenrollment on the probability of a past year across-state move: ASEC 2000-2007

Outcome:	**Any across state move**
Proportion in TN, pre-disenrollment	0.044
DD	-0.01
	(0.01)
Observations	88

Notes: The unit of observation is the state-year. Model estimated with LS and controls for individual characteristics, state demographics, and state year fixed effects. Block-bootstrap standard errors are reported in parentheses. The data are weighted by ASEC sample weights.
***,**, *= statistically different from zero at the 1%,5%,10% level.

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