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### LOSING MEDICAID AND CRIME

Monica Deza Thanh Lu Johanna Catherine Maclean Alberto Ortega

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#### ABSTRACT

We study the impact of losing health insurance on criminal activity by leveraging one of the most substantial Medicaid disenrollments in U.S. history, which occurred in Tennessee in 2005 and lead to 190,000 non–elderly and non–disabled adults without dependents unexpectedly losing coverage. Using police agency–level data and a difference–in–differences approach, we find that this mass insurance loss increased total crime rates with particularly strong effects for non–violent crime. We test for several potential mechanisms and find that our results may be explained by economic stability and access to healthcare, in particular mental healthcare.

Monica Deza Department of Economics Syracuse University Maxwell School of Citizenship and Public Affairs 426 Eggers Hall Syracuse, NY 13244 and NBER mdeza@syr.edu

Thanh Lu Health Economics Program Center for Public Health Methods RTI International 3040 East Cornwallis Road Research Triangle Park, NC 27709 tlu@rti.org Johanna Catherine Maclean Schar School of Policy and Government George Mason University Mason Square Van Metre Hall 3351 Fairfax Drive Arlington, VA 22201 and NBER jmaclea@gmu.edu

Alberto Ortega O'Neill School of Public and Environmental Affairs Indiana University 1315 E 10 St Bloomington, IN 47401 alorte@iu.edu

# 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.<sup>1</sup> While overall crime rates in the U.S. have decreased substantially since their peak in the 1990s, 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 approximately eight million crimes each year (Federal Bureau of Investigation, 2019), leading to three trillion dollars in economic and societal costs (Anderson, 2021). Thus, understanding and leveraging factors that can reduce crime could have substantial benefits for many Americans, factors that can be altered through policy may be particularly attractive.

The causes of crime are complex and multifaceted, however, access to healthcare has been demonstrated to decrease involvement with the criminal justice 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., mental health crisis or being impaired by substances in public), the propensity to commit crime, and risk of crime victimization. Health insurance, by reducing out-of-pocket costs faced by patients, can increase access to, and use of, healthcare services. However, many Americans, estimated to be 28 million, 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 studies use quasi-experimental methods and establish that <u>gaining</u> insurance coverage reduces crime outcomes. Most recently, several studies show that the Affordable Care Act's (ACA) Medicaid expansion<sup>2</sup> reduces both criminal behavior and recidivism (Wen et al., 2017; He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022). Medicaid covered 85.2 million lower-income 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

<sup>&</sup>lt;sup>1</sup>Medicaid is the largest insurer in the U.S. and is a public program covering predominately low–income non–elderly people with limited access to private insurance.

<sup>&</sup>lt;sup>2</sup>In states that adopted this policy, categorical eligibility for Medicaid was removed and the maximum income eligibility for coverage was raised to 138% of the Federal Poverty Level.

et al., 2023) and, of particular relevance in terms of crime, is the largest purchaser of mental healthcare and substance use disorder treatment (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. In particular, 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 lower-income people. 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, 2023). Estimates suggest that, if Medicaid work requirements were imposed federally (as proposed by some lawmakers) 1.5 million people would lose Medicaid (Guth and Musumeci, 2022) and eight to 24 million people, mostly adults, are expected to lose coverage with the PHE unwinding (Tolbert, 2023). Finally, a substantial number of the Congressional proposed budgets and fiscal plans in the last ten years have included curtailing the Medicaid program (The White House, 2023), which would reduce Medicaid coverage rates.

In addition to policy relevance, understanding the impacts of insurance losses and gains is economically interesting as such changes can potentially generate asymmetry on healthcare use and associated social outcomes. Thus, predictions for the impacts of insurance losses from evidence based on insurance gains may lead to incorrect conclusions. For example, people who lose coverage may retain 'patient education' that allows them to navigate the healthcare system 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 could harm patient health. Decision theory predicts that equal-sized income losses have 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. The provision of charity or discounted care may minimize the full blunt of insurance losses by creating options

for lower-cost care (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' 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 specific to insurance losses.

To study the effect of the Tennessee Medicaid disenrollment on crime outcomes, we combine data on police agencies 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). We exploit the intensity of the disenrollment across Tennessee counties based on pre-policy Medicaid coverage rates using difference-in-differences and event-study methods. Conceptually, our design compares trends in crime outcomes before and after the 2005 disenrollment between counties with relatively high and relatively low Medicaid coverage prior to the disenrollment.

We have several findings. First, we find a substantial decline in Medicaid coverage post-disenrollment, which confirms earlier work and establishes our 'first-stage.' Second, we focus on violent and non-violent aggregated separately and find that the disenrollment lead to a stark increase in non-violent crime and suggestive evidence of an increase in violent crime. Our findings are robust to using alternative research designs, study periods, and specifications, and are not driven by differential trends in crime outcomes across counties with varying levels of exposure to the policy shock. Third, the effect on crime is predominantly driven by increases in assault and theft, the most prevalent violent and non-violent crime categories, respectively. Finally, our mechanism analysis suggests that losing Medicaid induced changes in economic standing, healthcare utilization, and health, all of which are documented to be determinants of crime.

# 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 low-income individuals (Baicker et al., 2013). In particular, access to behavioral healthcare (e.g., mental health and substance use disorder treatment) can improve mental health and substance use issues (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). As a result, individuals, who receive healthcare, may face a higher opportunity cost of criminal activity. For instance, 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 of financially-motivated crimes (Arenberg et al., 2023).

Second, insurance can play a vital role in protecting beneficiaries from substantial medical bills associated with adverse, and costly, health shocks. There is a well documented relationship between access to health insurance, particularly evidence using Medicaid expansions as a source of quasi-experimental variation, and financial outcomes (Hu et al., 2018; Gruber and Sommers, 2019; Guth et al., 2020), even measures of extreme and unexpected financial hardship such as evictions (Allen et al., 2019; Zewde et al., 2019; Linde and Egede, 2023). Taken together, we hypothesize that lower disposable income and financial stability following an insurance loss may provide an incentive for criminal activity, particularly financially-motivated crimes.

Offering further premise for our study, previous research establishes a relationship between gaining access to Medicaid and crime (He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022), showing that improved health and financial protection as important mechanisms. Two studies examine state—level policies that attempt to continue Medicaid coverage for incarcerated populations upon re—entry. Gollu and Zapryanova (2022), using near national data, show that state policies, which temporarily suspend Medicaid during incarceration, reduce recidivism one to three years post—release relative to policies that fully terminate coverage. Packham and Slusky (2023) evaluate the effect of a South Carolina policy that reduces barriers to continuing Medicaid coverage post—release among incarcerated traditional enrollees<sup>3</sup> (i.e., parents and the disabled) did not affect recidivism. This policy affects traditional enrollees (i.e., parents and the disabled), who may be less prone to crime, which may explain the null findings.

To date, just two studies evaluate the importance of losing insurance on crime outcomes using quasi-experimental methods, and both studies focus on younger adults

<sup>&</sup>lt;sup>3</sup>South Carolina did not expand Medicaid with the ACA, thus the enrollees covered by this program are likely to be traditional populations.

experiencing predictable coverage losses. First, Jácome (2023) exploits the fact that the majority of children age out of Medicaid at 19. The author uses data from South Carolina and compares men just above and below age 19, documenting 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 two important studies provide timely and relevant information about insurance losses. Our work will build on them in several ways. We will exploit a large-scale and unexpected Medicaid disenrollment that lead to 190,000 adults quickly, and largely without any warning, losing coverage in 2005 (Chang and Steinberg, 2009). This contraction is one of the most substantial in the history of the Medicaid program. Unlike expected disenrollments, 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 to the disenvolument. Those individuals losing coverage in Tennessee represent a wide range of ages, non-elderly childless adults without disability. Given age-crime profiles where 55% of arrests are for those age 30-64(Deza et al., 2022a; FBI, 2019), our findings will be more generalizable to the population at risk for crime. Finally, because young adults (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 (relatively) older adults we study may be more salient to the target population. Collectively, our work and the earlier important and novel studies can shed light on insurance losses and crime.

