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LOSING INSURANCE AND BEHAVIORAL HEALTH HOSPITALIZATIONS: 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 – mental health and substance use disorder (SUD) – community hospitalizations. We leverage variation in public insurance coverage eligibility offered by a large-scale and unexpected Medicaid disenrollment in Tennessee. Losing insurance decreased SUD-related hospitalizations but mental illness hospitalizations were unchanged. Use of Medicaid to pay for behavioral health, mental illness and SUD, hospitalizations declined post-disenrollment. Mental illness hospitalization financing shifted to private insurance, Medicare, and patients, while SUD treatment financing shifted entirely to patients. We also investigate the implications of reliance on data that is not representative at the level of the treatment variable 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

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

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

1. Introduction

In this study, we provide the first 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'). TennCare generously covered a wide range of efficacious behavioral healthcare services including medications, counseling services, and specialty inpatient treatment; the disenrollment plausibly reduced access to affordable and valuable treatment. We examine 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).[1] This population has elevated prevalence of 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 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

[1] We note that the core provisions of the ACA, and most associated state Medicaid expansions, occurred in January 2014. Garthwaite et al. provide evidence that TennCare's treated population is more similar in terms of demographic characteristics to the ACA newly eligible population than the populations affected by the Massachusetts healthcare reform and the Oregon Health Insurance Experiment.

[2] In addition, see for example, https://www.politico.com/story/2019/01/11/trump-bypass-congress-medicaid-plan-1078885 (accessed June 7th, 2019).

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, 15 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).

Basic demand theory implies that insurance, by reducing the out-of-pocket price faced by consumers, should increase the quantity of healthcare demanded (Grossman 1972) and numerous studies document this relationship for behavioral healthcare services (Maclean and Saloner 2019, 2018, Maclean et al. 2018, Meinhofer and Witman 2018, Wen, Hockenberry, and Cummings 2017, Wen et al. 2017, Wen et al. 2013). An important contribution of our study is that we are able to test the effect of *losing*, as opposed to *gaining*, insurance. The prior literature has focused primarily on the effect of insurance *gains* due to available sources of exogenous variation, but the effects of insurance gains and losses are not likely symmetric (Tello-Trillo 2016, Ghosh and Simon 2015, Argys et al. 2017). For instance, an individual who loses insurance will likely 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 information may allow a patient to continue to maintain health after a coverage loss more effectively than a patient with no insurance experience. Studies in behavioral psychology provide evidence that there is asymmetry in gains vs. losses (Kahneman and Tversky 1984), implying that the benefits from gaining insurance may be smaller than the adverse reactions associated with losing insurance.

There are reasons to suspect that the noted asymmetry in insurance gains/losses differs for general vs. behavioral health and service use. 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 financing behavioral healthcare. Charity care may also act as a substitute for paid care, thereby muting the effect of an insurance loss on service use. Second, the risk of a fatal drug overdose is elevated after prolonged periods of abstinence among those with SUDs (Merrall et al. 2010). An abrupt termination in access to 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); 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 particularly important for behavioral health outcomes (e.g., forming relationships with non-substance users, staying away from situations in which substances are used, cognitive behavioral techniques to minimize anxiety). Finally, those with severe mental illnesses and SUDs face unique social, cognitive, and economic barriers that impede their ability to locate new providers/handle overall stress following an insurance loss.

We find that SUD community hospitalizations declined in Tennessee post-disenrollment, but mental illness hospitalizations were unchanged. A substantial share of behavioral health hospitalization financing shifted from Medicaid to private insurance, Medicare, and patients post-disenrollment. We observe heterogeneity across patients with mental illness and SUDs in their ability to find substitute insurance post-disenrollment: patients with mental illness were better able to secure alternative insurance to finance hospitalization expenditures (private coverage and Medicare) than were patients with SUDs.

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 surprisingly common in economics and policy analysis.[3] 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 community hospitalizations in Tennessee. Second, to address this issue

[3] For instance, many studies use 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 not emphasized. We are not suggesting that researchers forgo their project when data that is representative at the level of treatment is not available. Instead, we simply note that researchers, when faced with this empirical challenge, acknowledge the study limitation. See Currie and Gruber (1996), Schmeiser (2009), Kahn (2010), Kaestner and Yarnoff (2011), Kolstad and Kowalski (2012), Miller (2012b), Hamersma and Kim (2013), Maclean (2013), Maclean (2014), Anderson, Hansen, and Rees (2015), Maclean (2015), Pacula et al. (2015), Tello-Trillo (2016), Miller and Wherry (2017), Nicholas and Maclean (2019), and DeLeire (2018).

empirically, we propose a combination of NIS and administrative data. Our methods can be applied in other single-state case study analyses. At minimum, our findings suggest caution in interpreting findings from data that is not representative at the level of treatment.

2. Background, conceptual framework, and prior research

2.1 Behavioral healthcare

Studying factors related to behavioral healthcare use is important for public policies that seek to improve both individual and social well-being. 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.: in 2017 18.9% (46.6M) and 7.2% (19.2M) of U.S. adults met diagnostic criteria for a mental illness and an SUD respectively (Substance Abuse and Mental Health Services Administration 2018) Moreover, the U.S. is in the midst of an alarming and unprecedented fatal drug overdose epidemic, largely attributed to opioids: there are 130 fatal opioid overdoses each day (Centers for Disease Control and Prevention 2018a). In 2017, over 47,000 Americans committed suicide (Centers for Disease Control and Prevention 2018b) and the misuse of alcohol is associated with over 88,000 deaths each year (Centers for Disease Control and Prevention 2013). The costs associated with behavioral health conditions extend beyond the affected individual: each year mental illness and SUDs are estimated to 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).[4]

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). For instance, individuals with mental illness can be prescribed psychotropic medications or receive counseling

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[4] The original estimates are inflated by the authors to 2019 dollars using the Consumer Price Index (CPI)

services from primary care providers in office-based settings. Patients can obtain specialized treatment in outpatient, residential, or hospital settings from psychologists, psychiatrists, and other healthcare professionals. Informal or self-help treatment is also available (e.g., religious counseling). Similar modalities are available for SUDs. However, we note that the majority of inpatient behavioral healthcare is received in community hospitals (Substance Abuse and Mental Health Services Administration 2013), which is the setting in which 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 2017, less than half of U.S. adults who could benefit from mental healthcare did not receive any treatment while just one in ten of adults meeting diagnostic criteria for an SUD received care (Substance Abuse and Mental Health Services Administration 2018). Among individuals who seek care, but do not receive it, commonly reported barriers are inability to pay and lack of insurance coverage (Rowan, McAlpine, and Blewett 2013, Substance Abuse and Mental Health Services Administration 2018). Treatment is likely unaffordable for many low-income and uninsured individuals. For instance, reimbursement rates for a psychiatrist range from $72 to $133 per visit and treatment typically involves a series of visits (Mark et al. 2018).[5] Buprenorphine, a medication indicated for opioid use disorder, treatment can cost up to $1,950 per month for extended periods (Barnett 2009).[6] 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).

Treatment specialists argue that, for care to be effective, it must be appropriate to the patient's needs and be of sufficient duration to stabilize and manage the behavioral health 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

[5] Authors inflated the original estimates, derived from commercial claims and refer to in-network fees, to 2019 dollars using the CPI.

[6] Estimates, based on the Veterans' Affairs Hospital system, inflated by the authors to 2019 dollars using the CPI.

