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LOSING MEDICAID AND CRIME

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ABSTRACT

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

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1 Introduction

In this study, we evaluate the impact of losing health insurance on crime outcomes by studying one of the most consequential Medicaid disenrollments in the history of the United States.[1] While overall crime rates in the U.S. have decreased substantially since their peak in the 1990s – see Figure 1 and 2 – crime continues to be a top concern for many Americans (Gallup, 2023), especially with recent increases in violent crime and persistent crime spikes occurring in many major metro areas across the country (Federal Bureau of Investigation, 2020; Council on Criminal Justice, 2023). The U.S. reports eight million crimes each year (Federal Bureau of Investigation, 2019), leading to $3.3 trillion in economic and societal costs (Anderson, 2021).[2] Thus, understanding and leveraging factors that prevent crime could have substantial benefits for many Americans.

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., a 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[3] reduces both criminal behavior and recidivism (Wen et al., 2017; He and Barkowski, 2020; Vogler, 2020; Aslim et al., 2022). Medicaid covered 85.2 million lower–income people (Centers for Medicare & Medicaid Services, 2022) with expenditures of over $804 billion in 2022 or 17% of total national healthcare expenditures (Congressional Research Service, 2023; Kaiser Family Foundation, 2023). As such, Medicaid is the largest social insurance program in the U.S. in terms of expenditures (Buchmueller et al., 2015; Barnes et al., 2021; Tello-Trillo

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

[2]We inflate the original cost estimate ($1.701 trillion) from 1997 dollars to 2024 dollars using the Consumer Price Index – Urban Consumers.

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

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 are imposed federally (as proposed by some lawmakers) 1.5 million people will 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). A substantial number of Congressional proposed budgets and fiscal plans in the last ten years have included a curtailing of the Medicaid program (The White House, 2023), which would reduce Medicaid coverage rates. Finally, this topic is particularly timely as the current presidential administration has stated cutting Medicaid funding and implementing work requirements for this program as policy objectives.[4]

In addition to policy relevance, understanding the impacts of both insurance losses and gains is economically interesting, as such changes can potentially generate asymmetry in healthcare use and associated social outcomes. Thus, predictions for the 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 more adeptly and understand their health status following the loss of coverage (Tello-Trillo, 2021). A coverage loss – even if a patient is able to locate 'replacement' insurance given differences in networks – could lead to a change in providers and/or treatment options (Graves et al., 2020), which could

[4]Please see https://www.nytimes.com/2024/11/20/health/medicaid-cuts-republican-congress.html; website last accessed January 3rd, 2025.

harm patient health.[5] Decision theory predicts that equal−sized income losses have larger (in absolute value) impacts than gains on consumers (Kahneman et al., 1991). Medicaid is an in−kind income transfer and thus may have asymmetric effects. However, the provision of charity or discounted care may minimize the full blunt of insurance losses by creating options for lower−cost treatment among the newly uninsured (Dranove et al., 2016). While most insurance gains in recent U.S. history are well−announced and consumers may expect them, insurance losses may 'surprise' at least some patients (Tolbert, 2023), limiting time available to prepare for the insurance coverage change. Finally, certain psychological burdens (e.g., concerns about locating care or financing medical bills) are potentially specific to insurance losses.

To study the effect of the Tennessee Medicaid disenrollment on crime outcomes, we combine data on police agencies that report violent and non−violent crimes in each year 2002 to 2007 from the Federal Bureau of Investigation's (FBI) Uniform Crime Reports database (UCR). We exploit the intensity of the disenrollment across Tennessee counties based on pre−policy Medicaid coverage rates using difference−in−differences and event−study methods. Conceptually, our design compares trends in crime outcomes before and after the 2005 disenrollment between counties with relatively high and relatively low Medicaid coverage among non−elderly adults prior to the disenrollment.[6]

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

[5] 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.

[6] To date, two quasi−experimental approaches are utilized within the TennCare literature to evaluate the causal impact of the disenrollment (see Section 2): i) comparing Tennessee to other Southern states and ii) comparing counties within Tennessee differentially exposed to the policy shock. In our main analyses, we take the latter approach. Our rationale is that there are strong differences in both levels and trends in crime outcomes between Tennessee and other states during our study period. In particular, Tennessee has higher crime rates than the rest of the U.S, and this relatively high crime rate has persisted both before and after the Tenncare disenrollment. Please see https://247wallst.com/special-report/2024/02/02/tennessee-has-ranked-among-the-most-dangerous-states-in-the-country-for-decades/; website last accessed January 3rd, 2025. Figures 1 and 2 also highlight this pattern. Given these stark differences between Tennessee and other states, we choose to compare Tennessee counties with relatively high versus relatively low non−elderly adult Medicaid coverage prior to the disenrollment. Nonetheless, we also include results in the Appendix that compare Tennessee to other states both within the South region and nationally, and results are qualitatively similar though we document some evidence of differential pre−trends (not reported but available on request), which is i) in line with the above−noted differences between Tennessee and other areas of the U.S. and ii) further supports our use of the within−Tennessee analysis.

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

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 (i.e., 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). Thus, insurance coverage can increase the returns to working and 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 (Dobkin et al., 2018). 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 (Gross and Notowidigdo, 2011; Hu et al., 2018; Gruber and Sommers, 2019; Guth et al., 2020), even measures of extreme financial hardship such as evictions (Allen et al., 2019; Zewde et al., 2019; Linde and Egede, 2023). Thus, we hypothesize that lower disposable income and financial stability following an insurance loss provides an incentive for crime, in particular, for financially−motivated 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), demonstrating improved health and financial protection as important mechanisms. For example, ACA Medicaid expansions have been shown to reduce the probability of re−incarceration, accompanied by a corresponding increase in employment and wages (Badaracco et al., 2021), while decreasing the propensity to commit financially−motivated crimes (Arenberg et al., 2024). We note that, in contrast to these findings, Finkelstein et al. (2024) document that the 2008 Oregon Health Insurance Experiment, which randomized some low−income adults to eligibility for Medicaid, has limited impacts on criminal charges or convictions.[7] 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.

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

These studies provide important information about insurance losses. Our work will build on them in several ways. We will exploit a large−scale and unexpected Medicaid disenrollment that leads 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 coverage losses, such as aging out of Medicaid at 19 and parental private coverage at 26, the

[7] The populations made eligible for ACA Medicaid expansion and the Oregon Health Insurance Experiment differed in several ways that may lead to heterogeneous findings. For example, newly eligible people in Oregon had incomes up to 100% of the Federal Poverty Level while ACA Medicaid expansion conferred eligibility to people with incomes up to 138% of the Federal Poverty level and, due to other policy changes in Oregon, the authors track participants for less than two years after Medicaid coverage begins. Moreover, while findings are not statistically distinguishable from zero at conventional levels, the confidence intervals in the Finkelstein et al. (2024) include substantial reductions in crime that are comparable to those identified in studies that leverage variation from ACA Medicaid expansion.

Medicaid disenrollment we study was unexpected and enrollees did not have time to adjust their behavior in anticipation of the disenrollment. Further, 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 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.[8]

2.2 The TennCare program and impacts of the disenrollment

Historically, Medicaid has been mandated by the federal government to provide coverage to a limited number of 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 generally not eligible for Medicaid and had few coverage options (Maclean et al., 2023; Tello-Trillo, 2021; Tello-Trillo et al., 2023). States seeking to cover additional populations − often referred to as 'expansion' or 'optional' populations − had to receive approval from the federal government to do so. One mechanism used by states to cover expansion populations was a Section 1115 waiver to the Social Security Act ('1115 waiver').

In 1993, Tennessee applied for a 1115 waiver to the state's Medicaid program through the Health Care Financing Administration (the predecessor to the Centers for Medicare & Medicaid Services or 'CMS'). The waiver was approved and Tennessee was permitted to implement a Medicaid demonstration project ('TennCare') which was designed to remove categorical restrictions (e.g., pregnancy or disability) and make eligible low−income, non−elderly, non−disabled, and childless adults with a sustained period without insurance ('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 included preventive care, prescriptions, imaging, and hospital services with low cost−sharing (Far-

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

rar 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 healthcare delivered by primary care providers (Gaynes et al., 2009; Jetty et al., 2021) and expanded access to specialized behavioral healthcare through a carve−out plan (Farrar et al., 2007; Chang and Steinberg, 2009; Kaiser Family Foundation, 2021).[9] As a result, TennCare enrollees had relatively generous coverage for behavioral healthcare. 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.[10]

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 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 August 2005, all TennCare enrollees were removed from the program and Tennessee no longer covered the expansion population. In the second two quarters of 2005, 10% of the Medicaid population and 3% of the state population − 190,000 people − lost Medicaid coverage. Disenrollees were predominantly childless non−disabled non−elderly beneficiaries (Farrar et al., 2007; Chang and Steinberg, 2009; Garthwaite et al., 2014; Tello-Trillo et al., 2023) with income levels in the range of 100% and 175% of the Federal Poverty Level.

A series of studies uses the TennCare disenrollment to understand how losing insurance eligibility impacts access to insurance, use of healthcare, and health outcomes. Several studies document that Medicaid coverage declined post−disenrollment (Garthwaite et al., 2014; DeLeire, 2019; Tello-Trillo, 2021). Garthwaite et al. (2014) show a 33% reduction in the probability of Medicaid coverage post−shock using the Current Population Survey.[11] There is evidence that some people may have been able to locate

[9]With a carve−out plan, specific services (here behavioral healthcare) 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.

[10]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 healthcare treatment centers in Tennessee accept Medicaid as a form of payment.

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

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 outcomes worsened. There are also implications for healthcare providers: Garthwaite et al. (2018) document that hospitals provided more charity care post−disenrollment.

A potential concern among policymakers with the provision of public insurance is 'job−lock,' that is people enrolled in public coverage (such as Medicaid) may be hesitant to work, or to work more, as such efforts may lead to a loss of coverage eligibility.[12] The TennCare disenrollment offers an opportunity to investigate job−lock and a handful of studies have examined this question. The results to date are mixed with one study finding evidence of job−lock (i.e., the probability of employment among likely disenrollees increases post−disenrollment) and two studies demonstrating no such evidence (Garthwaite et al., 2014; DeLeire, 2019; Ham and Ueda, 2021).

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

The TennCare literature provides empirical support for several channels through which losing insurance can impact crime. In particular, post−disenrollment health (behavioral and physical) declines and financial stability measured by credit reports, evictions, and child support payment declines. The extent to which employment outcomes changed is more opaque at this point in time, but overall the literature provides premise for our study of health insurance losses and crime.

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

3 Data and methods

3.1 Crime data

We collect administrative 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 Sections 4.1 and 4.4, our results (both estimated in difference−in−differences and event−studies) are robust to including both earlier (back to 2000) and later (through 2010) years.