### 2.2 The TennCare program and impacts of the disenvolument

Historically, Medicaid has been mandated by the federal government to provide coverage to a limited number of low-income individuals, namely pregnant people, parents, and the disabled. Thus, pre-ACA, low-income childless non-elderly adults without disabilities were 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. One mechanism used by states to cover expansion population 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 and make eligible select low—income, non—elderly, non—disabled, and childless adults ('expansion population'). All Medicaid enrollees were placed in managed care plans in an attempt to curtail program costs, creating resources available to cover the expansion population, and TennCare was implemented in late 1993.

TennCare coverage was generous for physical and behavioral healthcare, and covered preventive care, prescriptions, imaging, and hospital services with low cost—sharing (Farrar et al., 2007a; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021; Maclean et al., 2023). Of particular relevance for our study, TennCare increased accessibility to behavioral health delivered by primary care providers (Gaynes et al., 2009; Jetty et al., 2021) and expanded access to specialized behavioral health services through a carve—out plan (Farrar et al., 2007a; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021).<sup>4</sup> As a result, TennCare enrollees had relatively generous coverage for behavioral health services, medications, and counseling. Given our focus on crime and linkages between crime and behavioral health (Jacome, 2023), the generous coverage of these services suggests that losing TennCare could be particularly important in our setting.<sup>5</sup>

TennCare was popular in Tennessee and enrollments surged, with one in four Tennessee adults enrolled in TennCare by late 2004, the highest adult Medicaid coverage rate in the country (Farrar et al., 2007a). Sustaining TennCare became financially untenable for Tennessee (Bennett, 2014), as the program accounted for over 30% of the state's budget by 2004 (Farrar et al., 2007a). As a result, the proposed termination of TennCare was announced in November 2004 by Governor Phil Bredesen (Chang and Steinberg, 2009), and later approved by CMS in March 2005. Beginning in July 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 -190,000 people - lost Medicaid. Disenrolles were predominantly childless non-disabled non-elderly beneficiaries (Farrar et al., 2007b; Chang and Steinberg, 2009; Garthwaite et al., 2014; Tello-Trillo et al., 2023) with income levels in the range of 100% and 175% of the Federal Poverty Level.

<sup>&</sup>lt;sup>4</sup>With a carve-out plan, specific services (here behavioral health) are delivered by a separate healthcare plan than other services. Typically, the care-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.

<sup>&</sup>lt;sup>5</sup>The extent to which providers are willing to accept Medicaid coverage will impact the value of this coverage to enrollees. In our analyses of the 2004 National Survey of Substance Abuse Treatment Services (described in Section 3.2), we find that 49% of behavioral health treatment centers (outpatient and residential) in Tennessee accept Medicaid as a form of payment.

A growing series of studies uses the TennCare disenrollment to understand how losing insurance impacts access to care, 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) show a 33% reduction in the probability of Medicaid coverage post-shock using the Current Population Survey. There is evidence that some people may have been able to locate replacement coverage, but many individuals became uninsured post-TennCare (Garthwaite et al., 2014; DeLeire, 2019; Tello-Trillo, 2021). Correspondingly, lower-income people used less healthcare – general, preventive, chronic condition management, and behavioral health; were more likely to report delay medical care due to cost; and experienced worse physical and behavioral health (Garthwaite et al., 2014; Tarazi et al., 2017; DeLeire, 2019; Tello-Trillo, 2021; Maclean et al., 2023; Tello-Trillo et al., 2023). There are implications for healthcare providers as well: Garthwaite et al. (2018) show that hospitals provided more charity care post-disenrollment, likely as fewer patients had insurance.

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 work more, as such efforts may lead to a loss of coverage eligibility. The TennCare disenrollment offers an opportunity to study job-lock and a handful of studies have examined this question. The results are mixed with one study finding evidence of job-lock (the probability of employment increases) and two studies demonstrating no such evidence (Garthwaite et al., 2014; DeLeire, 2019; Ham and Ueda, 2021).

Economists have explored spill—over 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 while 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 particular, 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.

# 3 Data and methods

#### 3.1 Crime data

We collect data from the FBI's Uniform Crime Reports (UCR), which provide information on crime—related outcomes, over the period 2002—2007. 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 recession between 2008 and 2010 (Garthwaite et al., 2014). However, as we show in Section 4.4, our results are robust to including both earlier and later 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, 2021b). To overcome any potentially selective reporting in the data, we conduct our analysis at the police agency-level and restrict the analysis sample to agencies that report crimes in every year of our sample period. We also relax this assumption in the Section 4 and show our findings for an unbalanced panel of police-agencies and consider a sample of solely large agencies.

### **3.2** Additional data sources

<u>Medicaid coverage</u>: Our primary research design exploits the intensity of the TennCare disenrollment across Tennessee counties based on pre-policy exposure. To this end, we use monthly data on the county-level Medicaid coverage rate in Q1 and Q2 of 2005 (i.e., just prior to the disenrollment) to measure exposure to the policy change (Argys et al., 2020).<sup>6</sup> These data are drawn from the Tennessee Department of Health, Division of TennCare. They include monthly counts of the number of people enrolled in TennCare since 2005 by county. We use population data from the U.S. Census to calculate TennCare enrollment rate in each county, which are defined as the share of the population covered by Medicaid. We also use this exposure variable to shed light on the first-stage effect: the impact of the disenrollment on Medicaid coverage. In this analysis, we use the share of the population covered by Medicaid as the outcome variable.

<sup>&</sup>lt;sup>6</sup>We thank Sebastian Tello–Trillo for kindly sharing data with us.

These data are available in each month from 2005 to 2007.

<u>Data on potential mechanisms</u>: To better understand our main crime findings, we conduct an analysis of mechanisms, that is we study potential channels through which losing Medicaid coverage could impact crime outcomes. We draw data from several different sources to explore mechanisms. We attempt to measure mechanisms at the county—level wherever possible, but some variables are only available at the level of the state. First, to study the impact of the disenrollment on economic outcomes, we collect data on county unemployment rate, median income, and poverty rates from the Bureau of Labor Statistics (BLS) and the Small Area Income and Poverty (SAIPE) estimates.

Second, we examine the effects on healthcare use using two different sources: i) access to general healthcare and delaying medical care due to cost, and ii) need for behavioral healthcare. We use county-level data on measures of healthcare access among individuals age 18–64 from the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS). This survey allows us to analyze respondent questions related to the likelihood of having insurance and whether an individual delayed 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 Saloner, 2019; Maclean et al., 2017), we obtain state-level prevalence of individuals that need, but do not receive, alcohol and drug treatment from the National Survey on Drug Use and Health (NSDUH) (Hollingsworth et al., 2022).<sup>7</sup>

Lastly, and following the literature exploring the link between Medicaid coverage and mortality (Miller et al., 2021; Maclean et al., 2023; Tello-Trillo et al., 2023), we estimate the effects of disenrollment on suicide, alcohol, and drug related mortality by collecting county-level data form the CDC's National Vital Statistics System (NVSS) restricted-data files. The NVSS data are based on official death certificates which include the cause of death, allowing us to isolate behavioral health deaths.

### 3.3 Methods

We estimate the effect of a large-scale reduction in Medicaid eligibility in Tennessee by comparing counties most exposed to TennCare disenvolument in Q1 and Q2 of 2005

<sup>&</sup>lt;sup>7</sup>We use the state-level NSDUH estimates. There is no information on mental healthcare use in the public use data. These data are available in two-year averages. We use the <u>first</u> year to match to the policy data. Results, available on request, are not appreciably different if we i) exclude the two-year averages for 2004–2005 (where data overlap the disenrollment) and ii) match using the second year in the two-year average. There are comparable data available at the sub-state level, but these data are not suitable for our purposes as they are only available for a very limited number of sub-state areas and in three-year averages.