Tennessee originally offered a fee-for-service Medicaid program. Due to high costs, the state transitioned to a managed care program that contracted with the renamed TennCare in 1994. State legislators anticipated that the transition would reduce overall program costs. The expected savings were allocated to support a large-scale increase in Medicaid eligibility to low-income, non-disabled childless adults and uninsurable adults, defined as adults with pre-existing conditions that lead to prohibitively high premiums (Farrar et al. 2007). The expansion was popular, and enrollments surged: TennCare covered 22.3% of the state's population in 2004 (Farrar et al. 2007). TennCare, which used a behavioral healthcare carve out in its early years, generously covered a wide range of efficacious behavioral healthcare services (e.g., medications, assessment and evaluation services, and counseling) at low cost-sharing with limited application of utilization management; e.g., stepped therapy or prior authorization (Kaiser Family Foundation 2015, Farrar et al. 2007, Chang and Steinberg 2014).

Due to its popularity and generosity, TennCare became financially unsustainable (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).

We emphasize disenrollment effects in our study, however, we note that, in addition to the insurance losses, coverage generosity was curtailed to some extent among continuing enrollees. Nonetheless, coverage remained restively 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., the ACA, Massachusetts healthcare reform) include various coverage changes.[7]

[7] Three features of the disenrollment are important to consider. First, coverage was curtailed for those individuals who remained eligible for TennCare. 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 $188M (2019 dollars; inflated 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 to the best of our knowledge. Reports indicate that registration with the MHSN by disenrollees with serious mental health disorders was 65%. Disenrollees who registered with MHSN were eligible for some mental healthcare services (e.g., assessment and evaluation, therapeutic sessions, specific medications, and

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 Notowidigdo (2014) find that, post-disenrollment, the probability of having Medicaid declined by 4.6 percentage points (33%) among low-income, childless, and non-disabled adults. DeLeire (2018) documents a similar decline in Medicaid coverage: 5.4 percentage points (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. 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. Garthwaite, Gross, and Notowidigdo (2018) use American Hospital Association data to 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) to study TennCare's effects on healthcare access and health. The author finds that post-disenrollment, primary care visits declined and reported physical health problems increased in Tennessee. There were no statistically significant changes in self-reported days in poor mental health or use of inpatient services, although preventive health behaviors increased post-disenrollment. 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 need for healthcare and reliance on charity care increased.

3. Data, variables, and methods

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psychiatric medication management). 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 $947 per disenrollee in 2019 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. 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 enrollment and coverage overall.

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.[8] The sample reflects a 20% stratified sample of U.S. community hospitals, with 5 to 8 million hospitalizations occurring at over 1,000 hospitals each year. Hospitals are sampled on region, ownership status, and bed size. In 2007 (the last year of our study period) the 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 or hospitals that specialize in SUD treatment. 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.[9]

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 was $12,380[10] 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. Further, compared to self-reported measures of mental illness and substance use, which are widely available in health surveys but may be difficult to relate to true health status

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[8] Due to the Institutions of Mental Disease (IMD) Exclusions, Medicaid cannot be used to pay for treatment received in some hospitals. Based on our review, there are approximately five IMDs in operation in Tennessee during our study period, suggesting that the influence of these facilities is 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 and substantial changes in these expenditures. Details available on request.

[9] We considered using elderly adults as a within-state comparison group in a triple difference estimator. The elderly have very different trends than the non-elderly. We suspect that elderly adults are different from non-elderly adults in terms of behavioral health; e.g., 7.6% of adults 18 years and older met diagnostic criteria for an SUD while the share was just 2.1% for elderly adults in 2017 (Center for Behavioral Health Statistics and Quality 2018).

[10] Inflated by the authors from 2016 dollars to 2019 dollars using the CPI.

(Bond and Lang 2014), hospitalizations, which list a diagnosis code provided by a healthcare professional, are potentially more objective measures of behavioral health. 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 of care, 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 2008-10 recession as recessions are linked with insurance (Cawley and Simon 2005), behavioral health (Hollingsworth, Ruhm, and Simon 2017, Ruhm 2015, Carpenter, McClellan, and Rees 2017), and behavioral healthcare (Bradford and Lastrapes 2013, Maclean, Cantor, and Horn 2019).

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.[11] Tennessee is a small state, with 5.9M residents or 2% of the U.S. population, in 2004; the year prior to the disenrollment (University of Kentucky Center for Poverty Research 2018). 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.[12] We propose an alternative approach, in which we use a state-representative data for Tennessee (from administrative sources) instead of the TN from NIS and then use the other southern states (control group) from NIS. Since we are combining data, we perform simulation to test if our strategy would provide accurate results.

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

[11] 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 (accessed June 7th, 2019).

[12] 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.

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.[13] 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 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.[14] Third, we perform various draws from the universe of hospitals: (1) a 100% sample; (2) a 20% sample by year, ownership, and bed size; (3) a 20% sample by year, ownership, and bed size and retaining only hospitals that provide behavioral healthcare and that treat non-elderly adult patients;[15] and (4) a 100% sample in Tennessee and a 20% sample by year, ownership, and bed size in other Southern states, retaining only the hospitals noted in (3). We select the data in this manner to reflect the universe of hospitals (1), the NIS sample (2), the NIS sample after making exclusions necessary for our research question (3), and the value of our proposed combination of NIS and other administrative data which we describe in more detail later (4). 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 apparent. First, all distributions of beta hat are centered around the true parameter value. 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 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.

[13] We use the six digit North American Industry Classification System code 622110.
[14] We generate 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 use the South region.
[15] We construct these variables to have different distributions in Tennessee and other Southern states and they are designed to mimic, albeit imperfectly, our focus on behavioral health hospitalizations among non-elderly adults.

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 generates a much more dispersed distribution, which is exacerbated when we exclude hospitals to form our analysis sample. 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 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.

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). This combination mimics (4) in our simulation and, we hypothesize, will allow more accurate estimates of treatment effects. We note that combining datasets in this manner is not uncommon (Farber et al. 2018, Altonji, Kahn, and Speer 2016, Webber 2016, Miller 2012a).[16]

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). The correlation between the DOH and NIS

[16] 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; accessed June 7th, 2019).

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.

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.[17] 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 and cautions from NIS administrators. For instance, in 2000 22.3% of all community hospitals in Tennessee appeared in the NIS while in 2004 the share had increased to 38.2%. In 2005 this share dropped to 31.7%, and by 2007 the share fell to 20.2%. 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 studies that have relied on smaller, non-state representative data for Tennessee. Other studies seeking to use NIS to investigate single-state treatments may consider such a combination.

3.2 Outcome variables

First, we consider the number of mental illness and SUD hospitalizations. We classify mental illness and SUD hospitalizations based on ICD-9 codes available on the discharge record (specific codes available on request).[18] 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 consider these outcomes for mental illness hospitalizations and SUD

[17] 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.

[18] 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; accessed June 7th, 2019).

hospitalizations separately. We also examine total hospitalizations and payments for comparison with Ghosh and Simon (2015).

3.3 Empirical model

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

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

$BH_{i,s,q,t}$ 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. 2017) and the poverty rate from the University of Kentucky Center for Poverty Research (2018). ϑ_q and τ_t are vectors of quarter and year fixed effects. δ_i is 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. We also estimate 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.

