Losing Medicaid and Crime

Monica Deza, Thanh Lu,
Johanna Catherine Maclean, Alberto Ortega*

Version: November 2, 2024

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.

Keywords: healthcare; insurance; crime; Medicaid; difference−in−differences.
JEL codes: I1; I11; H70; K00.

*Deza: Department of Economics, Syracuse University, & NBER, Maxwell School of Citizenship and Public Affairs, 426 Eggers Hall, Syracuse NY, 13244 USA, mdeza@syr.edu; Lu: Health Economics Program, RTI International, 3040 East Cornwallis Road, Research Triangle Park NC, USA, tlu@rti.org; Maclean (corresponding author): Schar School of Policy and Government, George Mason University, & NBER & IZA, 3351 Fairfax Drive, Arlington VA, USA, jmaclea@gmu.edu; Ortega: Paul H. O'Neill School of Public and Environmental Affairs, Indiana University, & NBER, 1315 E 10 St. Bloomington, IN 47405, alorte@iu.edu. Research reported in this publication was supported by the National Institute on Mental Health of the National Institutes of Health under Award Number 1R01MH132552 (PI: Johanna Catherine Maclean). The views expressed herein are those of the authors and do not necessarily reflect the views of the National Institutes of Health. We thank Sebastian Tello−Trillo for sharing data with us and seminar participants at George Mason University for helpful comments. All errors are our own.

1 Introduction

In this study, we evaluate the impact of losing health insurance on crime outcomes by studying one of the most consequential Medicaid disenrollments in the history of the United States.[1] While overall crime rates in the U.S. have decreased substantially since their peak in the 1990s − see Figure 1− crime continues to be a top concern for many Americans (Gallup, 2023), especially with recent increases in violent crime and persistent crime spikes occurring in many major metro areas across the country (Federal Bureau of Investigation, 2020; Council on Criminal Justice, 2023). The U.S. reports eight million crimes each year (Federal Bureau of Investigation, 2019), leading to three trillion dollars in economic and societal costs (Anderson, 2021). Thus, understanding and leveraging factors for crime prevention could have substantial benefits for many Americans, and 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, an estimated 28 million Americans remain uninsured (Cohen et al., 2023) despite substantial federal and state efforts to increase coverage rates, and twice that number are 'underinsured' (Halliday and Akee, 2020).

These facts suggest that health insurance may be a tool to reduce crime in the U.S. Indeed, a growing number of quasi−experimental studies establish that gaining insurance coverage reduces crime outcomes. Most recently, several studies show that the Affordable Care Act's (ACA) Medicaid expansion[2] reduced 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

[1] Medicaid is the largest insurer in the U.S. and is a public program covering predominately low−income non−elderly adults and children with limited access to private insurance.

[2] 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 in healthcare use and associated social outcomes. Thus, predictions for the impacts of insurance losses using evidence on the impacts of 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.[3] Decision theory predicts that equal−sized income losses have

[3]In the case of substance use and mental health disorders, an abrupt termination of treatment can lead to severe health consequences, for example, a fatal drug overdose. Maclean et al. (2023) find that, following the TennCare disenrollment that we study, deaths by suicides and fatal drug overdoses/alcohol poisonings increased.

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 use a difference−in−differences approach that compares the extent to which crime changed following the 2005 disenrollment in Tennessee, relative to other Southern states*

We have several findings. First, we document a 33% decline in Medicaid coverage in Tennessee post−disenrollment relative to other Southern states. This magnitude is in line with previous work, and confirms that the 2005 Tenncare disenrollment indeed led to a substantial decline in Medicaid coverage. Second, we find a 3% increase in crime rates following the disenrollment, with a 2.6% statistically significant increase for non−violent crimes and a 3.8% increase for violent crime increases that is not statistically significant at the conventional level. These effects are particularly driven by aggravated assaults among violent crimes, and by theft among property crimes. Our findings are robust to using alternative research designs, study periods, and specifications. Finally, our mechanism analysis suggests that losing Medicaid induced changes in economic standing, housing stability, and healthcare use and health (in particular mental health and substance use outcomes), 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 symptoms (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). Insured individuals may face a higher opportunity cost of criminal activity.

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 activities, in particular, for 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. For example, ACA Medicaid expansions have been shown to reduce the probability of re−incarceration, accompanied by a corresponding increase in employment and wages (Badaracco et al., 2021), while decreasing the propensity to commit financially−motivated crimes (Arenberg et al., 2023). Two recent studies examine state−level policies that attempt to continue Medicaid coverage for incarcerated populations upon re−entry. Gollu and Zapryanova (2022) use near national data and 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) find a South Carolina policy, that reduces barriers to continuing Medicaid coverage post−release among incarcerated traditional enrollees,[4] 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 quasi−experimental studies evaluate the importance of losing in-

[4]South Carolina did not expand Medicaid with the ACA, thus the enrollees covered by this program are likely to be traditional populations.

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

These studies provide important information 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 disenrollment is one of the most substantial contractions in the Medicaid program history. 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 of the disenrollment. 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 disenrollment

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 along with low−income children. 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 to do so. One mechanism used by states to cover expansion populations was a Section 1115 waiver to the Social Security Act ('1115 waiver').

In 1993, Tennessee applied for a 1115 waiver to the state's Medicaid program through the Health Care Financing Administration (the predecessor to the Centers for Medicare & Medicaid Services or 'CMS'). The waiver was approved and Tennessee was permitted to implement a Medicaid demonstration project ('TennCare') which was designed to remove categorical restrictions 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., 2007; 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., 2007; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021).[5] 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 (Deza et al., 2022b; Jácome, 2023), the generous coverage of these treatments suggests that losing TennCare could be important in our setting.[6]

TennCare was popular in Tennessee and enrollment 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., 2007). 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., 2007). 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., 2007; Chang and

[5]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.

[6]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 55% of specialized behavioral health treatment centers in Tennessee accept Medicaid as a form of payment.

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.

A series of studies uses the TennCare disenrollment to understand how losing insurance impacts access to insurance and 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.[7] 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 who used less healthcare − general, preventive, chronic condition management, and behavioral health − were more likely to report delayed medical care due to cost and experienced worse physical and behavioral health (Garthwaite et al., 2014; Tarazi et al., 2017; DeLeire, 2019; Tello-Trillo, 2021; Maclean et al., 2023; Tello-Trillo et al., 2023). Of particular relevance to our study, Maclean et al. (2023) show that behavioral healthcare hospitalizations declined post−disenromment and behavioral health worsened. There are also implications for healthcare providers: Garthwaite et al. (2018) document 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.[8] 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, evic-

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

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

tions, 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, 2021). 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 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

Medicaid coverage: *Our primary research design compares changes in Tennessee relative to other Southern states that were not experience Tenncare disenrollment. As an additional analysis, we exploit the variation in the intensity of the TennCare disenrollment across Tennessee counties based on pre−policy exposure within Tennessee only, as measured by the share of the eligible population in the county covered by Tenncare prior to the 2005 Tenncare disenrollment. 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).[9] *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 state to calculate TennCare enrollment rate in each county, which are defined as the share of the population covered by Medicaid. Given that no county has zero Tenncare coverage prior to Tenncare disenrollment, this approach is comparing counties that were all treated at the same time with each other, but taking into account that counties were treated with different intensities. While the limitation is that all counties are treated and therefore there is no proper control, this approach sheds light about the heterogeneity in the extent to which counties were treated even within Tennessee. Finally, we also use the exposure variable to establish that the disenrollment on Medicaid coverage indeed decreased Medicaid coverage. However, these data are available monthly from 2005 to 2007, so the period of study is limited*

Data on potential mechanisms: To better understand our main crime findings, we conduct an analysis of mechanisms to study potential channels through which losing Medicaid could impact crime. We draw data from several different sources. 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. We supplement this analysis with county eviction rates per 1,000 non−elderly adults using data on eviction filings and completed evictions from the Princeton University's Eviction Labe (Eviction Lab, 2021). Filings reflect a landlord placing a formal petition with the civil court for eviction, and completed evictions capture the result of a civil court hearing of an eviction case in which the landlord is permitted to evict the tenant.[10] See Bradford and Maclean (2024) for a full discussion.

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) use of and 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;

[9] We thank Sebastian Tello−Trillo for kindly sharing data with us.

[10] In the U.S., evictions cases are generally heard in civil, not criminal, court.

Grooms and Ortega, 2019; Maclean and Saloner, 2019; Maclean et al., 2017), we obtain county−level data on the number of annual admissions to specialized behavioral health treatment centers using data from the National Survey of Substance Abuse Treatment Services (N−SSATS) (Substance Abuse and Mental Health Services, ND).[11] We aggregate the data from the center− to county−level and convert annual admissions counts from N-SSATS to the rate per 1,000 county residents. We also use data on the 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).[12]

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 total mortality, and separately 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 are based on death certificates which include the cause of death, allowing us to isolate behavioral health deaths.

3.3 Methods

We follow Garthwaite et al. (2014), Tello-Trillo (2021), and Maclean et al. (2023) and estimate the effect of Tenncare disenrollment in Tennessee relative to other Southern states by estimating the following equation. The analysis is restricted to all Southern states, which leaves Tennessee as the treatment group and other Southern states as the comparison group,[13]. (TN_s) is an indicator for Tennessee and use only the Southern states in the analysis, and $(Post_t)$ is an indicator equal to 1 for years 2005 to 2007, and zero otherwise. Thus 2005 is a partially treated year as the disenrollment occurred in August 2005.

$$y_{ist} = \beta_0 + \alpha_i + \gamma_t + \beta TN_s \times Post_t + \gamma \mathbf{X_{st}} + v_{ist} \tag{1}$$

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

[12] 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 first 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.