(i.e., just before to the policy shock) to those less exposed. This design has been used to study policy shocks that may impact everyone in a geographic area and therefore do not offer a clean treatment and comparison group (Finkelstein, 2007; Andersen et al., 2023; Cohle and Ortega, 2023; Park and Powell, 2021; Alpert et al., 2018; Miller, 2012), including TennCare (Argys et al., 2020). Conceptually, consider two 'extreme' counties, one with 0% of the county 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 disenrollments. Our analyses relies on the assumption that the latter county is more impacted by the TennCare disenrollment than the former county, and that trends in crimes would have evolved in parallel beyond 2005 had the disenrollment not occurred. However, these 'extreme' counties with either 0% or 100% of the population covered by Medicaid do not exist in Tennessee. Thus, as we describe 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 average causal response of the TennCare disenvolument on crime using the difference—in—differences (DID) regression outlined in equation (1):

$$y_{ict} = \beta_0 + \alpha_i + \gamma_t + \beta Exposure_c \times Post_t + \gamma \mathbf{X}_{ct} + v_{ict}$$
(1)

Where  $y_{ict}$  is the crime rate (per 1,000 people served by the police agency) in agency *i* in county *c* in year *t*. The terms  $\alpha_i$  and  $\gamma_t$  represent agency and year fixed-effects, respectively.<sup>8</sup> Exposure<sub>c</sub> is the exposure variable equal to the share of the population covered by Medicaid in a county in Q1 and Q2 of 2005 (we average over these two quarters). The variable  $Post_t$  is an indicator equal to one for years 2005 to 2007, and zero otherwise. The vector  $\mathbf{X}_{ct}$  includes county-level demographic variables.<sup>9</sup> Data are weighted by the population served by the agency and standard errors are clustered at the county-level. There are 93 counties in our trimmed Tennessee sample – we exclude counties with baseline Medicaid coverage in the top and bottom 1%,<sup>10</sup> thus we have a sufficient number of clusters to allow for credible inference (Bertrand et al., 2004).

The coefficient of interest in equation (1) is  $\beta$ , which compares the extent to which increasing exposure (i.e., share of the population Medicaid coverage in Q1 and Q2 2005)

<sup>&</sup>lt;sup>8</sup>Agency fixed–effects subsume county fixed–effects.

<sup>&</sup>lt;sup>9</sup>We include 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 (SEER).

<sup>&</sup>lt;sup>10</sup>We trim these counties as they appear to display differential pre-trends in the event-study for total crimes. However, the DID (Table A4) and event-study (Figure A7) results are not appreciably different if we include these observations.

from 0% to 100% impacts crime rate following TennCare disenrollment. To provide a more practical illustration of TennCare impacts on crime, we present our coefficient estimates scaled by the pre-treatment exposure of the median county in Tennessee following Argys et al. (2020). We will refer to this parameter estimate as the 'scaled beta ( $\beta$ ),' more specifically we multiply each coefficient estimate by 0.258.<sup>11</sup>

In the absence of directly observable counterfactuals, inferring causality in our setting relies on crime rates evolving similarly in high and low exposure counties before the 2005 TennCare disenrollment. If we observe this patterns of results in the pre-treatment period, we can potentially assume a common trend in crime outcomes pre-disenrollment would have persisted into the post-period in the absence of this policy. If this assumption holds, agency fixed-effects will account for all cross-sectional differences that are time-invariant and time-varying covariates will adjust for additional factors, and low exposure counties will capture trends in crime rates over time, providing a counterfactual for how we can expect crime rates to evolve in the absence of the TennCare disenrollment. To provide suggestive evidence on the extent to which the common trends assumption holds, and to examine the dynamic effects in the years after the TennCare disenrollment, we employ an event-study shown in equation (2):

$$y_{ict} = \beta_0 + \alpha_i + \gamma_t + \sum_{\substack{j=2002\\j\neq 2004}}^{2007} \beta_j Exposure_c \mathbb{1}\{j=t\} + \mathbf{X}_{ct}\psi + v_{ict},$$
(2)

where  $1{j = t}$  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 equation (1). The coefficient estimates of interest are the  $\beta_j$ 's, which capture the effect of TennCare disenrollment over time – again (without scaling) comparing hypothetical counties with 0% and 100% Medicaid coverage, both before and after 2005. As described earlier, the key assumption of DID methods is common trends in the outcomes,  $y_{ict}$ , for treatment and comparison groups absent the policy shock. A suggestive test of this assumption is embedded in the event-study framework where any differences in pre-policy trends are captured by  $\beta_j$  for j < 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. That is, we can potentially assume that – absent the disenrollment – high and low exposure counties would have followed common trends

<sup>&</sup>lt;sup>11</sup>We weight the data by the county population in estimation of the median value.

in crime rates post-2005. The policy lag coefficient estimates,  $\beta_j$  for  $j \ge 2005$ , allow us to examine the dynamic effects for the years post-disenvolument.

We are not able to locate county-level data for all outcomes of interest, in particular outcomes that we consider in our analysis of mechanisms. To study outcomes only available at the state-year level, we follow Garthwaite et al. (2014), Tello-Trillo (2021), and Maclean et al. (2023) and estimate a specification similar to equation (1) where we replace the  $Exposure_c$  variable with an indicator for Tennessee  $(TN_s)$  and use only the Southern states in the analysis, which leaves Tennessee as the treatment group and other Southern states as the comparison group,<sup>12</sup> as in equation (3):

$$y_{ist} = \beta_0 + \alpha_i + \gamma_t + \beta T N_s \times Post_t + \gamma \mathbf{X_{st}} + v_{ist}$$
(3)

In robustness checking (Section 4.4), we show that our main crime rate findings are not appreciably different when we use equation 3. When using equation 3 we report heteroskedastity robust standard errors. Given the few state—level clusters in this analysis, we present wild cluster bootstrapped p-values (Cameron et al., 2008; Roodman et al., 2019), and corrected standard errors from a non—overlapping block bootstrap (Bertrand et al., 2004; Cameron et al., 2008).

#### 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, i.e., 2002-2004. We report summary statistics for counties above median exposure to the TennCare disenrollment (i.e., Medicaid coverage, the median value is 0.258) and at or below the median. Here we see that the average number of non-violent crimes is roughly 36 per 1,000 residents served by the agency and the average number of violent crimes is 23 per 1,000. Column (2) shows that counties above the median exposure have higher crime rates than less exposed counties.

Our identification strategy relies on variation in pre-disenrollment exposure to TennCare. Figure A2 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) ranges from 13.9% to 45.0%, with a mean (median) of 26.1% (25.8%), and the distribution is roughly bell-shaped with a slight right-skew, as presented in Figure A4. While there

<sup>&</sup>lt;sup>12</sup>The other Southern states include Alabama, Arkansas, Delaware, the District of Columbia (we treat DC as a state), Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Texas, Virginia, and West Virginia.

is some clustering of counties with higher and lower exposure, the figure suggests that there is reasonable variation across the state in Medicaid coverage.<sup>13</sup>

Figure 1 shows the crime rate trends for high versus low exposure counties. These stylized facts suggest that high exposure (above the median) counties experience a relative increase in crime rates post—enrollment.<sup>14</sup> In panel (a) we see that there is a relative increase in total crime rates in more exposed counties immediately following the policy change in 2005. There is a similar divergence for violent and non—violent crimes shown in panels (b) and (c), respectively. Given that the U.S. was experiencing a decline in crime rates nationally over this period (Pew Research Center, 2020), the rise we observe in Tennessee offers suggestive evidence that the disenrollment increased crime.