We estimate Equation (1) with OLS. We apply NIS weights to the (non-Tennessee) NIS data and weight the DOH data equally. Our primary analyses present only heteroscedasticity-robust (as opposed to clustered) standard errors due to the small number of potential clusters and single state treatment (MacKinnon and Webb 2017). We present other inference adjustments as robustness checks. To date the literature has not reached a consensus on the optimal approach to inference in our context. Instead the most suitable approach appears to be context-specific which appears to prevent an overall recommendation to researchers.

We follow the TennCare literature and use other Southern states included in the NIS as our comparison group (Argys et al. 2017, Tello-Trillo 2016, Ghosh and Simon 2015, Garthwaite, Gross, and Notowidigdo 2014): Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Texas, Virginia, and West Virginia.

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.[19]

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'). 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. Thus, we examine trends in our treatment group in the treated condition and the comparison group in the untreated condition to explore the possibility of parallel trends in our context. Either assumption is untestable as the treatment group is treated (or untreated in our context) 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 examine unadjusted trends in the treatment and comparison groups, and conduct an event study following Autor (2003).

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 number 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 34.7%, 40.3%, and 25.4% of mental illness, SUD, and total hospitalizations in Tennessee. The Medicaid shares in other Southern states are: 26.1 %, 22.1 %, and 24.7%.

4.2 Internal validity

We plot trends in our behavioral health community hospitalizations over the study period in Figures 5 to 7. We aggregate the hospitalization data to the treatment – quarter level. Trends

[19] We considered using synthetic control methods (SCM) (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 crosswalk across the two sets of codes for SUD outcomes. We have five pre-treatment years to establish trends which is not sufficient.

in outcomes appear to have moved broadly in parallel for Tennessee and other Southern states in the pre-disenrollment period.

We note that there is a sharp uptick in mental illness hospitalizations in Tennessee beginning in the 3rd quarter of 2007. We have investigated this increase in hospitalizations; we document later in the manuscript that our mental illness findings are somewhat sensitive to excluding/including this period. First, we examined official annual hospital reports provided to us by the DOH (available on request) to determine if any large hospitals entered the Tennessee healthcare market; we found no evidence of such an entrance. Second, we confirmed with the Tennessee DOH that there was no data entry error. Third, we examined the data ourselves for odd patterns; we found none. Fourth, the QCEW data used in our simulation did not reveal the entrance of a large hospital at this time. Although we exclude data after 2007 in our main analysis to avoid contamination from the Great Recession, we note that mental illness hospitalizations remain at this higher level in later periods (i.e., 2008 through 2010). Thus, we hypothesize that one or more hospitals increased mental illness services in that period.

We next 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 period. To smooth out noise in the data, we use six-month bins to form our leads and lags. The omitted category is the six-month period prior to the disenrollment (2005; Q1-Q2).

Event study estimates (Figures 8 to 10) do not reveal evidence of policy endogeneity or anticipatory behavior by beneficiaries (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 suggests that hospitalizations declined post-disenrollment, but that these declines may have dissipated over time for mental illness and total hospitalizations.

4.3 Differences-in-differences analysis of hospitalizations

Table 4 contains results from the basic DD model outlined in Equation (1). We observe no evidence that the disenrollment altered mental illness hospitalizations. There were 2.7 (7.4%)

fewer SUD hospitalizations per hospital-quarter in Tennessee relative to comparison states post-disenrollment. There were 144 hospitals in Tennessee in 2004, implying that overall there were 1,555 fewer SUD hospitalizations per year. The decline in SUD hospitalizations occurred immediately following the disenrollment but may have dissipated over time: while both coefficient estimates in the dynamic model carry a negative sign, only the 'during' indicator is precise. We find no statistically significant change in total hospitalizations post-disenrollment.[20]

4.4 Differences-in-differences analysis of hospitalization payments

We next document the effect of the TennCare disenrollment on the financing of hospital care (Table 5). Post-disenrollment, the probability of using Medicaid coverage to pay for treatment declined by 9.3 percentage point ('ppts'; 26.8%) and 11.6 ppts (28.8%) among mental illness and SUD treatment hospitalizations, respectively. Among all hospitalizations, the decline in Medicaid payments was 6.7 ppts (26.4%). The declines in Medicaid payment appear to have been stable over time: the point estimates on the two lag variables in the dynamic model are very similar. Thus, the decline in Medicaid as a source of payment following the disenrollment was substantial and relatively homogenous across hospitalizations for different conditions.

Overall use of any insurance to pay for treatment declined post-disenrollment by 3.5 ppts (3.7%), 10.0 ppts (11.5%), and 3.8 ppts (5.1%) among mental illness, SUD treatment, and all patients. TennCare payment effects are relatively stable over time. This pattern of results suggests that hospitalized SUD treatment patients were less able to find substitute coverage post-disenrollment than other patients. Indeed, examination of changes in the probability of using private insurance, Medicare, or self-payments to finance hospitalizations supports this hypothesis. Post-disenrollment, the decline in the use of Medicaid to pay for treatment was offset by an increased probability of using private insurance (2.3 ppts or 7.9%), Medicare (2.2 ppts or 6.9%), and self-payments (2.0 ppts or 47.6%) among mental illness patients. SUD patients offset the full decline in Medicaid financing: post-disenrollment, self-payments increased 8.7 ppts (68.5%), and there was no change in other forms of payment (although coefficient estimates on other forms of insurance are positive, they are imprecise). Among all

[20] In unreported analyses, we have estimated the effect of the TennCare disenrollment on non-behavioral health hospitalizations. We find no change in that outcome following the disenrollment. Results available on request.

patients, the decline in Medicaid was offset by increases in Medicare payment (1.7 ppts or 5.0%) and self-payments (1.6 ppts or 42.1%), with no change in private insurance payments.

These estimates suggest that 48% of mental illness patients ([4.5 ppts/9.3 ppts]*100%) and 25% of all patients ([1.7 ppts/6.7 ppts]*100%) filled the 'Medicaid gap' with private and/or Medicare coverage, with the remainder financed by patients themselves. SUD patients were unable to find alternative insurance. For brevity, we report results from the basic DD model.

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 to 8). Our findings based on the NIS depart from our main results in several non-trivial ways.

First, the baseline 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 in Table 3). Second, there is a decline in mental illness (12.3%), but not SUD, hospitalizations; a reversal of our main findings. Third, total hospitalizations declined by 3.4%; we find no statistically significant effect that total hospitalizations decline in our main findings. In terms of payments, we observe declines in Medicaid as a source of payments for mental illness, SUD, and total hospitalizations but the relative effect sizes are more modest: 19.0% in Table 7 vs. 26.8% in Table 5, 20.9% vs. 28.2%, and 17.8% vs. 26.4%, respectively. The absolute effect sizes are more comparable across datasets, but the baseline proportions in the NIS Tennessee data are lower than in the DOH data; for instance Medicaid coverage was 52.6%, 45.5%, and 47.1% among mental illness, SUD, and total hospitalizations pre-disenrollment vs. 34.7 %, 40.3%, and 25.4%. Interestingly, in the NIS data, we find no 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, the NIS data over-estimates the extent to which patients bore the costs of the disenrollment.