The UCR data include information on the number of offenses known to law enforcement. We focus our analysis on violent and non−violent Part I crimes. Violent Part I offenses include murder, manslaughter, rape, robbery, and aggravated assault. Burglary, larceny, motor vehicle theft, and arson are considered non−violent Part I crimes. The data compiled for the UCR are submitted voluntarily by city, county, and state law enforcement agencies. Many local municipalities do not consistently report crime data over time (Kaplan, 2021c). To overcome potentially selective reporting in the data, we conduct our analysis at the police agency−level and restrict the analysis sample to agencies that report crimes at least once in every year of our sample period. Our final sample includes 447 out of 576 (77.6%) agencies that ever reported data to the UCR Tennessee during our study period 2002−2007. We both tighten and relax this assumption in Section 4.4 and show that our findings are very similar using alternative samples.

3.2 Additional data sources

Medicaid coverage: Our primary research design exploits the intensity of TennCare disenrollment across Tennessee counties based on pre−policy exposure. To this end, we use monthly data on the county−level Medicaid coverage rate in Q1 and Q2 of 2005 (i.e., just prior to the TennCare disenrollment) to measure exposure to the policy change (Argys et al., 2020).[13] 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 by county. We create a proxy for the TennCare enrollment rate in each county, which is defined as the share of the population aged 21−64 covered by Medicaid

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

(Surveillance, Epidemiology, and End Results, 2022). We also use this exposure variable to shed light on the 'first−stage effect:' the impact of the policy shock on Medicaid coverage among likely TennCare disenrollees. In this analysis, we use the share of the population aged 21−64 covered by Medicaid as the outcome variable. These data are available for each month from 2005 to 2007. While our main exposure measure is an average of county−level Medicaid coverage rate among adults 21−64 years in Q1 and Q2 of 2005, we show in Section 4.4 that our results hold for using data from Q1 only or Q2 only as the exposure measure, and to defining our exposure measure to include enrollees of all ages, non−elderly adult male enrollees, and non−elderly adult female enrollees.

Data on potential mechanisms: To better understand our crime findings, we conduct an analysis of the mechanisms to study potential channels through which losing Medicaid could impact crime. To this end, we draw data from several different sources. First, to study the impact of disenrollment on economic outcomes, we collect data on county unemployment rate from the U.S. Bureau of Labor Statistics (2024), and data on median income and poverty rates from the Small Area Income and Poverty Estimates (U.S. Census Bureau, 2024). We supplement this analysis with eviction outcomes (eviction filings and completed evictions) per 1,000 non−elderly adults (Eviction Lab, 2021). Filings reflect a landlord placing a formal petition with the civil court for the eviction of a tenant, and completed evictions capture the result of a civil court hearing of an eviction case in which the judge determines that the landlord is permitted to evict the tenant.[14]

Second, we examine the effects on healthcare utilization using two different sources: i) access to general healthcare and delaying care due to cost, and ii) use of behavioral healthcare. We use county−level data on measures of healthcare access among individuals aged 21−64 from the Centers for Disease Control and Prevention (CDC) Behavioral Risk Factor Surveillance System (BRFSS) (2025). This survey allows us to analyze respondent questions related to the likelihood of having any insurance and delaying care due to cost. Given the established literature on access to public insurance and behavioral health treatment (Maclean et al., 2023; Ortega, 2023; Grooms and Ortega, 2019; Maclean and Saloner, 2019; Maclean et al., 2017), we obtain county−level data on the number of annual admissions to behavioral health treatment centers using data from the National Survey of Substance Abuse Treatment Services (N−SSATS) (Substance Abuse and Mental Health Services, ND). Centers included in N−SSATS can provide substance use and mental health treatment. For example in 2004, 35% of centers reported mental healthcare as the primary focus of the center.[15] We aggregate the data from the center−

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

[15]We include only centers that accept Medicaid and that offer outpatient services in our analysis. Due

to county−level and convert annual admissions counts from N−SSATS to the rate per 1,000 residents (Surveillance, Epidemiology, and End Results, 2022).

Lastly, and following the literature exploring the link between Medicaid 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 National Vital Statistics System (NVSS) restricted−data files (2025). The NVSS are based on death certificates which include the cause of death, allowing us to isolate behavioral health deaths.

3.3 Methods

We estimate the effect of a large−scale reduction in Medicaid eligibility in Tennessee by comparing counties most exposed to TennCare 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 (Finkelstein, 2007; Miller, 2012; Alpert et al., 2018; Park and Powell, 2021; Andersen et al., 2023; Cohle and Ortega, 2023; Hackmann et al., 2025), including TennCare (Argys et al., 2020). Consider two 'extreme' counties in Tennessee, one with 0% of the county population aged 21−64 covered by Medicaid in the first half of 2005 and the other county with 100% coverage. We compare trends in these two counties before and after the TennCare disenrollment. Our analyses rely on the assumption that the latter county is more impacted by the TennCare disenrollment than the former county. However, these 'extreme' counties we describe here do not exist in Tennessee. Thus, as we discuss later in this section, we will scale our coefficient estimates to produce more policy−relevant findings.

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

$$y_{ict} = \beta_0 + \alpha_i + \gamma_t + \beta Exposure_c \times Post_t + \gamma \mathbf{X_{ct}} + Rural_i \times \gamma_t + v_{ict} \tag{1}$$

Where y_{ict} is the crime rate (per 1,000 people served by the police agency) in agency i in county c in year t. The median Tennessee county in our analysis sample has four agencies. The terms α_i and γ_t represent agency and year fixed−effects, respectively.[16] $Exposure_c$ is the exposure variable equal to the share of the county population of age 21−64 covered by Medicaid in a county in Q1 and Q2 of 2005. The variable $Post_t$ is

to federal regulations, such as the Institutions of Mental Disease Exclusion in the Social Security Act, states are deterred from using Medicaid funds to pay for residential and hospital behavioral healthcare.

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

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.[17] The interaction $Rural_i \times \gamma_t$ corresponds to an interaction of the indicator for whether the agency is in a rural area interacted with the year fixed−effect.[18] Data are weighted by the population served by the agency.

Standard errors are clustered at the county−level. There are 95 counties in Tennessee, thus we have a sufficient number of clusters to allow for credible inference (Bertrand et al., 2004). We estimate OLS regressions, which are vulnerable to outlier bias (Wooldridge, 2010), and crime data are known to be subject to outliers (Mello, 2019). Thus, in our main analyses, we top−code the crime rates at the 90th percentile. However, we will report results in Section 4.4 in which we do not top−code or bottom− and top−code at different levels, and results are very similar.

The coefficient of interest in equation 1 is β, which compares the extent to which increasing exposure (i.e., share of the average population Medicaid coverage in Q1 and Q2 2005) from 0% to 100% impacts crime rate following TennCare disenrollment. As there are no counties with either 0% to 100% of their population aged 21−64 covered by Medicaid, we provide a more practical illustration of TennCare impacts on crime, and present our coefficient estimates scaled by the pre−treatment exposure of the median county in Tennessee following Argys et al. (2020). In particular, we present the scaled coefficient estimate and implied percent change in crime after TennCare disenrollment at a county with the median share of the population 21−64 covered prior to TennCare disenrollment. We will refer to this parameter estimate for the county with the median share of the population 21−64 covered prior to TennCare disenrollment as the 'scaled beta (β).' More specifically, we multiply the coefficient estimates in equation 1 by 0.19 which is the median coverage rate pre−disenrollment.

A causal interpretation of findings generated in equation 1 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 untreated by the disen-

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

[18] We use the U.S. Department of Agriculture's 2003 Rural-Urban Continuum Codes to distinguish between rural and urban counties (USDA, 2024).

rollment post−2005. To provide suggestive evidence on the ability of our data to satisfy the common trends assumption, we estimate an event−study. If we observe that crime rates evolved smoothly pre−disenrollment across counties with differential exposure to the policy shock, this pattern of results would provide suggestive evidence that our data can satisfy the common trends assumption.

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 2:

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

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

3.4 Descriptive analysis and first−stage

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

Our identification strategy relies on variation in pre−disenrollment exposure to TennCare. Figure 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 4.0% to 40.7%, with a mean (median) of 19.2% (19.0%), and the distribution is roughly bell−shaped with a slight right−skew. As presented in Figure A2a, there is some geographic clustering of counties with higher and lower exposure, but the figure suggests that there is reasonable variation across the state in Medicaid coverage.

The geographic distribution across Tennessee counties in 2004 of total crime rates, and violent and non−violent crime rates are reported in Figures A2b and A3. Figures A4 and A5 report trends in total crime, and then violent and non−violent crimes in counties above and below the median exposure to the TennCare disenrollment. In counties highly exposed to the TennCare disenrollment (i.e. those with a non−elderly adult Medicaid coverage rate above the median in Q1 and Q2 2005) crime rates, in particular non-violent crime rates, rose while trends for less exposed counties where more stagnant. Given that the U.S. was experiencing a decline in crime rates nationally over this period (Pew Research Center, 2020) − see Figures 1 and 2 for national trends in crime over the period 1990 to 2019 − the rise we observe in more exposed Tennessee counties offers suggestive evidence that the disenrollment increased crime.

We study a downstream consequence of Medicaid disenrollment, thus a necessary condition is that the disenrollment lead to meaningful change in Medicaid coverage. We examine the first−stage using equation 1. Results are reported in Table 1.[19] Event−study results are provided in Figure A6 (we use six month leads, July 2005 is the omitted category, and we include a full set of month lags, otherwise the specification is identical to equation 2). The event−study shows limited differential pre−trends for counties with varying exposure to the policy shock and a sharp decline in coverage in the post−period that persists through the end of 2007. The coefficient estimate of interest in equation 1 captures the extent to which monthly Medicaid coverage changes with exposure to the disenrollment. 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.

[19]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.

We scale the coefficient estimate ('scaled beta') by the median Medicaid coverage rate (0.19). We find that the median exposure county experienced a roughly five percentage point ('ppt') reduction in monthly Medicaid coverage post−disenrollment ($= -0.24 * 0.19$). Comparing this coefficient estimate with the baseline Medicaid coverage rate in counties with above−median exposure, we find a decline of 23.8% ($= -0.05/0.21 * 100\%$) in Medicaid coverage. A 23.8% reduction in Medicaid coverage suggests that in the median county (Humphreys) in terms of exposure, 466 non−elderly adults lost this form of health insurance coverage. TennCare coverage losses ranged from a low of 129 non−elderly adults to a high of 24,014 across the 95 counties in Tennessee.[20]

4 Results

4.1 Internal validity

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

Figure 3 plots the pre−and post−treatment effects of TennCare disenrollment on agency−level crime rates per 1,000 residents served. The top panel plots the coefficient estimates for total crime, while the middle and bottom panels present the comparable results for violent and non−violent crime rates, respectively. Across all panels, we see no evidence of a pre−trend in crime rates before the disenrollment. Furthermore, we see a clear trend break and sharp increase in total crime and non-violent crime post−disenrollment. This effect becomes statistically distinguishable from zero in 2006 (2005 is potentially a 'washout' year as the policy went into effect in August, but we use annual data and thus code all of 2005 as treated). We see limited evidence of an increase in violent crime post−disenrollment. Excluding time−varying covariates measured at the county−level (Figure A7) produces qualitatively similar findings, as does using longer time periods – 2000−2007 (Figure A8) and 2002−2010 (Figure A9).