[13] 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.

We report heteroskedastity robust standard errors in equation 1. 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 A2 reports the summary statistics for crime rates and time−varying control variables for the years before the disenrollment. We report summary statistics for counties above median exposure to the TennCare disenrollment (i.e., the median value is 0.258 in Medicaid coverage) 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.

Figure A3 shows the crime rate trends for Tennessee versus other Southern states. These stylized facts suggest that Tennessee experience a relative increase in crime rate after Tenncare disenrollment, particularly for violenc crime. In panel (a) we see that there is a relative increase in total crime rates in Tennessee following the policy change in 2005. There is a similar divergence for violent crimes shown in panel (b). Finally, panel (c) indicates no change in non−violent crimes in Tennessee, but a slight decrease in other southern states that started prior to Tenncare disenrollment.

Given that the U.S. was experiencing a decline in crime rates nationally over this period (Pew Research Center, 2020),[14] the rise we observe in Tennessee offers suggestive evidence that the disenrollment increased crime.

We study a downstream consequence of Medicaid disenrollment, thus a necessary condition is that the disenrollment lead to meaningful change in Medicaid coverage. We examine the first−stage using equation 1. Results are reported in Table .[15] When examining the extent to which Tenncare disenrollment decreases Medicaid coverage, we ensure that we can replicate previous studies investigating the effect of the disenrollment on Medicaid coverage (see Section 2). The TennCare literature predominately has used an approach similar to equation 1 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

[14] See Figure 1 for national trends in crime 1990−2019.

[15] 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.

Federal Poverty Level, thus a sample of lower−income adults likely to be impacted by the TennCare disenrollment.[16] The dependent variable is an indicator for whether the respondent reported having Medicaid coverage in calendar years between 2002 and 2007 (corresponding to survey years 2003 to 2008). Results are reported in Table A11. We find that, post−disenrollment, the probability that a respondent reports Medicaid coverage declines by 8.0 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 similar to the previous literature, for example Garthwaite et al. (2014) also estimate a 33% reduction in Medicaid coverage.

Event−study results are provided in Figure A4 (we use six month leads, July 2005 is the omitted category, and we include a full set of month lags, otherwise the specification is identical to equation 3). The event−study shows limited differential pre−trends for counties of different exposure to the policy shock and a sharp decline in coverage in the post−period that persists through the end of 2007. The coefficient of interest in equation 2 captures the extent to which monthly Medicaid coverage changes with exposure to the disenrollment. 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. 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 3.6 percentage point ('ppt') reduction in monthly Medicaid coverage post−disenrollment ($= -0.14 * 0.258$). Comparing this coefficient estimate with the baseline Medicaid coverage rate in counties with above−median exposure, we find a decline of 12.6% ($= -0.034/0.27 * 100\%$). Using the population of the median county, a 13.4% reduction in Medicaid coverage suggests that in the median county 1,034 people lost this form of coverage.[17]

[16] 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 similar to those reported here.

[17] The median population county in Tennessee in the first half of 2005 is Rhea County with a population of 29,919. The Medicaid coverage rate in this county and in this time period is 0.258, which implies there are 7,719 Medicaid enrollees. A 13.4% reduction suggests that 1,034 residents in this county lost coverage due to the disenrollment. If we estimate the number of individuals losing coverage for each of the 95 counties in Tennessee we calculate that just under 180,000 people were disenrolled, this number is very close to the 190,000 documented in other work.

4 Results

4.1 Internal validity

4.2 TennCare and crime

We summarize our main findings using the specification in equation 1, where we compare police agencies in Tennessee to those in other Southern states in a DID framework. 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.[18]

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 2 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 significantly 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 disenrollment may have pushed individuals (potentially close to poverty) over the poverty threshold, without simultaneously affecting labor market opportunities or financial resources for the average individual in Tennessee. Those losing coverage with the disenrollment had family incomes just above the poverty line (100% to 175% of the Federal Poverty Level, see Section 2.2) and thus could be 'at risk' for poverty following a shock. In columns (4) ad (5) of Table 3, we follow Ali et al. (2024) and estimate the effect of the TennCare

[18]We present results of this specification where we use a block bootstrap procedure to calculate standard errors in Table A10.

disenrollment on eviction outcomes. We find an increase in both eviction filings and completed evictions post−disenrollment.[19]

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 experienced 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). This decline in the probability of any coverage, coupled with results reported in Section 3.4, suggests that at least some disenrollees were not able to replace lost Medicaid with other insurance. 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.

Poor mental health and substance use (both alcohol and other drugs) are closely linked with crime outcomes and use of mental health and substance use disorder treatment has been shown to reduce crime (Bondurant et al., 2018; Deza et al., 2022b,a). Further, as described in Section 2.2, TennCare offered relatively generous treatment for these conditions. Thus, we consider the effects of Tennessee's Medicaid disenrollment on proxies for mental health and substance use disorder treatment utilization. First, using county−level data from N−SSATS, we show that admissions to specialized treatment centers declined post−disenrollment (Table 5). Next, drwaing 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 (our data do not include complementary measures of mental healthcare use). 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 1. These findings suggest a decrease in treatment use and an increase in the share of individuals needing substance use disorder treatment but unable to find or access such care.

In Table 6, returning to our primary regression specification outlined in equation 2, we report changes in mortality based on NVSS data. The coefficient estimates for all−cause mortality are 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

[19]To account for differences across counties in the cost of renting, we follow Ali et al. (2024) and control for the median property values. Results are similar, although less precise, if we do not include this variable in the eviction regressions. Our crime rate findings are not appreciably different if we include this variable in the crime regressions. Results are available on request.

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 are not sensitive to alternative specifications or samples, which further supports a causal interruption of our main findings.

The estimates based on our two designs (our primary specification compares counties in Tennessee with different exposure to the disenrollment while our second specification compares Tennessee to other Southern states) lead to somewhat different results in TennCare crime and coverage effects. Comparing crime and coverage effects across the two designs is challenging. In particular, the results reported in Tables A9 and A11 capture an average treatment on the treated (ATT) type parameter as the treatment variable is binary, estimtes based on equation 2 have 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).[20] 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, in our analyses of coverage effects, we rely on survey data in Table A11 and administrative data in Table 1, each of which has limitations in capturing Medicaid coverage (e.g., reporting error in survey data and limited demographics in administrative data). There are potentially other reasons for the divergence. Fully exploring the differences in Medicaid crime and coverage results (and ATT vs ACRT estimates generally) is beyond the scope of this study.

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 2 using alternative sub−samples (in Figure A9). 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

[20] See Figure 2 in Callaway et al. (2024) and the associated text.

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.[21] 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 relatively 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 A10, we conduct a 'leave−one−out' analysis by sequentially excluding each county in Tennessee at a time and re−estimating our main regression (equation 2). Overall, we observe an increase in crime in counties most exposed to the disenrollment across the leave−one−out samples. We note that excluding Shelby County (Memphis is the county seat) leads to a decline in the total and violent crime rate regressions.

4.5 Alternative approach

We estimate the effect of a large−scale reduction in Medicaid eligibility in Tennessee by comparing counties most exposed to TennCare disenrollment in Q1 and Q2 of 2005 (i.e., just before to the policy shock) to those less exposed. This design has been used to study policy shocks that may impact all observations 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 disenrollment. Our analyses rely on the assumption that the latter county is more impacted by the TennCare disenrollment than the former county. However, these 'extreme' counties we describe here with either 0% or 100% of the population covered by Medicaid do not exist in Tennessee. Thus, as we discuss later in this section, we will scale our coefficient estimates to produce more policy−relevant findings.

We restrict the analysis to Tennessee, and estimate the average causal response of the TennCare disenrollment on crime using the difference−in−differences (DID) regression

[21] 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.

outlined in equation 2:

$$y_{ict} = \beta_0 + \alpha_i + \gamma_t + \beta Exposure_c \times Post_t + \gamma \mathbf{X_{ct}} + v_{ict} \quad (2)$$

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 median Tennessee county in our analysis sample has two agencies. The terms α_i and γ_t represent agency and year fixed−effects, respectively.[22] $Exposure_c$ is the exposure variable equal to the share of the average population covered by Medicaid in a county in Q1 and Q2 of 2005. The variable $Post_t$ is an indicator equal to one for years 2005 to 2007, and zero otherwise. Thus, 2005 is a partially treated year as the disenrollment occurred in August, we expect effects to be muted in that year. The vector $\mathbf{X}_{ct}$ includes county−level demographic variables.[23] 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%,[24] thus we have a sufficient number of clusters to allow for credible inference (Bertrand et al., 2004).

The coefficient of interest in equation 2 is β, which compares the extent to which increasing exposure (i.e., share of the population Medicaid coverage in Q1 and Q2 2005) 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 (β),' more specifically we multiply each coefficient estimate by 0.258.[25]

A causal interpretation of findings generated in equation 2 relies on the common trends assumption. That is, had the TennCare disenrollment not occurred in Q3 2005, counties (regardless of pre−policy Medicaid coverage) would have followed similar trends in crime outcomes over the post−period. This assumption is untestable as we cannot observe counterfactual outcomes in which Tennessee counties are observed untreated by the disenrollment post−2005. To provide suggestive evidence on the ability of our data to satisfy the common trends assumption, we estimate an event−study. If we observe

[22] Agency fixed−effects subsume county fixed−effects.