4.6 Behavioral health outcomes

We next examine TennCare effects on behavioral health outcomes: suicides, and unintentional fatal alcohol poisonings and drug overdoses. We use the Centers for Disease Control and Prevention's National Vital Statistics System (NVSS) Underlying Cause of Death public use files. These data record the universe of deaths in the U.S. and classify deaths by cause, and are used by economists to study behavioral health (Lang 2013, Ruhm 2015, Popovici et al. 2018). We select all related deaths for adults 21 to 64 in each quarter 2000 to 2007 for Tennessee and other Southern states. Deaths are expressed as a quarterly rate per 100,000 adults 21 to 64 and weighted by the state non-elderly adult population (Table 8).[21] We find that suicide, and fatal alcohol poisonings/drug overdoses increased by 0.33 and 0.79 (7.7% and 28.9%) deaths per 100,000 non-elderly residents in Tennessee post-disenrollment.[22] [23]

6. Robustness checks

6.1 Alternative approaches to conducting inference

In our main analyses we rely on heteroscedasticity-robust standard errors. However, this method of inference likely results in inaccurate standard errors. First, we lack a sufficient number of clusters to reliably estimate standard errors (Cameron and Miller 2015). Second, as documented by MacKinnon and Webb (2017), the percentage of treated clusters in our data (Tennessee) is small which raises additional concern that standard inference approaches are not appropriate in our context. Hence, we explore alternative approaches to inference to probe the precision of our estimates. We report the following: classical standard errors that assume homoscedasticity, standard errors clustered at the state-level, standard errors using randomization inference,[24] and standard errors estimated using a modified version of block-bootstrap standard error as applied by Garthwaite, Gross, and Notowidigdo (2014). We report *p*-values in Appendix Tables 1A and 1B. The mental illness hospitalization outcome is not statistically

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[21] 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 value) or nine (the largest value). More details available on request from the corresponding author.

[22] We note that there is some evidence of pre-trends in fatal alcohol poisonings and drug overdoses. These trends explain some, but not all, of the finding reported in Table 8. Correcting the estimate for pre-trends suggests that the increase is 27.6%. We observe no evidence of pre-trends for suicides. Details available on request.

[23] In unreported analyses, we have examined the effect of the TennCare disenrollment on specialty treatment use in the National Survey of Substance Abuse Services. Overall, while our estimates are very noisy, we find no evidence that the disenrollment lead to changes in these outcomes. Details available on request.

[24] More specifically, we replicate our DD regressions ten times. Each time we treat a different Southern state as the 'treated' state and all other states as 'control' states. We rank the DD estimates from smallest to largest and use this empirical distribution to conduct inference. See Bohn, Lofstrom, and Raphael (2014) for an example.

significant in our baseline inference adjustment and this remains the case in most of the inference adjustments. The SUD hospitalization estimate remains significant in one of the approaches in addition to our baseline. Medicaid and any insurance estimate precision is stable across the approaches, while private coverage, Medicare, and self-pay are somewhat sensitive.

6.2 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 a large uptick in hospitalizations for mental illness in that time period; see Section 4.2), (iii) include the 2008 to 2010 recession period, (iv) drop Texas and Georgia from our comparison group (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 2015)), (v) estimate unweighted OLS regressions, (iv) include a separate linear trend for Tennessee and all other Southern states, and (vii) exclude time-varying controls. Results are reported in Appendix Tables 2A, 2B, and 2C.

While there are some changes in the point estimates and their precision, overall our findings on SUD are broadly robust to these various checks. However, there is an important departure from our main findings for mental illness hospitalizations. In our main specification, we find no evidence that the disenrollment leads to changes in mental illness hospitalizations, in several of our robustness checks we observe statistically significant evidence that such hospitalizations *declined*. For example, when we exclude the 3rd and 4th quarters of 2007, we observe that mental illness hospitalizations declined by 5.7% in Tennessee relative to other Southern states. Payment estimates are broadly stable across these different specifications.

6.3 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. 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 requirements on enrollees, all of which could reduce Medicaid enrollment and have been proposed by policy makers (Goodman-Bacon and Nikpay 2017).

We find evidence of a decline in SUD-related community hospitalizations post-disenrollment. Our results suggest that SUD treatment is more insurance-elastic than general healthcare, since we see declines in hospitalizations for SUD, and no decline for total hospitalizations. This finding is in line with work by Frank and McGuire (2000) and other studies on insurance elasticity for behavioral healthcare.[25] We also observe some evidence that mental illness-related community hospitalizations decline, but these findings are sensitive to specifications and thus we cannot draw firm conclusions on this relationship.

We show that use of Medicaid to pay for community hospitalization care declined in Tennessee relative to comparison states post-disenrollment, both for behavioral health and total hospitalizations. Declines in the use of Medicaid as a source of payment for both mental illness and total hospitalizations were partially offset by increases in the use of private insurance, Medicare, and self-pay, but self-payments fully offset declines in the use of Medicaid for SUD

[25] The Oregon experiment shows that medications for mental illness are more insurance elastic than other medications (Baicker et al. 2017), and evidence from the RAND health insurance expansion documents differentials across these services (Keeler, Manning, and Wells 1988).

hospitalizations. This pattern of results suggests that individuals with SUDs were less able to substitute other types of insurance to pay for hospitalization treatment. While we cannot test the reasons that lie behind this difference, we hypothesize that lack of generous coverage of SUD treatment in many private and (non-Medicaid) public plans during our study period contribute to this difference. Additionally, those with SUDs may be particularly vulnerable to insurance losses due to cognitive, social, or economic constraints, and/or the composition of SUD patients receiving community hospital care may have changed. Finally, efforts by the state to provide some transition care for patients with mental illness, but not SUDs, may have supported treatment for these conditions (Farrar et al. 2007).

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.

Given that many individuals do not have adequate resources to pay for hospital bills (Chappel, Kronick, and Glied 2011), the increase in adults expected to pay out-of-pocket (who are potentially uninsured) that we document suggests that the TennCare disenrollment may have increased uncompensated care for hospitals delivering treatment. Declines in Medicaid payment has been established in previous TennCare studies (Garthwaite, Gross, and Notowidigdo 2018, Ghosh and Simon 2015). We add to this literature by documenting that there may be heterogeneity across service lines in the financial burden to hospitals. Thus, hospitals that deliver substantial amounts of behavioral health services may be disproportionately financing care that was previously paid for by Medicaid.

We interpret our results to imply that lower income adults with behavioral health conditions were made worse off post-disenrollment. Among those with SUDs, hospitalizations declined, suggesting that some patients went without needed care. Patients overall financed a greater share of their healthcare costs, either in terms of private coverage costs or self-financing care. While we acknowledge that the asymmetry in insurance gains/losses complicates a direct comparison, the Oregon Medicaid experiment implies that gaining insurance improves mental health (Finkelstein et al. 2012) which could suggest that losing TennCare worsens mental health, we observed evidence of this phenomena in our analysis of suicide rates. We note that some patients were able to use Medicare to finance hospitalizations, which reflects cost-shifting from Tennessee to the federal government. Moreover, we observe that behavioral health worsened. From the perspective of the state's budget, one could argue that public financing of healthcare declined with may have allowed more flexibility in supporting other public objectives. However, as noted above, given that many self-paying patients are unable to finance the full bill, hospitals potentially shouldered a greater burden. In sum, the overall welfare effects of the TennCare disenrollment are difficult to establish but, at minimum, costs and benefits were potentially experienced unequally across affected groups.

