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LOSING MEDICAID AND CRIME

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ABSTRACT

We study the impact of losing health insurance on crime by leveraging one of the most substantial Medicaid disenrollments in U.S. history, which occurred in Tennessee in 2005 and led to 170,000 adults unexpectedly losing coverage. Using police agency-level data and a difference-in-differences approach, we find that this mass insurance loss reduced Medicaid enrollment and increased total crime rates with particularly strong effects for non-violent crime. An analysis of mechanisms suggests that the disenrollment had aggregate effects that extended beyond insurance losses. In particular, we show that the policy shock lead to changes in economic stability, healthcare access and health outcomes, and government spending, all of which could have contributed to the increase in crime we document.

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1 Introduction

In this study, we evaluate the impact of losing health insurance on crime outcomes by studying one of the most consequential Medicaid disenrollments in the history of the United States.[1] While overall crime rates in the U.S. have decreased substantially since their peak in the 1990s - see Figures 1 and 2 - crime continues to be a top concern for many Americans (Gallup, 2023), especially with recent increases in violent crime and persistent crime spikes occurring in many major metro areas across the country (Federal Bureau of Investigation, 2020; Council on Criminal Justice, 2023). The U.S. reports eight million crimes each year (Federal Bureau of Investigation, 2019), leading to $3.5 trillion in economic and societal costs (Anderson, 2021).[2] Thus, understanding and leveraging factors that prevent crime could have substantial benefits for many Americans.

While the causes of crime are complex and multifaceted, access to healthcare has been demonstrated to decrease involvement in the criminal legal system (Bondurant et al., 2018; Deza et al., 2022a,b, 2023; Jácome, 2023). Such access can improve health outcomes – in particular mental health and substance use – which in turn decrease interactions with police (e.g., a mental health crisis or being impaired by substances in public places), propensity to commit crime, and risks of crime victimization. Health insurance, by reducing out-of-pocket costs faced by patients, can increase access to, and use of, healthcare services. However, an estimated 28 million Americans remain uninsured (Cohen et al., 2023) despite substantial federal and state efforts to increase coverage rates, and twice that number are 'underinsured' (Halliday and Akee, 2020).

These facts suggest that health insurance may be a tool to reduce crime in the U.S. Indeed, a growing number of quasi-experimental studies establish that <u>gaining</u> insurance coverage reduces crime outcomes. Most recently, several studies have shown that the Affordable Care Act (ACA) Medicaid expansions[3] reduce both criminal behavior and recidivism (Wen et al., 2017; He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022). Medicaid covered 85.2 million people (Centers for Medicare & Medicaid Services, 2022) with expenditures of over $804 billion in 2022 or 17% of total national healthcare expenditures (Congressional Research Service, 2023; Kaiser Family Foundation, 2023). As such, Medicaid is the largest social insurance program in the U.S. in terms of expenditures (Buchmueller et al., 2015; Barnes et al., 2021; Tello-Trillo et al., 2023) and, of

[1] Medicaid is the largest insurer in the U.S. in terms of covered lives and is a public insurance program covering predominately people with low income and disabilities under 65 years of age.

[2] We inflate the original cost estimate ($1.701 trillion) from 1997 dollars to 2025 dollars using the Consumer Price Index - Urban Consumers.

[3] In states that adopt this policy, categorical eligibility for Medicaid is removed and the maximum income eligibility for coverage is raised to 138% of the Federal Poverty Level.

particular relevance for crime outcomes, is the largest purchaser of mental healthcare and substance use disorder treatment in the nation (Medicaid and CHIP Payment and Access Commission, 2015).

While these findings on the benefits of gaining health insurance coverage are important, crucial knowledge gaps remain. Specifically, we know little about whether losing insurance impacts crime outcomes. This dearth of evidence is concerning as, despite general increases in insurance coverage in the U.S. over the last several decades (Buchmueller et al., 2015), recent policies – proposed and implemented – will potentially lead to substantial reductions in coverage for many Americans, in particular people with low income. For example, states are increasingly imposing 'work requirements' to remain eligible for Medicaid coverage (Sommers et al., 2019; Chen and Sommers, 2020; Guth and Musumeci, 2022) and, commencing in March 2023, states began to 'unwind' continuous coverage provisions in Medicaid adopted during the COVID-19 pandemic as part of the U.S. government's Public Health Emergency (PHE) (Tolbert, 2023). The PHE provisions effectively halted states' regular re-certification of Medicaid eligibility and, in turn, enrollment in this program surged by 31% (or 21 million people) between February 2020 and March 2023 (Dague and Ukert, 2024). A substantial number of Congressional proposed budgets and fiscal plans in the last ten years have included a curtailing of the Medicaid program (The White House, 2023). Most recently, the U.S. House of Representatives (2025) passed the fiscal year 2025 budget-reconciliation bill, which mandates Medicaid work requirements and other cutbacks that the Congressional Budget Office estimates will reduce program funding by roughly $716 billion over ten years, and will result in the loss of Medicaid coverage for between 13 and 15 million people (Center on Budget and Policy Priorities, 2025).

In addition to policy relevance, understanding the impacts of both insurance losses and gains is economically interesting, as such changes can potentially generate asymmetry in healthcare use and associated social outcomes. Thus, predictions for the implications of insurance *losses* using evidence on the impacts of insurance *gains* could lead to incorrect conclusions. For example, people who lose coverage may retain 'patient education' which allows them to navigate the healthcare system more adeptly and understand their health status following the loss of coverage (Tello-Trillo, 2021). A coverage loss, even if a patient is able to locate 'replacement' insurance given differences in networks, could lead to a change in providers and/or treatment options (Graves et al., 2020), which may harm patient health.[4] Decision theory predicts that equal-sized income losses have

[4] In the case of substance use and mental health disorders, an abrupt termination of treatment can lead to severe health consequences, for example, a fatal drug overdose. Maclean et al. (2023) find that,

larger (in absolute value) impacts than gains on consumers (Kahneman et al., 1991). Medicaid is an in-kind income transfer and thus may have asymmetric effects. However, the provision of charity or discounted care may minimize the full blunt of insurance losses by creating options for lower-cost treatment among the newly uninsured (Dranove et al., 2016). While most insurance gains in recent U.S. history are well-announced and consumers may expect them, insurance losses may 'surprise' at least some patients (Tolbert, 2023), limiting time available to prepare for the insurance coverage change. Finally, certain psychological burdens (e.g., concerns about locating care or financing medical bills) are potentially specific to insurance losses.

To study the effect of the Tennessee Medicaid disenrollment on crime outcomes, we combine data on police agencies in Tennessee that report violent and non-violent crimes in each year 2002 to 2007 from the Federal Bureau of Investigation's (FBI) Uniform Crime Reports database (UCR). Conceptually, our design compares trends in crime outcomes before and after the 2005 disenrollment across Tennessee counties experiencing varying intensity of the policy shock using difference-in-differences and event-study methods. We measure intensity of exposure to the disenrollment using pre-policy Medicaid coverage rates among residents between age 21 and 64, as these individuals were the most likely to lose Medicaid after the disenrollment.[5]

We have several findings. First, we document a substantial decline in Medicaid coverage post-disenrollment, which confirms earlier work and establishes our 'first-stage.' Second, we find an increase in crime rates following the disenrollment, with particularly

following the TennCare disenrollment that we study, deaths by suicide, fatal drug overdose, and alcohol poisoning increased in Tennessee.

[5]To date, two quasi-experimental approaches are utilized within the literature to evaluate the causal impact of the disenrollment (see Section 2): i) comparing Tennessee to other Southern states and ii) comparing counties within Tennessee differentially exposed to the policy shock. We take the latter approach. Our rationale is that there are meaningful differences in both levels and trends in crime outcomes between Tennessee and other states during our study period. In particular, Tennessee has higher crime rates than the rest of the U.S, and these relatively high crime rates persisted both before and after the 2005 Medicaid disenrollment. Please see https://247wallst.com/special-report/2024/02/02/tennessee-has-ranked-among-the-most-dangerous-states-in-the-country-for-decades/; website last accessed January 3rd, 2025. Figures 1 and 2 also highlight this pattern. Moreover, no other state Medicaid program covered an expansion population as did Tennessee during our study period, with most states not covering adults without disabilities or dependents at any level and, among those that did cover this population, income levels were well below 100% of the Federal Poverty Level while Tennessee covered this population through 175% of the Federal Poverty Level. Thus, using other states as the comparison group requires assuming that, essentially, traditionally Medicaid eligible populations (i.e., children, pregnant women, parents, and the disabled) offer a reasonable counterfactual for crime outcomes in Tennessee post-disenrollment. This assumption seems more concerning in the context of crime relative to other pertinent outcomes that have been explored within the economics literature (e.g., insurance and healthcare use) as traditional populations are much less likely to commit crime than the expansion population, described later in the manuscript, we examine. Given these issues, we choose to compare Tennessee counties with different exposure to the disenrollment.

strong effects for non-violent crime. Our results are robust to using alternative specifications and study periods, and are not driven by differential trends in crime outcomes across counties with varying levels of exposure to the policy shock.

These overall findings capture the aggregate effect of disenrollment on crime, which includes both direct effects on those losing coverage and indirect effects that propagate across the healthcare sector, government expenditures, and labor markets (Finkelstein, 2007). To contextualize our main findings, we conduct an analysis of mechanisms – paying attention to both direct and indirect pathways that could link the disenrollment to increased crime. This analysis suggests that the Tennessee disenrollment induced a set of changes in the healthcare sector, economic conditions, housing stability, government expenditures, healthcare use, and health (in particular mental health and substance use disorder outcomes), and these broader social changes – and potentially others – contributed to the increase in crime that we document.

2 Institutional background and literature

2.1 Health insurance and crime

Health insurance can affect crime outcomes through at least two channels. First, access to healthcare can improve health outcomes (American Psychiatric Association, 2006; National Institute of Mental Health, 2020; National Alliance on Mental Ilness, 2020), including for individuals with lower incomes (Baicker et al., 2013). More specifically, access to behavioral healthcare (i.e., mental health and substance use disorder treatment) can improve symptoms associated with these complex conditions (Baicker et al., 2013; Swensen, 2015), which are important predictors of criminal activity (Frank and McGuire, 2000; Swanson et al., 2001; Heller et al., 2017; Bronson and Berzofsky, 2017). Evidence of this relationship is provided in recent studies finding that better access to behavioral healthcare reduces crime (Heller et al., 2017; Bondurant et al., 2018; Deza et al., 2022b,a, 2023). Moreover, improved behavioral and physical health can enhance labor market outcomes (Ettner et al., 1997; Currie and Madrian, 1999; Ettner et al., 2011), by boosting labor productivity, retention, and earnings, and lowering work absenteeism (Burns and Dague, 2023). Thus, insurance coverage can increase the returns to working and people with insurance may face a higher opportunity cost of crime.

Second, insurance can play a vital role in protecting beneficiaries from substantial medical bills associated with adverse, and costly, health shocks (Dobkin et al., 2018). There is a well-documented relationship between access to health insurance and financial outcomes (Gross and Notowidigdo, 2011; Hu et al., 2018; Gruber and Sommers, 2019; Guth et al., 2020), even measures of extreme financial hardship such as evictions (Allen et al., 2019; Zewde et al., 2019; Linde and Egede, 2023). Thus, we hypothesize that lower disposable income and financial stability following an insurance loss provides an incentive for crime, in particular, for financially-motivated crime.

These two channels reflect relationships between an individual's health insurance status and crime. However, insurance policies may also have indirect effects that extend beyond just the individuals who experience a change in their insurance status. For example, Finkelstein (2007) studies the 'aggregate' effects of the introduction of Medicare in 1965 on the U.S. healthcare market. While Medicare covers adults 65 years and older and those with end-stage renal disease, the impact of this policy had cascading effects across the healthcare sector. The author finds that Medicare's impact on hospital spending was more than six times larger than what would be predicted by individual gains in health insurance coverage alone, and attributes the disproportionally large impacts to market-wide responses to the new insurance program. While Medicare is a much larger program than the program in Tennessee that we study in absolute terms, we will show that – relative to the broader Tennessee insurance market – this program was a substantial insurer (Section 2.2), suggesting that the impacts of terminating this program could have induced similar cascading changes across the state. Additionally, while the disenrollment primarily impacted adults without dependents, these individuals typically reside with at least one other person in their household.[6] As a result, the disenrollment could have led to negative externalities within the household.

Offering further premise for our study, previous research establishes a relationship between <u>gaining</u> access to Medicaid and crime (He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022), demonstrating improved health and financial protection as important mechanisms. For example, ACA Medicaid expansions have been shown to reduce the probability of re-incarceration, accompanied by a corresponding increase in employment and wages (Badaracco et al., 2021), while decreasing the propensity to commit financially-motivated crimes (Arenberg et al., 2024). We note that, in contrast to these findings, Finkelstein et al. (2024) document that the 2008 Oregon Health Insurance Experiment, which randomized some adults with low income to eligibility for Medicaid, has limited impacts on criminal charges and convictions.[7] Two recent studies examine state-

[6] This estimate is based on the author's calculations using Current Population Survey data from 2004 (Flood et al., 2022).

[7] The populations made eligible for ACA Medicaid expansion and the Oregon Health Insurance Experiment differed in several ways that may lead to heterogeneous findings. For example, newly eligible people in Oregon had incomes up to 100% of the Federal Poverty Level while ACA Medicaid expansion

level policies that attempt to continue Medicaid coverage for incarcerated populations. Gollu and Zapryanova (2022) uses near-national data and shows that state policies, which temporarily suspend Medicaid enrollment during incarceration, reduce recidivism one to three years post-release relative to policies that fully terminate coverage. Packham and Slusky (2023) finds that reducing barriers to continuing Medicaid coverage post-release among incarcerated traditional enrollees in South Carolina does not affect recidivism, despite increasing Medicaid enrollment and healthcare use. However, Packham and Slusky (2023)'s estimated confidence intervals include non-trivial declines in crime outcomes.

To date, just two quasi-experimental studies evaluate the importance of losing insurance on crime outcomes and both focus on younger adults experiencing predictable coverage losses. First, Jácome (2023) exploits the fact that the majority of children age out of Medicaid eligibility at 19 using data from South Carolina. Comparing men just above and below age 19, the author documents that losing Medicaid eligibility increases the probability of incarceration, with particularly strong impacts among men with mental health disorders and for non-violent crimes. Second, Fone et al. (2023) finds increased non-violent, but not violent, arrest rates for young adults who age out of eligibility for private coverage through parental plans at 26 years of age.

These studies provide important information on insurance losses. Our work will build on them in several ways. We will exploit a large-scale and unexpected Medicaid disenrollment that lead to 170,000 adults quickly, and largely without any warning, losing coverage in 2005 (Chang and Steinberg, 2009). This disenrollment is one of the most substantial contractions in the Medicaid program history. Unlike expected coverage losses, such as aging out of Medicaid at 19 and parental private coverage at 26, the Medicaid disenrollment we study was unexpected and enrollees did not have time to adjust their behavior in anticipation of the disenrollment. Further, those individuals who lost coverage in Tennessee represent a wide range of ages – adults under age 65 without children and disabilities. Given age-crime profiles where 55% of arrests are for those age 30-64 (Deza et al., 2022a; FBI, 2019), our findings may be more generalizable to the population at risk for crime. Moreover, because adults in their late teens and mid-20s – such as those impacted by the policies studied by Jácome (2023) and Fone et al. (2023) – are less likely to face costly health conditions, the financial and health impact of losing coverage on the adults 21-64 years of age that we study may be more

conferred eligibility to people with incomes up to 138% of the Federal Poverty level and, due to other policy changes in Oregon, the authors track participants for less than two years after Medicaid coverage begins. Moreover, while findings are not statistically distinguishable from zero at conventional levels, the confidence intervals in Finkelstein et al. (2024) include substantial reductions in crime that are comparable to those identified in studies that leverage variation from ACA Medicaid expansion.

salient to the target population. Finally, predictable aging out of insurance coverage (where the cohort aging out of coverage is 'replaced' with a younger cohort) is not likely to lead to 'aggregate' effects on society overall, while the substantial shock we consider could have such cascading effects. Collectively, our work and the earlier important and novel studies can shed light on insurance losses and crime.[8]

2.2 The TennCare program and impacts of the disenrollment

Historically, Medicaid has been mandated by the federal government to provide coverage to a limited number of people with low income, namely pregnant people, parents, and the disabled along with children in families with low income. Thus, pre-ACA, adults younger than 65 years of age with low-income and without children or disabilities were generally not eligible for Medicaid and had few coverage options (Maclean et al., 2023; Tello-Trillo, 2021; Tello-Trillo et al., 2023). States seeking to cover additional populations – often referred to as 'expansion' or 'optional' populations – had to receive approval from the federal government to do so. One mechanism used by states to cover expansion populations was a Section 1115 waiver to the Social Security Act ('1115 waiver').