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

[24] We trim these counties as they appear to display some modest evidence of differential pre−trends in the event−study for the total crime outcome. However, the DID (Table A1) and event−study (Figure A5) results are not appreciably different if we include these observations.

[25] Data are weighted by the county population prior to calculating the median value.

that crime rates evolved smoothly pre−disenrollment across counties with differential exposure to the policy shock, this pattern of results would provide suggestive evidence that our data satisfy the common trends assumption.

If the common trends assumption holds, then agency fixed−effects will account for all cross−sectional differences that are time−invariant, time−varying covariates will adjust for additional factors, and low exposure counties will capture trends in crime rates over time and provide a counterfactual for how we can expect crime rates to evolve in the absence of the disenrollment. We employ the event−study shown in equation 3:

$$y_{ict} = \beta_0 + \alpha_i + \gamma_t + \sum_{\substack{j=2002 \\ j\neq 2004}}^{2007} \beta_j Exposure_c \mathbb{1}\{j = t\} + \mathbf{X}_{ct}\psi + v_{ict}, \tag{3}$$

where $\mathbb{1}\{j = t\}$ is an indicator variable set equal to one if the observation is in year $j = 2002 - 2007$ for $j \neq 2004$ and zero otherwise. All other variables are as described in equation 2. The coefficient estimates of interest are the β_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 β_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 in crime rates post−2005. The policy lag coefficient estimates, β_j for $j \geq 2005$, allow us to examine the dynamic effects for the years post−disenrollment.

Our identification strategy relies on variation in pre−disenrollment exposure to TennCare. Figure A1 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 A2, there is some clustering of counties with higher and lower exposure, but the figure suggests that there

is reasonable variation across the state in Medicaid coverage.[26]

4.6 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 disenrollment 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 disenrollees 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[27] in each county in Missouri and estimate a regression comparable to that outlined in equation 2. The median Medicaid coverage rate was 24.7% in 2004 and we scale coefficient estimates by that number.

DID results are reported in Table A12 and event−study results are reported in Figure

[26]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.

[27]We use Medicaid eligibility as a proxy for Medicaid coverage. We obtain data on eligibility from the Missouri Department of Social Services. Data on county−level enrollment in Medicaid, to the best of our knowledge, is not available over our study period, thus we use eligibility as a proxy. We note this as a study limitation.

A11. 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 per agency 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 (and potentially other) 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) and 'unwinding' 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 uses 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 levels 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, though we note that the violent crime finding is somewhat sensitive to specification. Interesting, though we study an insurance loss within a different (older) population, our findings are qualitatively similar to Jácome (2023) and Fone et al. (2023), who study expected 'aging−out' of public and private coverage, in that losing insurance is more strongly associated with non−violent than violent crime. We examine the impact of the 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 Jácome (2023) for young adults aging out of Medicaid at age 19. In particular, we find that admissions to behavioral healthcare treatment declined, 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 1,030 fewer Medicaid enrollees in the median Tennessee county of 29,919 people in the first two quarters of 2004 (see Section 3.4) as a result of the 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∗11,795/1,000∗2) in the median county. This back−of−the envelope calculation suggests that the TennCare disenrollment results in 0.26 total crimes per newly disenrolled person in the median county. Applying the same calculation to specific types of crime we find roughly 0.13 assaults and 0.14 thefts per newly disenrolled individual. Comparing our effect sizes with studies documenting that crime declines following ACA Medicaid expansion (see for example Vogler (2020)) is somewhat challenging for reasons discussed in Section 4.4, changes insurance options between 2005 and 2014, and due to

the fact that there may be asymmetries in coverage gains and losses.

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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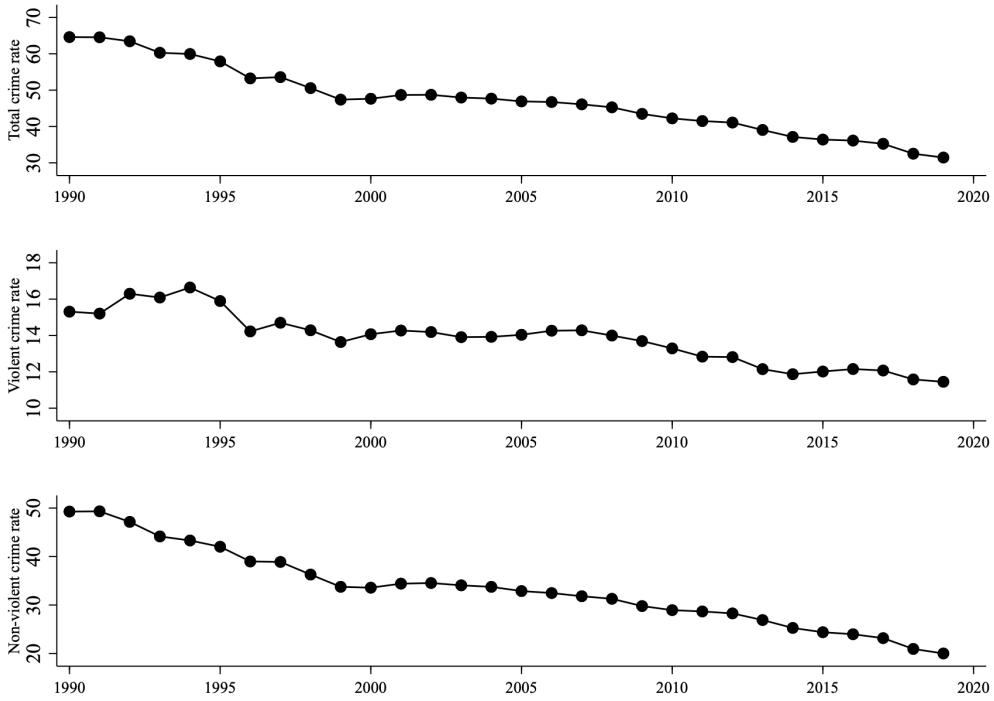
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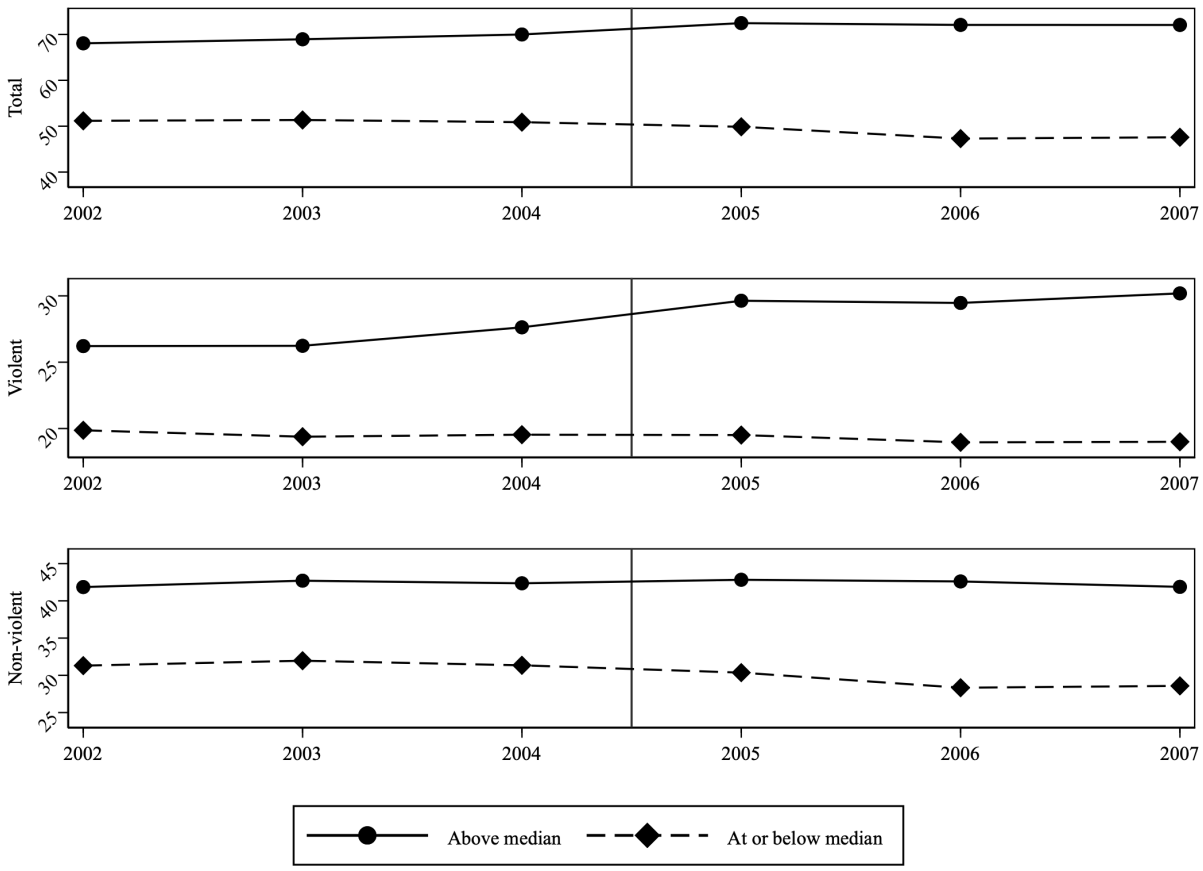
6 Figures and tables