In summary, we offer the first evidence of the effect of losing insurance on behavioral healthcare. We show that such losses lead to a decrease in SUD hospitalizations and a transfer of financial responsibility from Medicaid to private insurers, Medicare, patients, and hospitals. 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	0.347	0.261
Any insurance	0.956	0.764
Private insurance	0.290	0.342
Medicare	0.319	0.248
Self-pay	0.042	0.134
Expected payer SUD hospitalizations		
Medicaid	0.403	0.221
Any insurance	0.866	0.549
Private insurance	0.226	0.215
Medicare	0.236	0.162
Self-pay	0.127	0.222
Expected payer total hospitalizations		
Medicaid	0.254	0.247
Any insurance	0.739	0.815
Private insurance	0.337	0.447
Medicare	0.148	0.190
Self-pay	0.038	0.157
State level regulations and characteristics:		
Age	36.04	35.67
% female	51.1	51.2
% African American	17.0	17.0
% other race	2.2	3.9
% Hispanic	4.7	16.0
% population with high school	26.29	24.19
% population with some college	19.06	19.36
% population with 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.

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
Baseline model			
DD	0.493	-2.668**	-10.554
	(2.958)	(1.240)	(9.836)
Dynamic model			
During (2005;Q3-2006;Q2)	-2.343	-4.265***	-9.017
	(2.916)	(1.345)	(9.595)
After (2006;Q3-2007;Q4)	2.845	-1.341	-11.841
	(3.885)	(1.576)	(11.939)
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 regulations and characteristics, and quarter, year, and hospital fixed effects. Robust 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% 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	0.347	0.956	0.290	0.319	0.042
Baseline model					
DD	-0.093***	-0.035***	0.023***	0.022***	0.020***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.006)
Dynamic model					
During (2005;Q3-2006;Q2)	-0.082***	-0.031***	0.028***	0.018	0.009
	(0.010)	(0.008)	(0.010)	(0.010)	(0.007)
After (2006;Q3-2007;Q4)	-0.101***	-0.039***	0.019**	0.026**	0.028***
	(0.010)	(0.008)	(0.010)	(0.010)	(0.008)
Observations	15,522	15,522	15,522	15,522	15,522
SUD hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.403	0.866	0.226	0.236	0.127
Baseline model					
DD	-0.116***	-0.100***	0.003	0.011	0.087***
	(0.011)	(0.011)	(0.009)	(0.010)	(0.010)
Dynamic model					
During (2005;Q3-2006;Q2)	-0.103***	-0.093***	0.005	0.004	0.068***
	(0.013)	(0.013)	(0.011)	(0.012)	(0.011)
After (2006;Q3-2007;Q4)	-0.126***	-0.107***	0.001	0.017	0.103***
	(0.013)	(0.013)	(0.011)	(0.012)	(0.012)
Observations	15,276	15,276	15,276	15,276	15,276
Total hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.254	0.739	0.148	0.337	0.038
Baseline model					
DD	-0.067***	-0.038***	-0.0024	0.017***	0.016***
	(0.005)	(0.007)	(0.005)	(0.005)	(0.006)
Dynamic model					
During (2005;Q3-2006;Q2)	-0.057***	-0.020**	0.005	0.021***	0.008
	(0.006)	(0.009)	(0.006)	(0.005)	(0.006)
After (2006;Q3-2007;Q4)	-0.075***	-0.052***	-0.009	0.014**	0.023***
	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)
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 regulations and characteristics, and quarter, year, and hospital fixed effects. Robust 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% 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	-11.251***	-0.048	-26.223**
	(2.996)	(1.494)	(11.396)
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 regulations and characteristics, and quarter, year, and hospital fixed effects. Robust standard errors are reported in parentheses. The data are weighted by NIS weights.
***,**= statistically different from zero at the 1%,5% 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	0.526	0.846	0.263	0.303	0.065
Baseline model					
DD	-0.100***	-0.057***	0.017	0.009	0.042***
	(0.013)	(0.012)	(0.011)	(0.012)	(0.009)
Observations	12,580	12,580	12,580	12,580	12,580
SUD hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.455	0.669	0.169	0.192	0.121
Baseline model					
DD	-0.095***	-0.089***	-0.011	0.015	0.077***
	(0.017)	(0.017)	(0.013)	(0.014)	(0.013)
Observations	12,580	12,580	12,580	12,580	12,580
Total hospitalizations					
Proportion in TN adults 21-64 years, pre-disenrollment	0.471	0.899	0.385	0.230	0.084
Baseline model					
DD	-0.084***	-0.069***	0.001	0.000	0.050***
	(0.008)	(0.007)	(0.008)	(0.005)	(0.008)
Observations	12,580	12,580	12,580	12,580	12,580

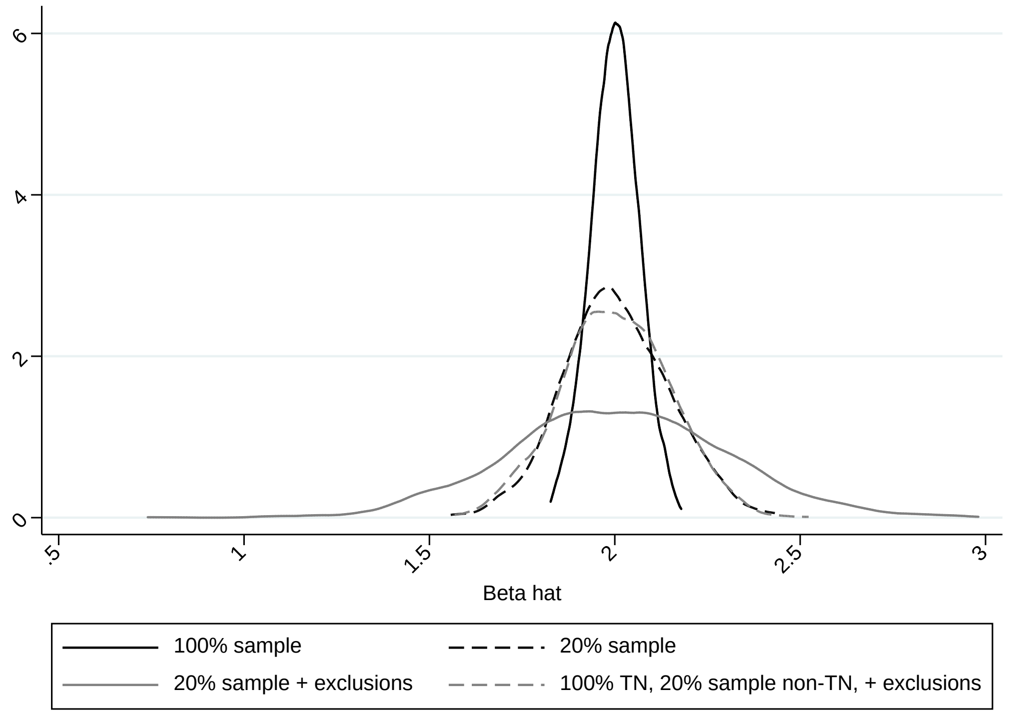
Notes: The unit of observation is the hospital-state-quarter. All models estimated with LPM and control for state regulations and characteristics, and quarter, year, and hospital fixed effects. Robust standard errors are reported in parentheses. The data are equally weighted by NIS weights for the comparison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

Table 8. 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	4.248	2.720
Baseline model		
DD	0.324**	0.785***
	(0.163)	(0.167)
Observations	544	544