We study the downstream consequences of Medicaid disenrollment, thus a necessary condition is that the disenvolument lead to meaningful change in Medicaid coverage. We examine the first-stage using equation 1. Results are reported in Table 1.<sup>15</sup> Results from an event-study are provided in Figure A5 (we use five month leads, June 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 of different exposure to the policy shock, but in the post-period we observe a sharp decline in coverage that persists through the end of 2007. The coefficient of interest in equation 1 captures the extent to which monthly Medicaid coverage changes with exposure to the disenvolument. As described in Section 3.3, the coefficient estimate compares changes in coverage for a county with 0% Medicaid coverage to a county with 100% coverage. To provide a more policy-relevant estimate, we scale the coefficient estimate ('scaled beta') by the median Medicaid coverage rate in the first half of 2005 (0.258). We find that the median exposure county experienced a 3 ppt reduction in monthly Medicaid coverage post-disenrollment ( $= -0.13 \times 0.258$ ). Comparing this coefficient estimate with the baseline Medicaid coverage rate, we find a decline of 11% (= -0.03/0.27\*100%). Using the population of the median county <sup>16</sup> out estimates suggest roughly 710 fewer enrollees post disenrollment.

 $<sup>^{13}</sup>$ The white shade shows the two counties trimmed from the sample as they are outliers in terms of Medicaid coverage: Fentress and Williamson counties. See Section 3.

<sup>&</sup>lt;sup>14</sup>We report a comparable figure for Tennessee versus other Southern states in Appendix Figure A1. We observe roughly similar trends pre-treatment, with a relative increase in crime rates post-treatment in Tennessee.

<sup>&</sup>lt;sup>15</sup>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.

<sup>&</sup>lt;sup>16</sup>The average population county in Tennessee is Hickman County with a population of 23,676.

# 4 Results

### 4.1 Internal validity

Our main analysis examines the effect of Medicaid disenvolument 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 dynamics in the post period.

Figure 2 plots the pre-and post-treatment effects of TennCare disenrollment on agency-level crime rates per 1,000 in Tennessee.<sup>17</sup> Panel (a) plots the coefficient estimates for total crime. Panels (b) and (c) present the comparable results for violent and non-violent crime rates respectively. When examining total crime in panel (a), there is some (imprecise) evidence of a slight pre-trend in total crime rates before the disenrollment. Nonetheless, there is a clear trend break and sharp increase after the disenrollment in 2005 and we will show that our main DID results are not different when we estimate and remove any potential pre-trends (see Section 4.2). In panel (b) we see no evidence of a pre-trend difference followed by an increase in violent crimes the two years following disenrollment. This effect becomes statistically distinguishable from zero in 2006 (2005 is potentially a 'wash out' year as the policy went into effect in August, but we have annual data and thus code all of 2005 as treated). We find a similar, but more immediate, effect on non-violent crime. Once more, our event-study estimates show no pre-treatment differences and provide evidence of a stark increase in crime rates after 2005 in counties most exposed to disenrollment for at least two years after the policy.

### 4.2 TennCare and crime

We summarize our main findings in Table 2 by presenting our static DID (equation [1]) results for crime rates. Column (1) presents the effect of disenvolument on total crime, while columns (2) and (3) depict estimates of the effects on violent and non-violent crime, respectively. In line with the results in Figure 2, column (1) suggest a statistically significant increase in the total crime rate in counties most exposed to the 2005 disenvolument. Given that a county with median exposure has 25.8% of the population covered by Medicaid prior to TennCare disenvolument, the coefficient estimate implies that the disenvolument led to 11.46 additional crimes per 1,000 residents for a police-agency in the median exposure county (= 44.42 \* 0.258). Comparing the coefficient estimate to

<sup>&</sup>lt;sup>17</sup>Figure A6 shows that the event-study coefficient estimates are very similar when excluding time-varying covariates. We also find similar results when we include all counties in Tennessee (see Figure A7).

the baseline mean implies a 16.6% increase in the total crime rate. In columns (2) and (3), we report the coefficient estimates for violent and non-violent crimes. Following the disenrollment, the median county's violent and non-violent crime rates increased by roughly 5.5 and 6 per 1,000 residents or 20.6% and 14.1%, respectively, in an agency. We note that the coefficient estimate for violent crimes is only marginally statistically significant (10% level). However, recall that Figure 2 suggest that the effect on violent crime gets larger over time. When we include later years (i.e., 2008 and 2009) in our analysis, our results become statistically significant at the 5% level (see Figure A8). Given the average pre-treatment population served by a police agency in the median county in Tennessee (11,795), our results indicate an additional 65 violent and 71 non-violent crimes in the median county post-treatment.

As described in Section 4.1, we see some (imprecise) evidence of a potential different pre-trend for counties of different TennCare exposure levels. To dig deeper into the empirical importance of this potential divergence, we have estimated separate trends in total, violent, and non-violent crime rates for each Tennessee county over the pre-treatment period, and removed that trend from the data. Results using the de-trended crime rate variables are identical to our main DID results (Table A8) out to five decimal places (not shown, available on request), which offers suggestive evidence that potentially differential pre-trends do not lead to substantial bias in our results.

We next examine which specific types of crimes are driving our aggregate findings in Tables A5 and A6. For violent crimes, we find no statistically significant effect of the disenrollment on murder, rape, or robbery rates in columns (1) to (3) of Table A5. The increase in violent crime appears to be driven by assaults, presented in column (4). Post-disenrollment, assaults increased by 5.3 per 1,000 residents or 21.6%. In column (2) of Table A6 we see that the non-violent crime result is driven by theft, which increased by roughly 6 per 1,000 post-disenrollment or by 23%. We find no evidence that the TennCare disenrollment affects burglary, motor vehicle thefts, or arson rates.

Recent economic work also considers the role of police in reducing crime, establishing that police force size and composition can lower crime (Miller and Segal, 2019; Cox et al., 2022a,b; Chalfin et al., 2022). 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). Given the observed increase in crime, particularly non-violent crime, post-disenrollment we might expect that there could be a corresponding increase in the number of police-civilian interactions, and as a result, an increase in on-duty assaults on officers by civilians. In Table A7 we investigate the effects of disenrollment on assaults of police officers, overall and stratifying by whether the on-duty assault leads to an injury or not for the officer.<sup>18</sup> We find no evidence that this policy shock affected police officer assaults at the hand of civilians.

#### 4.3 Mechanisms

Our main results suggest an increase in crime resulting from Tennessee's 2005 Medicaid disenrollment. We now consider possible pathways that may explain this finding.

We first examine the role of economic stability in Table 3 given that that economic opportunity and income are strong predictors of criminal activity (Raphael and Winter-Ebmer, 2001; Lin, 2008; Akee et al., 2010). We extend our regression from equation (1) to examine county-level unemployment rates, poverty rates, and median income in columns (1), (2), and (3), respectively. The findings in Table 3 suggest that Medicaid disenrollment did not impact unemployment, the coefficient is negative which is suggestive of job-lock, but not precise. Conversely, column (2) suggests an increase in the poverty rate. Although imprecisely estimated, the results reported in column (3) buttresses the poverty finding by showing a decrease in county median income. While we cannot isolate the effect on the individuals particularly close to the poverty line, these findings collectively provide suggestive evidence that Medicaid disenvolument may have have pushed individuals (potentially close to poverty) over the poverty threshold, without simultaneously affecting labor market opportunities for the average individual in Tennessee. Those losing coverage with the disenvolument 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 shock.

We complement this analysis with BRFSS data, which allow us to examine whether the TennCare disenrollment affected the cost of access to healthcare. For this analysis, we focus on non-elderly childless adults. Column (1) of Table 4 suggests that counties in Tennessee most exposed to the disenrollment led to a decrease of 10% in the likelihood of being covered by health insurance (BRFSS, over our study period, does not allow us to separately consider Medicaid coverage). Column (2) indicates that respondents reported delaying healthcare due to cost. In the median exposure county, the probability of delaying care due to cost more than doubled. We observe no change in the likelihood of reporting very good or excellent health post-disenrollment.