Figure 1: Trends in national crime rates



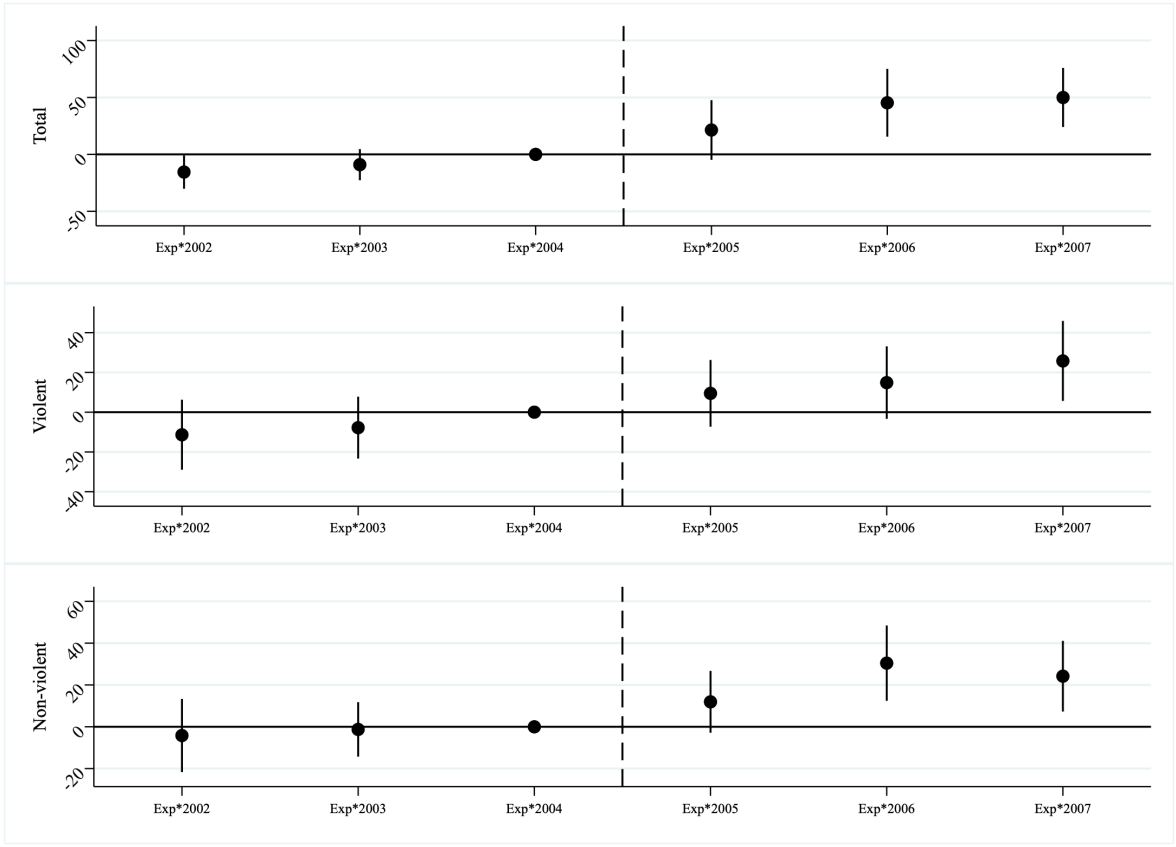
Notes: Data Source: UCR 1990−2019. Crimes rates are per 1,000 individuals.

Figure 2: 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 3: 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 × post	-0.14***
	(0.03)
Scaled β	-0.036
Pre−treatment mean, >mean exposure	0.27
Observations	3348

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 county in a month in a year. The scaled β 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
	Panel A: All ages		
Exposure × post	44.42***	21.35*	23.07***
	(12.23)	(10.87)	(6.38)
Scaled β	11.46	5.51	5.95
Pre−treatment mean, >mean exposure	69.01	26.70	42.31
Observations	2628	2628	2628
	Panel B: 21−64 years		
Exposure × post	37.35***	11.74	25.61***
	(12.63)	(10.49)	(7.46)
Scaled β	7.58	2.38	5.20
Pre−treatment mean, >mean exposure	69.01	26.70	42.31
Observations	2628	2628	2628

Notes: In Panel A, we use our main exposure measure which is based on each county's overall Medicaid coverage rate pre−disenrollment. In Panel B, we use an alternative measure of exposure that is based on each county's Medicaid coverage rate among those 21−64 years of age pre−disenrollment. 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 β 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 3: Effect of the TennCare disenrollment on economic and eviction outcomes: BLS, SAIPE, and the Eviction Lab 2002-2007

Outcome:	Unemployment rate	Poverty rates	Median income	Eviction filings	Completed evictions
Exposure × post	-1.47	11.81***	-3590.57	19.12**	8.95*
	(1.06)	(2.79)	(3723.91)	(9.05)	(5.33)
Scaled β	-0.38	3.05	-926.37	4.93	2.31
Pre−treatment mean, >mean exp.	6.31	16.18	34726.42	7.86	3.51
Observations	558	558	558	496	496

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 β 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/ex. health
Exposure × post	-0.37***	0.46***	0.20
	(0.12)	(0.14)	(0.16)
Scaled β	-0.10	0.12	0.05
Pre−treatment mean, >mean exposure	0.86	0.10	0.52
Observations	6677	6646	6676

Notes: Ex. = excellent. 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 β 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 TennCare disenrollment on behavioral health treatment admissions and needing, but not receiving, substance use disorder treatment: N−SSATS & NSDUH 2002−2007

Outcome:	Admissions	Drug treatment	Alcohol treatment
Tennessee × post	-14.90*	0.002***	0.008***
	(7.70)	(0.001)	(0.002)
Bootstrap $p-$value	–	0.0980	0.0960
Scaled β	-3.84	–	–
Pre−treatment mean, >mean exposure	2.81	0.026	0.060
Observations	558	102	102

Notes: The regression in column (1) includes time−varying county−level covariates, county fixed−effects, and year fixed−effects. The regression in columns (2) and (3) includes time−varying state−level covariates, state fixed−effects, and year fixed−effects. The unit of observation in column (1) is a county in a state in a year and in columns (2) and (3) is a state in a year. Data are weighted by the county population in column (1) and the state population in columns (2) and (3). In column (1), the scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.258 Medicaid coverage rate). Regressions estimated with OLS. In column (1), standard errors clustered at the county−level are reported in parentheses. In columns (2) and (3), 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) in columns (2) and (3). ***, **, * = statistically different from zero at the 1%, 5%, and 10% level.

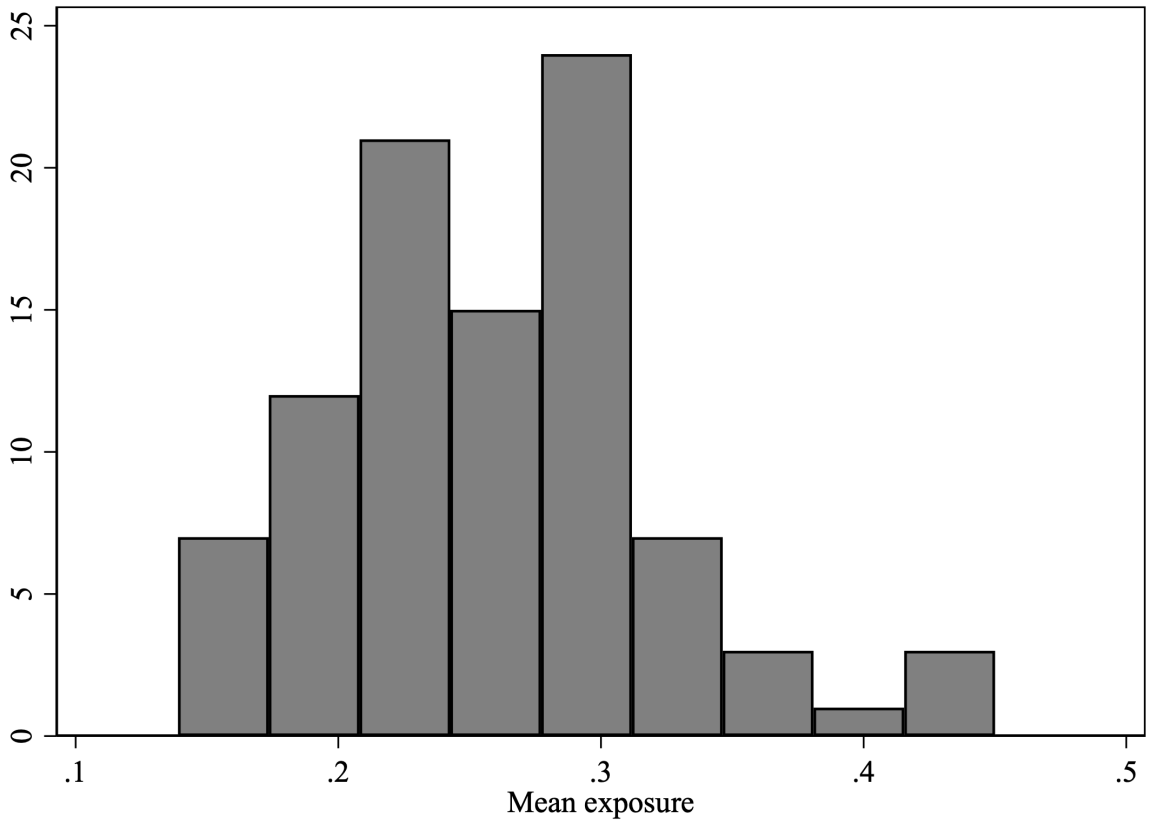
Table 6: Effect of the TennCare disenrollment on mortality outcomes: NVSS 2002−2007

Outcome:	All−cause	Suicide	Alcohol	Drug
Exposure × post	0.43	-0.02	0.02	0.60***
	(0.66)	(0.12)	(0.02)	(0.18)
Scaled β	0.11	-0.00	0.00	0.15
Pre−treatment mean, >mean exposure	4.991	0.177	0.002	0.152
Observations	558	558	558	558

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 β 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.