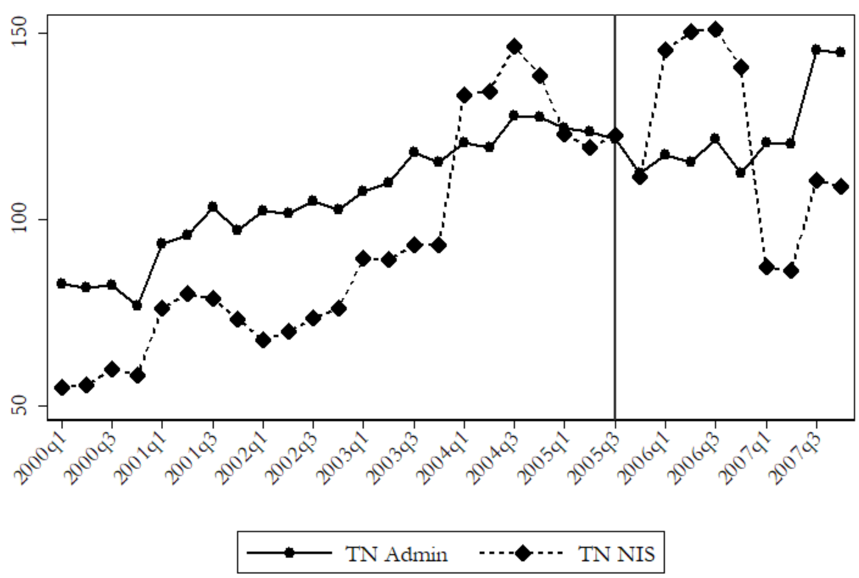
Notes: The unit of observation is the state-year-quarter. All models estimated with LS and control for state regulations and characteristics, and state, year, and quarter fixed effects. Robust standard errors are reported in parentheses. The data are weighted by the state population ages 21-64 years.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

Figure 1. Monte Carlo simulation of estimated treatment effects



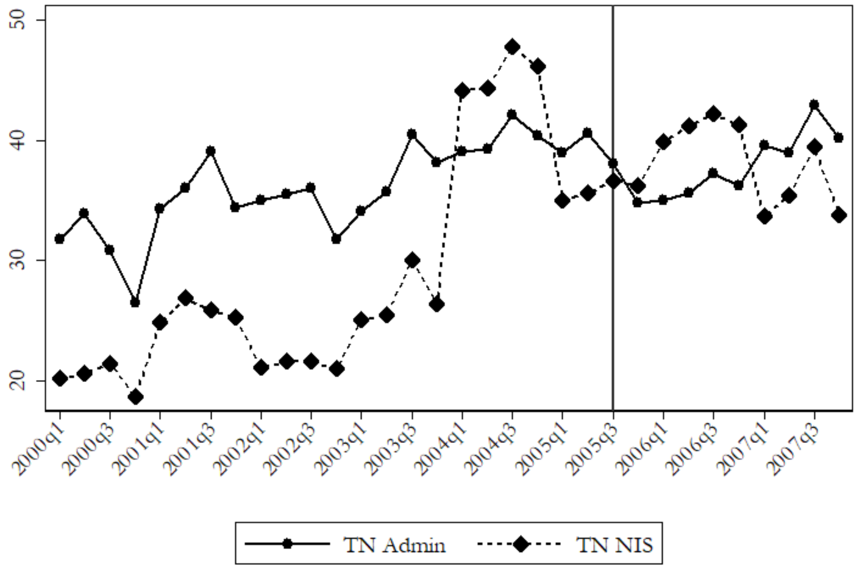
Notes: Each of the four simulations are conducted using 1,000 repetitions. Data is generated such that the true value of the treatment effect is 2. See text for full details.

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



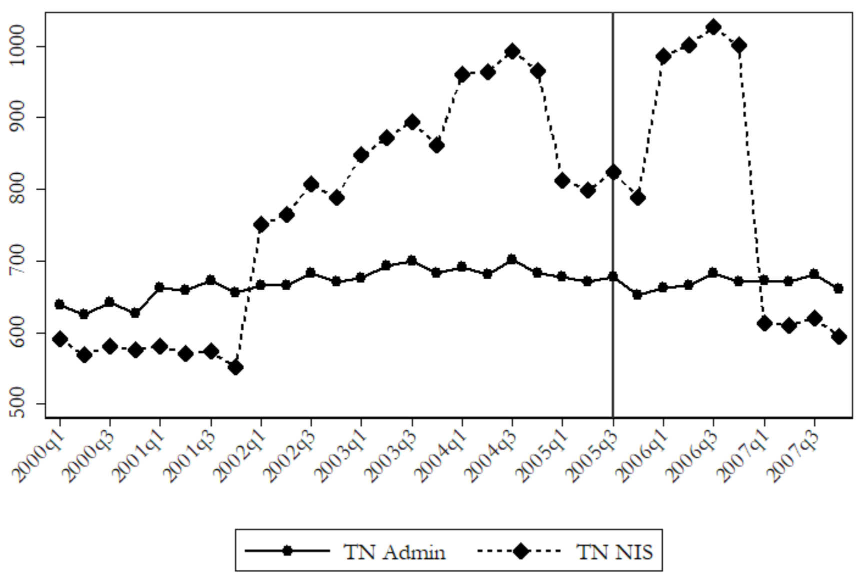
Notes: Outcomes are quarterly averages of hospitalizations among patients 21-64 years. DOH = Tennessee Department of Health data.

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



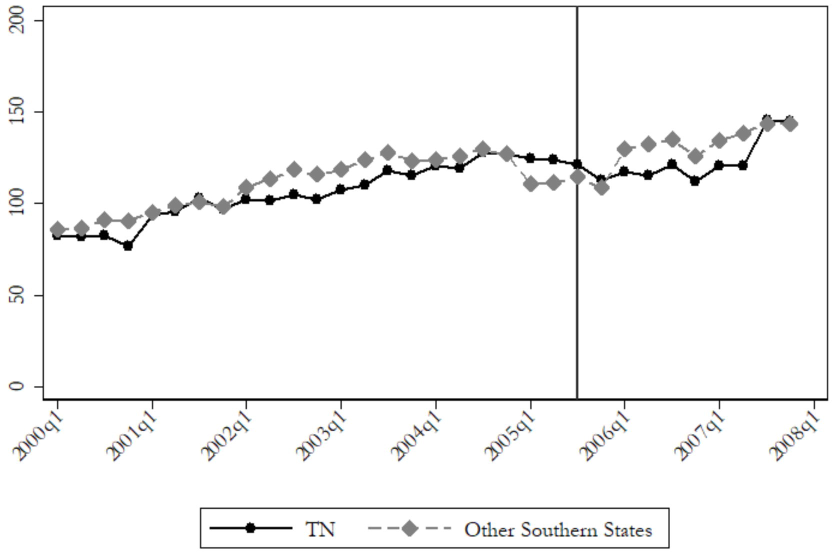
Notes: Outcomes are quarterly averages of hospitalizations among patients 21-64 years. DOH = Tennessee Department of Health data.