In 1993, Tennessee applied for a 1115 waiver to the state's Medicaid program through the Health Care Financing Administration (the predecessor to the Centers for Medicare & Medicaid Services or 'CMS'). The waiver was approved and Tennessee was permitted to implement a Medicaid demonstration project ('TennCare') which was designed to remove categorical restrictions (e.g., pregnancy or disability) and make eligible adults under 65 years of age without dependents or disability with a sustained period of uninsurance ('expansion population'). All Medicaid enrollees were placed in managed care plans[9] in an attempt to curtail overall program costs, creating resources available to cover the expansion population, and TennCare was implemented in late 1993.

TennCare coverage included preventive care, prescriptions, imaging, and hospital services with low cost-sharing (Farrar et al., 2007; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021; Maclean et al., 2023). Of particular relevance for our study,

[8] We focus on offenses rather than incarceration or arrests in our analysis. Arrests and incarceration can be driven by police behaviors, the court system, and so forth. Health insurance policies could interact with these factors and thus by examining offenses known (though we will show in Section 4 no evidence of interactions in our setting), we are able to minimize such confounding.

[9] Managed care generally organizes healthcare through a network of contracted providers and uses administrative tools to control costs. Plans negotiate rates, direct patients to in-network clinicians and facilities, and apply techniques to reduce unnecessary healthcare utilization (e.g., primary care gatekeeping, prior authorization, formularies, and utilization review). Healthcare professional compensation is typically structured to reduce over-provision of care, for example, using capitation or risk-sharing tied to plan-defined cost and quality targets. Patient cost-sharing is low for in-network care, but coverage for out-of-network treatent is limited.

TennCare coverage included a broad set of behavioral healthcare services. Thus, gaining coverage increased accessibility to behavioral healthcare delivered by primary care providers (Gaynes et al., 2009; Jetty et al., 2021) and expanded access to specialized behavioral healthcare through a carve-out plan (Farrar et al., 2007; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021).[10] As a result, people enrolled in TennCare had relatively generous coverage for behavioral healthcare. Given the link between crime and behavioral health (Deza et al., 2022b; Jácome, 2023), the generous coverage of these treatments suggests that losing TennCare could be important in our setting.[11]

TennCare was popular in Tennessee and enrollment surged, with one in four adults enrolled in TennCare by late 2004, the highest adult Medicaid coverage rate in the country (Farrar et al., 2007). Sustaining the TennCare program became financially untenable for Tennessee (Bennett, 2014), as the program accounted for over 30% of the state budget by 2004 (Farrar et al., 2007). As a result, the proposed termination of TennCare was announced in November 2004 by Governor Phil Bredesen (Chang and Steinberg, 2009), and approved by CMS in March 2005. Beginning in August 2005, all TennCare enrollees were removed from the program and Tennessee no longer covered the expansion population. In the second two quarters of 2005, 10% of the Medicaid population and 3% of the state population – 170,000 people – lost Medicaid coverage. Those disenrolled were predominately adults under 65 years of age without dependents or disabilities (Farrar et al., 2007; Chang and Steinberg, 2009; Garthwaite et al., 2014; Tello-Trillo et al., 2023) with income 100%-175% of the Federal Poverty Level.

A series of studies uses the TennCare disenrollment to understand how losing insurance eligibility impacts access to insurance, use of healthcare, and health outcomes. Several studies document that Medicaid coverage declined post-disenrollment (Garthwaite et al., 2014; DeLeire, 2019; Tello-Trillo, 2021). Garthwaite et al. (2014) shows a 33% reduction in the probability of Medicaid coverage post-shock using the Current Population Survey.[12] There is evidence that some people may have been able to locate replacement coverage, but many individuals became uninsured post-TennCare (Garth-

[10]With a carve-out plan, specific services (here behavioral healthcare) are delivered by a separate healthcare plan than other services. Typically, the carve-out plan provider specializes in delivery of the 'carved-out' services and thus is able to, conceptually, provide higher quality services at reasonable cost through this specialization.

[11]The extent to which providers are willing to accept Medicaid coverage will impact the value of this coverage to enrollees. In our analyses, not reported but available on request, of the 2004 National Survey of Substance Abuse Treatment Services (described in Section 3.2), we find that 55% of specialized behavioral healthcare treatment centers in Tennessee accept Medicaid as a form of payment.

[12]The authors include various forms of public coverage available in the Annual Social and Economic Supplement to the Current Population Survey in their definition of Medicaid to account for potential reporting error in survey data (Lo Sasso and Buchmueller, 2004).

waite et al., 2014; DeLeire, 2019; Tello-Trillo, 2021). Correspondingly, people with lower income who used less healthcare – general, preventive, chronic condition management, and behavioral health – were more likely to report delayed medical care due to cost and experienced worse physical and behavioral health conditions (Garthwaite et al., 2014; Tarazi et al., 2017; DeLeire, 2019; Tello-Trillo, 2021; Maclean et al., 2023; Tello-Trillo et al., 2023). Of particular relevance to our study, Maclean et al. (2023) show that behavioral healthcare hospitalizations declined post-disenrollment and behavioral health outcomes worsened. There are also implications for healthcare providers: Garthwaite et al. (2018) document that hospitals provided more charity care post-disenrollment.

A potential concern among policymakers with the provision of public insurance is 'job-lock,' that is, people enrolled in public coverage (such as Medicaid) may be hesitant to work, or to work more, as such efforts may lead to a loss of coverage eligibility.[13] The TennCare disenrollment offers an opportunity to investigate job-lock and a handful of studies have examined this question. The results to date are mixed with one study documenting evidence of job-lock (i.e., the probability of employment among likely disenrollees increases post-disenrollment) and two studies demonstrating no such evidence (Garthwaite et al., 2014; DeLeire, 2019; Ham and Ueda, 2021).

Economists have explored spillover effects from the TennCare disenrollment beyond healthcare and labor markets. Argys et al. (2020) find that financial well-being, as measured by credit reports declined – potentially due to increased medical debt, following the TennCare disenrollment. Ali et al. (2024) document an increase in evictions and Bullinger and Tello-Trillo (2021) show a decline in child-support payments.

The TennCare literature provides empirical support for several channels through which losing insurance can impact crime – in addition to aggregate effects across society as could occur with a large-scale insurance policy change (Finkelstein, 2007). More specifically, post-disenrollment health (behavioral and physical) declines and financial stability measured by credit reports, evictions, and child support payment declines. The extent to which employment outcomes changed is more opaque at this point in time, but overall the literature provides premise for our study of health insurance losses and crime.

[13] Job-lock is not limited to public insurance. A large literature shows that workers remain in jobs to retain employer-sponsored health insurance (Madrian, 1994; Maclean and Webber, 2022).

3 Data and methods

3.1 Crime data

We use administrative data from the FBI's Uniform Crime Reports (UCR), which provide information on crime-related outcomes, over the period 2002-2007 in Tennessee. We begin the study period in 2002 as in that year Tennessee implemented a large-scale re-certification of enrollees, leading to changes in the composition of those covered by TennCare (Maclean et al., 2023). We close the study period in 2007 to avoid confounding effects from the Great Recession 2008-2010 (Garthwaite et al., 2014). However, as we show in Sections 4.1 and 4.3, our results (using both difference-in-differences and event-studies) are robust to including earlier (back to 2000) and later (through 2010) years.

The UCR data include information on the number of offenses known to law enforcement. We focus our analysis on violent and non-violent Part I crimes. Violent Part I offenses include murder, manslaughter, rape, robbery, and aggravated assault. Burglary, larceny, motor vehicle theft, and arson are considered non-violent Part I crimes. The data compiled for the UCR are submitted voluntarily by city, county, and state law enforcement agencies. Many local municipalities do not consistently report crime data over time (Kaplan, 2021c). To overcome potentially selective reporting in the data, we conduct our analysis at the police agency-level and restrict the sample to agencies that report crimes at least once in each year of our sample period. Our final sample includes 447 out of 576 (77.6%) agencies that ever report data to the UCR Tennessee during our study period 2002-2007. We tighten and relax this assumption in Section 4.3 and show that our findings are very similar using alternative samples.

3.2 Additional data sources

Medicaid coverage: Our primary research design exploits the intensity of the TennCare disenrollment across Tennessee counties based on pre-policy exposure. We measure pre-policy exposure as the share of individuals between age 21 to 64 who are covered by Medicaid in Q1 and Q2 of 2005 (i.e., just prior to the TennCare disenrollment) – we expect this population to be most likely to lose coverage following the policy change (Chang and Steinberg, 2009).[14] To construct the pre-policy coverage rate we divide the number of adults 21 to 64 years enrolled in Medicaid from the Department of Health, Division of TennCare by the county population in this age group (Surveillance, Epidemi-

[14]These data do not include information on dependents, disability status, or other factors that determined TennCare eligibility.

ology, and End Results, 2022).[15] We also use this exposure variable to shed light on the 'first-stage effect:' the impact of the policy shock on Medicaid coverage among people likely to lose TennCare. In this analysis, we use the share of the population aged 21-64 covered by Medicaid as the outcome variable. These data are available for each month from 2005 to 2007. While our main exposure measure is an average of county-level Medicaid coverage rate among adults 21-64 years of age across Q1 and Q2 of 2005, we show in Section 4.3 that our results hold for using data from Q1 only or Q2 only as the exposure measure, and other potential proxies for exposure to the shock.

Data on potential mechanisms: To better understand our crime findings, we conduct an analysis of potential mechanisms to study plausible channels through which losing Medicaid could impact crime – placing emphasis on both likely direct and indirect effects that we capture in our overall estimate of the aggregate effects of the TennCare disenrollment. To this end, we draw data from several different sources.

First, to study the impact of the disenrollment on economic outcomes, we collect data on county unemployment rates from the U.S. Bureau of Labor Statistics (2024) and on median income and poverty rates from the Small Area Income and Poverty Estimates (U.S. Census Bureau, 2024). We supplement this analysis with eviction outcomes – both eviction filings and completed evictions – per 1,000 adults 21-64 years (Eviction Lab, 2021). Filings reflect a landlord placing a formal petition in civil court for the eviction of a tenant, and completed evictions capture the result of a civil court hearing of an eviction case in which the judge determines that the landlord is permitted to evict the tenant.[16] Additionally, we examine potential changes in population sizes using data drawn from the Surveillance, Epidemiology, and End Results (2022) program – if economic conditions respond to the disenrollment, then some Tennessee residents may choose to migrate towards counties with improved economic circumstances.

Second, we examine the effects on healthcare utilization using two different metrics: i) access to general healthcare and delaying care due to cost, and ii) use of behavioral healthcare. We use county-level data on measures of healthcare access among individuals aged 21-64 from the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS) (2025). This survey allows us to analyze respondent questions related to the likelihood of having any insurance and delaying care due to cost. Given the established literature on access to public insurance and behavioral health treatment (Maclean et al., 2023; Ortega, 2023; Grooms and Ortega, 2019; Maclean and

[15] We thank Sebastian Tello-Trillo for kindly sharing Medicaid enrollment data with us.

[16] In the U.S., evictions cases are generally heard in civil, not criminal, court. See Bradford and Maclean (2024) for a full discussion.

Saloner, 2019; Maclean et al., 2017), we obtain county-level data on the number of annual admissions to behavioral health treatment centers using data from the National Survey of Substance Abuse Treatment Services (N-SSATS) (Substance Abuse and Mental Health Services, ND). Centers included in N-SSATS can provide substance use and mental health treatment. For example in 2004, 35% of centers reported mental healthcare as the primary focus of the center.[17] We aggregate the data from the center- to county-level and convert annual admissions counts from N-SSATS to the rate per 1,000 residents (Surveillance, Epidemiology, and End Results, 2022).

Third, we estimate the effects of disenrollment on total mortality, and separately on suicide-, alcohol-, and drug-related mortality by collecting county-level data from the National Vital Statistics System (NVSS) (2025) restricted use-data files. The NVSS are based on death certificates which include the official cause of death, allowing us to isolate behavioral health-related deaths.

Fourth, we explore whether the disenrollment impacted the size and composition of the police force. To do so, we measure the number of officer and civilian employees per agency using administrative data from the Law Enforcement Officers Killed and Assaulted or 'LEOKA' (Kaplan, 2020). We also examine the number of on-duty assaults on officers by civilians, both those assaults that involve an injury on the officers and those that do not, from the same source.

Fifth, to understand whether the disenrollment influenced government expenditures, we utilize data on county-level overall payroll expenditures and for several major payroll categories using the U.S. Census Bureau's Annual Survey of Public Employment and Payroll (ASPEP) sourced from Kaplan (2021a).

Sixth, we also consider the healthcare establishments and employees in these establishments using data from the U.S. Census Bureau (2022b) County Business Patterns, given the large shock to the overall healthcare sector associated with the TennCare disenrollment, there could be changes in the number of providers. These data reflect the universe of known establishments in the U.S. in March of each year. We supplement the County Business Patterns data with imputed employment values from Eckert et al. (2020) as the U.S. Census Bureau suppresses values for a substantial portion of the observations in this variable. The healthcare providers (North American Industry Classification System code) we include are as follows: 1) offices of general physicians (621111), 2) community hospitals (622110), 3) offices of physicians specializing in behavioral health

[17] We include only centers that accept Medicaid and that offer outpatient services in our analysis. Due to federal regulations, such as the Institutions of Mental Disease Exclusion in the Social Security Act, states are deterred from using Medicaid funds to pay for residential and hospital behavioral healthcare.

(621112), 4) offices of non-physicians specializing in behavioral health (621330), 5) outpatient treatment centers (621420), 6) residential treatment centers (623220), 7) behavioral health hospitals (622210), and 8) crisis centers (624190).

3.3 Methods

We estimate the effect of the TennCare disenrollment by comparing counties differentially exposed to this policy shock. We measure exposure as the share of individuals 21 to 64 years enrolled in Medicaid in the first half of 2005, as these individuals would potentially lose Medicaid coverage upon TennCare disenrollment. This design has been used to study policy shocks that impact all observations in a geographic area (Finkelstein, 2007; Miller, 2012; Alpert et al., 2018; Park and Powell, 2021; Andersen et al., 2023; Cohle and Ortega, 2023; Hackmann et al., 2025), including TennCare (Argys et al., 2020).

Consider two 'extreme' counties in Tennessee, one with 0% of the county population aged 21-64 covered by Medicaid in the first half of 2005 and the other county with 100% coverage. We compare trends in these two counties before and after the TennCare disenrollment. Our analyses rely on the assumption that the latter county is more impacted by the TennCare disenrollment than the former county. However, these 'extreme' counties with either 0% or 100% Medicaid coverage among people 21-64 years old we describe here do not exist in Tennessee. Thus, as we discuss later in this section, we will scale our coefficient estimates to produce more policy-relevant findings.

We restrict the analysis to Tennessee and estimate the effect of the disenrollment on crime using the difference-in-differences (DID) regression outlined in equation 1:

$$y_{icrt} = \beta_0 + \alpha_i + \gamma_{tr} + \beta Exposure_c \times Post_t + \mathbf{X_{crt}}\gamma + v_{icrt} \tag{1}$$

Where y_{icrt} is the crime rate (per 1,000 people served by the police agency) in agency i in county c that is rural/urban in year t. The median county in our analysis sample has four agencies. The terms α_i and γ_{tr} represent agency and year-by-rural area fixed effects, respectively.[18] We use the USDA (2024) Rural-Urban Continuum Codes to distinguish between rural and urban counties. $Exposure_c$ is the share of the county population ages 21-64 covered by Medicaid in Q1 and Q2 of 2005 (i.e., just before to the policy shock). The variable $Post_t$ is an indicator equal to one for years 2005 to 2007, and zero otherwise. Thus, 2005 is a partially treated year as the disenrollment occurred in August, we expect effects to be muted in that year. The vector $\mathbf{X}_{crt}$ includes county-level

[18]Specifically, to construct the year-by-rural area fixed effects, we interact an indicator for whether the agency is in a rural area with the year fixed effect. Agency fixed effects subsume county fixed effects.

demographic variables.[19] Data are weighted by the population served by the agency.