Alcohol and drug use is closely linked with crime outcomes and use of 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

<sup>&</sup>lt;sup>18</sup>These data are drawn from from Law Enforcement Officers Killed and Assaulted (LEOKA) Data Collection and sourced from Kaplan (2021a).

treatment for these conditions. Thus, we consider the effects of Tennessee's Medicaid disenrollment on proxies for substance use disorder treatment utilization. Using data from the public use two—year average NSDUH data, Table 5 reports results from our analysis of unmet need for alcohol and drug use treatment. As described in Section 3, these data are not available at the county—level and thus we examine this question using state—level data and a DID design that compares trends in outcomes between Tennessee and other Southern states pre— and post—disenrollment as outlined in equation 3. These findings suggest an increase in the share of individuals needing substance use disorder treatment but unable to find or access such care. However, note that once we account for the small number of state clusters our result is significant at the 10% level.

We add to the NSDUH analysis by examining county-level NVSS mortality outcomes in Table 6, returning to our primary regression specification outlined in equation (1). Given the decline in access to healthcare, in particular mental health and substance use disorder treatment (see Table 5), we consider the effect of the TennCare disenrollment on county-level rates of overall morality and death by suicide, and fatal alcohol poisoning and drug overdose death rates. We present these findings in Table 6. The coefficient estimates for all-cause mortality is positive, suggesting a 2% increase for the median exposure county, but does not rise to the level of statistical significance. We find an increase of 25% for the median exposure county in drug overdose deaths post-disenrollment, but no observable change in suicide- and alcohol-related deaths. The fact that we finding statistically significant effects for drug-related deaths, but not other deaths, is perhaps not surprising as the TennCare disenrollment occurred during the initial wave of the opioid crisis, and during this time period non-elderly adults were particularly hard hit by the crisis and fatal opioid overdoses in Tennessee were above the national average (Kiang et al., 2019).

#### 4.4 Robustness

In this section we report results from a range of robustness checks. Overall, our results not sensitive to alternative specifications or samples, which further supports a causal interruption of our main findings.

In Table A9, we employ a specification similar to Maclean et al. (2023) where we compare police agencies in Tennessee to those in other Southern states in a DID framework, as we did for the CPS and NSDUH outcomes (equation [3]). The results from this regression suggest an increase of 1.83 per 1,000 (or 3.1% relative to the pre-policy mean in Tennessee) in total crime for police agencies in Tennessee relative to other Southern

states post-disenrollment (2.7%). This effect is driven by non-violent crimes, while the positive coefficient on violent crime is not precise at the conventional level.<sup>19</sup>

Our main UCR data sample consists of police agencies that report crimes in every year of the sample period (2002-2007). We relax this restriction and re-estimate equation 1 using alternative sub-samples (in Figure A8). The top, middle, and bottom panel report the DID effects for total, violent, and non-violent crime rates. The first column of this figure reports our baseline estimates from Table 2. In the second column, we expand the years to include a balanced panel of agencies that report criminal activity between 2000 and 2007 (this period includes data prior to the major Medicaid re-certification effort in Tennessee in 2002). In the third column, we expand the sample period to 2002-2009, thereby including the Great Recession period.<sup>20</sup> Column (4) includes all agencies, regardless of reporting pattern, between 2000 and 2007. Lastly, column (5) includes agencies in jurisdictions with more than 10,000 individuals. In line with our previous analysis, the results are robust to these different specifications with violent crimes as the only possible exception, as we lose precision when restricting the sample to agencies that cover populations of over 10,000. Given that Tennessee is a highly rural state, this specification excludes 68% of police agencies in our main sample, and the substantially smaller sample likely contributes to the precision loss.

In Figure A9, we conduct a leave—one—out analysis by excluding a county in Tennessee at a time and re—estimating our main regression (equation [1]). Overall, we observe an increase in crime in counties most exposed to Medicaid disenrollment across the leave—one—out samples.

We next ensure that we can replicate what previous studies have found as it relates to the effect of the disenrollment on Medicaid coverage (see Section 2). The TennCare literature predominately has used an approach similar to equation 3 to study Medicaid coverage effects. That is, trends in Tennessee are compared with trends in other Southern states, and the analysis sample includes adults between ages 21 and 64 without children. We use this sample and specification, and we trim the sample to include those with income up to 300% of the Federal Poverty Level, thus a sample of lower-income adults likely to be impacted by the TennCare disenrollment.<sup>21</sup> The dependent variable an

 $<sup>^{19}</sup>$ We present results of this specification where we use a block bootstrap procedure to calculate standard errors in Table A10.

<sup>&</sup>lt;sup>20</sup>Early provisions of the ACA were implemented in 2010, including a provision that allowed adults through age 26 to remain on their parents' private insurance plans. This provision has been associated with crime (Fone et al., 2023). Thus, we do not extend our study period beyond 2009.

<sup>&</sup>lt;sup>21</sup>We have estimated this regression on samples of non–elderly and childless adults with higher and lower incomes. Different studies have used various income thresholds, and to the best of our knowledge there is no standard cut–off, thus we have explored a range. Results, available on request, are very

indicator for whether the respondent reported having Medicaid coverage in calendar years between 2002 and 2007 (which corresponded to survey years 2003 to 2008). Results are reported in Table A2. We find that, post-disenrollment, the probability that a CPS respondent reports Medicaid coverage declines by 8.0 percentage points (ppts). Comparing this coefficient estimate to the baseline coverage rate in Tennessee implies a 33% (= -0.08/0.24 \* 100%) decrease in Medicaid coverage among TennCare eligible individuals in Tennessee relative to other Southern states. This 33% decrease is very similar to the previous literature, for example Garthwaite et al. (2014) also estimate a 33% reduction in Medicaid coverage.

The estimates based on these two designs lead to somewhat different results in TennCare coverage effects, with estimates based on the contrast of Tennessee vs. other Southern states being larger than comparisons of counties within Tennessee. Comparing findings across Table 1 and Table A2 is challenging for a number of reasons.

First, the results reported in Table A2 capture an average treatment on the treated (ATT) type parameter as the treatment variable is binary, while the estimate reported in Table 1 has the flavor of an average causal response on the treated (ACRT) estimate. Thus, we are estimating different target parameters that are not easily compared (Callaway et al., 2024).<sup>22</sup> The ATT parameter compares potential outcomes in the treated state vs. the untreated state, whereas the ACRT parameter reflects the derivative of the average causal response function at a particular dose level (i.e., Medicaid coverage rate). Second, the two estimators rely on different assumptions. In Table A2, the assumption is that other Southern states can reveal the counterfactual trend in Medicaid coverage for Tennessee absent the disenvolument, while in Table A2 we are assuming that lower exposure counties within Tennessee serve as a counterfactual for higher exposure counties. If counties within the same state are a more credible counterfactual than are other Southern states for Tennessee, then the coefficient estimates reported in Table  $A_2$ may capture a combination of the ATT and differential pre-trends. Contrawise, if the reverse is true, then we would expect expect Table A2 results to capture treatment effect of the disenrollment plus differential trends.<sup>23</sup> Third, results reported in Table A2 may better isolate individuals impacted by the disenvolument than those presented in Table 1. In the CPS, we exclude adults without children in the household and who would not be directly impacted by the disenvolument, but our Medicaid coverage variable used to

similar to those reported here.

 $<sup>^{22}</sup>$ See Figure 2 in Callaway et al. (2024) and the associated text.

 $<sup>^{23}</sup>$ Further, as described by Callaway et al. (2024), Table A2 relies on a more 'standard' parallel trend assumption, while Table 1 relies on 'strong parallel' trends which is needed to rule out selection into treatment dose.

generate results reported in Table 1 includes all individuals covered by Medicaid, some of whom would have been impacted by the disenrollment and others who would not.