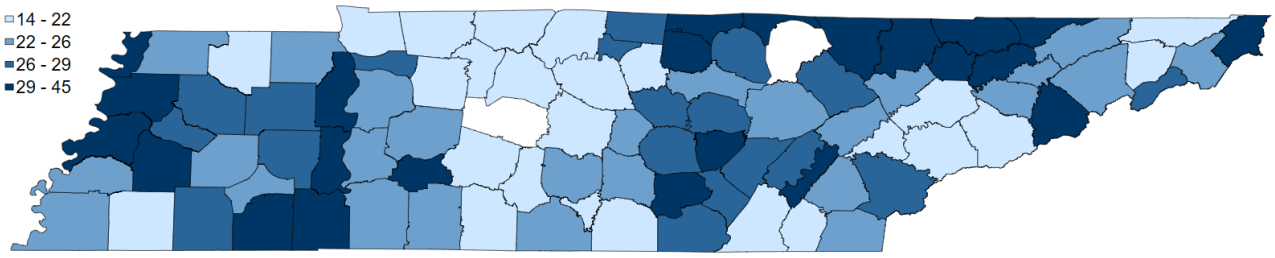
7 Appendix: For Online Publication Only

Figure A1: Distribution of Medicaid coverage exposure to the TennCare disenrollment



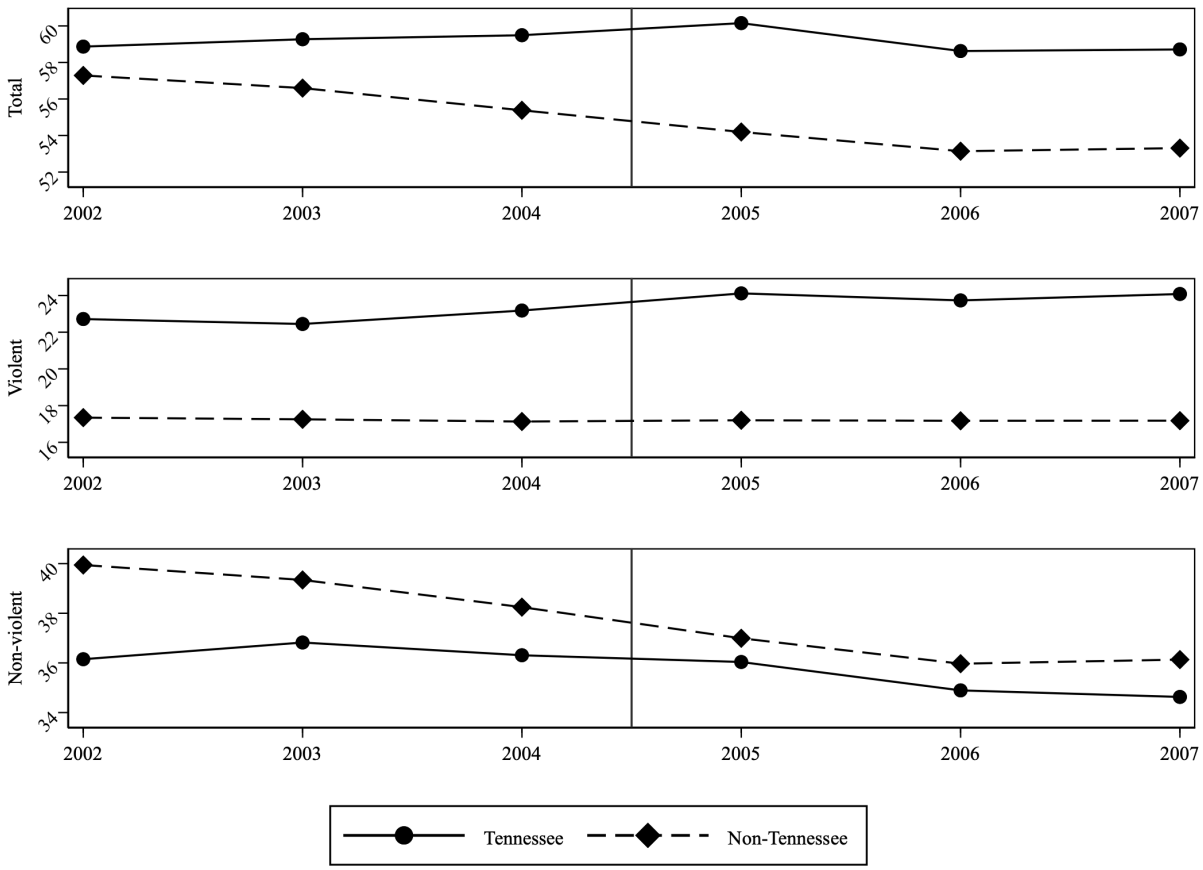
Notes: Data are aggregated to the county−level over the period Q1 and Q2 2005.

Figure A2: Distribution of exposure across Tennessee counties



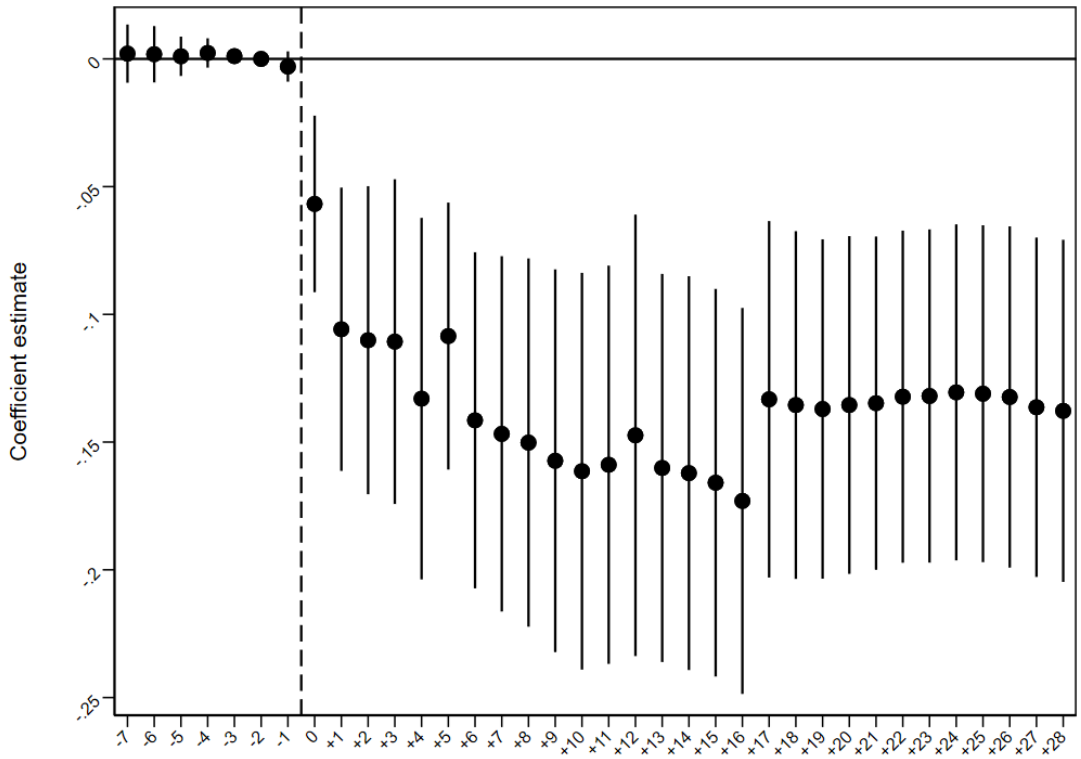
Notes: Data are aggregated to the county−level over the period Q1 and Q2 2005.