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



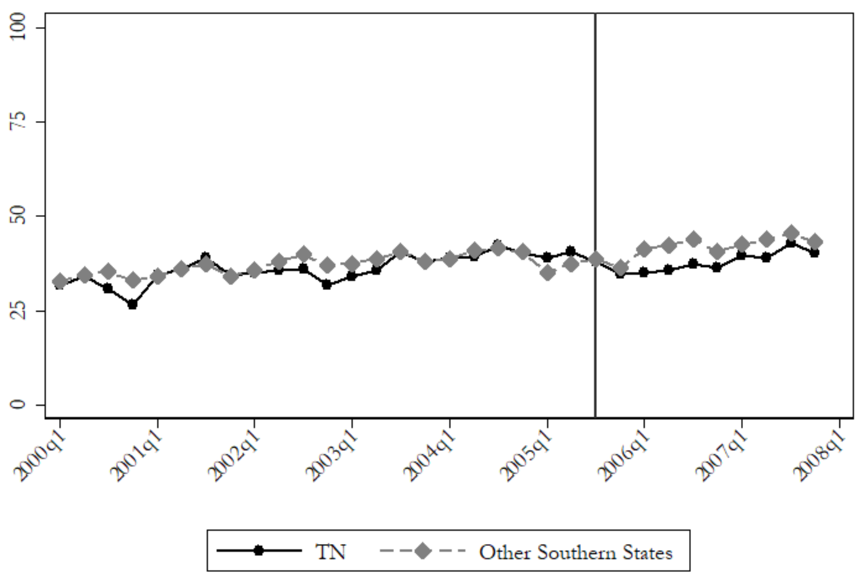
Notes: Outcomes are quarterly averages of hospitalizations among patients 21-64 years. DOH = Tennessee Department of Health data.

Figure 5. Trends in mental illness hospitalizations by adults ages 21-64 years per hospital-quarter: Hospitalization data 2000-2007



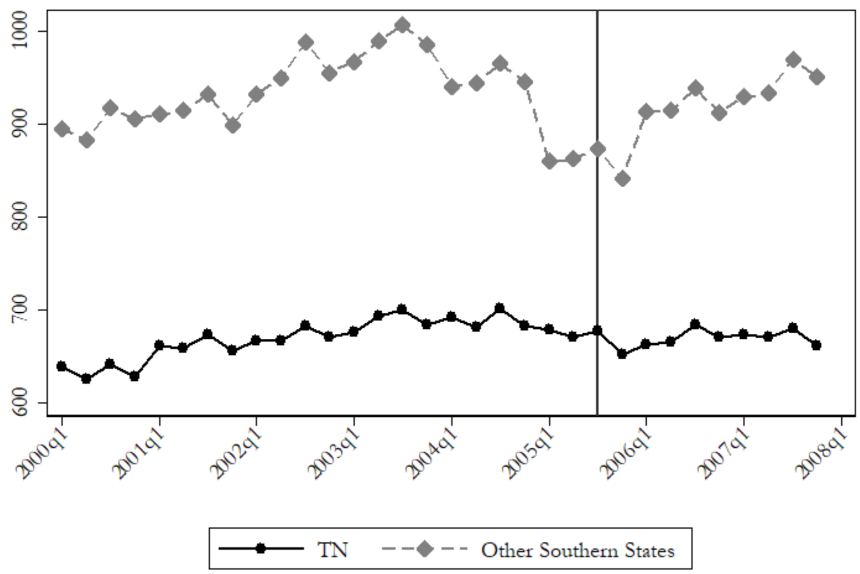
Notes: Data are aggregated to the treatment – quarter level. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.

Figure 6. Trends in SUD hospitalizations by adults ages 21-64 years per hospital-quarter: Hospitalization data 2000-2007



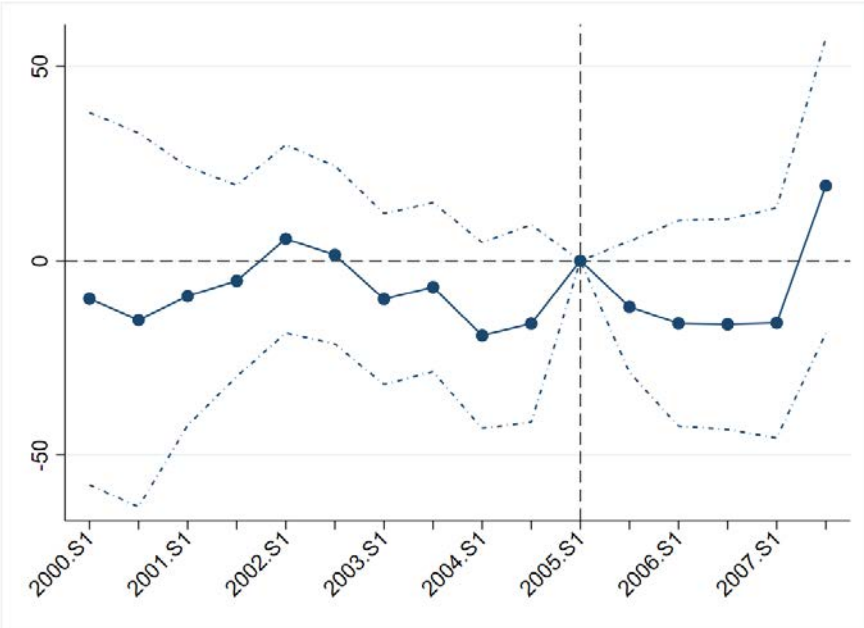
Notes: Data are aggregated to the treatment – quarter level. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.

Figure 7. Total hospitalizations by adults ages 21-64 years per hospital-quarter: Hospitalization data 2000-2007



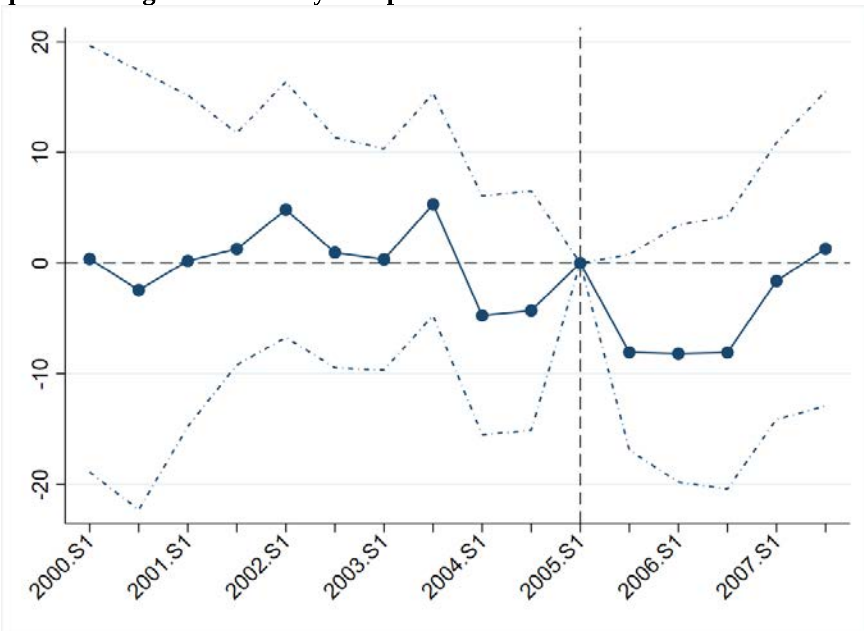
Notes: Data are aggregated to the treatment – quarter level. The data are equally weighted in the DOH data and weighted by NIS weights for the comparison group. DOH = Tennessee Department of Health data.