Finally, we note that the unscaled beta (= -0.13) indicates the effect of transitioning from the entire population being covered to the entire population being disenrolled. Therefore, the 48% (= -0.13/0.27 \* 100%) reduction in Medicaid coverage that arises from such transition is more comparable to the findings captured in Table A2. Fully exploring the differences in Medicaid coverage results across Tables 1 and A2 is beyond the scope of this study.

### 4.5 Contrasting TennnCare with other Medicaid contractions

This section puts our TennCare disenrollment results in context with another Medicaid contraction that affected a different demographic with a lower propensity for criminal activity. We study a policy change in 2005 in the state of Missouri (Zuckerman et al., 2009; Garthwaite et al., 2018; Bailey et al., 2024). The Missouri contraction led to approximately 100,000 residents losing Medicaid, Missouri did not cover an expansion population and all enrollees were part of traditionally eligible groups.

Thus, the TennCare disenrollment and the Missouri contraction differ in important ways. While the TennCare disenvolument led to the state ceasing to cover a complete categorical group (i.e., the expansion population), Missouri's contraction was driven by a tightening of income eligibility thresholds and termination of a disabled workers program. For working parents, the maximum income eligibility was reduced from 75% of the Federal Poverty Level to between 17% to 22% (Zuckerman et al., 2009; Bailey et al., 2024). Among the elderly and disabled, those with incomes between 80% and 100% of the Federal Poverty Level were no longer eligible for Medicaid (Zuckerman et al., 2009; Bailey et al., 2024). The populations losing coverage were quite different. In Tennessee, disenrollees were largely non-elderly, non-disabled, and childless adults, while in Missouri, those losing coverage were predominately parents, the elderly, and the disabled. TennCare disenvolves were, ex ante, arguably more likely to be involved in crime than those losing coverage in Missouri. While TennCare was terminated due to high cost, the Missouri Medicaid contraction was just one component of a larger government response curtailing a range of social programs to a state—wide budget shortfall occurring over several years, which may complicate interpretation of treatment effects.

Next, we use a similar exposure design to evaluate the impact of the Missouri Medicaid contraction on crime. In particular, we construct an exposure measure based on 2004 county—level Medicaid coverage rates in each county in Missouri and estimate a regression comparable to that outlined in equation (1). The median Medicaid coverage rate was 24.7% in 2004 and we scale coefficient estimates by that number.

DID results are reported in Table A11 and event—study results are reported in Figure A10. As expected, we observe less evidence that crime rates were impacted by the Missouri contraction than documented in Tennessee. In particular, we only observe an increase in violent crimes rates by 8.6% in the median county, but it is not statistically significant at the conventional level. We do not observe an effect on total crime or non—violent crime. Given the population impacted by the Missouri contraction, this finding could be driven by an increase in victimization of those who lost coverage; however, we cannot distinguish between crimes where the victim or offender was among the population that lost coverage. The Missouri—Tennessee comparison is useful as the results suggest that not all contractions will lead to the same social costs. The insurance loss among non—elderly, non—disabled, and childless adult population leads to increased crime, but there is less evidence of this rise in the traditional population.

Similarly, Packham and Slusky (2023), again focusing on traditional Medicaid enrollees in South Carolina, find limited evidence that a policy designed to provide access to Medicaid among previously incarcerated individuals reduced crime rates. Collectively, these studies, earlier work on Medicaid expansion, and our own work here highlight the importance of understanding the policy change and composition of the target population when thinking through the implications of changing Medicaid access 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), 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. Studying the effect of losing health insurance is timely, as states are increasing the requirements to remain eligible for Medicaid coverage (Sommers et al., 2019; Chen and Sommers, 2020; Guth and Musumeci, 2022), 'unwind' Medicaid coverage provisions adopted during the U.S. government's PHE driven by the COVID-19 pandemic (Tolbert, 2023), and lawmakers propose policies that reduce Medicaid eligibility (The White House, 2023).

This paper utilizes Tennessee's Medicaid disenrollment in 2005 to shed new light on

the insurance-crime relation. The disenrollment, one of the most substantial reductions in coverage in the history of the Medicaid program, lead to 190,000 non-elderly, able-bodied, childless adults unexpectedly losing Medicaid over a six-month period. We compare counties with differential level of policy exposure based on Medicaid coverage rates prior to the disenrollment. We find that the median county (=0.258 in pre-policy Medicaid coverage rates) experienced a 16.6% increase in crime rates, with violent and non-violent crime rates rising by 20.6% and 14.1% respectively. We examine the impact of the disenrollment on each violent and non-violent offense separately to better understand what crimes are influenced by an insurance loss. Our overall effects are driven by assault and theft, the most common violent and non-violent offenses respectively.

We present evidence of a 'first-stage,' as TennCare disenrollment decreases 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. In our analysis of mechanisms, 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 Jacome (2023) for young adults aging out of Medicaid at age 19. In particular, we find that the probability of needing (but not receiving) substance use disorder treatment increased and deaths related to substances increased post-disenrollment.

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 leads to 710 fewer Medicaid enrollees in the median Tennessee county of 23,676 people in 2004 (=23,676\* -0.03 - results from Table 1) each year post-disenrollment. At the same time, given that a police agency covers a population of 11,795 and there are two agencies in the median county, the TennCare disenrollment leads to 270 crimes (=11.46\*11,795/1000\*2) in the median county. This back-of-the envelop calculation suggests that the TennCare disenrollment results in 0.38 total crimes per newly disenrolled person in the median county. Applying the same calculation to specific types of crime we find roughly .18 assaults and thefts per newly disenrolled individual, respectively.

Given that our ACRT estimates of Medicaid disenrollment are not directly comparable to other Medicaid expansion studies that estimate ATTs (Callaway et al., 2024), it is challenging to situate our estimates within this literature. While our implied NTT estimate is larger in magnitude (in absolute value) than estimates reported by Vogler (2020) of one aggravated assault averted for every 112 newly-covered non-elderly individuals (using ACA Medicaid expansion, thus an insurance gain, as the source of variation), we contend that our findings remain reasonable for several reasons. First, insurance gains and losses need not have symmetric effects; losing insurance may be more deleterious in terms of crime than gaining access to health insurance. In particular, if access to behavioral healthcare (mental health and substance use) is an important channel linking crime and insurance - our analysis of mechanisms hints that they are - then abruptly and unexpectedly losing insurance that covers these services could lead to worsening of conditions that are closely linked to crime. Second, there have been important changes to coverage option differences for lower-income Americans between the TennCare disenrollment and ACA Medicaid expansion, which may imply that changes in the availability of Medicaid could have had heterogeneous effects over time. More specifically, in addition to expanding Medicaid for states that choose to implement this policy, the ACA made numerous changes to the U.S. health insurance market, including providing subsidies for private coverage for those with family incomes up to 400% of the Federal Poverty Level. Thus, TennCare disenvollees (who had family income between 100% and 175%of the Federal Poverty Level and therefore would have been eligible for ACA subsidies) would have had fewer coverage options than similar individuals looking for non-Medicaid coverage options in the post-ACA period. Third, the criminology literature suggests a concentration of crime among a small subset of the overall population (Wolfgang et al., 1987; Farrington et al., 2001), indicating that individuals committing crimes are repeat offenders. Lastly, estimates from our state-level analysis suggest a three percent decrease in total crimes, which is in line with Medicaid expansion effects from Vogler (2020) and He and Barkowski (2020), highlighting the difference between continuous treatment and binary treatments (Callaway et al., 2024).