Standard errors are clustered at the county-level. There are 95 counties in Tennessee, thus we have a sufficient number of clusters to allow for credible inference (Bertrand et al., 2004). However, we estimate OLS regressions, which are vulnerable to outlier bias (Wooldridge, 2010), and crime data are known to be subject to outliers (Mello, 2019). In our main analyses, we top-code the crime rates at the 90th percentile. However, as we report in Section 4.3, results are robust to alternative treatments of outlier observations.

The coefficient of interest in equation 1 is β, which compares the extent to which increasing exposure (i.e., the share of the county population ages 21 to 64 years covered by Medicaid averaged over Q1 and Q2 2005) from 0% to 100% impacted crime rate following TennCare disenrollment. As there are no counties with either 0% to 100% of their population aged 21-64 covered by Medicaid, we scale β by the difference between the 75th (22% coverage) and 25th (15% coverage) percentile of exposure, which is seven percentage points. We will refer to this difference as the 'scaled beta (β).' More specifically, we multiply the coefficient estimates generated in equation 1 by 0.07.

A causal interpretation of findings generated in equation 1 relies on the common trends assumption. That is, had the TennCare disenrollment not occurred in August 2005, counties (regardless of pre-policy Medicaid coverage) would have followed similar trends in crime outcomes over the post-period. This assumption is untestable as we cannot observe counterfactual outcomes in which Tennessee counties are untreated by the disenrollment post-2005. To provide suggestive evidence on the ability of our data to satisfy the common trends assumption, we estimate an event-study. If we observe that crime rates evolved smoothly pre-disenrollment across counties with differential exposure to the policy shock, this pattern of results would provide suggestive evidence that our data can satisfy the common trends assumption.

We employ the event-study shown in equation 2:

$$y_{icrt} = \beta_0 + \alpha_i + \gamma_{rt} + \sum_{\substack{j=2002 \\ j\neq 2004}}^{2007} \beta_j Exposure_c \mathbb{1}\{j=t\} + \mathbf{X}_{crt}\psi + v_{ictr}, \tag{2}$$

where $\mathbb{1}\{j=t\}$ is an indicator variable set equal to one if the observation is in year $j = 2002 - 2007$ for $j \neq 2004$ and zero otherwise. All other variables are as described in

[19]We utilize data on population rates by race (White and non-White, with non-White as the omitted group), ethnicity (Hispanic and non-Hispanic, with non-Hispanic as the omitted group) and age (zero to 20 years, 21 to 64 years, and 65 years and older, with zero to 20 years as the omitted group) from the Surveillance, Epidemiology, and End Results (2022) program.

equation 1. The coefficient estimates of interest are the β_j's, which capture the effect of the TennCare disenrollment over time - again (without scaling) comparing hypothetical counties with 0% and 100% Medicaid coverage among residents 21-64 years of age, both before and after 2005. If we observe that coefficient estimates on the policy 'leads' (i.e., pre-period) are not statistically distinguishable from zero and small in magnitude, then this pattern of results offers suggestive evidence that the data can satisfy common trends. The policy lag coefficient estimates, β_j for $j \geq 2005$, allow us to examine the dynamic effects for the years post-disenrollment.

3.4 Descriptive analysis and first-stage

Table A1 reports the summary statistics for crime rates and time-varying control variables for the years before the disenrollment. We report summary statistics for counties above median exposure to the TennCare disenrollment among those of age 21-64 (i.e., the median value is 0.19) and at or below the median. Here we see that the average number of total crimes is 56.3 per 1,000 residents served by the agency. 61.5% of crimes are non-violent (34.6 per 1,000 residents) and the remaining 38.5% are violent crimes (21.4 per 1,000 residents). Comparing columns (2) and (3) shows that counties above the median exposure to the disenrollment have higher crime rates than less exposed counties.

Our identification strategy relies on variation in pre-disenrollment exposure to TennCare. Figure A1a reports a histogram of TennCare exposure in Q1 and Q2 of 2005, just before the policy change. We average exposure for each county in Tennessee across the two quarters. The exposure pre-policy (weighted by the county population 21-64 years) ranges from 4.0% to 40.7%, with a 25th percentile of 15%, a 75th percentile of 22%, a mean of 19.2%, a median of 19%, and the distribution is roughly bell-shaped with a slight right-skew. As presented in Figure A1b, there is some geographic clustering of counties with higher and lower exposure, but overall the figure suggests that there is reasonable variation across the state in Medicaid coverage.

The geographic distribution across Tennessee counties in 2004 of total, violent and non-violent crime rates is reported in Figure A2. Figures A3 and A4 report trends in total crime, and then violent and non-violent crimes in counties in the top and bottom quartile of exposure to the disenrollment. In counties highly exposed to the disenrollment (i.e., those with a Medicaid coverage rate among adults 21-64 years of age in the top quartile during the first half of 2005), crime rates, in particular non-violent crime rates, rose while trends for less exposed counties where more stagnant, and even slightly decreased. Given that the U.S. was experiencing a decline in crime rates nationally over this period (Pew

Research Center, 2020) - see Figures 1 and 2 for national trends in crime over the period 1990 to 2019 - the rise we observe in more exposed Tennessee counties offers suggestive evidence that the disenrollment increased crime.

We study a downstream consequence of Medicaid disenrollment, thus a necessary condition is that the disenrollment lead to meaningful change in Medicaid coverage. We examine the first-stage using equation 1. Results are reported in Table 1.[20] Event-study results are provided in Figure A5. We modify the event-study slightly given that we have monthly Medicaid enrollment data 2005-2007. More specifically, we use six month leads, July 2005 is the omitted category, and we include a full set of month lags, otherwise the specification is identical to equation 2. The event-study shows limited differential pre-trends for counties with varying pre-disenrollment exposure, and a sharp and immediate decline in coverage in the post-period in counties with higher pre-disenrollment exposure, proxied by a higher share of 21-64 year old individuals covered by Medicaid in the first half of 2005. This decline persists through the end of 2007.

The coefficient estimate of interest in equation 1 captures the extent to which monthly Medicaid coverage changes with exposure to the disenrollment for a hypothetical county with 100% of residents 21-64 years of age enrolled in Medicaid vs. a county with 0% coverage within this age group. We find that the former county within Tennessee experienced roughly a 24 percentage point ('ppt') decline in monthly Medicaid coverage post-disenrollment among residents 21-64 years of age compared to the latter county. Relative to the 25th percentile county, the 75th percentile exposure county experienced a roughly two ppt reduction in Medicaid coverage post-disenrollment (= -0.24 $\times$ 0.07).

4 Results

4.1 TennCare and crime

Our main analysis examines the effect of Medicaid disenrollment on crime. We first present results based on the event-study outlined in equation 2. The event-study offers the opportunity to explore trends in crime outcomes between high- and low-exposure counties prior to the policy change, and to investigate the dynamics in the post-period.

Figure 3 plots the pre-and post-treatment effects of TennCare disenrollment on agency-level crime rates per 1,000 residents served for three outcomes: total, violent and non-violent crime rates, respectively. For each outcome, we present coefficient estimates both

[20]Because we have monthly data, we include period (month-year) fixed effects. That is, we include a separate indicator for each month-year pair that we observe in the data.

with and without covariates. Across all sets of coefficient estimates, we observe no evidence of a pre-trend in crime rates before the disenrollment. Furthermore, we find a clear trend break and a sharp increase in total crime and non-violent crime following disenrollment. This effect becomes statistically distinguishable from zero in 2006 (2005 is potentially a 'washout' year as the policy went into effect in August, but we use annual data and thus code all of 2005 as treated). Figure 3 shows that the coefficient estimates are robust to the inclusion of time-varying covariates. Furthermore, results from a covariate balance test, in which separate regressions are conducted for each control variable on the TennCare exposure measure, county fixed effects, and urbanicity-by-year fixed effects, are presented in Figure A6. We conduct these regressions at the county-level, the level at which treatment varies. We find that counties are reasonably well balanced. Notably, our DID results are robust to the inclusion or exclusion of these controls.

Figure 4 plots the pre-and post-treatment effects using our preferred time period (2002-2007) and two alternative periods: 2000-2007 and 2002-2010. The overall pattern of results holds across these different samples, though there are some differences observed early in the 2000-2007 period which we attribute to a re-certification of Medicaid eligibility undertaken by the state (see Section 2.2). However, and importantly for our design, differences moderate in years just prior to the disenrollment, suggesting that any divergence in crime rate trends across counties pre-shock was transient and not likely to bias our main findings. When using the longer post-period, we observe that the trends in crime outcomes continued, despite the Great Recession of 2008-2010.

We summarize our main findings in Table 2 by presenting our static DID (equation 1) results for crime rates. Table A2 shows the DID estimates when excluding time-varying covariates. Column (1) presents the effect of disenrollment on total crime. In line with the results in Figure 3, column (1) suggests a statistically significant increase in the total crime rate in counties most exposed to the 2005 disenrollment.

The coefficient estimate implies that the disenrollment led to 1.67 additional crimes per 1,000 agency-covered residents for a police agency at the 75th vs. the 25th percentile of pre-shock exposure ($= 23.81 \times 0.07$). Comparing the coefficient estimate with the baseline mean implies that a police agency in the 75th percentile pre-disenrollment exposure county experienced a 2.61% increase in the total crime rate post-disenrollment, relative to a police agency in the 25th percentile pre-disenrollment exposure county.

In columns (2) and (3), we report the coefficient estimates for violent and non-violent crimes, respectively. Following the disenrollment, a police agency at the 75th (vs. the 25th) percentile pre-disenrollment exposure experienced an increase in total and non-violent crime of 0.13 and 1.76 per 1,000 residents or 0.49% and 4.42%, respectively.

Though positive, the coefficient estimate for violent crime is imprecise.

We next examine which specific types of crimes are driving our aggregate findings in Table A3. For violent crimes presented in Panel A, we find no statistically significant effect of the disenrollment on any of the specific crimes (murder, rape, robbery, or aggravated assaults). For non-violent crime presented in Panel B, we see that the result is driven by thefts, which increased by 1.82 additional thefts per 1,000 residents at an agency in the 75th percentile of pre-disenrollment exposure relative to an agency in the 25th percentile of exposure, or by 6.99%. We find no evidence that the TennCare disenrollment affected burglary, motor vehicle theft, or arson rates. The fact that our findings are concentrated among thefts hints that losing Medicaid led some people to commit economically-motivated crimes, potentially in response to financial strain from medical bills, worse labor market outcomes as health declines, or reduced ability to weigh the costs and benefits of such crimes due to impeded behavioral health. People not directly impacted by the policy shock (e.g., those individuals affected through cascading or secondary effects of the disenrollment) could also be influenced through similar channels. Later in this section, we will more formally investigate mechanisms.

We next look at the costs of crimes to society by adjusting crime types according to their expected social costs. In particular, we use the following weights (see Table 1 in Chalfin and McCrary (2018), values are reported in 2010 dollars): homicide ($7,000,000), rape ($142,020), robbery ($12,624), aggravated assault ($38,924), burglary ($2,104), theft ($473), and motor vehicle theft ($5,786). These weights capture the relative cost to society per crime. We then convert cost-adjusted crimes to per 1,000 residents. Overall, Table A4 shows that the TennCare disenrollment has limited effects on the social costs of crime. While we documented earlier that the disenrollment led to an increase in crime rates, especially non-violent crime, due to theft, theft imposes the lowest costs on society; thus, the null findings for crime costs are not surprising.

4.2 Mechanisms

Our main results, showing an increase in crime, likely capture the aggregate effects of disenrollment in Tennessee in addition to the direct costs on those people who lost Medicaid coverage. That is, while the policy directly removed coverage for a subset of individuals, the disenrollment could have cascading effects across the population. For example, following the disenrollment, there may have been reductions in the size of the healthcare workforce or closures of healthcare facilities, which could have implications for access to care regardless of insurance status. Moreover, in addition to covering a large share of the population, TennCare provided relatively generous coverage for a wide-range of medical services (see Section 2.2), which may imply that healthcare professionals could have altered their practices in response, potentially shifting away from services previously covered by TennCare for all patients in the practice. Glazer and McGuire (2002) argue that the multi-payer nature of the U.S. healthcare market can result in patients receiving the same quality of care regardless of their insurance status, the authors refer to this phenomenon as the 'commonality of care.' A series of studies, in addition to analyses conducted by Glazer and McGuire (2002), provide empirical support for this hypothesis – see for example, Baker (2003), Einav et al. (2020), and Barnett et al. (2023). Thus, there may have been changes in the quality of care across all patients post-disenrollment. Healthcare is a major employer in many communities (Nguyen et al., 2023), and Medicaid in particular provides important financial resources to many healthcare facilities (Blavin, 2016), thus declines in this sector could lead to increases in unemployment among healthcare workers and for those employed in sectors that provide support services to healthcare facilities (e.g., food services, construction, technology). Such changes in employment opportunities could, in turn, lead some individuals to migrate from counties more exposed to the policy shock to counties less exposed in efforts to locate jobs.

At the height of enrollment in 2004, TennCare covered roughly 25% of the state's population and represented over 30% of the budget or more than \$7.1 billion in 2004 dollars (see Section 2.2),[21] thus the disenrollment potentially made available substantial resources that could be used for other purposes (e.g., public safety, other social assistance programs, or education). Given these possibilities, our main findings likely capture both the 'mechanical' effect of Medicaid coverage loss for disenrollees and broader disruptions in healthcare access and providers' practice styles, and economic conditions, and changes in public spending. We now consider some of these possible pathways – and those that may be more closely linked to the experienced of disenrollees who were directly affected by the policy – that may explain our findings.[22]

4.2.1 Economic stability

We first examine the role of economic stability in Table 3 given that economic opportunity and income are strong predictors of criminal activity (Raphael and Winter-Ebmer,

[21] In fiscal year 2004-2005, the budget for Tennessee was \$23.8 billion (State of Tennessee, Department of Finance and Administration, 2003).

[22] We also estimate event-studies for these potential mechanisms (results available on request), which confirm the effects post-disenrollment. Some of the mechanisms exhibit evidence of differential pretrends, and thus we interpret results presented in this section as suggestive evidence of mechanisms.

2001; Lin, 2008; Akee et al., 2010). We extend our regression from equation 1 to examine county-level unemployment rates, poverty rates, median income, and eviction outcomes in Panels (A)-(C). The findings in Table 3 suggest that Medicaid disenrollment significantly impacted unemployment in Panel A; the coefficient estimate is negative, which is suggestive of job-lock. In particular, a county in the 75th percentile of pre-disenrollment exposure experienced a 2.85% decrease in unemployment following the TennCare disenrollment, relative to a county in the 25th percentile of pre-disenrollment exposure.

Conversely, Panel B suggests an increase in the poverty rate. Although imprecisely estimated, the results reported in column (3) buttress the poverty finding by showing a decrease in county median income. In particular, a county in the 75th percentile of pre-disenrollment exposure experienced a 4.51% increase (1.08% decrease) in poverty (median income) following the TennCare disenrollment, relative to a county in the 25th percentile of pre-disenrollment exposure. While we cannot isolate the effect on the individuals particularly close to the poverty line, these findings collectively provide suggestive evidence that Medicaid disenrollment may have pushed such individuals over the poverty threshold, without simultaneously affecting labor market opportunities or financial resources for the average individual in Tennessee. Those losing coverage with the disenrollment had family incomes just above the poverty line (100% to 175% of the Federal Poverty Level, see Section 2.2) and thus could be 'at risk' for poverty following a negative shock.