Figure 8. 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



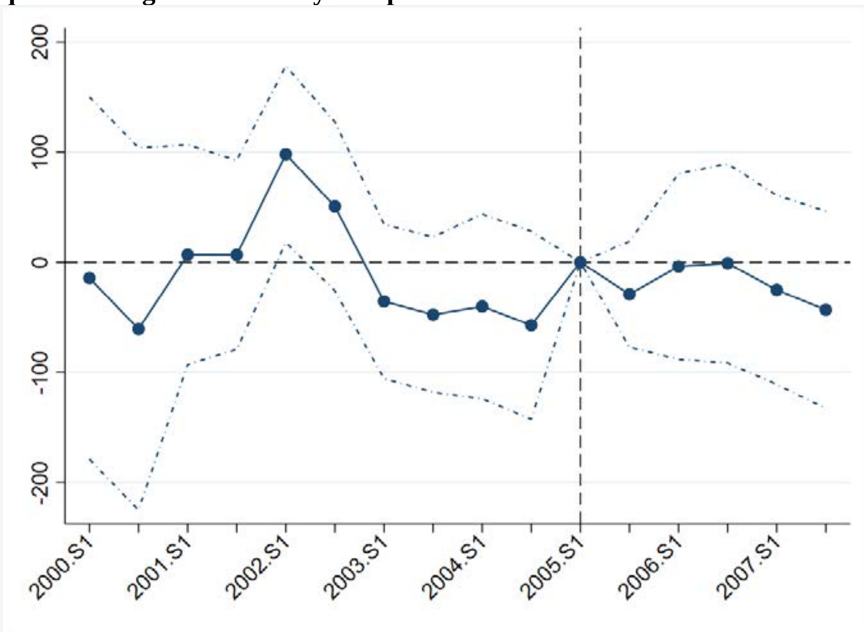
Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state regulations and characteristics, and 6 month, year, and hospital fixed effects. 95% confidence intervals reported with dashed lines. 2005 Q1-Q2 is the omitted category. The data are equally 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 9. 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 regulations and characteristics, and state, quarter, 6 month, year, and hospital fixed effects. 95% confidence intervals reported with dashed lines. 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 10. 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 regulations and characteristics, and state, 6 month, year, and hospital fixed effects. 95% confidence intervals reported with dashed lines. 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 3A. 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	0.868	0.031
Cluster SE by state	0.946	0.433
Randomization inference	3/10	4/10
Block bootstrap SE	0.960	0.549
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 regulations and characteristics, 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 3B. 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	0.008	0.003
Cluster SE by state	<0.001	0.007	0.009	0.005	0.086
Randomization inference	10/10	10/10	2/10	2/10	1/10
Block bootstrap SE	<0.001	0.009	0.068	0.062	0.095
Observations	15,522	15,522	15,522	15,522	15,522
SUD hospitalizations					
Classical SE	<0.001	<0.001	0.766	0.260	<0.001
Cluster SE by state	<0.001	<0.001	0.664	0.291	<0.001
Randomization inference	10/10	10/10	4/10	3/10	1/10
Block bootstrap SE	<0.001	<0.001	0.837	0.390	<0.001
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 regulations and characteristics, 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 4A. 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	4.627	-2.631
	(4.147)	(1.657)
Observations	13,510	13,510
2000-2007q2	-6.106**	-4.149***
	(2.971)	(1.306)
Observations	14,531	14,531
2000-2010	-0.441	-2.908***
	(2.674)	(1.059)
Observations	21,771	21,771
2000-2007 (drop TX & GA)	-1.198	-4.004***
	(3.181)	(1.305)
Observations	10,761	10,761
2000-2007 (No Weight Adjustment)	-1.080	-3.198***
	(2.678)	(1.191)
Observations	15,554	15,554
2000-2007 (separate trend for TN and other states)	-4.786	-3.363**
	(3.755)	(1.646)
Observations	15,554	15,554
No Controls	-7.813***	-5.978***
	(2.491)	(1.059)
Observations	15,554	15,554

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state regulations and characteristics, and quarter, year, and hospital fixed effects. Robust 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% level.

Appendix Table 4B. 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	-0.103***	-0.033***	0.030***	0.025**	0.018**
	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)
Observations	13,480	13,480	13,480	13,480	13,480
2000-2007q2	-0.087***	-0.034***	0.026***	0.018**	0.019***
	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Observations	14,499	14,499	14,499	14,499	14,499
2000-2010	-0.131***	-0.056***	0.002	0.038***	0.037***
	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)
Observations	21,733	21,733	21,733	21,733	21,733
2000-2007 (drop TX & GA)	-0.077***	-0.023***	0.034***	0.026***	0.011
	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Observations	10,729	10,729	10,729	10,729	10,729
2000-2007 (No Weight Adjustment)	-0.087***	-0.030***	0.027***	0.020**	0.021***
	(0.009)	(0.006)	(0.008)	(0.008)	(0.006)
Observations	15,522	15,522	15,522	15,522	15,522
2000-2007 (separate trend for TN and other states)	-0.039***	-0.017	0.053***	0.002	0.044***
	(0.013)	(0.010)	(0.012)	(0.013)	(0.009)
Observations	15,522	15,522	15,522	15,522	15,522
No Controls	-0.095***	-0.038***	0.014**	0.013	0.014***
	(0.007)	(0.004)	(0.006)	(0.006)	(0.004)
Observations	15,522	15,522	15,522	15,522	15,522

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state regulations and characteristics, and quarter, year, and hospital fixed effects. Robust 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% level.

Appendix Table 4C. 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	-0.135***	-0.100***	0.004	0.029**	0.094***
	(0.013)	(0.014)	(0.011)	(0.012)	(0.012)
Observations	13,275	13,275	13,275	13,275	13,275
2000-2007q2	-0.112***	-0.104***	0.003	0.001	0.084***
	(0.011)	(0.012)	(0.010)	(0.010)	(0.010)
Observations	14,271	14,271	14,271	14,271	14,271
2000-2010	-0.157***	-0.131***	-0.005	0.017**	0.121***
	(0.009)	(0.009)	(0.007)	(0.008)	(0.008)
Observations	21,395	21,395	21,395	21,395	21,395
2000-2007 (drop TX & GA)	-0.103***	-0.090***	0.005	0.013	0.072***
	(0.012)	(0.012)	(0.009)	(0.010)	(0.011)
Observations	10,483	10,483	10,483	10,483	10,483
2000-2007 (No Weight Adjustment)	-0.105***	-0.098***	0.002	0.002	0.081***
	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)
Observations	15,276	15,276	15,276	15,276	15,276
2000-2007 (separate trend for TN and other states)	-0.063***	-0.092***	0.013	-0.027	0.066***
	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)
Observations	15,276	15,276	15,276	15,276	15,276
No Controls	-0.137***	-0.114***	0.002	0.005	0.087***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Observations	15,276	15,276	15,276	15,276	15,276

Notes: The unit of observation is the hospital-state-quarter. All models estimated with LS and control for state regulations and characteristics, and quarter, year, and hospital fixed effects. Robust 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% level.

Appendix Table 7. Effect of TennCare disenrollment on the probability of a past year across-state move: ASEC 2001-2008

Outcome:	Past year across-state move
Proportion in TN, pre-disenrollment	0.036
DD	-0.005
	(0.005)
Observations	170,863

Notes: The unit of observation is the respondent-state-year. Model estimated with an LPM and controls for individual characteristics, state regulations, and state year fixed effects. Robust standard errors are reported in parentheses. The data are weighted by ASEC sample weights. The period 2001-2008 corresponds to migration over the period 2000-2007. Details available on request.
***,**= statistically different from zero at the 1%,5% level.

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