Our study suggests that losing Medicaid coverage may have indirect societal cost, such as increasing crime, which are primarily driven by assault and theft. To put this potential cost in perspective, we discuss the gap in the social cost attributed to crime (in particular, assault and theft, these offenses drive our overall crime findings) incurred by a county with the median exposure. Our coefficient estimates indicate that a given police agency at the median exposure experienced an additional 5.31 (= 0.258 \* 20.62) assault incidents per 1,000 residents. Using an estimate of the cost of an assault from Chalfin and McCrary (2018) and inflating it to 2023 U.S. dollars, the additional social cost attributed to assaults in a county at the median exposure is \$288,811 (= 5.31 \* \$54,390) per 1,000 residents. While the cost per theft incident (\$662) is significantly lower than the cost per assault incident (\$54,390) (Chalfin and McCrary, 2018), theft incidents are prevalent. We estimate that a police agency located in a county with median exposure experienced additional 5.97 (= 0.258 \* 23.16) theft incidents translating to a cost of \$3,952 (=5.97 \*

\$662) per 1,000 residents following TennCare disenrollment.

Our study is not without limitations. First, because TennCare enrollment primarily targeted non-elderly, non-disabled, low-income adults without children, policymakers extrapolating our findings to the general Medicaid-covered population may not be appropriate. Second, we study a historical policy change and insurance markets have developed over time, with lower-income groups 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.

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 more generally. Going against historical trends, recent policies — in place and proposed — will likely lead to many Americans losing Medicaid and other insurance, or the costs of healthcare (even among the insured) increasing and rendering healthcare, in particular mental healthcare and substance use disorder treatment, un—affordable (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 crime rates: High vs low exposure counties

*Notes:* Data Source: UCR 2002–2007. Data are weighted by the population served by each agency prior to aggregating to the treatment–year.



Figure 2: Effect of the TennCare disenrollment on crime rates using an event-study: UCR 2002-2007

*Notes:* This figure plots the coefficient estimates from an event-study OLS regression of crime rates on indicators with years to and years since the TennCare disenrollment. The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. Coefficient estimates are reported with circles and 95% confidence intervals that account for within-county clustering. The omitted category is 2004, the year prior to the disenrollment.

Table 1: Effect of the TennCare disenrollment on Medicaid coverage: Medicaid 2005-2007

Outcome:	Medicaid
Exposure $\times$ post	-0.13***
	(0.01)
Scaled $\beta$	-0.03
Pre-treatment mean	0.27
Observations	3348

Notes: The regression includes time-varying county-level covariates, county fixed effects, and year fixed effects. The unit of observation is a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by the county population. 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.

Table 2: Effect of the TennCare disenrollment on crime rates: UCR 2002--2007

Outcome:	Total crime	Violent crime	Non-violent crime
Exposure $\times$ post	44.42***	21.35*	23.07***
	(12.23)	(10.87)	(6.38)
Scaled $\beta$	11.46	5.51	5.95
Pre-treatment mean	69.01	26.70	42.31
Observations	2628	2628	2628

Notes: The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). 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.

Outcome:	Unemployment rate	Poverty rates	Median income
Exposure $\times$ post	-1.47	11.81***	-3590.57
	(1.06)	(2.79)	(3723.91)
Scaled $\beta$	-0.38	3.05	-926.37
Pre-treatment mean	6.31	16.18	34726.42
Observations	558	558	558

Table 3: Effect of the TennCare disenrollment on economic outcomes: BLS and SAIPE 2002-2007

Notes: The regression includes time-varying county-level covariates, county fixed effects, and year fixed effects. The unit of observation is a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by the county population. Regressions estimated with OLS. Standard errors are clustered by the county and are reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Table 4: Effect of the TennCare disenrollment on insurance, healthcare, and health among non-elderly childless adults: BRFSS 2002-2007

Outcome:	Health insurance	Delay care for cost	Very good/excellent cost
Exposure $\times$ post	-0.37***	0.46***	0.20
	(0.12)	(0.14)	(0.16)
Scaled $\beta$	-0.10	0.12	0.05
Pre-treatment mean	0.86	0.10	0.52
Observations	6677	6646	6676

Notes: The regression includes time-varying county-level covariates, county fixed effects, month fixed effects, and year fixed effects. The unit of observation is a respondent in a county in a month in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by BRFSS provided-weights. Regressions estimated with OLS. Standard errors are clustered by the county and are reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Table 5: Effect of the Tenn	nCare disenrollment	on needing, but	not receiving,	substance
use disorder treatment: NS	SDUH 2002-2007			

Outcome:	Drug treatment	Alcohol treatment
Tennessee $\times$ post	0.002***	0.008***
	(0.001)	(0.002)
Bootstrap p-value	0.0980	0.0960
Pre-treatment mean	0.026	0.060
Observations	102	102

Notes: The regression includes time-varying state-level covariates, state fixed effects, and year fixed effects. The unit of observation is a respondent in a state in a year. Data are weighted by the state population. Regressions estimated with OLS. Robust standard errors are reported in parentheses. Reported *p*-values are calculated using the wild bootstrap to account for small number of state clusters (Roodman et al., 2019). \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Outcome:	All-cause	Suicide	Alcohol	Drug
Exposure $\times$ post	0.43	-0.02	0.02	0.60***
	(0.66)	(0.12)	(0.02)	(0.18)
Scaled $\beta$	0.11	-0.00	0.00	0.15
Pre-treatment mean	4.991	0.177	0.002	0.152
Observations	558	558	558	558

Table 6: Effect of the TennCare disenrollment on mortality outcomes: NVSS 2002-2007

Notes: The regression includes time-varying county-level covariates, county fixed effects, and year fixed effects. The unit of observation is a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by the county population. Regressions estimated with OLS. Standard errors are clustered by the county and are reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

# 7 Appendix



Figure A1: Trends in crime rates: Tennessee vs. other Southern states

*Notes:* Data Source: UCR 2002-2007. Data are weighted by the population served by each agency prior to aggregating to the treatment year.



Figure A2: Distribution of Medicaid coverage exposure to the TennCare disenrollment

Notes: Data are aggregated to the county-level over the period Q1 and Q2 2005.



Figure A3: Distribution of exposure across counties



Figure A4: Covariate balance test



Notes: This figure plots coefficient estimates from separate regressions of the variable reported on the x-axis on the TennCare exposure measure, county fixed effects, and year fixed effects. The unit of observation is a county in a year. Data are weighted by the county population. Coefficient estimates are reported with circles and 95% confidence intervals that account for within—county clustering are reported with vertical lines.



Figure A5: Effect of TennCare disenrollment on Medicaid coverage using an event-study

*Notes:* This figure plots the estimates from an event-study OLS regression of county Medicaid coverage on indicators with months to and months since Medicaid disenrollment. The regression includes agency fixed fixed and year-by-month fixed effects. The unit of observation is a county in a month in a year. Data are weighted by the county population. Coefficient estimates are reported with circles and 95% confidence intervals that account for within-county clustering are reported with vertical lines. The omitted category is June 2005, the month prior to the disenrollment.





*Notes:* This figure plots the estimates from an event-study OLS regression of crime rates on indicators with years to and years since Medicaid disenrollment. The regression includes agency fixed fixed and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. Coefficient estimates are reported with circles and 95% confidence intervals that account for within-county clustering are reported with vertical lines. The omitted category is 2004, the year prior to the disenrollment.

Figure A7: Effect of TennCare disenrollment on crime rates using an event-study and all counties in Tennessee: UCR 2002–2007



*Notes:* The sample does not exclude counties with exposure measures below the 1st percentile or above the 99th percentile. This figure plots the estimates from an event-study OLS regression of crime rates on indicators with years to and years since Medicaid disenrollment. All Tennessee counties are included. The regression includes agency fixed fixed and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. Coefficient estimates are reported with circles and 95% confidence intervals that account for within-county clustering are reported with vertical lines. The omitted category is 2004, the year prior to the disenrollment.