In Panel C, we follow Ali et al. (2024) and estimate the effect of the TennCare disenrollment on eviction outcomes. We find an increase in both eviction filings and completed evictions post-disenrollment. In particular, a county in the 75th percentile of pre-disenrollment exposure experienced a 46.06% (23.28%) decrease in evictions filings (completed evictions) following the TennCare disenrollment, relative to a county in the 25th percentile of pre-disenrollment exposure.[23] Panel D reports results of a regression of the county population on exposure to the TennCare disenrollment, we use Surveillance, Epidemiology, and End Results (2022) population counts. We observe no evidence that the policy shock led to changes in population.

4.2.2 Health and access to healthcare

We complement this analysis with BRFSS data, which allow us to examine whether the disenrollment affected access to care and the cost healthcare. For this analysis, we focus on adults 21-64 years without minor children in the household. Column (1) of Table

[23]To account for differences across counties in the cost of renting, we follow Ali et al. (2024) and control for the median property values. Results are similar, although less precise, if we do not include this variable in the eviction regressions (results available on request). We show in Section 4.3 that including these additional controls in our crime regressions does not alter our main findings.

4 suggests that a county in the 75th (vs. 25th) percentile of pre-disenrollment exposure experienced a decrease of 2.44% in the likelihood of being covered by health insurance (BRFSS, over our study period, does not allow us to separately consider Medicaid coverage). This decline in the probability of any coverage, coupled with results reported in Section 3.4, suggests that at least some disenrollees were unable to replace lost Medicaid with other insurance. Column (2) indicates that respondents reported delaying healthcare due to cost. Comparing the 75th to the 25th percentile pre-disenrollment exposure county, the probability of delaying care due to cost increased by 6.25%. We observe no change in the probability of reporting very good or excellent health in Column (3).

4.2.3 Mental health and substance use disorder treatment

Poor mental health and substance use (both alcohol and other drugs) are closely linked with crime outcomes, and use of mental health and substance use disorder treatment has been shown to reduce crime (Bondurant et al., 2018; Deza et al., 2022b,a). Further, as described in Section 2.2, TennCare offered relatively generous treatment for these conditions. Thus, we consider the effects of Tennessee's Medicaid disenrollment on proxies for mental health and substance use disorder treatment utilization. Using county-level data from N-SSATS, we show that admissions to specialized treatment centers declined post-disenrollment (Table 5). In particular, a county in the 75th percentile of pre-disenrollment exposure experienced a 48.15% decrease in admissions relative to counties in the 25th percentile, following TennCare disenrollment.

4.2.4 Mortality

In Table 6 we report changes in mortality based on NVSS data. We observe no evidence that all-cause mortality rates increased in response to the disenrollment, indeed, the coefficient estimate is negative, but does not rise to the level of statistical significance. On the other hand, we find that TennCare disenrollment led to a 21.74% increase in drug overdose deaths in counties in the 75th percentile of exposure relative to counties in the 25th percentile of exposure post-disenrollment. The coefficient estimates for deaths by suicide and fatal alcohol poisonings are positive, suggesting that deaths for these causes increased in more exposed counties post-disenrollment, but the findings are noisy.

4.2.5 Law enforcement

We next evaluate whether TennCare disenrollment impacted other determinants of crime and implications for police officers (e.g., size and composition of police force as well as on-duty officer assaults). The disenrollment potentially made available financial resources to the state which could have been used to fund public services, such as law enforcement. Given the observed increase in crime post-disenrollment, we might be concerned that this increase in police-civilian interactions may lead to an increase in on-duty assaults on officers by civilians.[24] In Table 7, we investigate the effects of disenrollment on the number of police officers and civilian employees, separately, and assaults on police officers overall and stratifying by whether the on-duty assault leads to an injury or not for the officer. We find suggestive evidence that total on-duty assaults on officers increase post-disenrollment in counties most exposed to the disenrollment shock.

4.2.6 Government expenditures

Next, as a complementary analysis of potential crime determinants, we explore whether the TennCare disenrollment impacted other government expenditures in Table 8. For example, resources not spent on TennCare could be allocated to fund other public services, which, in turn, may impact crime outcomes. To study this possibility, we turn to county-level data on per-capita payroll outcomes based on the Annual Survey of Government Employment. The survey provides local payroll expenditures by governmental function, such as police officers only (persons with power of arrest), other police employees (persons who do not have the power of arrest.), health, hospital, education (elementary and secondary instructional employees), and streets (streets and highways).

Following the disenrollment, we observe a decline in total payroll expenditures, driven by a curtailment in expenditures for police/public safety and health, in counties more exposed to the policy shock. The findings for payroll expenditures – in combination with the null findings for the number of employees – might suggest that, while the police force size did not vary following the disenrollment, officer or civilian employees might have worked fewer hours or potentially received lower compensation. Prior to the disenrollment, the state was experiencing financial strain and curtailed expenditures, because budgets are set in advance, some of these declines may have planned during that period of budget tightening. Given the effect of police and police resources on crime deterrence (Cox et al., 2022b,b; Chalfin et al., 2022; Miller and Segal, 2019), the findings in Table 8 suggest that a decline in police investments may contribute to the increase in crime that we find. Further, the reduction in health expenditures could include the direct effects

[24] Recent economic work considers the role of police in reducing crime, establishing that the size and composition of police force can lower crime (Miller and Segal, 2019; Chalfin et al., 2022; Cox et al., 2022a,b). Additionally, a small set of studies explores determinants of on-duty police officer assaults in the context of criminal activity and public safety (Chalfin et al., 2022; Deza et al., 2023).

of the disenrollment (with fewer peopled enrolled in Medicaid, state Medicaid spending should decline) but could also reflect broader trends in expenditures on healthcare. However, when including these payroll measures as covariates in the crime regression (Section 4.3), we observe qualitatively similar results to our main crime finding. This pattern of results offers suggestive evidence that broader changes in government expenditures, including those targeting crime and public safety, contribute to, but do not fully explain, our main crime findings.

4.2.7 Healthcare establishments and employment

TennCare disenrollment mechanically changed access to healthcare. This section examines whether the supply of healthcare, as measured by healthcare establishments and healthcare employment, responded to TennCare disenrollment. Table 9 shows that a county in the 75th percentile of pre-disenrollment exposure experienced a decrease of 13.54% in general healthcare establishments and 13.23% in healthcare employment relative to counties in the 25th percentile, upon TennCare disenrollment.

Notably, counties with higher levels of pre-disenrollment exposure experienced an increase in supply of behavioral health outpatient treatment centers, as measured by the number of establishments and employees. While we cannot fully explore this finding with our data, we can offer a hypothesis. Beginning in the 1990s, consolidation of behavioral healthcare providers became increasingly common (Lazarus, 1995; Cuéllar and Haas-Wilson, 2009) and the disenrollment may have muted this trend in Tennessee. Put differently, fewer centers merged that would have occurred in the counterfactual setting of the state continuing to cover the expansion population in Medicaid.

4.3 Robustness and placebo analysis

In this section, we report results from a range of robustness checks for our main crime findings and conduct placebo analyses. Overall, our results are not sensitive to alternative specifications or samples and we cannot replicate our main findings in the placebo analysis, which further supports a causal interpretation of our main findings.

4.3.1 Alternative samples and specifications

Figure A7 report the DID effects for total, violent, and non-violent crime rates using different samples and specifications. The purpose of these exercises is to ensure that our findings are not driven by researcher choice. We first reproduce our baseline coefficient estimates from Table 2 for comparison.

We change our sample restrictions and re-estimate equation 1 using alternative subsamples. First, we restrict the sample to agencies reporting criminal activity in all months and all years; all months in at least one year; agencies serving at least 10,000 people; and all agencies in the UCR database regardless of reporting or size of the population served. Second, we consider different approaches to handling outliers in crime rates: bottom code observations below the 10th percentile; top code observations above the 25th, 5th, and 1st, percentiles; and exclude observations above the 90th percentile of crime rates. We also vary the way in which we weight the data: unweighted regression, and use the 1st population and mean population as the weight. Third, we compute our measure of exposure to the disenrollment using the following Medicaid coverage rates: 1) all ages, sexes, and quarters; 2) 21-64 years and all sexes Q1 2005; 3) 21-64 years and all sexes Q2 2005; 4) 21-64 year old males in all quarters; and 21-64 year old females in all quarters.

We also vary the controls we include in the regression. We replace urbanicity-by-year fixed effects with year fixed effects. We additionally control for rental market variables (median property values and rent burden from the Eviction Lab (2021)) and economic and public safety covariates (officer and civilian employees per agency (Kaplan, 2021b), overall payroll in the county (U.S. Census Bureau, 2022a), and the county-level unemployment rate (Bureau of Labor Statistics, 2022)), separately. Finally, in Figure A8, we conduct a 'leave-one-out' analysis by sequentially excluding each county in Tennessee one at a time and re-estimating our main regression (equation 1).

4.3.2 Placebo analyses

We further confirm our results by estimating equation 1, but artificially set 2003 and 2004 as alternative placebo years of disenrollment. We exclude the post-treatment years. Figure A9 displays the coefficient estimates on total, violent, and non-violent crime rates from the main specification using the actual 2005 TennCare disenrollment year, and placebo policy years of 2003 and 2004, separately, for comparison. The figure shows that the estimated coefficients of these placebo policies are null for all outcomes.

We conduct a second placebo test with the goal to assess how likely we are to observe the coefficient estimates reported in Table 2 due to spurious correlation in the absence of any actual TennCare effects on crime. More specifically, we randomly assign the treatment variable (i.e., pre-policy Medicaid coverage among adults 21-64 years $\times$ the post-period) to each observation and re-estimate equation 1 200 times. Each panel of Figure A10 displays the estimated treatment effect in the first iteration (large diamond) and the coefficient estimate for each of the 200 interactions (small dots) which are placebo estimates. Intuitively, if our placebo estimate estimates are generally similar in size, sign, and statistical significance to the main estimated coefficient, that pattern of results would suggest that our estimated coefficient could be spurious. Figure A10 indicates that none of the placebo coefficient estimates reach the magnitude of our main estimated TennCare effects, which provides reassurance that our estimated main effects capture the true effect of the TennCare disenrollment on crime outcomes.

5 Discussion

This paper contributes to the growing literature that establishes a negative relationship between access to healthcare and crime (Bondurant et al., 2018; Deza et al., 2022a,b, 2023; Jácome, 2023). A series of studies show that gaining insurance coverage, in particular Medicaid coverage (Cuellar and Markowitz, 2007; Wen et al., 2017; He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022),[25] reduces crime. However, much less is known about the importance of losing insurance, and conceptually, the impact of gaining and losing coverage need not be symmetric. Examining the impact of losing health insurance is particularly relevant at this time, as states are tightening the requirements for maintaining Medicaid coverage eligibility (Sommers et al., 2019; Chen and Sommers, 2020; Guth and Musumeci, 2022). Additionally, the 'unwinding' of Medicaid coverage provisions that were put in place during the U.S. government's public health emergency due to the COVID-19 pandemic is underway (Tolbert, 2023). Furthermore, lawmakers are proposing policies aimed at reducing Medicaid eligibility (The White House, 2023).

This paper uses Tennessee's Medicaid disenrollment in 2005 to shed new light on the insurance-crime relationship. The disenrollment, one of the most substantial reductions in coverage in the history of the Medicaid program, resulted in 170,000 adults 19-64 years of age without dependents and disabilities unexpectedly losing Medicaid coverage over a six-month period. We compare counties within Tennessee with differential levels of policy exposure based on Medicaid coverage rates before disenrollment. To this end, we exploit differences in the extent to which Tennessee counties were exposed to the policy shock based on pre-disenrollment Medicaid coverage rates.

We find that agencies in the 75th percentile of pre-disenrollment exposure (= 0.22 in pre-policy Medicaid coverage rates) experienced a 2.61% increase in crime rates, with violent and non-violent crime rates rising by 0.53% and 4.43% respectively, relative to agencies in the 25th percentile of pre-disenrollment exposure (= 0.15 in pre-policy Medicaid coverage rates), though we note that the violent crime finding is imprecisely

[25] We acknowledge that a full consensus has not yet been reached: Finkelstein et al. (2024) finds limited crime effects among adults under 65 years of age randomized to Medicaid enrollment in Oregon.

estimated. While we study an insurance loss within a different (older) population, our findings are qualitatively similar to Jácome (2023) and Fone et al. (2023), who study expected 'aging-out' of public and private coverage, in that losing insurance is more strongly associated with non-violent than violent crime. We examine the impact of the TennCare disenrollment on each type of offense, violent and non-violent, to better understand which crimes are influenced by an insurance loss. Our overall crime effects are driven by theft, the most common non-violent offense, suggesting that losing insurance leads to financially motivated crimes.

We present evidence of a 'first-stage,' as TennCare disenrollment decreased the probability of having health insurance, both Medicaid coverage and coverage overall, thus at least some disenrollees were unable to replace lost Medicaid with other insurance forms. Our analysis of mechanisms suggests that the crime effects were driven by worsening financial standing and overall and behavioral-health wellbeing. We show that poverty rates and the probability of delaying overall medical care due to cost increased post-policy. Changes in mental health and substance use disorder outcomes appear to be particularly salient, which is in line with the findings of Jácome (2023) for people aging out of Medicaid at age 19. More specifically, we find that admissions to behavioral healthcare treatment decline and deaths related to substances increase post-disenrollment. Combining our findings on theft with the results of our mechanisms analysis suggests that losing insurance reduces economic stability and negatively impacted behavioral health. Disenrollees may resort to financially motivated crimes to make ends meet and, due to declines in behavioral health, may struggle to properly assess the risks and consequences of engaging in criminal activity, and may be at elevated risk for victimization.

Large changes in health insurance markets can have both direct and indirect effects on communities (Finkelstein, 2007). Thus, our results likely capture the 'aggregate' effects of the TennCare disenrollment, which include both insurance losses among those people disenrolled from the program and broader changes in access to and quality of healthcare, economic conditions, and government expenditures, which potentially impacted a substantial swath of the population. Our analyses of mechanisms (described above) highlight some of the potential 'indirect' effects of the policy shock, but there are likely other factors at play that also contribute to our overall estimate.

Using our coefficient estimates for Medicaid coverage and total crime rates, we calculate an implied number-needed-to-treat (NTT). We find that the TennCare disenrollment led to a 24% decrease in the number of 21-64 year olds covered by Medicaid in a county, translating to 352 (841) fewer people enrolled in Medicaid in the county at the 75th

(25th) percentile of pre-disenrollment exposure.[26] At the same time, a police agency in the 75th (25th) percentile of exposure experienced 5.24 (3.57) additional crimes per 1,000 covered population by the agency.[27] Given that the population covered by an agency in the 75th (25th) percentile was 3,868 (8,144), and there were three (five) agencies in counties at 75th (25th) percentile of exposure this change translates into 20 (29) additional crimes per agency,[28] or 61 additional crimes per county – 20.26 × 3 for the 75th percentile county, and 29.08 × 5 for the 25th percentile of exposure. This back-of-the-envelope calculation suggests that the TennCare disenrollment led to 0.17 total crimes per person newly disenrolled.[29] Notably, we expect these effects to be driven only partially by new disenrollees becoming crime offenders or victims, as we expect that our estimated coefficients capture the aggregate effects of the disenrollment which, as we have shown, had cascading impacts across communities.

Our study is not without limitations. First, because TennCare enrollment primarily targeted adults with low income and below age 65 without children and disabilities, extrapolating our findings to the overall Medicaid-covered population may be inappropriate. Second, we study a historical policy change and insurance markets have developed over time, with individuals having more insurance options in the post-ACA period than in the mid-2000s. Third, our pre-period is somewhat short due to other Medicaid changes that occurred in Tennessee in the early 2000s, though we report findings using a longer pre-treatment period and results are not different.

Our findings provide evidence on the value of insurance, in particular, the value to society that extends beyond the insured individual. Crime imposes costs on government budgets, crime victims, and society. Going against historical trends, recent policies – in place and proposed – could lead to many Americans losing Medicaid and other forms of

[26] Prior to the TennCare disenrollment, the 75th percentile of exposure county had 1,468 enrollees (22% of the number of 21-64 population = 0.22 × 6,674) and 6,674 individuals aged 21-64. Following the TennCare disenrollment, there was a 5.28 ppt (= $\hat{\beta} \times 0.22$) decline in the share of adults age 21-64 years covered by Medicaid. This change implies that the number of new disenrollees in the 75th percentile exposure county was 352 (= 0.0528 × 6,674).