Figure A3: Trends in crime rates: Tennessee vs. other Southern states



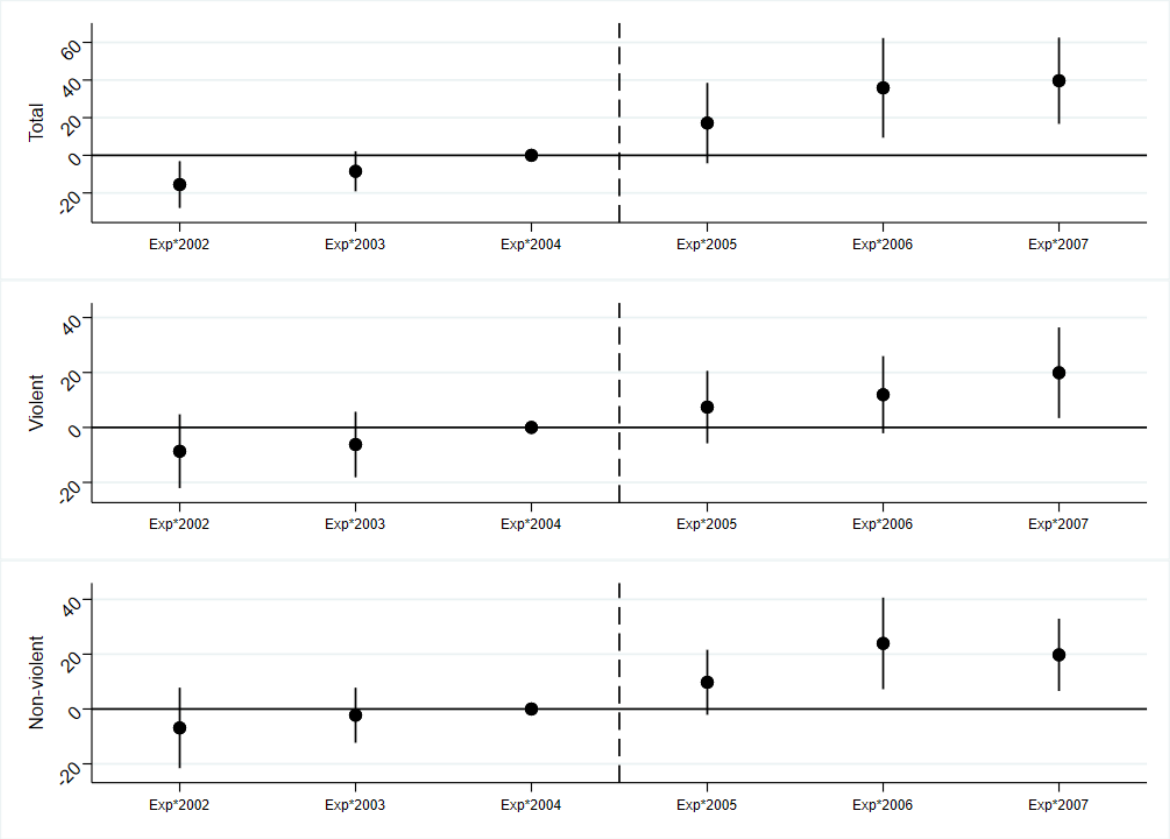
Notes: Data Source: UCR 2002−2007. Data are weighted by the population served by each agency prior to aggregating to the treatment year.

Figure A4: Effect of TennCare disenrollment on Medicaid coverage using an event−study



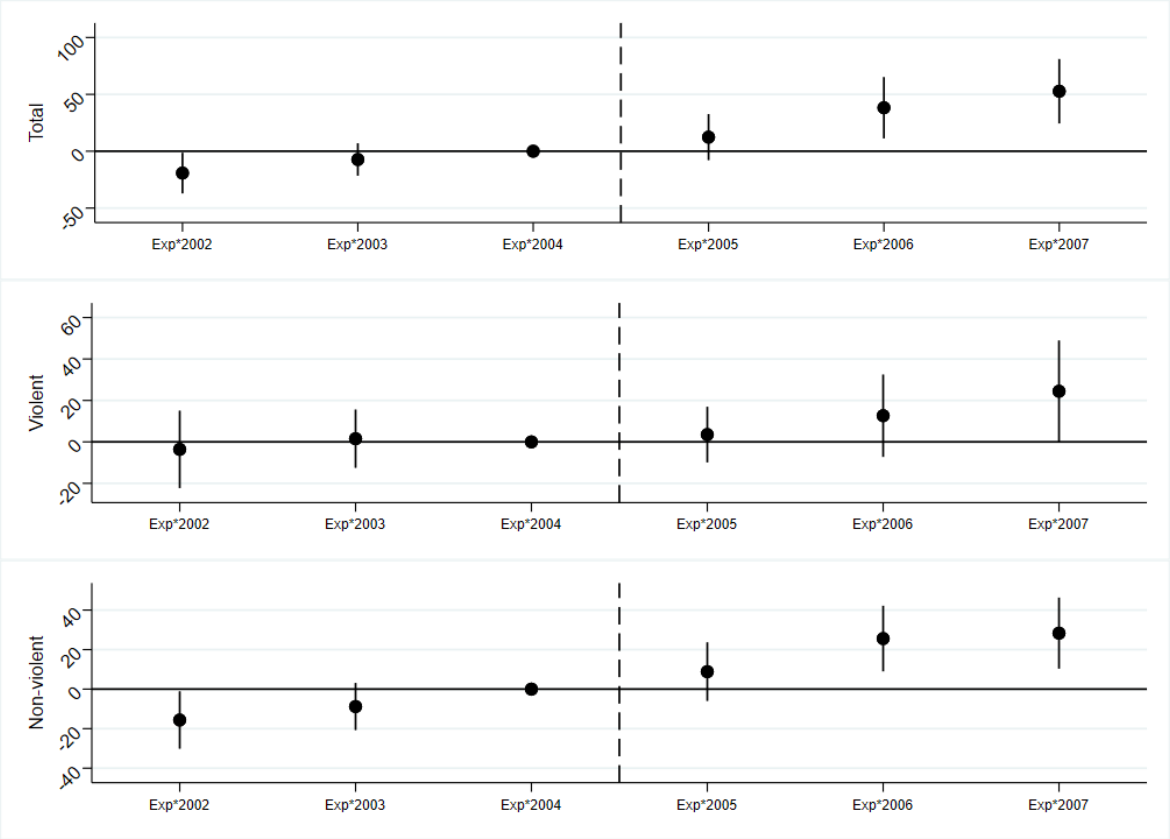
Notes: This figure plots the estimates from an event−study OLS regression of county Medicaid coverage on indicators with months to and months since Medicaid disenrollment. The regression includes agency fixed−effect and year−by−month fixed−effects. The unit of observation is a county in a month in a 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.

Figure A5: Effect of TennCare disenrollment on crime rates using an event−study and all counties in Tennessee: UCR 2002−2007



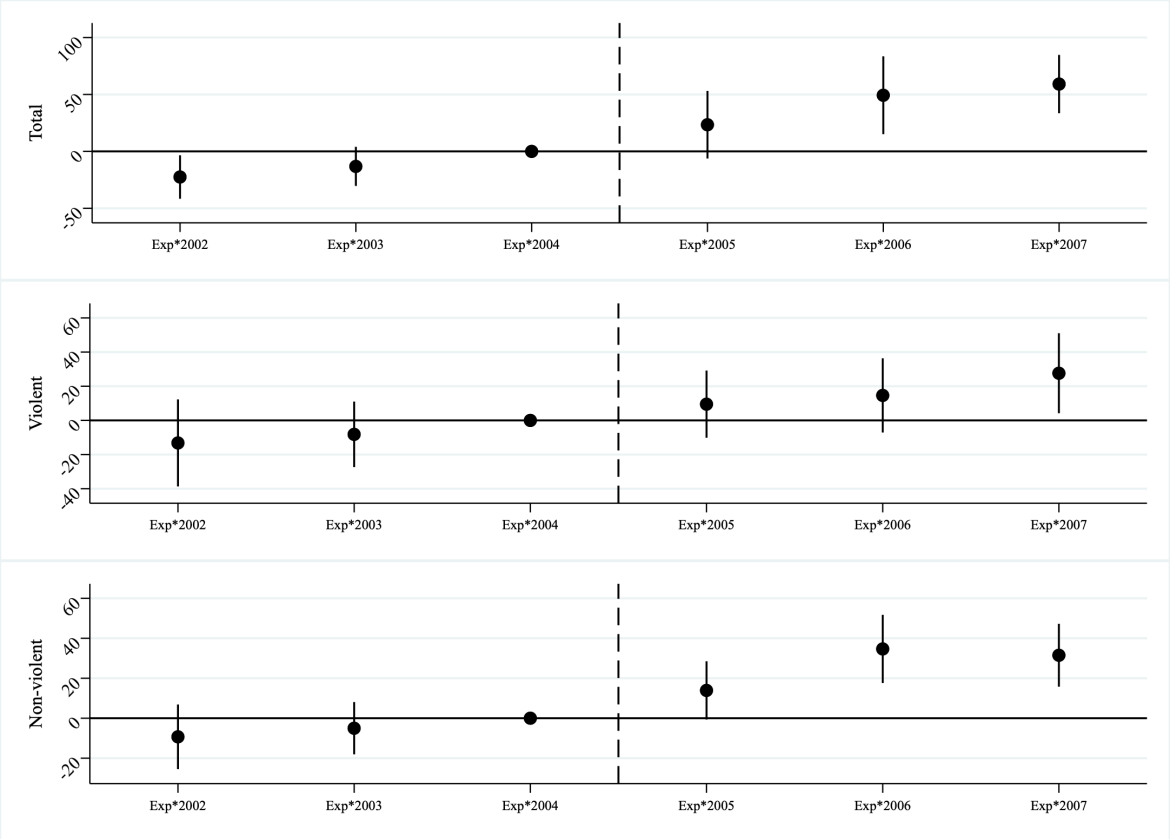
Notes: The sample does not exclude counties with exposure measures below the 1st percentile or above the 99th percentile, all Tennessee counties are included. This figure plots the estimates from an event−study OLS regression of crime rates on indicators with years to and years since Medicaid disenrollment. The regression includes agency fixed−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 are reported with vertical lines. The omitted category is 2004, the year prior to the disenrollment.