Figure A10 presents estimates of a covariate balance test in which we conduct separate regressions of each control variable on the TennCare exposure measure, county fixed−effects, and urbanicity−by−year fixed−effects. We conduct these regressions at the county−level since this is the level of observations for the control and exposure mea-

[20] If we estimate the number of individuals losing coverage for each of the 95 counties in Tennessee (results available on request), we calculate that just under 160,000 non−elderly adults were disenrolled, this number is close to the 190,000 documented in other work.

sures. We find that counties are well balanced with respect to age, but potentially less balanced in terms of race and ethnicity. Reassuringly, we find that our DID results are robust to including or excluding these controls.

4.2 TennCare and crime

We summarize our main findings in Table 2 by presenting our static DID (equation 1) results for crime rates.[21] Column (1) presents the effect of disenrollment on total crime. In line with the results in Figure 3, column (1) suggests a statistically significant increase in the total crime rate in counties most exposed to the 2005 disenrollment. Given that a county with median exposure has 19.0% of the population covered by Medicaid prior to TennCare disenrollment, the coefficient estimate implies that the disenrollment led to 4.52 additional crimes per 1,000 agency-covered residents for a police agency in the median exposure county ($= 23.81 * 0.19$). Comparing the coefficient estimate with the baseline mean implies that a police agency in the median county experiences a 7.1% increase in the total crime rate post−disenrollment. In columns (2) and (3), we report the coefficient estimates for violent and non−violent crimes, respectively. Following the disenrollment, a police agency's violent and non−violent crime rates in the median county increased by 1.81 and 25.09 per 1,000 residents or 1.4% and 12.0%, respectively. However, our results for violent crimes are imprecise and statistically insignificant. Given the average pre−treatment population served by a police agency in our sample in the median county in Tennessee (7,307), our results indicate an additional 35 non−violent crimes per agency in the median county post−treatment.

We next examine which specific types of crimes are driving our aggregate findings in Table A3. For violent crimes presented in Panel A, we find no statistically significant effect of the disenrollment on any of the specific crimes (murder, rape, robbery, or aggravated assaults). For non−violent crime presented in Panel B, we see that the result is driven by theft, which increased by 4.95 per 1,000 residents or by 19.0% in a police agency in the median county post−disenrollment. We find no evidence that the TennCare disenrollment affected burglary, motor vehicle theft, or arson rates. The fact that our findings are concentrated among thefts hints that losing Medicaid leads some disenrollees to commit financially−motivated crimes, potentially in response to financial strain from medical bills, worse labor market outcomes as health declines, or reduced ability to weigh the costs and benefits of such crimes due to impeded behavioral health. Later in this section we will more formally investigate mechanisms.

[21] Table A2 shows the DID estimates when excluding time−varying covariates.

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

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 economic opportunity and income are strong predictors of criminal activity (Raphael and Winter-Ebmer, 2001; Lin, 2008; Akee et al., 2010). We extend our regression from equation 1 to examine county−level unemployment rates, poverty rates, median income, and eviction outcomes in Panels (1)−(3). The findings in Table 3 suggest that Medicaid disenrollment significantly impact unemployment in Panel A, the coefficient estimate is negative which hints of job−lock. Conversely, Panel B 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 Panel C, we follow Ali et al. (2024) and estimate the effect of the TennCare disenrollment on eviction outcomes. We find an increase in both eviction filings and completed evictions post−disenrollment.[22]

[22]To account for differences across counties in the cost of renting, we follow Ali et al. (2024) and control for the median property values. Results are similar, although less precise, if we do not include this variable in the eviction regressions (results available on request). We show in Section 4.4 that including these additional controls in our crime regressions does not alter our main findings.

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 median counties in Tennessee experienced a decrease of 6.1% 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 increased by 25.0%. 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. Using county−level data from N−SSATS, we show that admissions to specialized treatment centers declined post−disenrollment (Table 5).

In Table 6, we report changes in mortality based on NVSS data. The coefficient estimate for all−cause mortality is positive, but does not rise to the level of statistical significance. We find an increase of 20.0% for the median−exposure county in drug overdose deaths post−disenrollment, but no observable change in suicide− and alcohol−related deaths. The fact that we find 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; Maclean et al., 2022).

We next evaluate whether TennCare disenrollment impacts other determinants of crime (e.g. size and composition of police force as well as government expenditures). Given the observed increase in crime post−disenrollment, we might be concerned that this increase in police−civilian interactions may lead to an increase in on−duty assaults on officers by civilians.[23] In Table 7, we investigate the effects of disenrollment on the

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

number of police officers and civilian employees, separately, and assaults of police officers overall and stratifying by whether the on−duty assault leads to an injury or not for the officer.[24] We find no evidence that this policy shock affected the number of police officer or civilians employees, or police officer assaults by civilians.

Next, as a complementary analysis of potential crime determinants, we explore whether the TennCare disenrollment impacted other government expenditures in Table 8. For example, resources not spent on TennCare could be allocated to fund other public services, which, in turn, may impact crime outcomes. To study this possibility, we turn to county−level data on per−capita payroll outcomes based on Annual Survey of Government Employment from the U.S. Census Bureau.[25] The survey provides local payroll expenditures by governmental function, such as police officers only (persons with power of arrest), other police employees (persons who do not have the power of arrest.), health, hospital, education (elementary and secondary instructional employees), and streets (streets and highways). Following the disenrollment, we observe a decline in total payroll expenditures, driven by a decline in expenditures for police, in counties more exposed to the policy shock. Furthermore, when including these payroll measures as covariates in the crime regression (see Section 4.4), we observe qualitatively similar results to our main crime finding. This pattern of results offers suggestive evidence that broader changes in government expenditures, including those targeting crime and public safety, do not explain our main crime findings.

4.4 Robustness

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

In Table A5, we employ a specification similar to Maclean et al. (2023) where we compare police agencies in Tennessee to those in other Southern states before and after the mass disenrollment using a canonical DID. The results from this regression are reported in Panel A and suggest, on average, an increase of 1.76 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 (3.0%). This effect is driven by non−violent crimes. In Panel B, we instead use police agencies in all other states as an alternative comparison group and results suggest an average increase of 2.21 per 1,000 or 3.7%

[24] These data are drawn from from Law Enforcement Officers Killed and Assaulted (LEOKA) Data Collection and sourced from Kaplan (2021b).

[25] We obtain the data from Kaplan (2021a) and U.S. Census Bureau (2022).

Figure A11 report the DID effects for total, violent, and non−violent crime rates using different samples and specifications. The purpose of these exercises is to ensure that our findings are not driven by the selection of a particular sample or specification. We first reproduce our baseline estimates from Table 2 for comparison. Our main UCR data sample consists of police agencies that report crimes for any months of data in all years of the sample period (2002−2007). We first alter this restriction and re−estimate equation 1 using alternative sub−samples to show that the main finding of increased crime documented in this study is not driven by our preferred sample construction. In particular, we restrict the sample to agencies reporting criminal activity in all months and all years; all months in at least one year; agencies serving at least 10,000 people; and all agencies in the UCR database regardless of reporting or size of the population served. We then expand the post−treatment years to include data then through 2010 (this period includes the Great Recession) and back to 2000 (this period includes data prior to the major Medicaid re−certification effort in Tennessee in 2002). Next we consider different degrees of top− (and bottom−) coding in our outcomes and exposure variables: exclude high− and low− exposure (to the disenrollment as measured by non−elderly adult Medicaid coverage in the first two quarters of 2005) counties (i.e., below the 1st percentile of the exposure distribution pre−disenrollment and above the 99th percentile), and exclude observations below the 10th and above the 75th, 95th, and 99th percentile of the crime rate distribution (similar to the main specification, we impose bottom− and top−coding separately for each of the three crime rate variables).

Next, we hold our sample constant and vary the specifications. We estimate an unweighted regression, and use alternative weight measures such as the population served in the first year that an agency reported data or the average population served across all years. We then use the overall (i.e., all ages) Medicaid coverage rate, use the the first and second quarter of 2005 among non−elderly adults, male non−elderly adults, and female non−elderly adults as alternative exposure measures. We next replace urbanicity−by−year fixed−effects with year fixed−effects. We additionally control for rental market variables (median property values and rent burden (Eviction Lab, 2021)) and economic and public safety covariates (officer and civilian employees per agency (Kaplan, 2021b), overall payroll in the county (U.S. Census Bureau, 2022), and the county-level unemployment rate (Bureau of Labor Statistics, 2022)), separately.

In Figure A12, we conduct a 'leave−one−out' analysis by sequentially excluding each county in Tennessee one at a time and re−estimating our main regression (equation 1). Overall, we observe an increase in crime across the leave−one−out samples.

4.5 Contrasting TennnCare with other Medicaid contractions

This section puts our TennCare disenrollment results in context with another Medicaid contraction that affected a different demographic with a lower propensity for criminal activity. As noted in Section 1, most Medicaid policies in the U.S. have expanded the program and there are few changes that curtail coverage. Here, we study another 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 losing coverage 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% and 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). Thus, the populations losing coverage were quite different across the two states. 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 perpetrators of crime than those losing coverage in Missouri, while enrollees losing coverage in Missouri may have been more likely to be crime victims. We study overall offenses, thus predicting which contraction should ex ante be expected to yield larger impacts on crime is unclear. Further, while TennCare was terminated due to high cost within a very short time period (roughly six months, see Section 2.2) and thus the policy change was largely isolated to a reduction in the size of the Medicaid−eligible population, 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 estimated in Missouri. Despite these differences, the Missouri−Tennessee comparison is useful as the results can offer suggestive evidence on the extent to which the social costs of curtailing Medicaid may vary across state, target population, and likely other factors.

With this background, we use a similar exposure design to evaluate the impact of the Missouri Medicaid contraction on crime by comparing counties in that state with higher and lower Medicaid coverage pre−shock. In particular, we construct an exposure measure based on 2004 county−level Medicaid coverage rates[26] in each county in Missouri and estimate a regression comparable to that outlined in equation 1. The median Medicaid coverage rate was 18.0% in 2004 and we scale coefficient estimates by this number.

Event−study results are reported in Figure A13. Although we observe some evidence of pre−trend differences, we observe declines in crime rates in more exposed counties post−2005. In particular, we observe an increase in non−violent crime that is roughly one−third the size of what we observe in Tennessee, or 4.7% to 12.0%.

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),[27] 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 public heath emergency 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, within Tennessee, with differential levels of policy exposure based on Medicaid coverage rates prior to the disenrollment. We find that agencies in the median county (=0.19 in pre−policy Medicaid coverage rates) experienced a 7.1% increase in crime rates, with violent and non−violent crime rates rising by 1.4% and 12.0% respectively, though we note that the violent crime finding is imprecisely estimated and

[26] 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.