[27] We calculate these values as follows: 5.24 (= $\hat{\beta} \times \textit{exposure} = 23.81 \times 0.22$) for an agency in the 75th percentile of exposure; or 3.57 (= 23.81 × 0.15) for an agency at the 25th percentile of exposure.

[28] We calculate these values as follows. 5.24 × 3,868 ÷ 1,000 for the 75th percentile and 3.57 × 8,144 ÷ 1,000 for the 25th percentile.

[29] We calculate these values as follows: = 61 ÷ 352 in the 75th percentile county and = 145 ÷ 841 in the 25th percentile county. Comparing our effect sizes with studies documenting that crime declines following ACA Medicaid expansion – e.g., Vogler (2020) – is somewhat challenging given differences in assumed counterfactuals and empirical designs, changes in insurance options between 2005 and 2014, and potential asymmetries in coverage gains and losses. Moreover, we find evidence that the TennCare disenrollment had aggregate effects that could also contribute to the increases in crime we document. For example, we document decrease in public safety expenditures, which have also been shown to increase crime, independent of Medicaid enrollment - e.g., Chalfin et al. (2022) and Cox et al. (2022b).

insurance, or the costs of healthcare (even among the insured) increasing and rendering healthcare, in particular mental healthcare and substance use disorder treatment, unaffordable (Walker et al., 2015; Ali et al., 2017). Our findings suggest that these policies may have unexpected and negative consequences for communities across the country. Moreover, our work contributes to the broader line of literature documenting the importance of insurance for crime outcomes, and further suggests that insurance offers a potential tool to reduce crime outcomes in the U.S.

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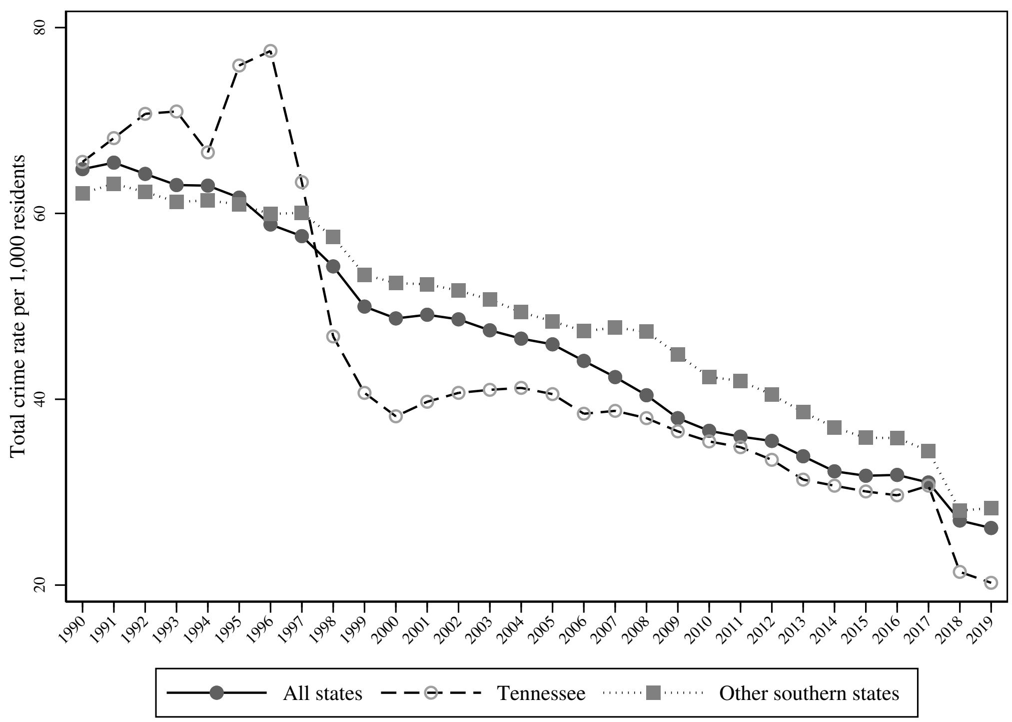
6 Figures and tables

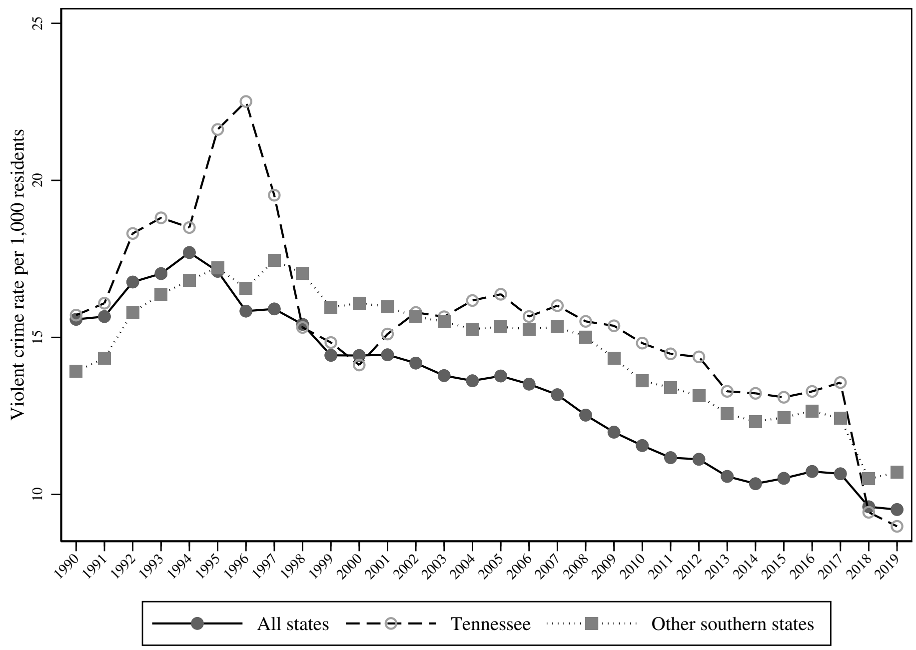
Figure 1: Trends in national crime rates: Uniform Crime Reports 1990-2019



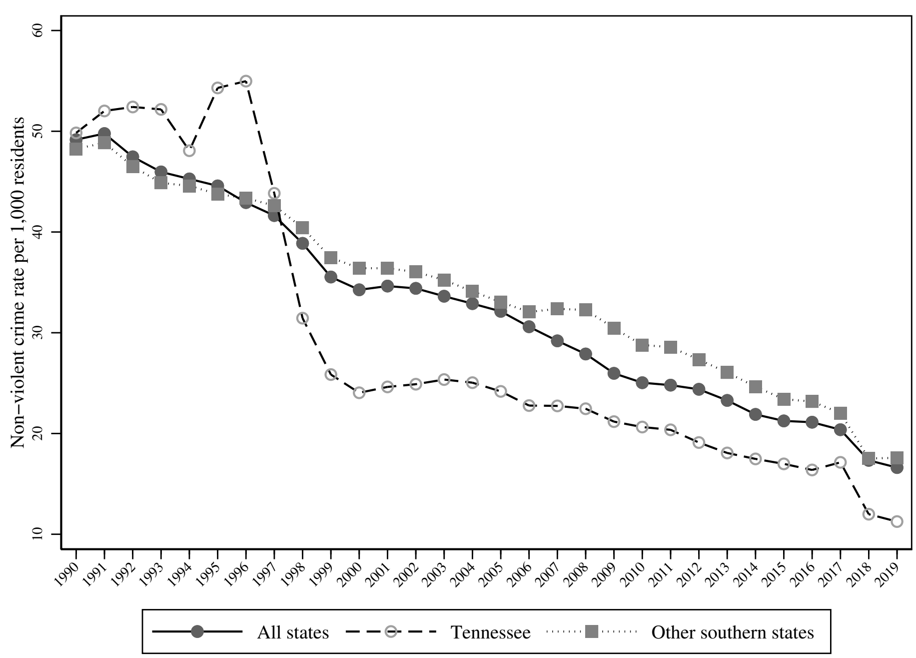
Notes: This figure plots average annual crime rates over time. Crime rates are per 1,000 residents served by the agency. Data are weighted by the population served by the agency. Agencies serving populations greater than 10,000 people are included in the sample.

Figure 2: Trends in national violent and non-violent crime rates: Uniform Crime Reports 1990-2019

(a) Panel A: Violent crime

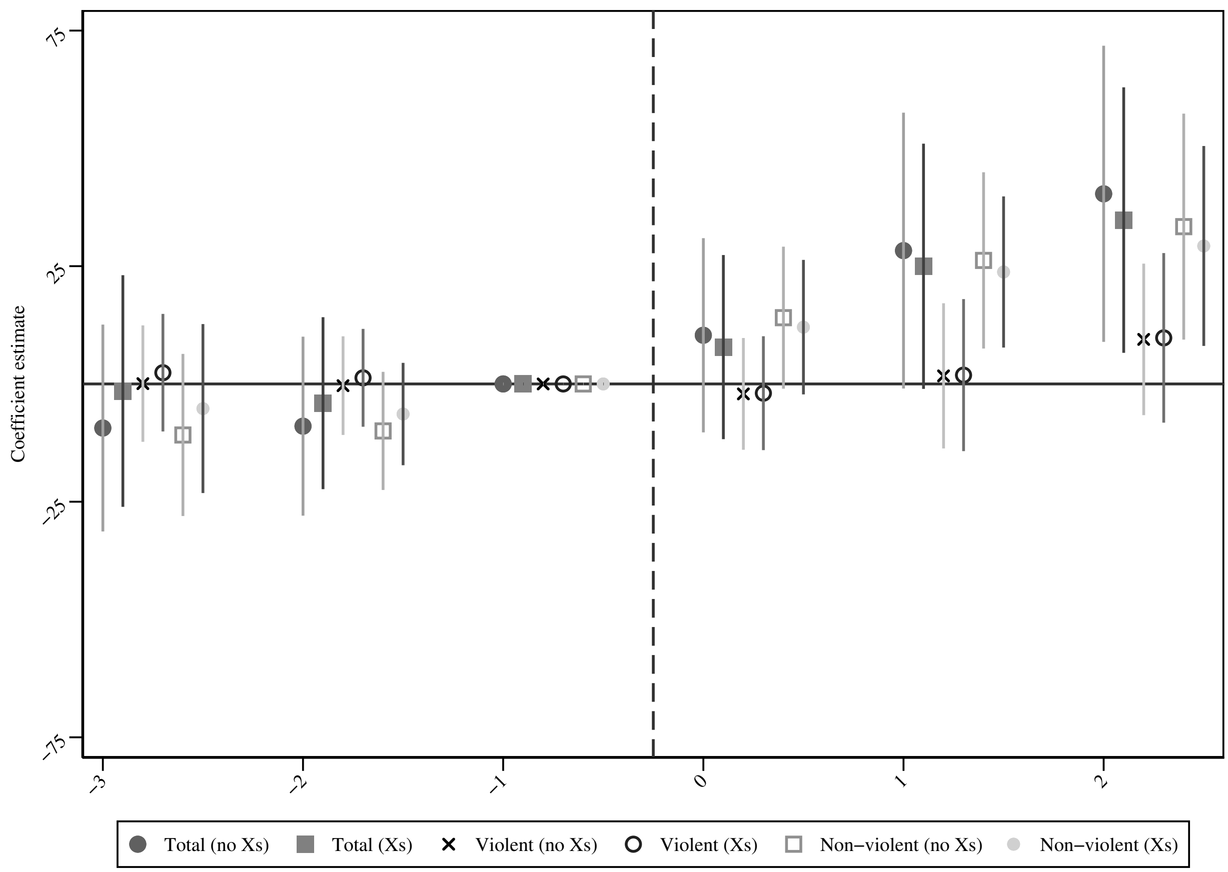


(b) Panel B: Non-violent crime



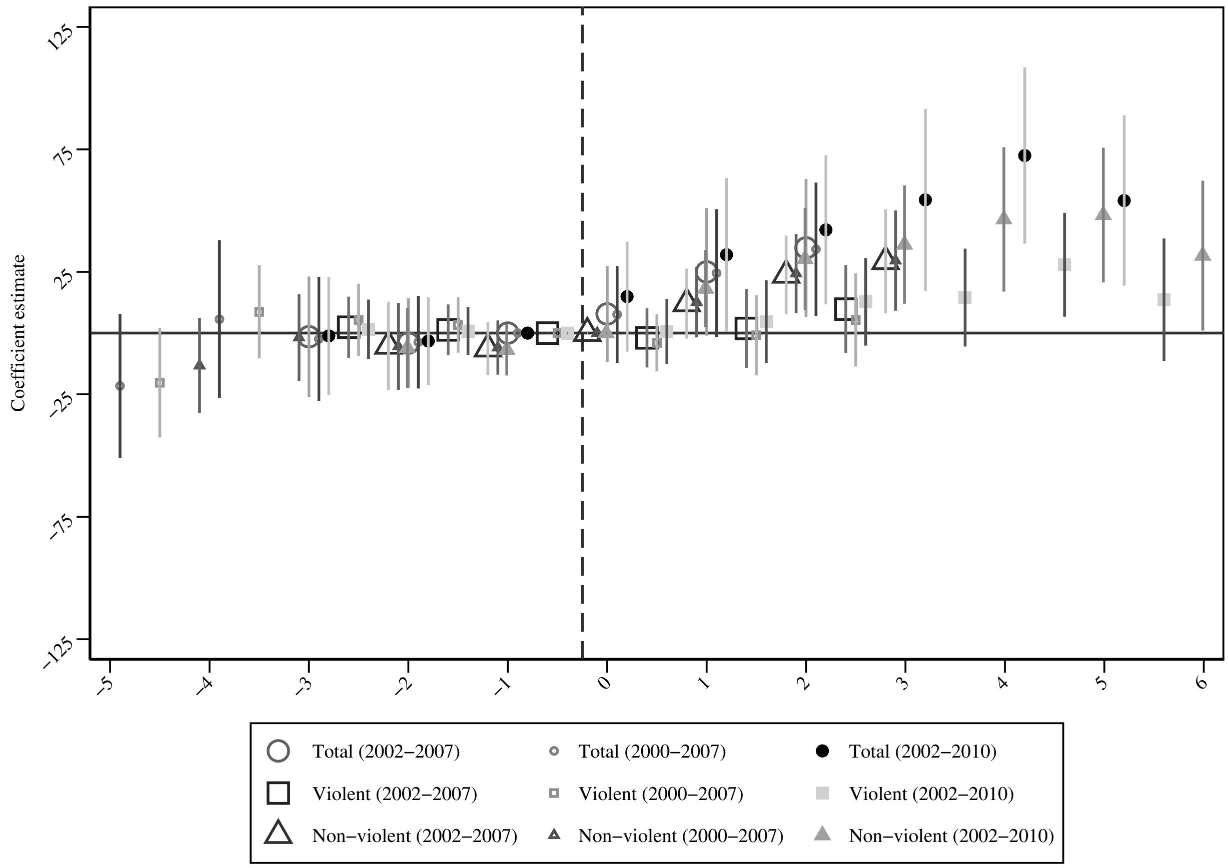
Notes: This figure plots average annual violent (Panel A) and non-violent (Panel B) crime rates over time. Crime rates are per 1,000 residents served by the agency. Data are weighted by the population served by the agency. Agencies serving populations greater than 10,000 people are included in the sample.

Figure 3: The effect of the TennCare disenrollment on crime rates using an event-study: Uniform Crime Reports 2002-2007



Notes: This figure reports coefficient estimates from a regression of crime rates on county-level exposure to the TennCare disenrollent × indicators for time to the disenrollment and other controls. The omitted category is 2004, the year prior to the disenrollment. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects unless otherwise noted. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. The regression is estimated with OLS. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering.

Figure 4: The effect of the TennCare disenrollment on crime rates using an event-study with different time periods: Uniform Crime Reports 2000-2010



Notes: This figure reports coefficient estimates from a regression of crime rates on county-level exposure to the TennCare disenrollent × indicators for time to the disenrollment and other controls. The omitted category is 2004, the year prior to the disenrollment. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects unless otherwise noted. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. The regression is estimated with OLS. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering.