Figure A8: Effect of TennCare disenrollment on crime rates: Alternative UCR samples

*Notes:* This figure plots the estimates from an DID OLS regression of high edxposure to medicaid exposure on crime rates for different sample specifications. Column (1) reports our baseline estimates that includes police agencies that report crimes in every year between 2002 and 2007. Column (2) includes a balanced panel of agencies that report criminal activity between 2000 and 2007. Column (3) includes a balanced panel of agencies that report criminal activity between 2002 and 2007. Column (3) includes a balanced panel of agencies that report criminal activity between 2002 and 2009. Column 4 includes all agencies, regardless of whether they reported every year or not (i.e., unbalanced panel), between 2000 and 2007. Column 5 includes an unbalanced panel of agencies whose jurisdictions contain over 10,000 individuals. The regression includes time-varying covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency.



Figure A9: Effect of TennCare disenrollment on crime rates: Leave-one-out analysis

*Notes:* This figure plots the estimates from an DID OLS regression of high exposure to Medicaid disenrollment on crime rates when omitting one of the 93 counties in Tennessee one at a time. The regression includes time-varying count-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency.



Figure A10: Effect of Missouri disenrollment on crime rates using an event-study: UCR  $2002{-}2007$ 

*Notes:* This figure plots the coefficient estimates from an event-study OLS regression of crime rates on indicators with years to and years since the Medicaid disenrollment. The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. Coefficient estimates are reported with circles and 95% confidence intervals that account for within-county clustering. The omitted category is 2004, the year prior to the disenrollment.

	All	Counties $\geq$	Counties $<$
Sample:	counties	median exposure	median exposure
Total crimes per 1,000 residents	59.9	69.0	51.1
Violent crimes per 1,000 residents	23.1	26.7	19.6
Non-violent crimes per 1,000 residents	36.8	42.3	31.5
Pre-disenrollment exposure	0.22	0.26	0.18
White (County)	0.79	0.79	0.78
Hispanic (County)	0.034	0.024	0.044
Age $19-64$ (County)	0.63	0.61	0.64
Age $65+$ (County)	0.12	0.13	0.11
Population served by agency	158839.8	152013.7	165401.0
Observations	1314	1020	294

Table A1: Summary statistics: UCR 2002-2004

*Notes*: The unit of observation is a police agency in a county in a year. This table reports summary statistics for the UCR database covering the years 2002–2004.

Table A2:	Effect	of the	TennCare	disenrollment	on	Medicaid	coverage:	CPS 2002-	-2007
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Outcome:	Medicaid
Tennessee×post	-0.08***
	(0.01)
Pre-treatment mean	0.24
Observations	42292

*Notes:* The regression includes time-varying state-level covariates, state fixed effects, and year fixed effects. The unit of observation is a respondent in a state in a year. Data are weighted by CPS-provided survey weights. Regressions estimated with OLS. Robust standard errors are reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Table A3: Effect of the TennCare disenvolument on crime rates not including time-varying county-level covariates: UCR 2002-2007

Outcome:	Total crime	Violent crime	Non-violent crime
Exposure×post	55.95***	24.43	31.52***
	(16.76)	(16.41)	(6.23)
Scaled $\beta$	14.44	6.30	8.13
Pre-treatment mean	69.01	26.70	42.31
Observations	2628	2628	2628

Notes: The regression includes agency fixed-effects and year fixed-effects. The unit of observation is an agency in a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by the population served by the agency. Standard errors are clustered around the county and reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Table A4: Effect of the TennCare disenrollment on crime rates include all counties: UCR 2002–2007

Outcome:	Total crime	Violent crime	Non-violent crime
Exposure×post	37.31***	17.12**	20.20***
	(10.02)	(8.46)	(4.79)
Scaled $\beta$	9.63	4.42	5.21
Pre-treatment mean	68.63	26.51	42.12
Observations	2682	2682	2682

Notes: The sample includes counties all 95 counties in Tennessee, including the two counties trimmed from the main analysis sample. The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in a county in a year and all counties in Tennessee are included. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). Data are weighted by the population served by the agency. The scaled  $\beta$  estimates moving from the 10th percentile of exposure to the 90th percentile of exposure by multiplying each coefficient estimate by 1.405. Standard errors are clustered around the county and reported in parentheses. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Outcome:	Murder	Rape	Robbery	Assault
Exposure $\times$ post	0.02	-0.09	0.80	20.62**
	(0.06)	(0.14)	(0.78)	(10.33)
Scaled $\beta$	0.01	-0.02	0.21	5.32
Pre-treatment mean	0.07	0.36	1.59	24.68
Observations	2628	2628	2628	2628

Table A5: Effect of the TennCare disenrollment on specific violent crime rates: UCR 2002–2007

Notes: The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). 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.

Table A6: Effect of the TennCare disenrollment on specific non-violent crime rates: UCR 2002-2007

Outcome:	Burglary	Theft	MV theft	Arson
Exposure $\times$ post	1.11	23.16***	-1.26	0.07
	(2.70)	(7.03)	(1.52)	(0.24)
Scaled $\beta$	0.29	5.97	-0.32	0.02
Pre-treatment mean	11.51	26.04	4.50	0.26
Observations	2628	2628	2628	2628

Notes: The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). The unit of observation is an agency in county in a year. 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.

Outcome:	Total	Injurious	Non-injurious
Exposure $\times$ post	-0.38	-0.08	-0.30
	(0.28)	(0.11)	(0.22)
Scaled $\beta$	-0.10	-0.02	-0.08
Pre-treatment mean	0.40	0.13	0.26

2628

Observations

2628

2628

Table A7: Effect of the TennCare disenrollment on on-duty officer assaults: UCR 2002–2007

Notes: The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). 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.

Table A8: Effect of the TennCare disenrollment on detrended crime rates: UCR 2002–2007

Outcome:	Total crime	Violent crime	Non-violent crime
Exposure $\times$ post	44.42***	$21.35^{*}$	23.07***
	(12.23)	(10.87)	(6.38)
Scaled $\beta$	11.46	5.51	5.95
Pre-treatment mean	67.99	25.97	42.02
Observations	2628	2628	2628

*Notes:* The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in a county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Tennessee pre-disenrollment (median exposure = 0.258 Medicaid coverage rate). 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.

Outcome:	Total crime	Violent crime	Non-violent crime
Tennessee $\times$ post	1.844**	0.883	0.961**
	(0.749)	(0.561)	(0.428)
Bootstrap p-value	0.0170	0.125	0.0220
Pre-treatment mean	59.21	22.79	36.43
Observations	28812	28812	28812

Table A9: Effect of the TennCare disenvolument on crime rates comparing Tennessee to other Southern states): UCR 2002-2007

*Notes:* The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a state in a year. Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors reported in parentheses. Reported *p*-values are calculated using the wild bootstrap to account for small number of state clusters (Roodman et al., 2019). \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

Table A10: Effect of the TennCare disenvolument on crime rates comparing Tennessee to other Southern states) using non-parametric bootstrap: UCR 2002-2007

Outcome:	Total crime	Violent crime	Non-violent crime
Tennessee $\times$ post	1.844**	0.883	0.961**
	(0.870)	(0.651)	(0.487)
Pre-treatment mean	59.21	22.79	36.43
Observations	28812	28812	28812

*Notes:* The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a state in a year. Data are weighted by the population served by the agency. Regressions estimated with OLS. Standard errors reported in parentheses are clustered around the county and calculated using a paired (nonparametric) bootsrapping procedure. \*\*\*, \*\*, \* = statistically different from zero at the 1%, 5%, and 10% level.

	Total crime	Violent crime	Non-violent crime
Exposure $\times$ post	3.87	8.05*	-4.18
	(7.65)	(4.16)	(7.04)
Scaled $\beta$	0.96	1.99	-1.03
Pre-treatment mean	70.89	19.59	51.30
Observations	3258	3258	3258

Table A11: Effect of the Missouri Medicaid contraction on crime rates: UCR 2002-2007

Notes: The regression includes time-varying county-level covariates, agency fixed effects, and year fixed effects. The unit of observation is an agency in county in a year. The scaled  $\beta$  reports the predicted effect size for the median Medicaid-exposed county in Missouri pre-disenrollment (median exposure = 0.247 Medicaid coverage rate). 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.