[27] We acknowledge that a full consensus has not yet been reached: Finkelstein et al. (2024) find limited crime effects among non−elderly adults randomized to Medicaid enrollment in Oregon.

statistically insignificant. While we study an insurance loss within a different (older) population, our findings are qualitatively similar to Jácome (2023) and Fone et al. (2023), who study expected 'aging−out' of public and private coverage, in that losing insurance is more strongly associated with non−violent than violent crime. We examine the impact of the 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 theft, the most common non−violent offense. The fact that our findings are driven by thefts suggests that losing insurance leads to financially−motivated crimes.

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. We find that the crime effects are driven by worsening financial standings and overall and behavioral−health wellbeing 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 decline and deaths related to substances increase post−disenrollment. Combining our findings on theft with the results of our mechanisms analysis suggests that losing insurance reduces economic stability and negatively impacts behavioral health. Disenrollees may resort to financially motivated crimes to make ends meet and, due to declines in behavioral health, may struggle to properly assess the risks and consequences of engaging in criminal activity.

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 414 fewer Medicaid enrollees in the median Tennessee county of 17,233 people aged 21−64 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 7,307 and there are four agencies in the median county, the TennCare disenrollment leads to 132 crimes (=4.52∗7,307/1,000∗4) in the median county. This back−of−the−envelope calculation suggests that the TennCare disenrollment results in 0.32 total crimes per newly disenrolled person in the median county. Comparing our effect sizes with studies documenting that crime declines following ACA Medicaid expansion (e.g., Vogler (2020)) is somewhat challenging for reasons discussed in Section 4.4, changes in insurance options between 2005 and 2014, and due to the fact that there may be asymmetries in coverage gains and losses. Moreover, we find evidence of a decrease in public safety, which has also been shown to increase crime, independent of Medicaid enrollment − see, for example, Chalfin et al. (2022) and Cox et al. (2022b).

Our study suggests that losing Medicaid coverage may have indirect societal cost, such as increasing crime, which is primarily driven by theft. To put this potential cost in perspective, we discuss the gap in the social cost attributed to crime incurred by a county with the median exposure. Our coefficient estimates indicate that a given police agency at the median exposure experienced an additional 4.95 ($= 0.19 * 26.06$) thefts per 1,000 residents. Using an estimate of the cost of a theft from Chalfin and McCrary (2018) and inflating it to 2023 U.S. dollars, the additional social cost attributed to theft ($662) for a police agency located in a county with median exposure is $3,277 (=4.95 ∗ $662) per 1,000 residents following TennCare disenrollment.[28]

Our study is not without limitations. First, because TennCare enrollment primarily targeted non−elderly, non−disabled, low−income adults without children, extrapolating our findings to the general Medicaid− covered populations may be inappropriate. 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, though we report results using a longer pre−treatment period and results are not different.

Our findings provide evidence on the value of insurance, in particular, the value to society that extends beyond the insured individual. Crime imposes costs on government budgets, crime victims, and society. Going against historical trends, recent policies − in place and proposed − 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.

[28]As outlined in Section 4, we do not find that overall social costs of crime increase following the disenrollment. We attribute the null findings for overall costs to the fact that our crime rate results are driven by increases in thefts which are less costly to society than other crimes such as murders.

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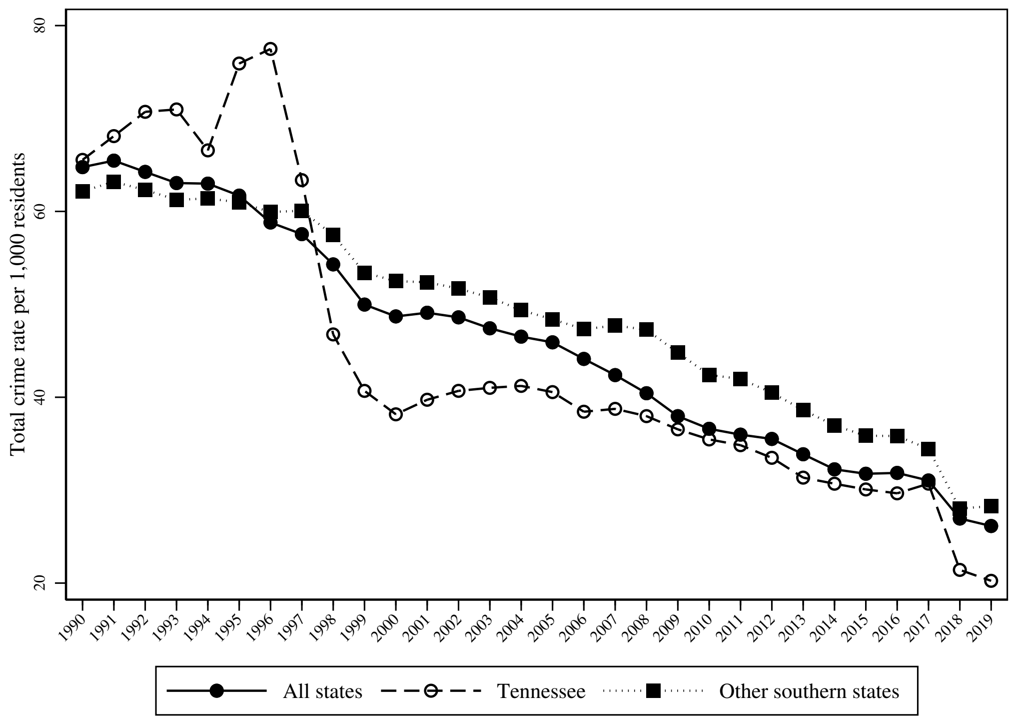
6 Figures and tables

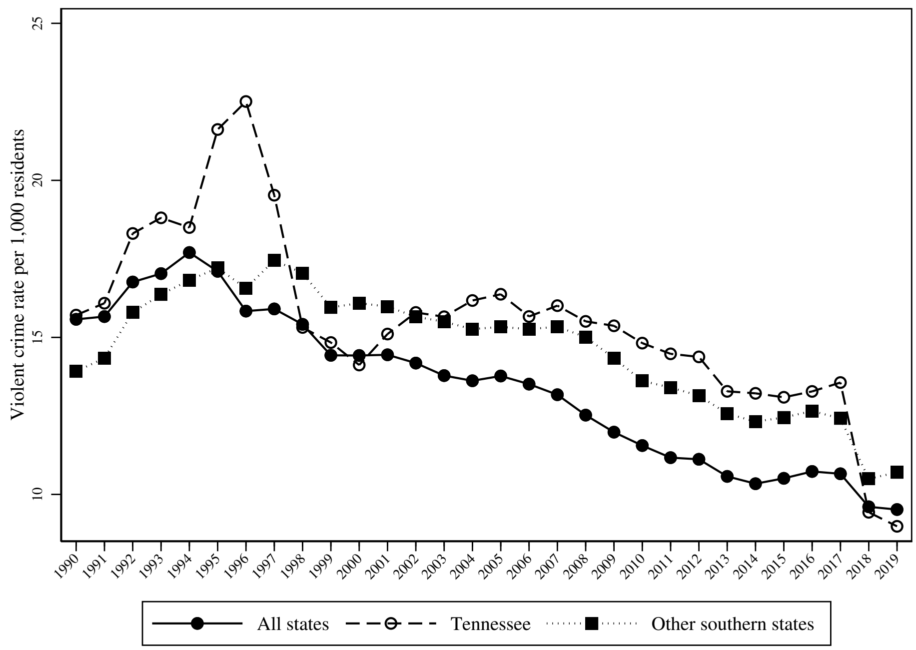
Figure 1: Trends in national crime rates: Uniform Crime Reports 1990-2019



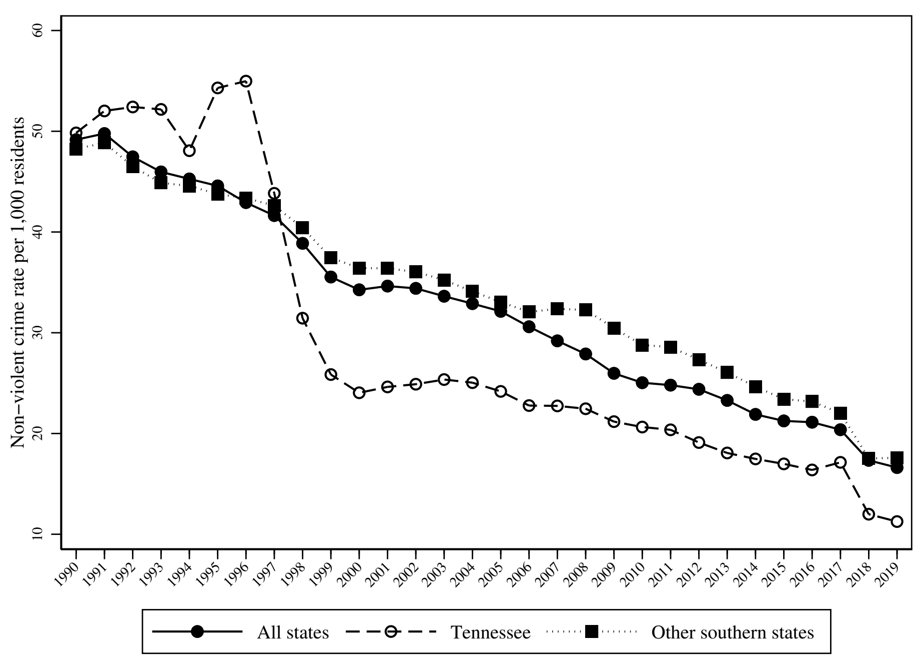
Notes: This figure plots average annual crime rates over time. Crime rates are per 1,000 residents served by the agency. Data are weighted by the population served by the agency. Agencies serving populations greater than 10,000 people are included in the sample.