Figure A6: Effect of TennCare disenrollment on crime rates using an event−study in Tennessee using an exposure measure based on Medicaid enrollment among those 21−64 years only: UCR 2002−2007



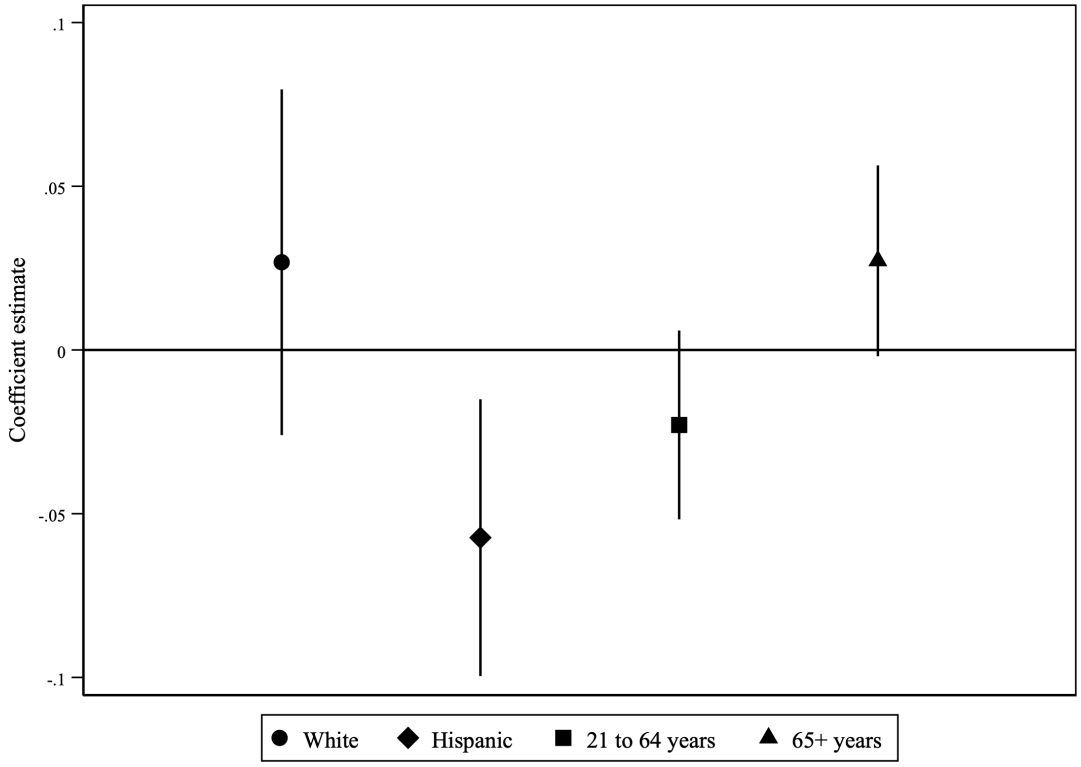
Notes: The exposure measure in this analysis is based on Medicaid coverage among those 21−64 years pre-disenrollment. This figure plots the estimates from an event−study OLS regression of crime rates on indicators with years to and years since Medicaid disenrollment. The regression includes agency fixed−effects 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 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 excluding time−varying covariates: UCR 2002−2007



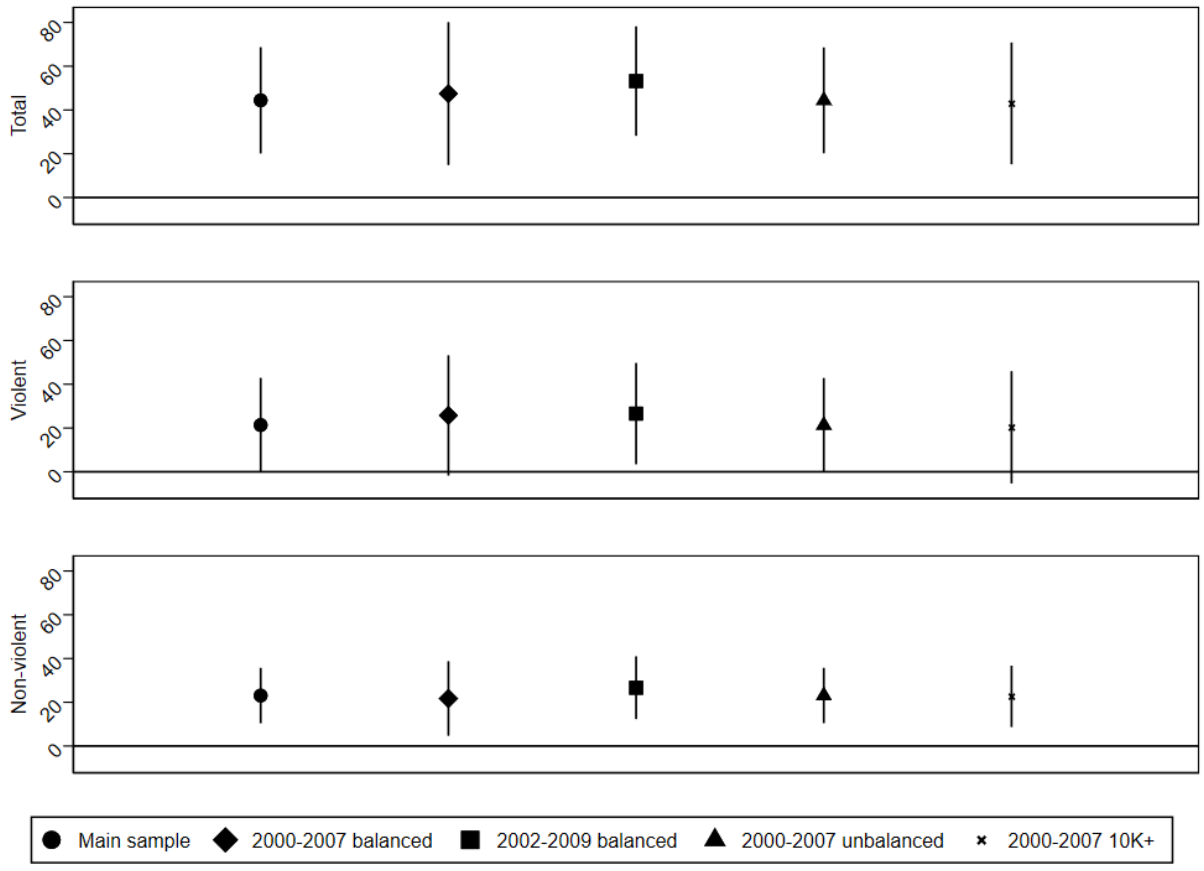
Notes: This figure plots the estimates from an event−study OLS regression of crime rates on indicators with years to and years since Medicaid disenrollment. The regression includes agency fixed−effect and year fixed−effects. The unit of observation is an agency in county in a year. Data are weighted 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: Covariate balance test



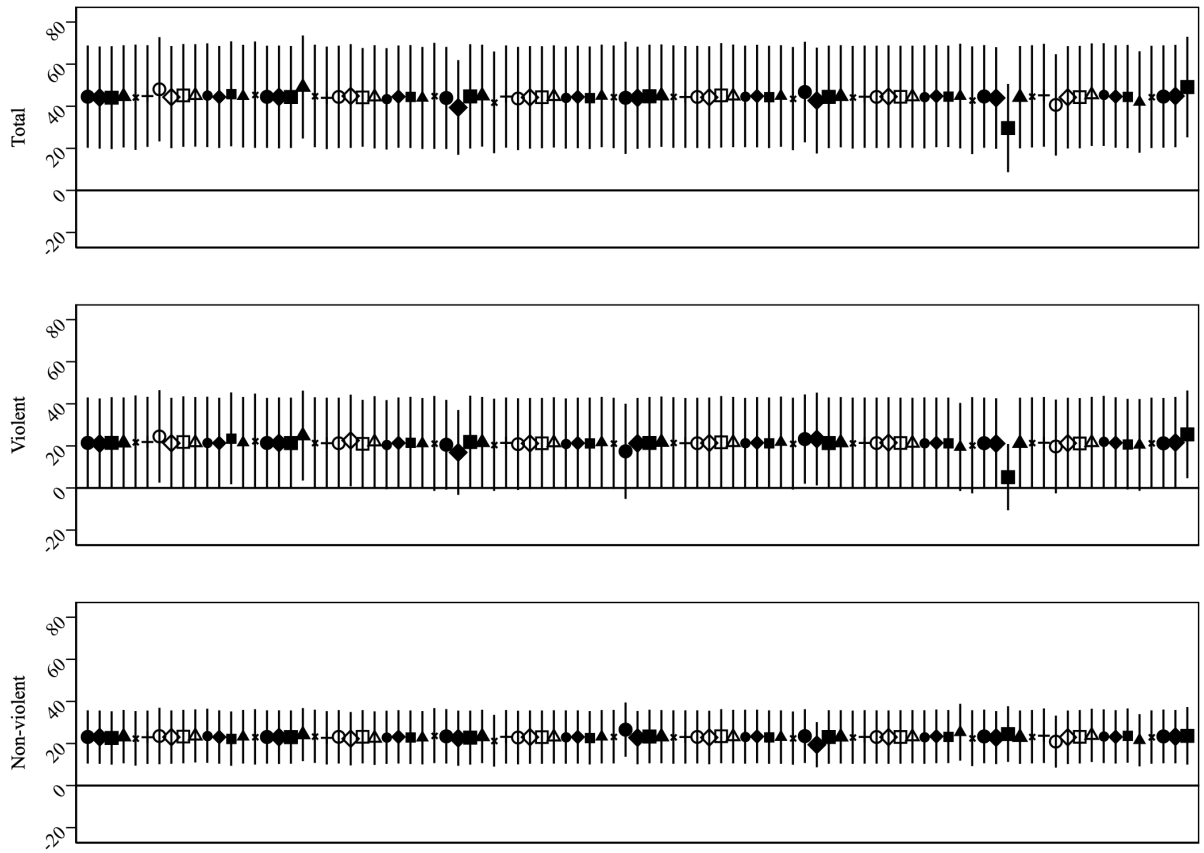
Notes: This figure plots coefficient estimates from separate regressions of the variable reported on the x-axis on the TennCare exposure measure, county fixed−effects, and year fixed−effects. The unit of observation is a county in a year. Data are weighted by the county population. Coefficient estimates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