Table 1: The effect of the TennCare disenrollment on Medicaid coverage: Tennessee Department of Health 2005-2007

Include time-varying controls:	Yes	No
Exposure × post period	-0.24***	-0.24***
	(0.05)	(0.04)
β scaled to 25th-75th percentile	-0.02	-0.02
Percent change (scaled 25th-75th percentile)	-8.33	-8.33
25th-75th percentile	0.07	0.07
Pre-treatment mean, high exposure counties†	0.24	0.24
Observations	3384	3384

Notes: This table reports coefficient estimates from a difference-in-differences regression of Medicaid enrollment on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes county-level covariates, county fixed effects and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the county population ages 21 to 64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.

***,**,* = statistically different from zero at the 1%, 5%, and 10% level.

†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 2: The effect of the TennCare disenrollment on crime rates: Uniform Crime Reports 2000-2010

Outcome:	Total	Violent	Non-violent
Study period: 2002-2007	23.81***	1.81	25.09***
	(8.99)	(6.88)	(7.02)
β scaled to 25th-75th percentile	1.67	0.13	1.76
Percent change (scaled 25th-75th percentile)	2.61	0.53	4.43
25th-75th percentile	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	64.02	24.42	39.76
Observations	2682	2682	2682
Study period: 2000-2007	25.85**	0.18	27.02***
	(10.01)	(8.72)	(7.00)
β scaled to 25th-75th percentile	1.81	0.01	1.89
Percent change (scaled 25th-75th percentile)	2.83	0.04	4.80
25th-75th percentile	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	63.90	24.49	39.38
Observations	3256	3256	3256
Study period: 2002-2010	37.78***	7.96	34.84***
	(9.48)	(7.44)	(7.73)
β scaled to 25th-75th percentile	2.64	0.56	2.44
Percent change (scaled 25th-75th percentile)	4.16	2.30	6.19
25th-75th percentile	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	63.42	24.39	39.42
Observations	4014	4014	4014

Notes: This table reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 3: The effect of the TennCare disenrollment on economic outcomes: Bureau of Labor Statistics, U.S Census Bureau, Eviction Lab, and Surveillance, Epidemiology, and End Results 2002-2007

Panel A: Bureau of Labor Statistics		
Outcome:		Unemployment
Exposure × post period		-2.57**
		(1.11)
β scaled to 25th-75th percentile		-0.18
Percent change (scaled 25th-75th percentile)		-2.85
25th-75th percentile		0.07
Pre-treatment mean, high exposure counties†		6.32
Observations		564
Panel B: U.S. Census Bureau		
Outcome:	Poverty	Median income
Exposure × post period	10.52***	-5179.53
	(2.56)	(4198.35)
β scaled to 25th-75th percentile	0.74	-362.57
Percent change (scaled 25th-75th percentile)	4.51	-1.08
25th-75th percentile	0.07	0.07
Pre-treatment mean, high exposure counties†	16.41	33565.87
Observations	564	564
Panel C: Eviction Lab		
Eviction outcome:	Filings	Completed
Exposure × post period	16.73**	7.76*
	(7.90)	(4.45)
β scaled to 25th-75th percentile	1.17	0.54
Percent change (scaled 25th-75th percentile)	46.06	23.28
25th-75th percentile	0.07	0.07
Pre-treatment mean, high exposure counties†	2.54	2.32
Observations	500	500
Panel D: Surveillance, Epidemiology, and End Results		
Outcome:		Population
Exposure × post period		-74.45
		(18746.02)
β scaled to 25th-75th percentile		-5.21
Percent change (scaled 25th-75th percentile)		-0.01
25th-75th percentile		0.07
Pre-treatment mean, high exposure counties†		153764.99
Observations		2682

Notes: This table reports coefficient estimates from a difference-in-differences regression of economic outcomes on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by county population 21-64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 4: The effect of the TennCare disenrollment on insurance, healthcare, and health among non-elderly childless adults: Behavioral Risk Factor Surveillance Survey 2002-2007

Outcome:	Health insurance	Delay care for cost	Very good or ex. health
Exposure × post period	-0.30*	0.29*	-0.03
	(0.17)	(0.15)	(0.31)
β scaled to 25th-75th percentile	-0.02	0.01	0.00
Percent change (scaled 25th-75th percentile)	-2.44	6.25	0.00
25th-75th percentile	0.05	0.05	0.05
Pre-treatment mean, high exposure counties†	0.82	0.16	0.49
Observations	6922	6891	6923

Notes: This table reports coefficient estimates from a difference-in-differences regression of insurance, healthcare, and health on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes individual characteristics, time-varying county demographics, county fixed effects, month fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a respondent in county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by Behavioral Risk Factor Surveillance Survey-provided survey weights. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 5: The effect of the TennCare disenrollment on behavioral health treatment admissions: National Survey of Substance Abuse Treatment Services 2002-2007

Outcome:	Admissions
Exposure $\times$ post period	-31.58**
	(13.98)
β scaled to 25th-75th percentile	-2.21
Percent change (scaled 25th-75th percentile)	-48.15
25th-75th percentile	0.07
Pre-treatment mean, high exposure counties†	4.59
Observations	564

Notes: This table reports coefficient estimates from a difference-in-differences regression of behavioral health admissions on county-level exposure to the TennCare disenrollment $\times$ an indicator for the post-period and other controls. The regression includes time-varying county demographics, county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by county population 21-64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 6: The effect of the TennCare disenrollment on mortality rates: Centers for Disease Control and Prevention 2002-2007

Outcome:	All-cause	Suicide	Alcohol	Drug
Exposure $\times$ post period	-0.40	0.06	0.01	0.74***
	(0.84)	(0.16)	(0.02)	(0.22)
β scaled to 25th-75th percentile	-0.03	0.004	0.0001	0.05
Percent change (scaled 25th-75th percentile)	-0.58	0.00	0.001	21.74
25th-75th percentile	0.07	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	5.19	0.21	0.00	0.23
Observations	564	564	564	564

Notes: This table reports coefficient estimates from a difference-in-differences regression of mortality outcomes on county-level exposure to the TennCare disenrollment $\times$ an indicator for the post-period and other controls. The regression includes time-varying county demographics, county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by county population 21-64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 7: The effect of the TennCare disenrollment on the number of officer or civilian employees, and on-duty officer assaults per 1,000 residents: Law Enforcement Officers Killed and Assaulted 2002-2007

Outcome:	Employees		On-duty officer assaults		
	Officers	Civilians	Total	Injurious	Non-inj.
Exposure × post period	0.13	-0.86	0.70*	0.33	0.37
	(0.50)	(0.78)	(0.38)	(0.22)	(0.23)
Beta scaled to 25th-75th percentile	0.01	-0.06	0.05	0.02	0.03
Percent change (scaled 25th-75th percentile)	0.42	-4.11	55.56	100.00	50.00
25th-75th percentile	0.07	0.07	0.07	0.07	0.07
Pre-treatment mean, high-exposure counties†	2.40	1.46	0.09	0.02	0.06
Observations	2682	2682	2682	2682	2682

Notes: This table reports coefficient estimates from a difference-in-differences regression of law enforcement employment and injury rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the population served by the agency. Regressions are estimated with OLS. Standard errors are clustered at the county level and reported in parentheses. ***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table 8: The effect of the TennCare disenrollment on per-capita payroll outcomes: Annual Survey of Public Employment and Payroll 2002-2007

Outcome ↓	Coefficient estimate (Standard error)
Expenditures: All	-150.37
	(193.77)
β scaled to 25th-75th percentile	-10.53
Percent change (scaled 25th-75th percentile)	-6.32
Pre-treatment mean, high exposure counties†	166.65
Observations	432
Expenditures: Police	-33.99**
	(13.60)
β scaled to 25th-75th percentile	-2.38
Percent change (scaled 25th-75th percentile)	-17.36
Pre-treatment mean, high exposure counties†	13.71
Observations	303
Expenditures: Public safety	-8.54*
	(4.70)
β scaled to 25th-75th percentile	-0.60
Percent change (scaled 25th-75th percentile)	-13.36
Pre-treatment mean, high exposure counties†	4.49
Observations	275
Expenditures: Health	-202.13*
	(111.03)
β scaled to 25th-75th percentile	-14.15
Percent change (scaled 25th-75th percentile)	-19.83
Pre-treatment mean, high exposure counties†	71.34
Observations	127
Expenditures: Education	44.26
	(119.78)
β scaled to 25th-75th percentile	3.10
Percent change (scaled 25th-75th percentile)	1.98
Pre-treatment mean, high exposure counties†	156.76
Observations	341
Expenditures: Streets & parks	-11.85
	(7.98)
β scaled to 25th-75th percentile	-0.83
Percent change (scaled 25th-75th percentile)	-10.96
Pre-treatment mean, high exposure counties†	7.57
Observations	323
25th-75th percentile	0.07

Notes: This table reports coefficient estimates from a difference-in-differences regression of per capita pay roll outcomes on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by county population 21-64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

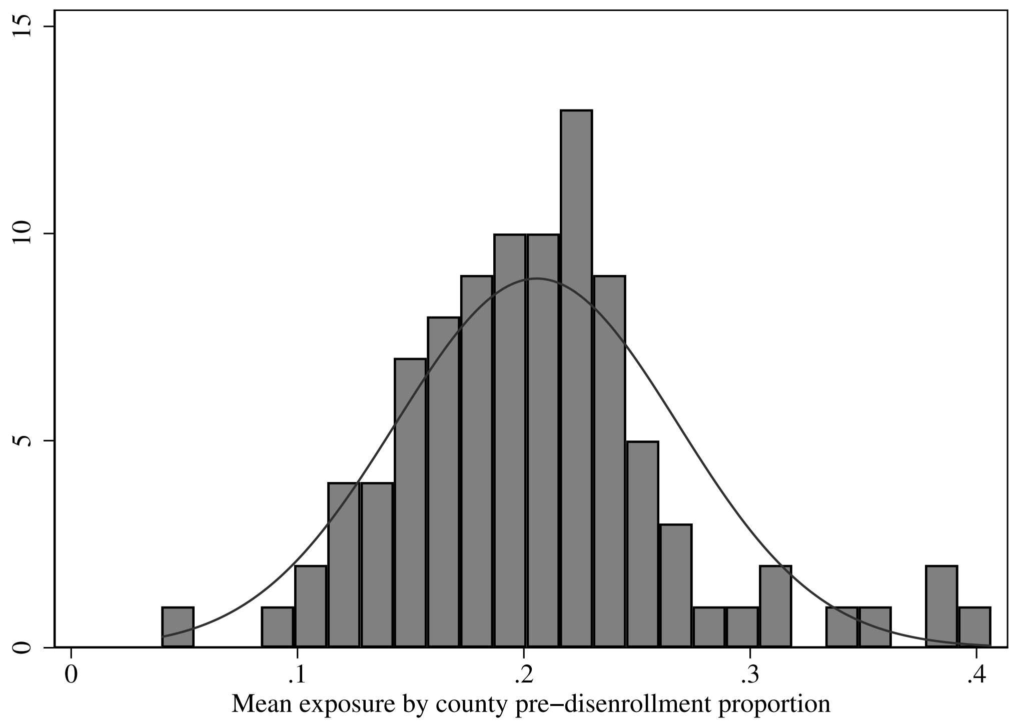
Table 9: The effect of the TennCare disenrollment on per-capita healthcare establishments and employment: County Business Patterns 2002-2007

Outcome →	Establishments	Employees
General physician offices	-1.92**	-18.80*
	(0.91)	(11.06)
β scaled to 25th-75th percentile	-0.13	-1.32
Percent change (scaled 25th-75th percentile)	-13.54	-13.23
Pre-treatment mean, high exposure counties†	0.96	9.98
Community hospitals	0.04	24.62
	(0.04)	(17.55)
β scaled to 25th-75th percentile	0.00	1.72
Percent change (scaled 25th-75th percentile)	0.00	7.63
Pre-treatment mean, high exposure counties†	0.06	22.55
Behavioral health physician offices	-0.03	-0.16
	(0.03)	(0.33)
β scaled to 25th-75th percentile	0.00	-0.01
Percent change (scaled 25th-75th percentile)	0.00	-11.11
Pre-treatment mean, high exposure counties†	0.02	0.09
Behavioral health non-physician offices	0.05	1.09
	(0.06)	(1.01)
β scaled to 25th-75th percentile	0.00	0.08
Percent change (scaled 25th-75th percentile)	0.00	80.00
Pre-treatment mean, high exposure counties†	0.03	0.10
Behavioral health outpatient treatment centers	0.10***	5.82**
	(0.03)	(2.44)
β scaled to 25th-75th percentile	0.01	0.41
Percent change (scaled 25th-75th percentile)	20.00	46.07
Pre-treatment mean, high exposure counties†	0.05	0.89
Behavioral health residential treatment centers	0.02	-0.51
	(0.04)	(1.51)
β scaled to 25th-75th percentile	0.00	-0.04
Percent change (scaled 25th-75th percentile)	0.00	-9.09
Pre-treatment mean, high exposure counties†	0.02	0.44
Behavioral health hospitals	-0.01	0.88
	(0.01)	(0.67)
β scaled to 25th-75th percentile	0.00	0.06
Percent change (scaled 25th-75th percentile)	0.00	8.22
Pre-treatment mean, high exposure counties†	0.00	0.73
Crisis centers	0.06	-2.80
	(0.11)	(2.89)
β scaled to 25th-75th percentile	0.00	-0.20
Percent change (scaled 25th-75th percentile)	0.00	-16.00
Pre-treatment mean, high exposure counties†	0.10	1.25
25th-75th percentile	0.07	0.07
Observations	564	564

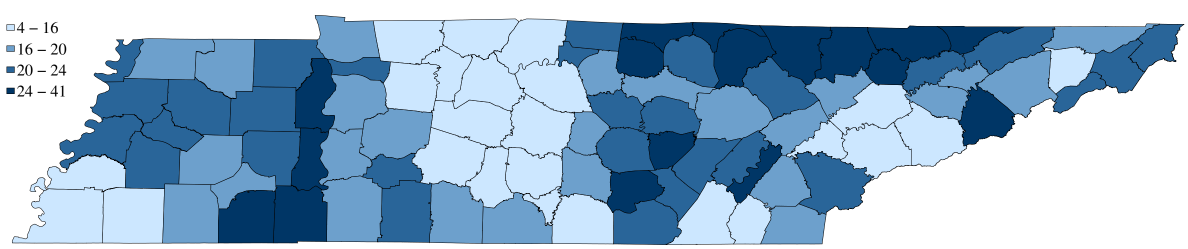
Notes: This table reports coefficient estimates from a difference-in-differences regression of per capita healthcare establishments and employment outcomes on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by county population 21-64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Figure A1: Geographic distribution of Medicaid coverage exposure to the TennCare disenrollment: Tennessee Department of Health, 2005

(a) Histogram of exposure to the TennCare disenrollment



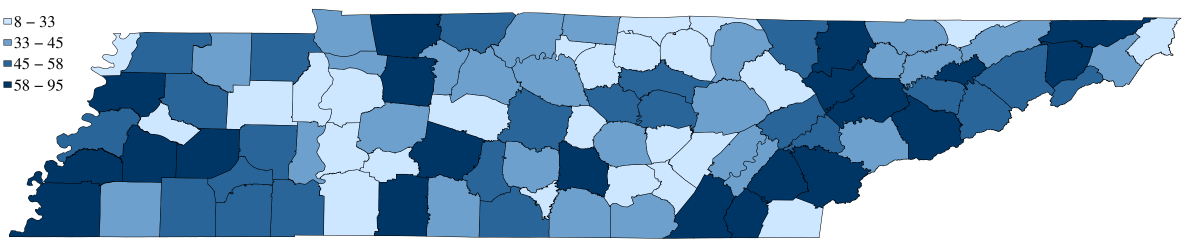
(b) Geographic distribution of exposure to the TennCare disenrollment



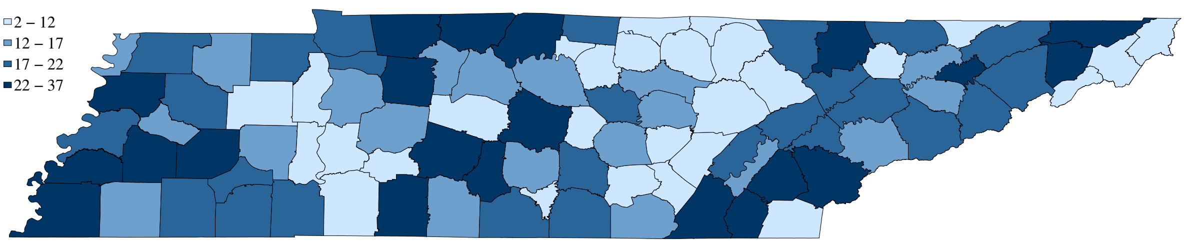
Notes: Panel A plots the distribution and Panel B plots the geographic distribution of county-level exposure to the TennCare disenrollment where exposure is defined as the share of the population 21-64 years of age enrolled in Medicaid in Q1 and Q2 of 2005. Data are aggregated to the county-level over the period Q1 and Q2 2005. Data are weighted by the county population 21-64 years.