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

(a) Panel A: Violent

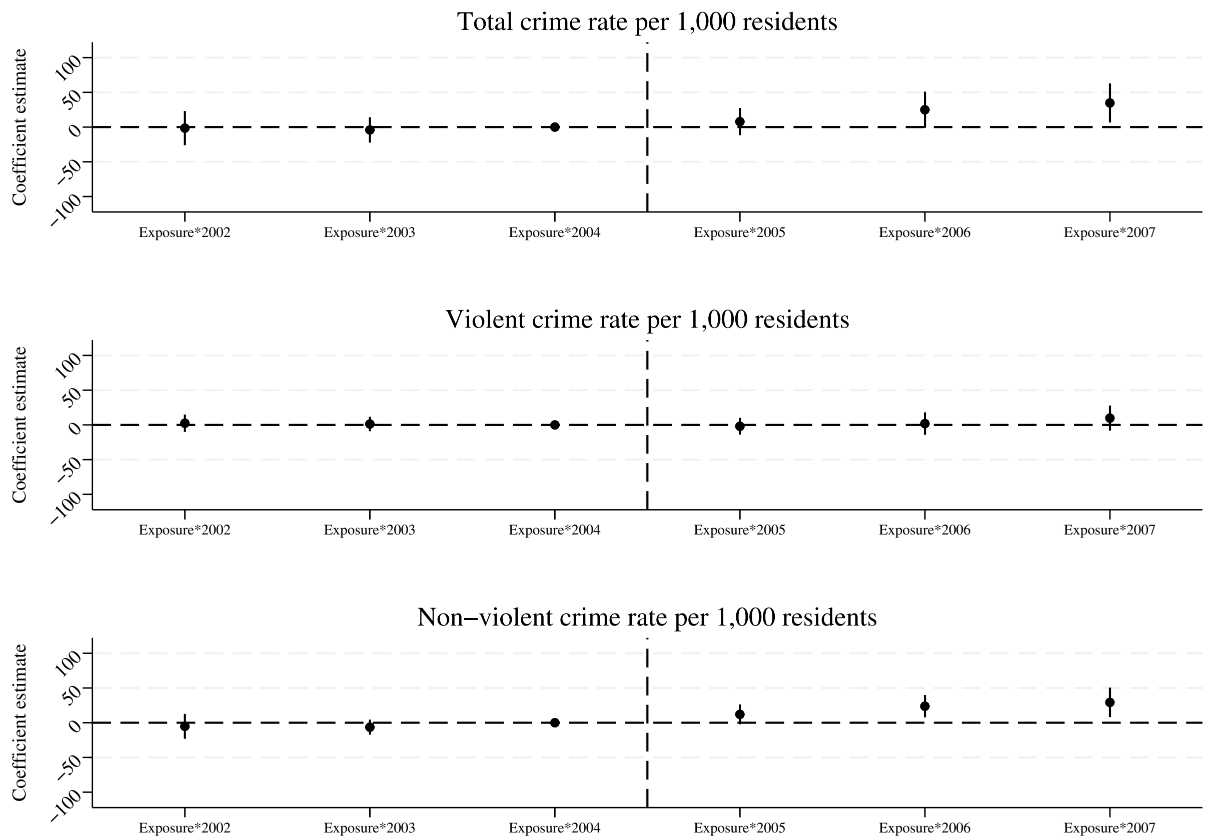


(b) Panel B: Non−violent



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

Figure 3: Effect of the TennCare disenrollment on crime rates using an event−study: Uniform Crime Reports 2002−2007



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

Table 1: Effect of the TennCare disenrollment on Medicaid coverage: Tennessee Department of Health 2005−2007

Specification:	Time−varying controls	Exclude time−varying controls
Exposure × post	-0.24***	-0.24***
	(0.05)	(0.04)
β scaled to median county	-0.05	-0.05
Percent change (scaled β)	-23.81	-23.81
Median exposure	0.20	0.20
Pre-treatment mean	0.21	0.21
Observations	3384	3384

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on an interaction between exposure to the TennCare disenrollment and the post−period. The regression includes time−varying county−level covariates, county fixed−effects, month fixed−effects, and urbanicity−by−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 = 0.19 Medicaid coverage rate). Data are weighted by the county population. Regressions are estimated with OLS. Standard errors are clustered at the county level and reported in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Effect of the TennCare disenrollment on crime rates: Uniform Crime Reports 2002−2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure × post	23.81***	1.81	25.09***
	(8.99)	(6.88)	(7.02)
β scaled to median county	4.52	0.34	4.77
Percent change (scaled β)	7.06	1.39	12.00
Median exposure	0.19	0.19	0.19
Pre−treatment mean, high exposure counties	64.02	24.42	39.76
Observations	2682	2682	2682

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on an interaction between exposure to the TennCare disenrollment and the post−period. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is an agency in a county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 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.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Effect of the TennCare disenrollment on economic outcomes: 2002−2007

Panel A: Bureau of Labor Statistics		
Outcome:		Unemployment
Exposure × post		-2.57**
		(1.11)
β scaled to median county		-0.51
Percent change (scaled β)		-8.07
Median exposure		0.20
Pre−treatment mean, high exposure counties		6.32
Observations		564
Panel B: Small Area Income and Poverty		
Outcome:	Poverty	Median income
Exposure × post	10.52***	-5179.53
	(2.56)	(4198.35)
β scaled to median county	2.10	-1035.91
Percent change (scaled β)	12.80	-3.09
Median exposure	0.20	0.20
Pre−treatment mean, high exposure counties	16.41	33565.87
Observations	564	564
Panel C: Eviction Lab		
Outcome:	Completed Evictions	Eviction Filings
Exposure × post	16.73**	7.76*
	(7.90)	(4.45)
β scaled to median county	3.35	1.55
Percent change (scaled β)	131.89	66.81
Median exposure	0.20	0.20
Pre−treatment mean, high exposure counties	2.54	2.32
Observations	500	500

Notes: This table reports coefficient estimates from a difference−in−differences regression of economic outcomes on an interaction between exposure to the TennCare disenrollment and the post−period. The regression includes time−varying county demographics, county fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Data are weighted by county population 21−64 years. Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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

Outcome:	Health insurance	Delay care for cost	Very good /ex. health
Exposure × post	-0.30*	0.29*	-0.03
	(0.17)	(0.15)	(0.31)
β scaled to median county	-0.05	0.04	0.00
Percent change (scaled β)	-6.10	25.00	0.00
Median exposure	0.15	0.15	0.15
Pre−treatment mean, high exposure counties	0.82	0.16	0.49
Observations	6922	6891	6923

Notes: This table reports coefficient estimates from difference−in−differences regressions of health outcomes on an interaction between exposure to the TennCare disenrollment and the post−period. Ex. = excellent. The regression includes individual characteristics, time−varying county demographics, county fixed−effects, month fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a respondent in 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 = 0.19 Medicaid coverage rate). Data are weighted by Behavioral Risk Factor Surveillance Survey provided weights. Regressions estimated with OLS. Standard errors are clustered by the county and are reported in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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

Outcome:	Admissions
Exposure × post	-31.58**
	(13.98)
β scaled to median county	-6.32
Percent change (scaled β)	-137.69
Median exposure	0.20
Pre−treatment mean, high exposure counties	4.59
Observations	564

Notes: This table reports coefficient estimates from a difference−in−differences regression of admission rates on the interaction between exposure to the TennCare disenrollment and the post−period. The regression includes time−varying county demographics, county fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a county in a year. Data are weighted by county population 21−64 years. The unit of observation is a county in a state in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

Table 6: Effect of the TennCare disenrollment on mortality outcomes: Centers for Disease Control and Prevention 2002−2007

Outcome:	All−cause	Suicide	Alcohol	Drug
Exposure × post	-0.40	0.06	0.01	0.74***
	(0.84)	(0.16)	(0.02)	(0.22)
β scaled to median county	-0.08	0.01	0.00	0.15
Percent change (scaled β)	-1.54	4.76	.	65.22
Median exposure	0.20	0.20	0.20	0.20
Pre−treatment mean, high exposure counties	5.19	0.21	0.00	0.23
Observations	564	564	564	564

Notes: This table reports coefficient estimates from a difference−in−differences regression of mortality rates on an interaction between exposure to the TennCare disenrollment and the post−period. The regression includes time−varying county demographics, county fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a county in a year. Data are weighted by county population 21−64 years. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Regressions estimated with OLS. Standard errors are clustered by the county and are reported in parentheses. ***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

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

Outcome:	Employees		On−duty officer assaults		
	Officers	Civilians	Total	Injurious	Non−inj.
Exposure × post	0.07	-1.05	-0.37	-0.14	-0.28
	(0.47)	(0.80)	(0.32)	(0.10)	(0.26)
β scaled to median county	0.01	-0.20	-0.07	-0.03	-0.05
Percent change (scaled β)	0.43	-13.99	-17.95	-23.08	-20.00
Median exposure	0.19	0.19	0.19	0.19	0.19
Pre−treatment mean, high-exposure counties	2.32	1.43	0.39	0.13	0.25
Observations	2682	2682	2682	2682	2682

Notes: This table reports coefficient estimates from a difference−in−differences regression of the police employee outcomes on exposure to the TennCare disenrollment and an indicator for the post−period. Non−inj. = non−injurious. The regression includes time−varying county demographics, agency fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Data are weighted by the population served by the agency. Regressions are estimated with OLS. Standard errors are clustered at the county level and reported in parentheses.
***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

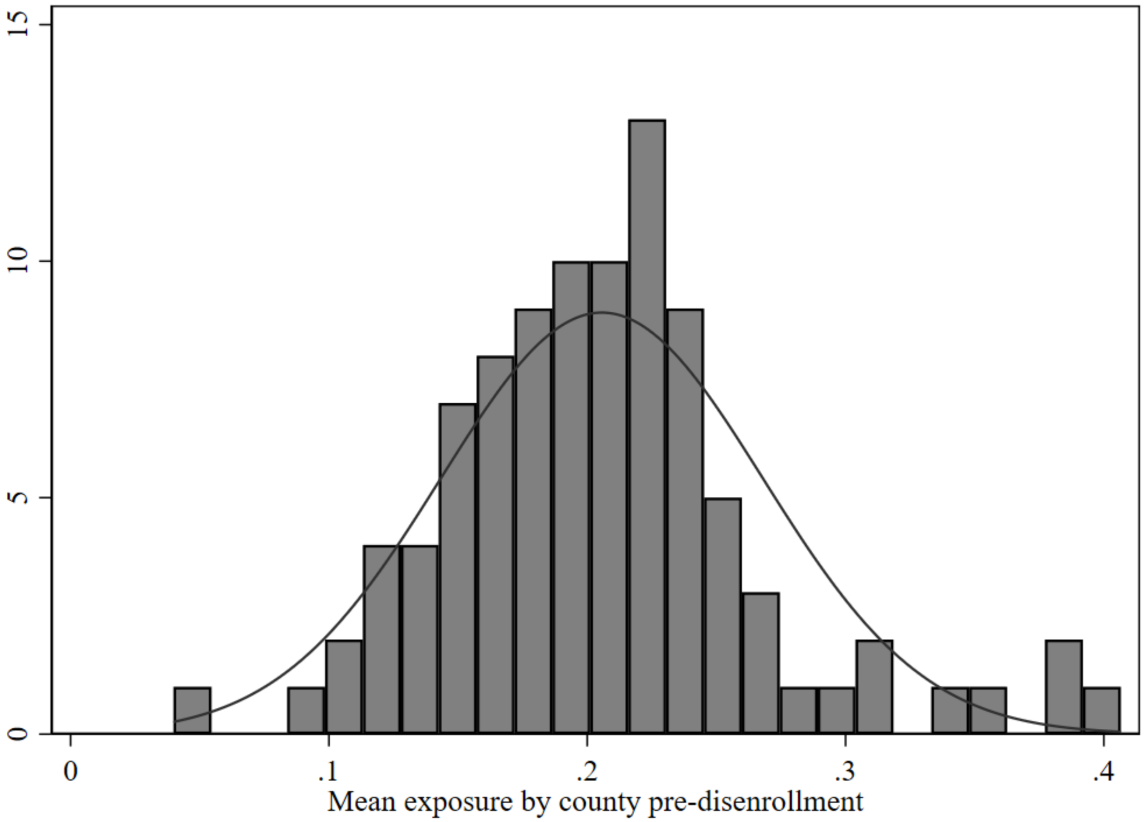
Table 8: Effect of TennCare Disenrollment on per−capita payroll outcomes: Annual Survey of Public Employment & Payroll 2002−2007