Figure A9: Effect of TennCare disenrollment on crime rates: Alternative UCR samples



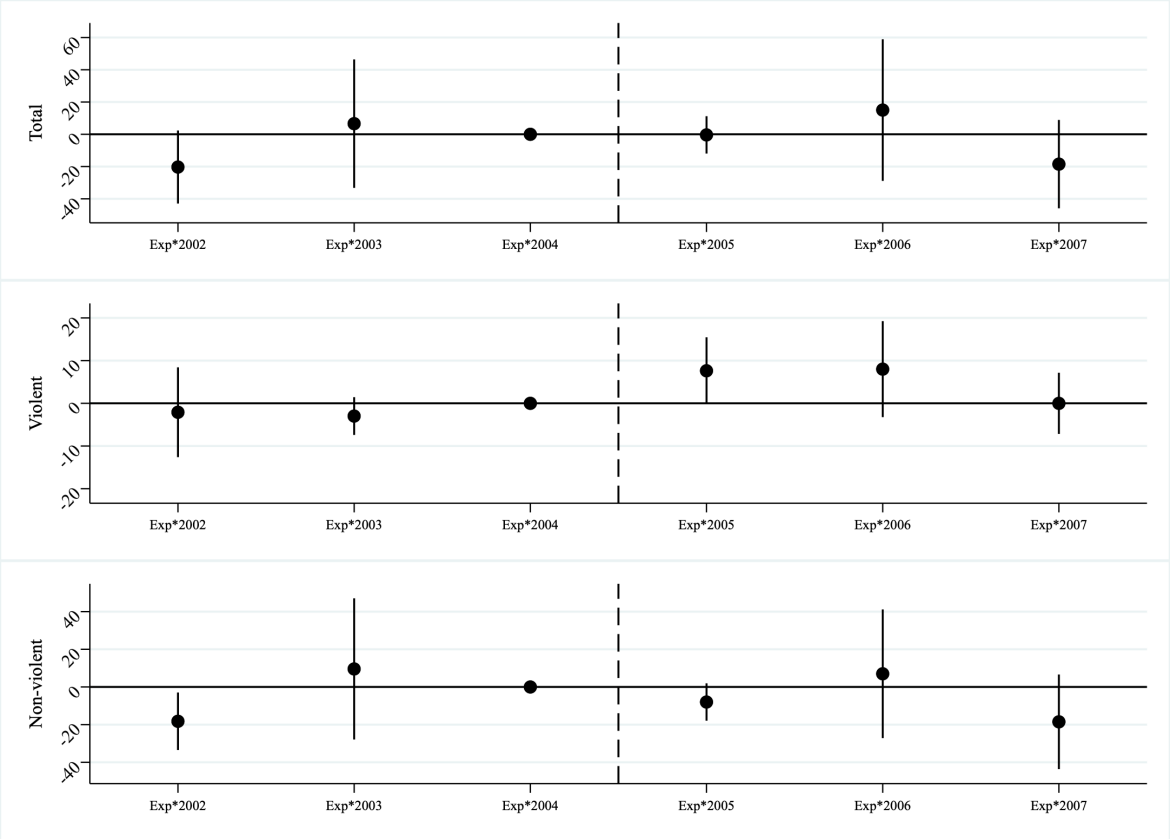
Notes: This figure plots the estimates from an DID OLS regression of crime rates on exposure to the Medicaid coverage rates interacted with the post−period for different samples. Column (1) reports our baseline estimates that includes police agencies that report crimes in every year between 2002 and 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 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 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 are reported with vertical lines.

Figure A10: Effect of TennCare disenrollment on crime rates: Leave−one−out analysis



Notes: This figure plots the estimates from an DID OLS regression of crime rates on exposure to the Medicaid coverage rates interacted with the post−period omitting one of the 93 counties in Tennessee one at a time. 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 are reported with vertical lines.

Figure A11: 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.

Table A1: 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 β	9.63	4.42	5.21
Pre−treatment mean, > mean exposure	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. The scaled β 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 A2: Summary statistics: UCR 2002−2004

Sample:	All counties	Counties ≥ median exposure	Counties < 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	0.79	0.79	0.78
Hispanic	0.034	0.024	0.044
Age 19−64	0.63	0.61	0.64
Age 65+	0.12	0.13	0.11
Population served by agency	158839.8	152013.7	165401.0
Observations	1314	1020	294

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 A3: Effect of the TennCare disenrollment 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 β	14.44	6.30	8.13
Pre−treatment mean, > mean exposure	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 β 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 TennCare disenrollment on crime rates (control for police expenditures): UCR 2002-2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure×post	44.65***	21.63**	23.01***
	(12.04)	(10.73)	(6.49)
Scaled β	11.52	5.58	5.94
Pre−treatment mean > mean exposure	69.01	26.70	42.31
Observations	2568	2568	2568

Notes: The regression includes time−varying county−level covariates, including police expenditures, 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. Regressions estimated with OLS. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.258 Medicaid coverage rate). Standard errors are clustered around the county and reported in parentheses. ***,**,* = statistically different from zero at the 1%, 5%, and 10% level.

Table A5: Effect of the TennCare disenrollment on de−trended crime rates: UCR 2002−-2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure × post	44.42***	21.35*	23.07***
	(12.23)	(10.87)	(6.38)
Scaled β	11.46	5.51	5.95
Pre−treatment mean > mean exposure	67.99	25.97	42.02
Observations	2628	2628	2628

Notes: Outcome variables are de−trended prior to estimation, see text in Section 4 for details. 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 β 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 violent crime rates: UCR 2002−2007

Outcome:	Murder	Rape	Robbery	Assault
Exposure × post	0.02	-0.09	0.80	20.62**
	(0.06)	(0.14)	(0.78)	(10.33)
Scaled β	0.01	-0.02	0.21	5.32
Pre−treatment mean	0.07	0.36	1.59	24.68
> mean exposure				
Observations	2628	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 county in a year. The scaled β 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 A7: Effect of the TennCare disenrollment on specific non−violent crime rates: UCR 2002−2007

Outcome:	Burglary	Theft	MV theft	Arson
Exposure × post	1.11	23.16***	-1.26	0.07
	(2.70)	(7.03)	(1.52)	(0.24)
Scaled β	0.29	5.97	-0.32	0.02
Pre−treatment mean	11.51	26.04	4.50	0.26
> mean exposure				
Observations	2628	2628	2628	2628

Notes: MV = motor vehicle. The regression includes time−varying county−level covariates, agency fixed−effects, and year fixed−effects. The scaled β 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.

Table A8: Effect of the TennCare disenrollment on on−duty officer assaults: UCR 2002−2007

Outcome:	Total	Injurious	Non−injurious
Exposure × post	-0.38	-0.08	-0.30
	(0.28)	(0.11)	(0.22)
Scaled β	-0.10	-0.02	-0.08
Pre−treatment mean > mean exposure	0.40	0.13	0.26
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 county in a year. The scaled β 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 A9: Effect of the TennCare disenrollment on crime rates comparing Tennessee to other Southern states: UCR 2002−2007

Outcome:	Total crime	Violent crime	Non−violent crime
Tennessee × 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, Tennessee	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. 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 disenrollment on crime rates comparing Tennessee to other Southern states using a non−parametric bootstrap: UCR 2002−2007

Outcome:	Total crime	Violent crime	Non−violent crime
Tennessee × post	1.844**	0.883	0.961**
	(0.870)	(0.651)	(0.487)
Pr*e*−treatment mean Tennessee	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) bootstrapping procedure. ***, **, * = statistically different from zero at the 1%, 5%, and 10% level.

Table A11: Effect of the TennCare disenrollment on Medicaid coverage comparing Tennessee to other Southern: CPS 2002−2007

Outcome:	Medicaid
Tennessee×post	-0.08***
	(0.01)
Pre−treatment mean, Tennessee	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 A12: Effect of the Missouri Medicaid contraction on crime rates: UCR 2002−2007

	Total crime	Violent crime	Non−violent crime
Exposure × post	3.87	8.05*	-4.18
	(7.65)	(4.16)	(7.04)
Scaled β	0.96	1.99	-1.03
Pre−treatment mean	70.89	19.59	51.30
> mean exposure			
Observations	3258	3258	3258

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 β 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.