Figure A2: Geographic distribution of crime rates across Tennessee counties: Uniform Crime Reports 2004

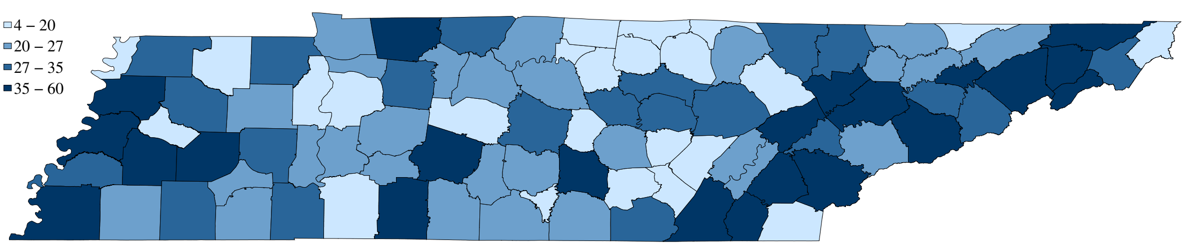
(a) Total



(b) Violent

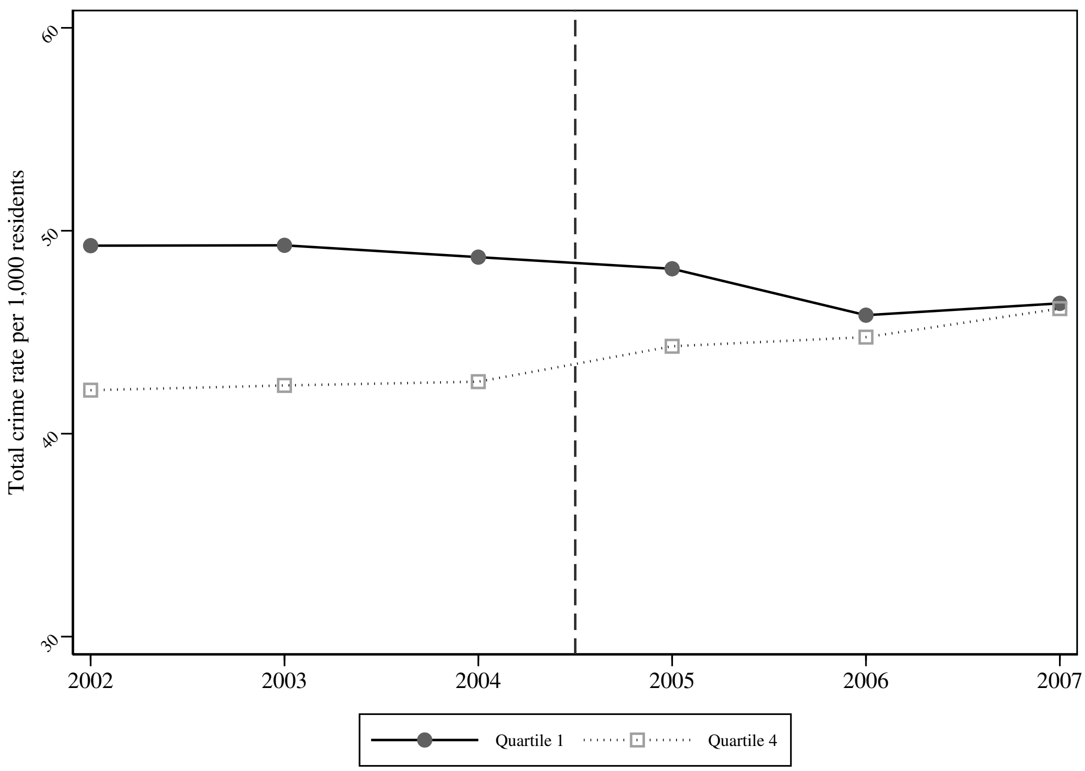


(c) Non-violent



Notes: Panels A-C of this figure plot the geographic distribution of county-level total, violent, and non-violent crime rates in 2004, respectively. Data are aggregated to the county-level in 2004. The data source is the Uniform Crime Reports. Data are weighted by the population served by police agencies.

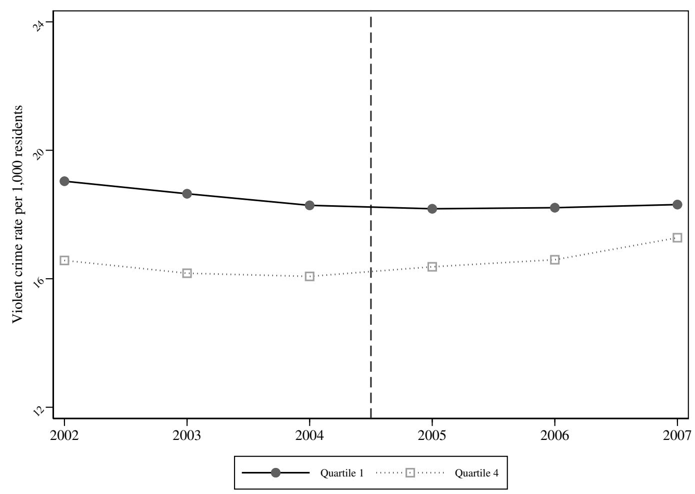
Figure A3: Trends in crime rates in the 1st versus 4th quartile exposure counties: Uniform Crime Reports 2002-2007



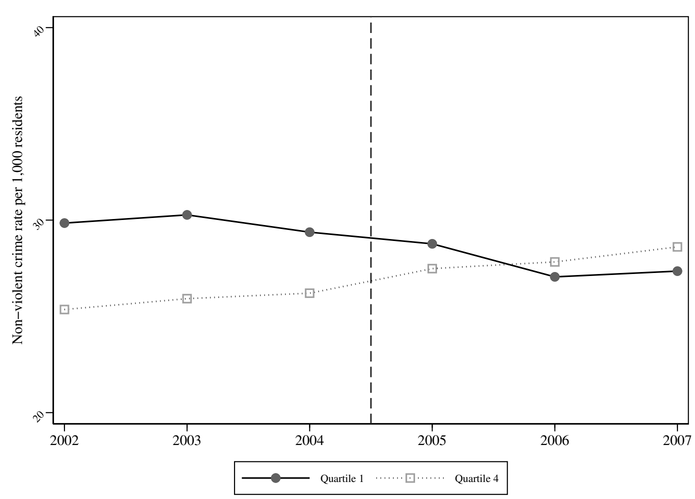
Notes: This figure plots the average annual total crime rate in counties in the 1st and 4th quartile of Tenncare disenrollment exposure in Tennessee during the first two quarters of 2005. Data are weighted by the population served by each agency prior to aggregating to the exposure level-year.

Figure A4: Trends in violent and non-violent crime rates in the 1st versus 4th quartile exposure counties: Uniform Crime Reports 2002-2007

(a) Violent

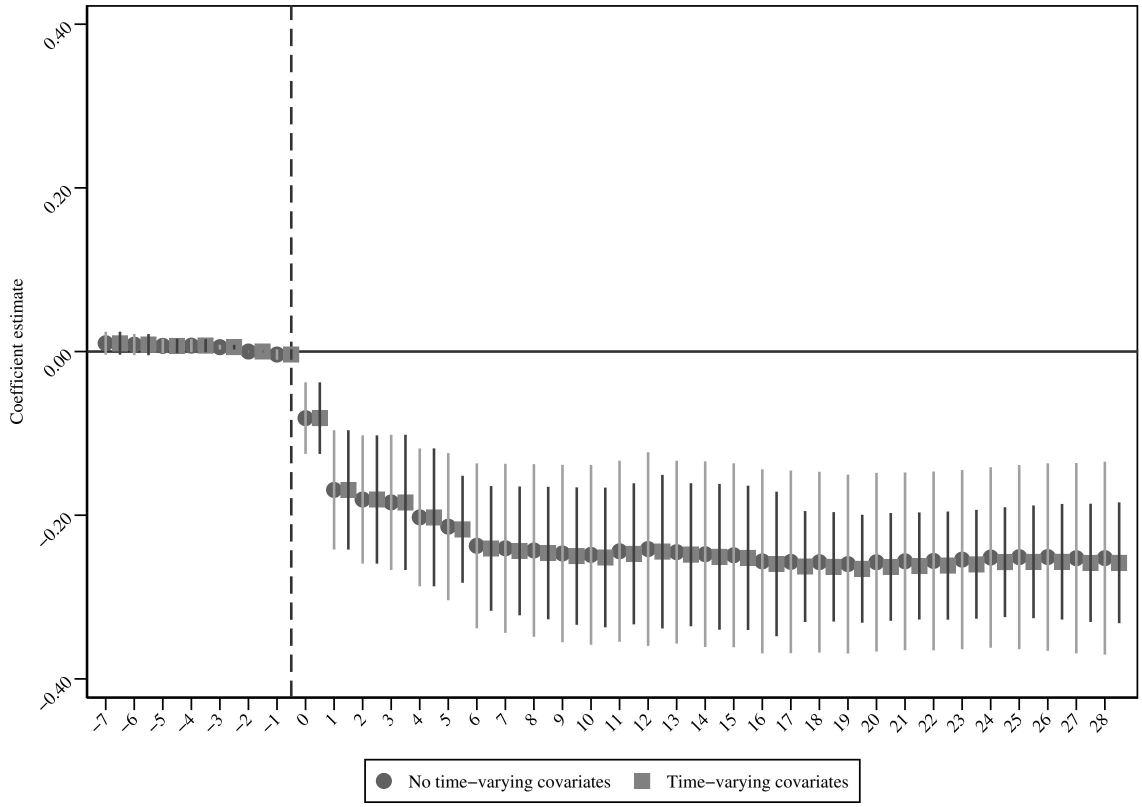


(b) Non-violent



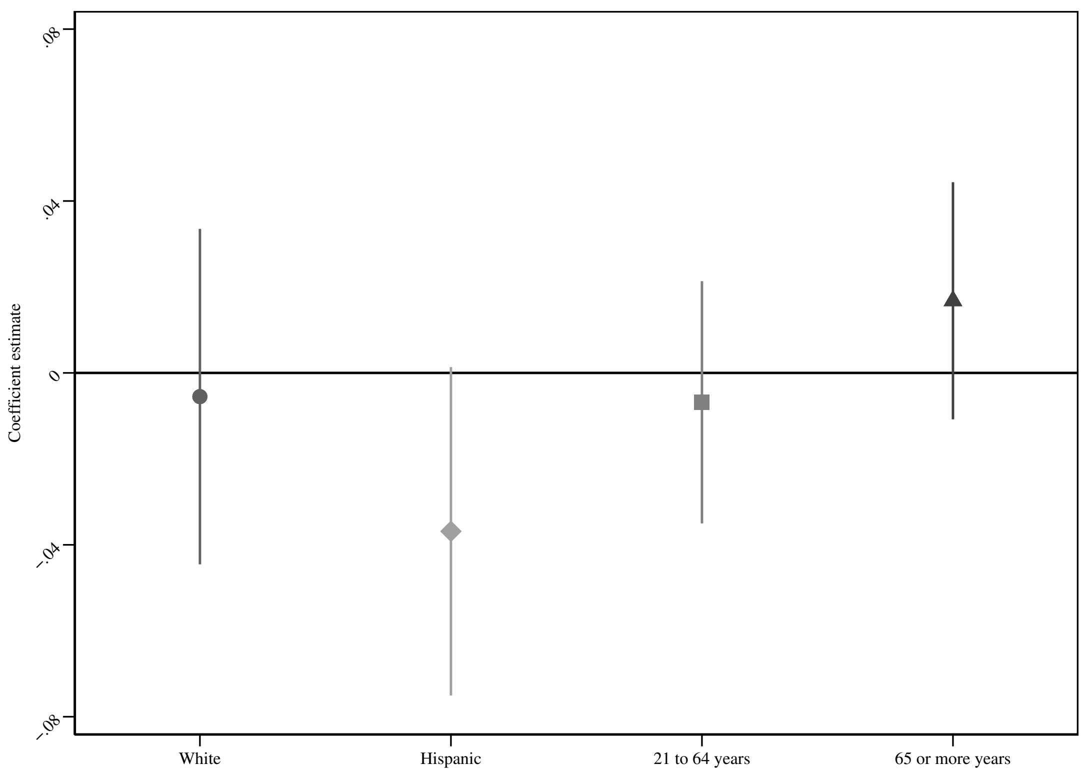
Notes: Panel A of this figure plots annual average violent crime rates in counties in the 1st and 4th quartile of Tenncare disenrollment exposure in Tennessee during the first two quarters of 2005. Panel B of this figure plots annual average non-violent crime rates in counties in the 1st and 4th quartile of Tenncare disenrollment exposure in Tennessee during the first two quarters of 2005. Data are weighted by the population served by each agency prior to aggregating to the exposure level-year.