	All	Police Officers	Police Others	Health	Hospital	Education	Streets
Exposure × Post	-52.84*	-9.26**	-4.10***	0.38	-5.39	6.89	0.11
	(30.65)	(4.24)	(1.25)	(0.29)	(7.15)	(7.95)	(0.38)
β scaled to median county	-10.57	-1.85	-0.82	0.08	-1.08	1.38	0.02
Percent change (scaled β)	-27.49	-50.27	-54.67	34.78	-30.25	5.14	3.70
Median exposure	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Pre−treatment mean, high exposure counties	38.45	3.68	1.50	0.23	3.57	26.87	0.54
Observations	432	303	275	229	133	341	323

Notes: This table reports coefficient estimates from a difference−in−differences regression of payroll outcomes on exposure to the TennCare disenrollment and an indicator for the post−period. The regression includes time−varying county demographics, county fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Data are weighted by county population 21−64 years. Regressions estimated with OLS. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

7 Appendix: For Online Publication Only

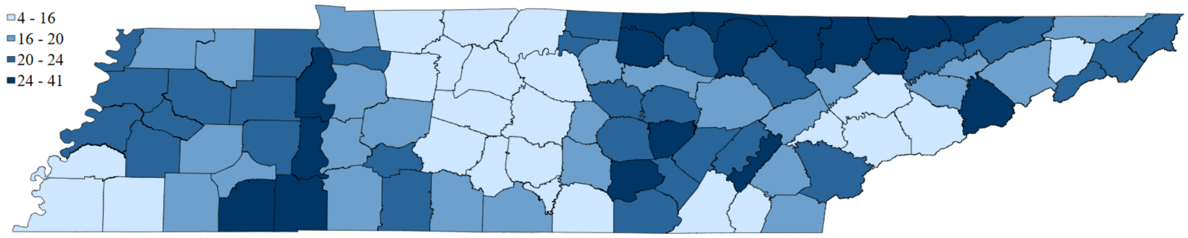
Figure A1: Distribution of Medicaid coverage exposure to the TennCare disenrollment: Tennessee Department of Health



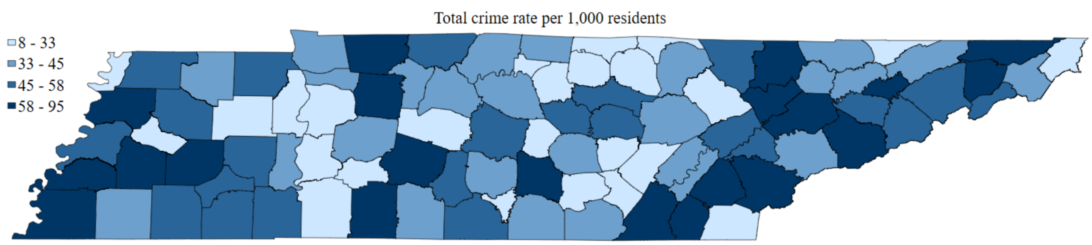
Notes: This figure plots the distribution of county−level exposure to the TennCare disenrollment where exposure is defined as the share of the population 21−64 years of age enrolled in Medicaid in Q1 and Q2 of 2005. Data are aggregated to the county−level over the period Q1 and Q2 2005. Data are weighted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

Figure A2: Geographic distribution of exposure to the TennCare disenrollment and total crime rate across Tennessee counties

(a) Panel A: Exposure to the TennCare disenrollment



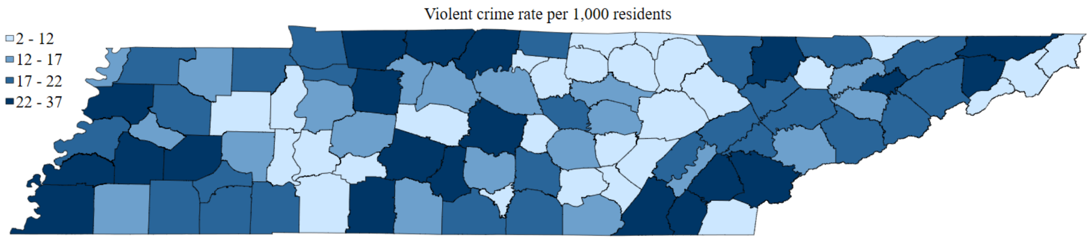
(b) Panel B: County−level total crime rates



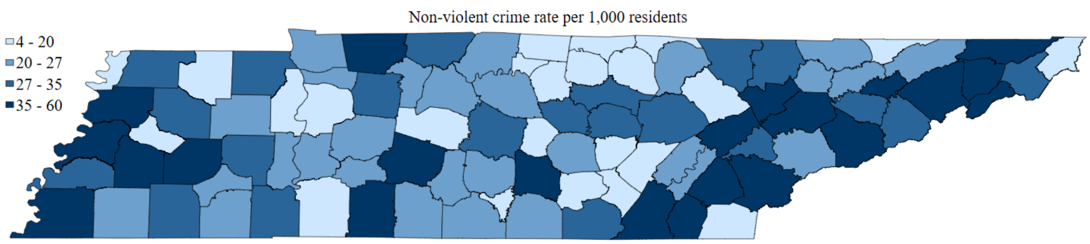
Notes: Panel A in this figure plots the geographic distribution of county−level exposure to the TennCare disenrollment where exposure is defined as the share of the population 21−64 years of age enrolled in Medicaid in Q1 and Q2 of 2005. Panel B in this figure plots the geographic distribution of county−level total crime rates in 2004. Data are aggregated to the county−level over the period Q1 and Q2 2005 in Panel A and 2004 in Panel B. The data source in Panel A is the Tennessee Department of Health and the data source in Panel B is the Uniform Crime Reports. Data are weighted by the county population 21−64 years in Panel A and the population served by police agencies.

Figure A3: Geographic distribution of violent and non−violent crime rates across Tennessee counties: Uniform Crime Reports 2004

(a) Panel A: Violent

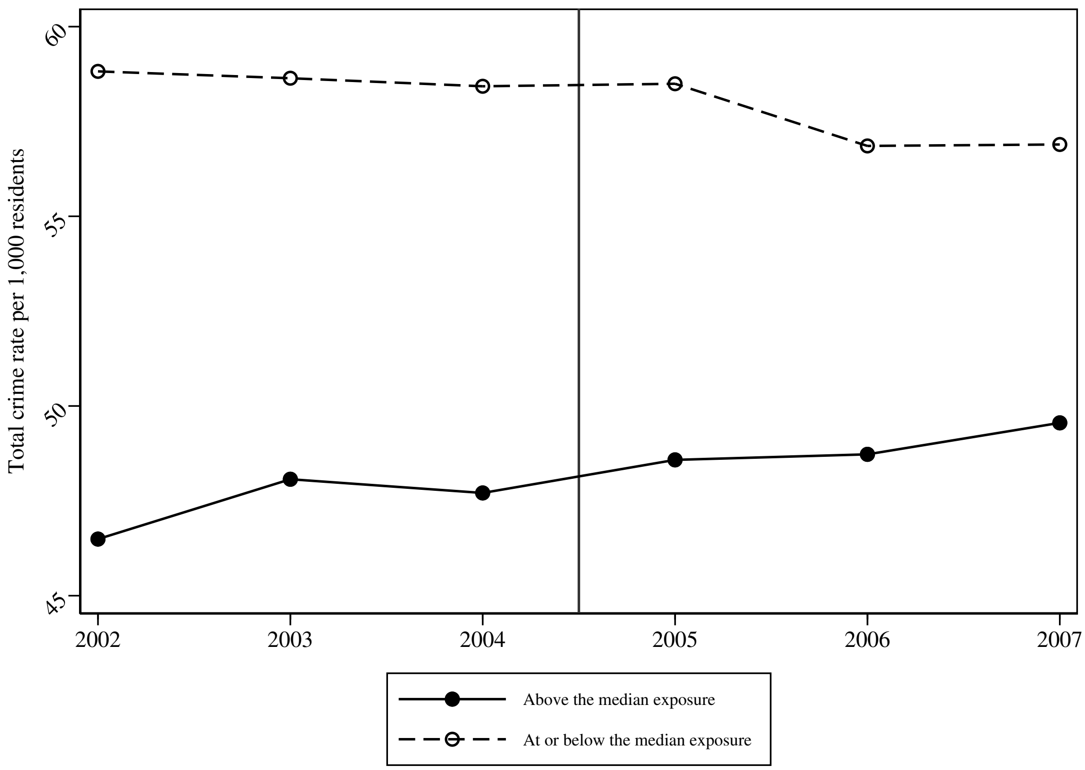


(b) Panel B: Non−Violent



Notes: Panel A of this figure plots the geographic distribution of county−level violent crime rates in 2004. Panel B of this figure plots the geographic distribution of county−level non−violent crime rates in 2004. Data are aggregated to the county−level in 2004. The data source is the Uniform Crime Reports. Data are weighted by the population served by police agencies.

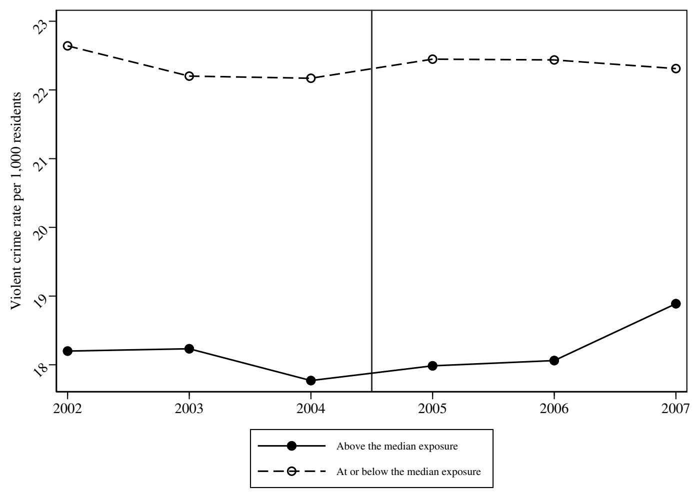
Figure A4: Trends in crime rates: High vs low exposure counties



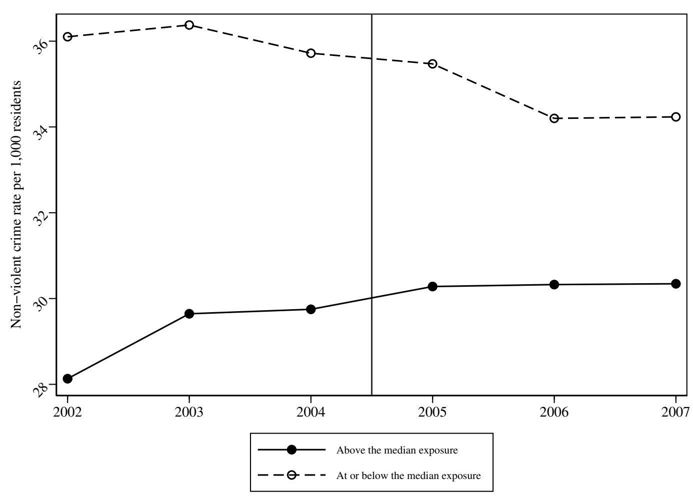
Notes: This figure plots the average annual total crime rate in counties highly exposed and not highly exposed to the TennCare disenrollment. Data are weighted by the population served by each agency prior to aggregating to the treatment−year. A high exposure county is defined as a county with a non−elderly adult Medicaid coverage rate above the Tennessee median value in Q1 and Q2 of 2005 (0.19). A low exposure county is defined as a county with a non−elderly adult Medicaid coverage rate at or below the Tennessee median value in Q1 and Q2 2005 (0.19).

Figure A5: Trends in violent and non−violent crime rates: High vs. low exposure counties

(a) Panel A: Violent



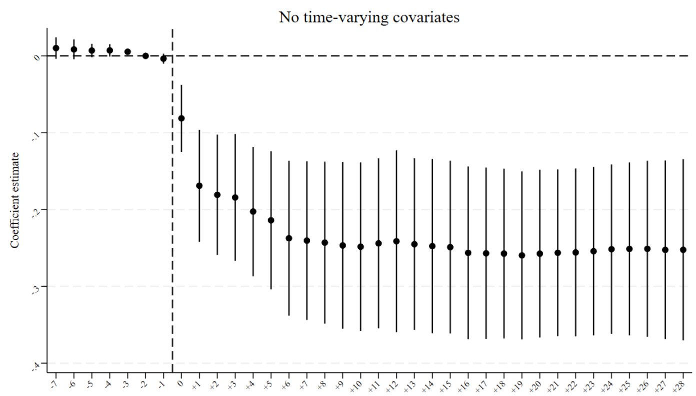
(b) Panel B: Non−violent



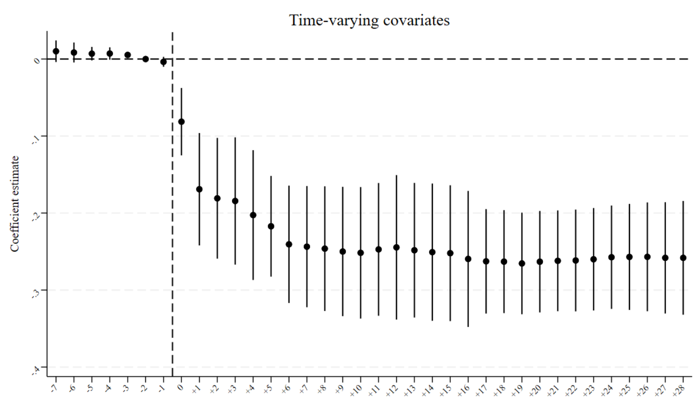
Notes: Panel A of this figure plots annual average violent crime rates in counties highly exposed and not highly exposed to the TennCare disenrollment. Panel B of this figure plots annual average non−violent crime rates in counties highly exposed and not highly exposed to the TennCare disenrollment. Data are weighted by the population served by each agency prior to aggregating to the treatment−year. A high exposure county is defined as a county with a non−elderly adult Medicaid coverage rate above the Tennessee median value in Q1 and Q2 of 2005 (0.19). A low exposure county is defined as a county with a non−elderly adult Medicaid coverage rate at or below the Tennessee median value in Q1 and Q2 2005 (0.19).

Figure A6: Effect of the TennCare disenrollment on Medicaid coverage using an event−study: **Tennessee Department of Health** 2005−2007

(a) Panel A: No time−varying covariates

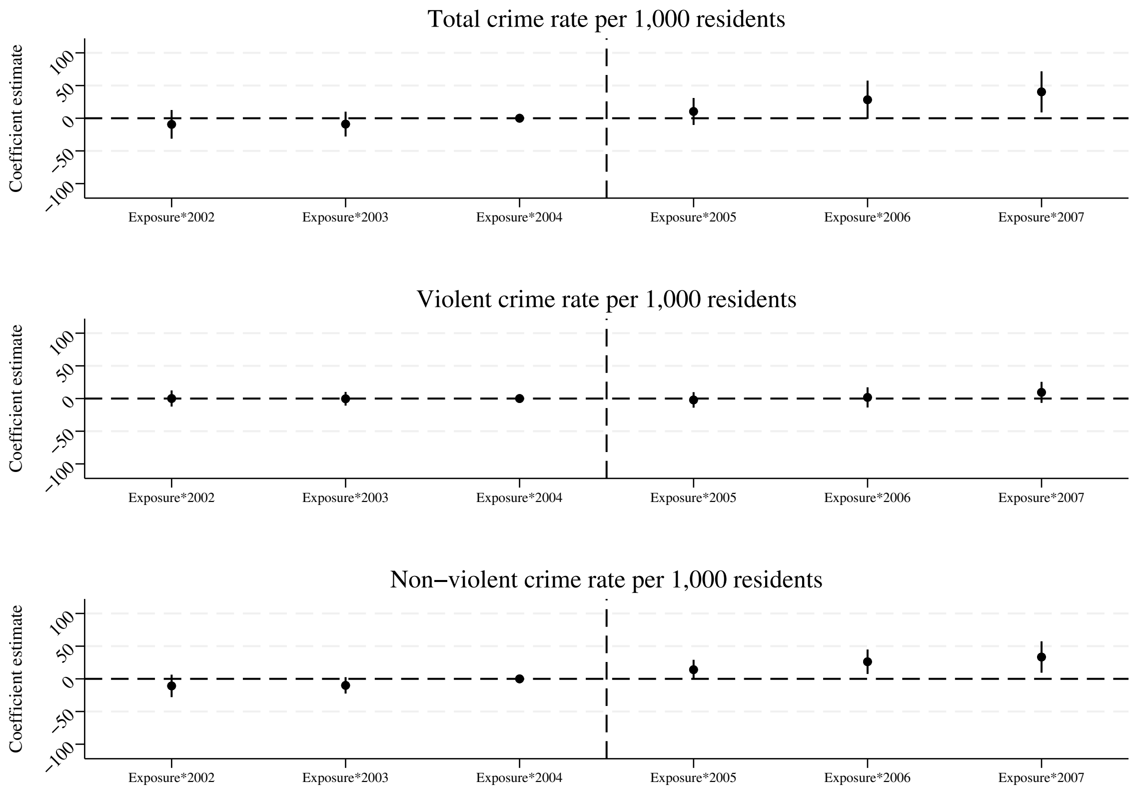


(b) Panel B: Time−varying covariates



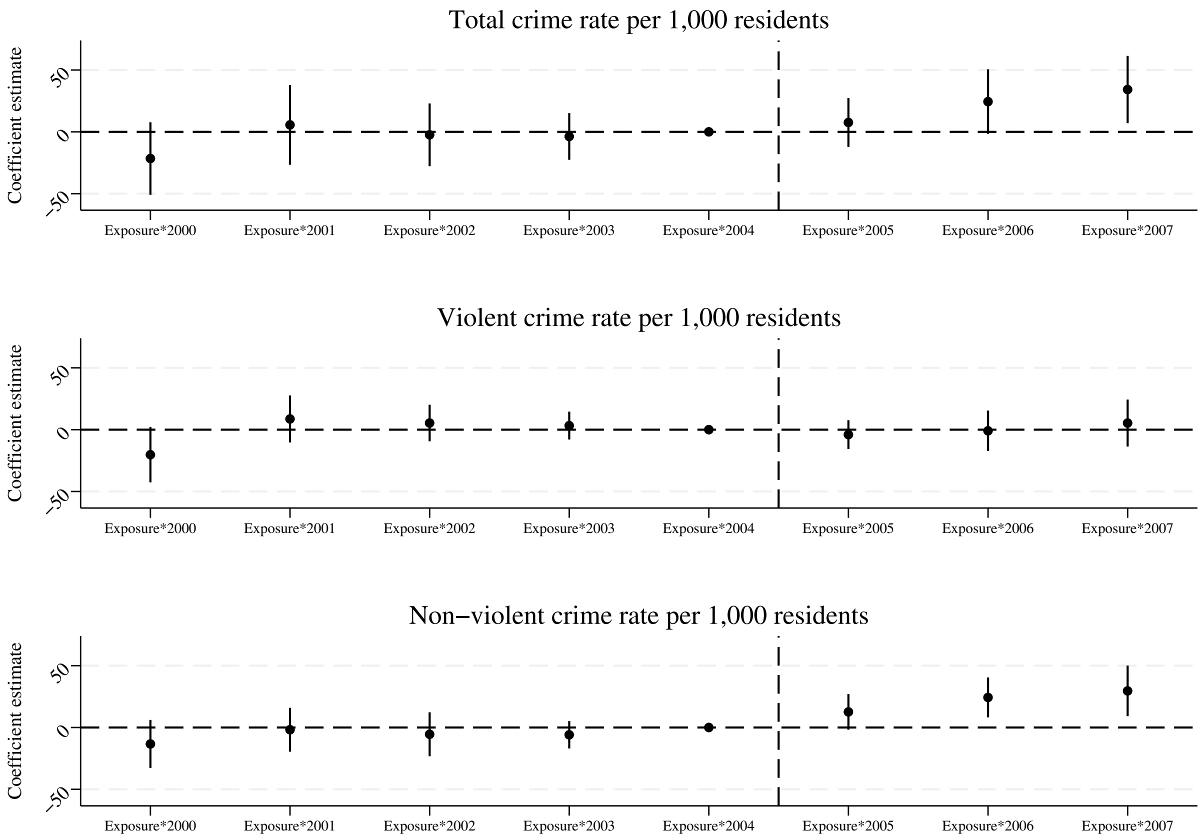
Notes: This figure plots the coefficient estimates from an event−study of county Medicaid coverage on interactions between exposure to the TennCare disenrollment and months relative to the disenrollment. The regression includes agency fixed−effects and urbanicity−year−by−month fixed−effects. Panel A excludes time−varying covariates and Panel B includes time−varying covariates. The omitted category is July 2005, the month prior to the disenrollment. The unit of observation is a county in a month in a year. Data are weighted by the county population. Regressions estimated with OLS. Coefficient estimates are reported with circles, and 95% confidence intervals that account for within-county clustering are reported with vertical lines.