Figure A5: The effect of the TennCare disenrollment on Medicaid coverage using an event-study: Tennessee Department of Health 2005-2007



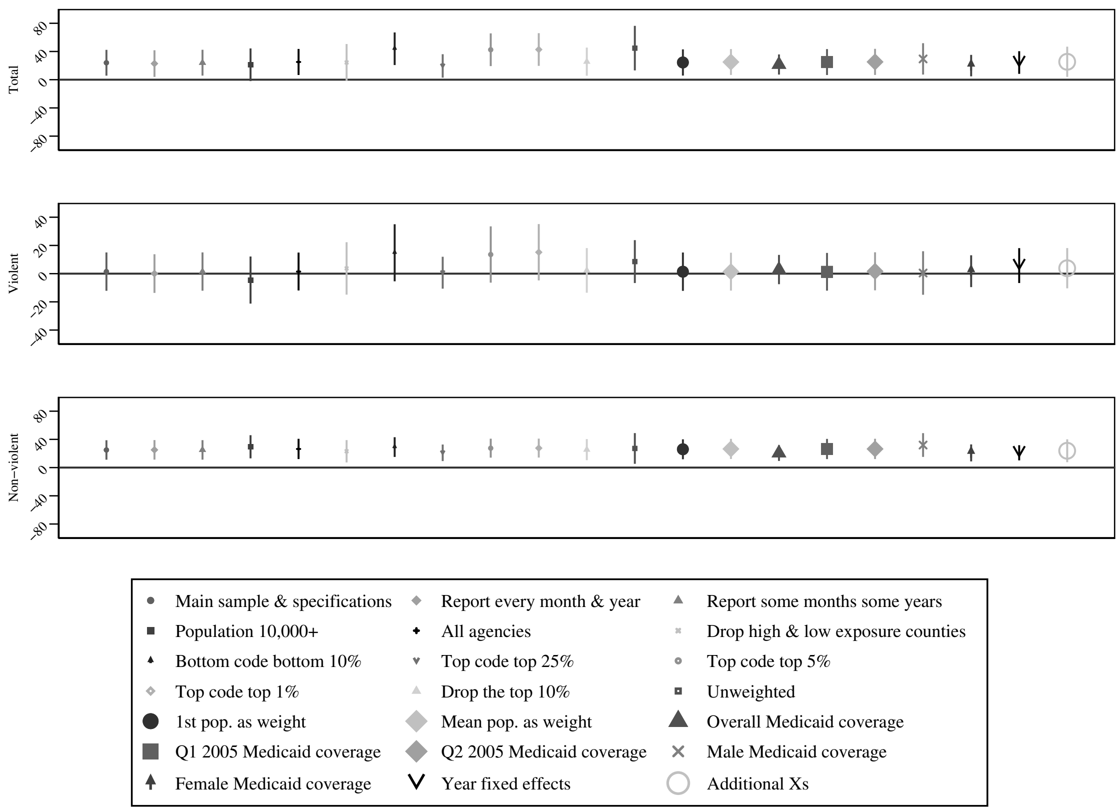
Notes: This figure reports coefficient estimates from a regression of Medicaid enrollment rates on county-level exposure to the TennCare disenrollent × indicators for time to the disenrollment and other controls. The regression includes agency fixed effects and urbanicity-year-by-month fixed effects. Panel A excludes time-varying covariates in the regression and Panel B includes time-varying covariates in the regression. The omitted category is July 2005, the month prior to the disenrollment. The unit of observation is a county in a month in a year. Data are weighted by the county population. Regressions estimated with OLS. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A6: Covariate balance test



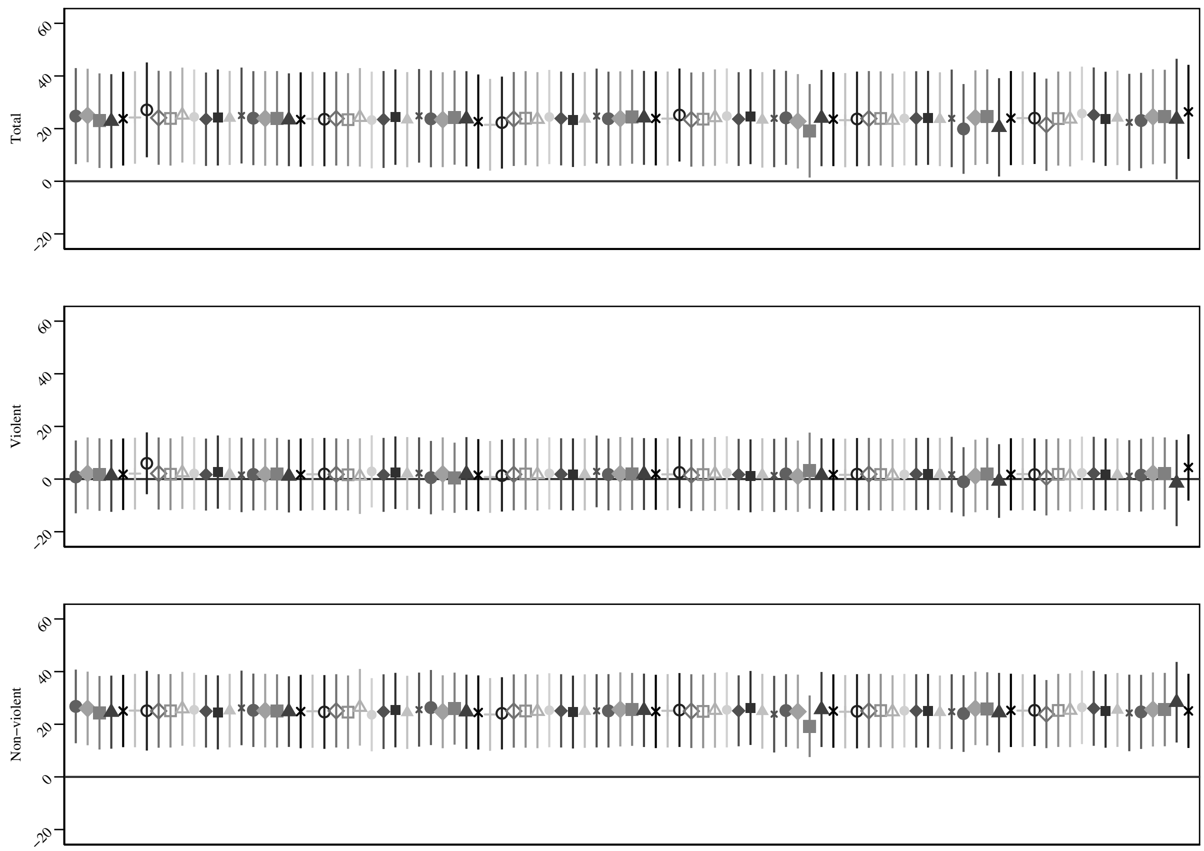
Notes: This figure reports coefficient estimates from a difference-in-differences regression of a control variable in equation 1 on county-level exposure to the TennCare disenrollment × an indicator for the post-period and fixed effects. The outcome in each regression is reported on the x-axis. Regressions include county fixed effects, and urbanicity-by-year fixed effects. The unit of observation is a county in a year. Data are weighted by the county population 21-64 years. Regressions estimated with OLS. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A7: The effect of the TennCare disenrollment on crime rates using alternative samples and specifications: Uniform Crime Reports 2002-2007



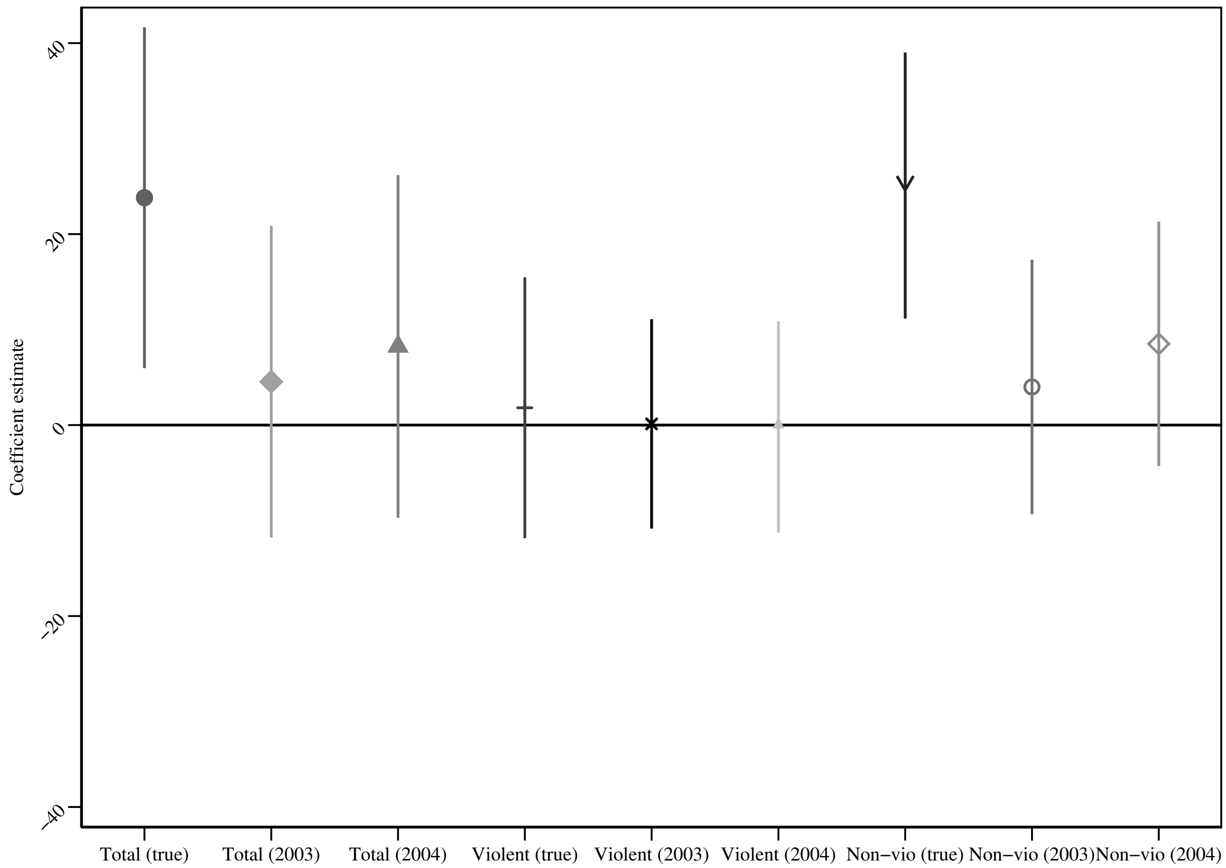
Notes: This figure reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes agency fixed effect and urbanicity-by-year fixed effects unless otherwise noted. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency unless otherwise noted. Regressions estimated with OLS. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A8: The effect of the TennCare disenrollment on crime rates leaving one county out of the analysis sample at time: Uniform Crime Reports 2002-2007



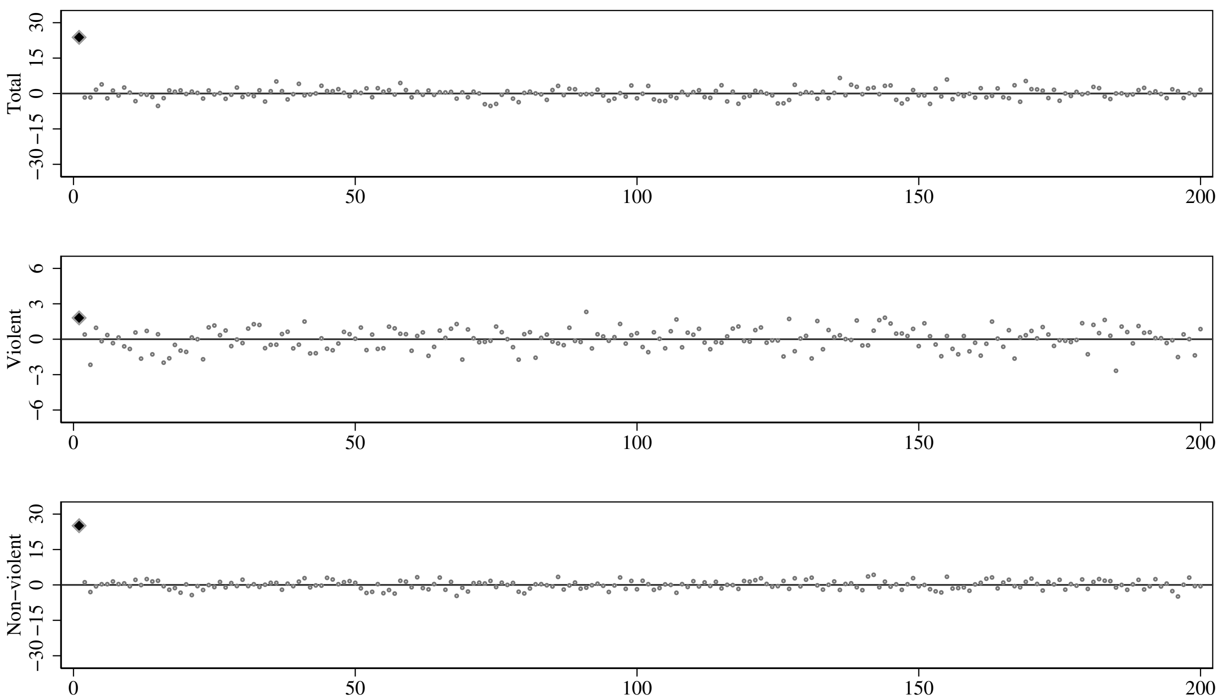
Notes: This figure reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and fixed effects omitting each of the 95 counties in Tennessee one at a time. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. Regressions are estimated with OLS. Data are weighted by the population served by the agency. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A9: Placebo analysis of the effect of the TennCare disenrollment on crime rates: Uniform Crime Reports 2002-2004



Notes: This figure reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment $\times$ an indicator for the post-period and fixed effects treating 2003 and 2004 as the false effective date, respectively. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. Regressions are estimated with OLS. Data are weighted by the population served by the agency. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A10: Randomization placebo analysis of the effect of the TennCare disenrollment on crime rates: Uniform Crime Reports 2002-2007



Notes: This figure reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and fixed effects randomly assigning the treatment variable across counties. The main coefficient estimate is reported with a black diamond and the placebo coefficient estimates are reported with gray circles. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. Regressions are estimated with OLS. Data are weighted by the population served by the agency. Coefficient estimates are reported with shapes and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Table A1: Summary statistics: Uniform Crime Reports 2002-2004

Sample:	All counties	Counties ≥ median exposure	Counties < median exposure
Total crimes per 1,000 residents	56.3	63.8	49.7
Violent crimes per 1,000 residents	21.4	24.4	18.9
Non-violent crimes per 1,000 residents	34.6	39.6	30.3
Pre-disenrollment exposure (21-64 years)	0.16	0.20	0.12
Proportion White	0.79	0.80	0.79
Proportion Hispanic	0.034	0.024	0.043
Proportion Age 19-64 years	0.62	0.61	0.64
Proportion Age 65+ years	0.12	0.13	0.11
Population served by agency	156279.5	155544.6	156922.2
Observations	1341	996	345
Number of unique counties	95	77	18

Notes: This table reports summary statistics. The unit of observation is a police agency in a county in a year. Data are weighted by the population served by the agency.

Table A2: The effect of the TennCare disenrollment on crime rates not controlling for county-level characteristics: Uniform Crime Reports 2002–2007

Outcome (crime type):	Total	Violent	Non-violent
Exposure × post period	32.58***	3.19	31.56***
	(11.60)	(6.58)	(9.29)
β scaled to 25th-75th percentile	2.28	0.22	2.21
Percent change (scaled 25th-75th percentile)	3.56	0.90	5.56
25th-75th percentile	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	64.02	24.42	39.76
Observations	2682	2682	2682

Notes: This table reports coefficient estimates from a difference-in-differences regression of crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in a county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table A3: The effect of the TennCare disenrollment on specific crime rates: Uniform Crime Reports 2002-2007

	Panel A: Violent crime			
Outcome:	Murder	Rape	Robbery	AA
Exposure × post period	-0.06	-0.17	-0.20	2.61
	(0.04)	(0.11)	(0.22)	(6.83)
β scaled to 25th-75th percentile	0.00	-0.01	-0.01	0.18
Percent change (scaled 25th-75th percentile)	0.00	-3.23	-1.82	0.77
25th-75th percentile	0.07	0.07	0.07	0.07
Pre-treatment mean, high exposure counties †	0.04	0.31	0.55	23.42
Observations	2682	2682	2682	2682
	Panel B: Non-violent crime			
Outcome:	Burglary	Theft	MVT	Arson
Exposure × post period	0.19	26.06***	0.52	-0.13
	(2.93)	(7.87)	(0.83)	(0.19)
β scaled to 25th-75th percentile	0.01	1.82	0.04	-0.01
Percent change (scaled 25th-75th percentile)	0.11	6.99	1.38	-4.35
25th-75th percentile	0.07	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	9.30	26.05	2.89	0.23
Observations	2682	2682	2682	2682

Notes: AA = aggravated assault. MVT = motor vehicle theft. This table reports coefficient estimates from a difference-in-differences regression of specific crime rates on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county-level covariates, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.

Table A4: The effect of the TennCare disenrollment on the cost of crime rates: Uniform Crime Reports 2002-2007

Outcome (crime type):	Total	Violent	Non-violent
Exposure × post	-488.00	-497.81	13.71
	(429.25)	(421.13)	(8.98)
β scaled to 25th-75th percentile	-34.16	-34.85	0.96
Percent change (scaled 25th-75th percentile)	-2.51	-2.66	1.94
25th-75th percentile	0.07	0.07	0.07
Pre-treatment mean, high exposure counties†	1359.79	1308.56	49.58
Observations	2682	2682	2682

Notes: This table reports coefficient estimates from a difference-in-differences regression of cost of crime on county-level exposure to the TennCare disenrollment × an indicator for the post-period and other controls. The regression includes time-varying county demographics, agency fixed effects, and urbanicity-by-year fixed effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size comparing the county at the 75th percentile (22.0%) of the county-level exposure to the TennCare disenrollment to the 25th percentile (15.0%). Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***,**,* = statistically different from zero at the 1%, 5%, and 10% level.
†High exposure counties = counties with Medicaid enrollment rate above the median value.