Figure A7: Effect of the TennCare disenrollment on crime rates using an event−study and excluding time−varying covariates: Uniform Crime Reports 2002−2007



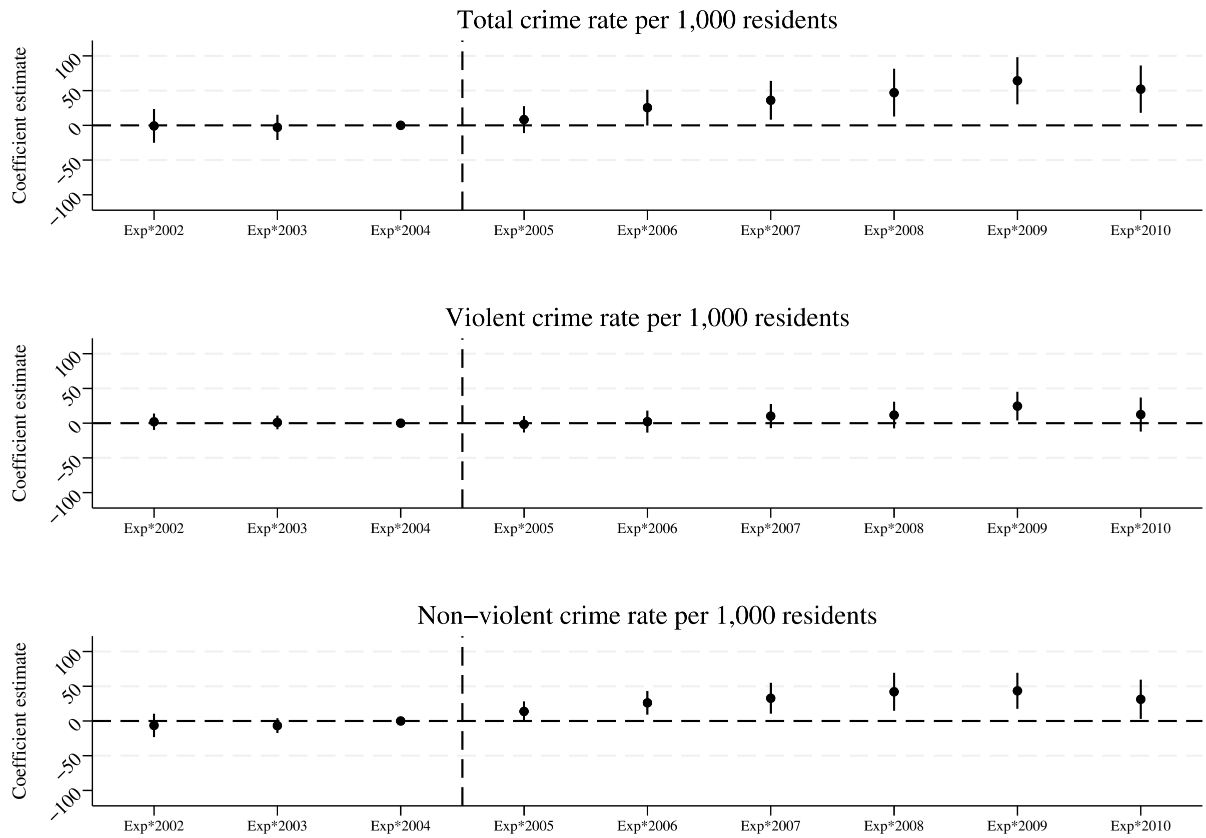
Notes: This figure plots the coefficient estimates from an event−study of crime rates on interactions between exposure to the TennCare disenrollment and indicators for years relative to the disenrollment. The regression includes agency fixed−effect and urbanicity−by−year fixed−effects. The omitted category is 2004, the year prior to the disenrollment. 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. Coefficient estimates are reported with circles and 95% confidence intervals that account for within−county clustering are reported with vertical lines.

Figure A8: Effect of the TennCare disenrollment on crime rates using an event−study: Uniform Crime Reports 2000−2007



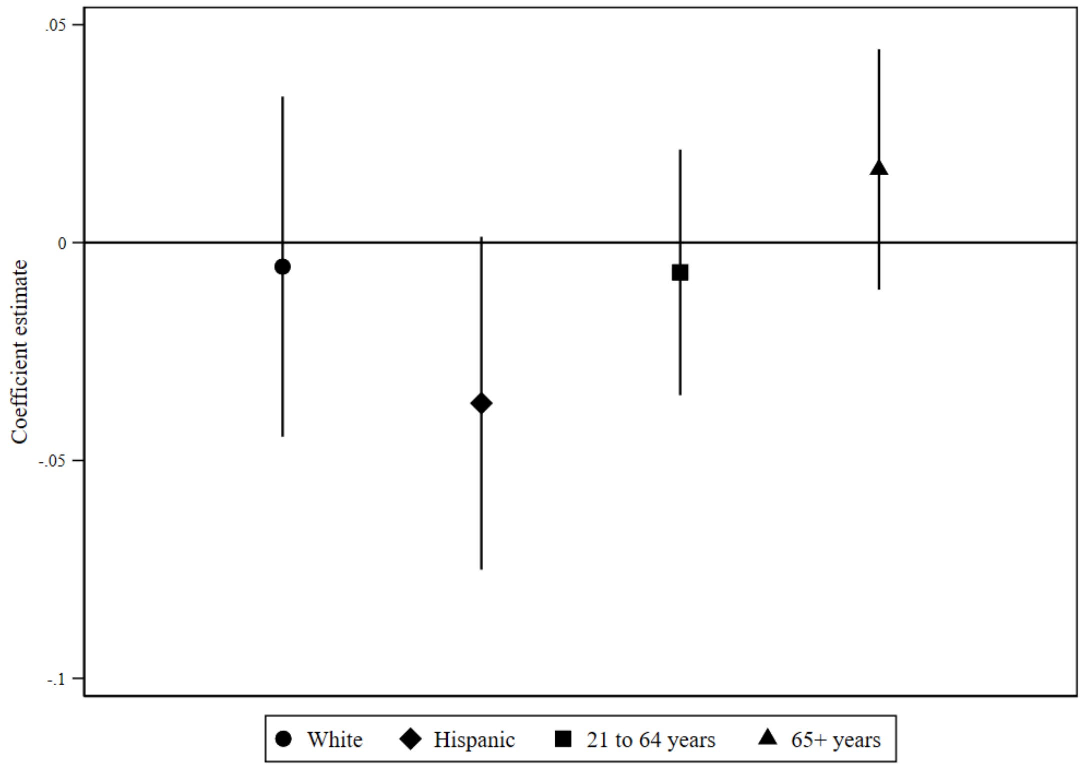
Notes: This figure plots the coefficient estimates from an event−study of crime rates on interactions between exposure to the TennCare disenrollment and indicators for years relative to the disenrollment. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The omitted category is 2004, the year prior to the disenrollment. 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. Coefficient estimates are reported with circles and 95% confidence intervals that account for within−county clustering.

Figure A9: Effect of the TennCare disenrollment on crime rates using an event−study: Uniform Crime Reports 2002−2010



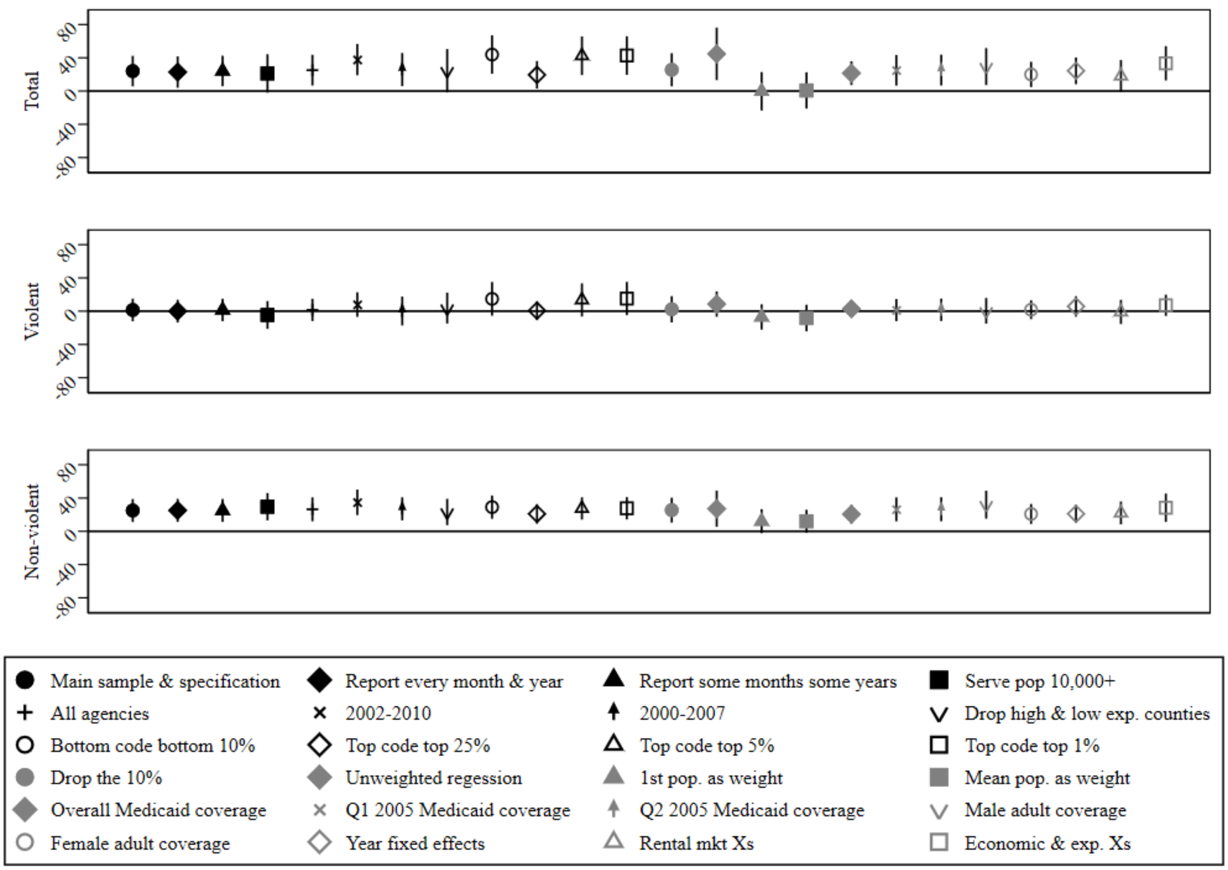
Notes: This figure plots the coefficient estimates from an event−study of crime rates on interactions between exposure to the TennCare disenrollment and indicators for years relative to the disenrollment. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The omitted category is 2004, the year prior to the disenrollment. 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. Coefficient estimates are reported with circles and 95% confidence intervals that account for within−county clustering.

Figure A10: Covariate balance test



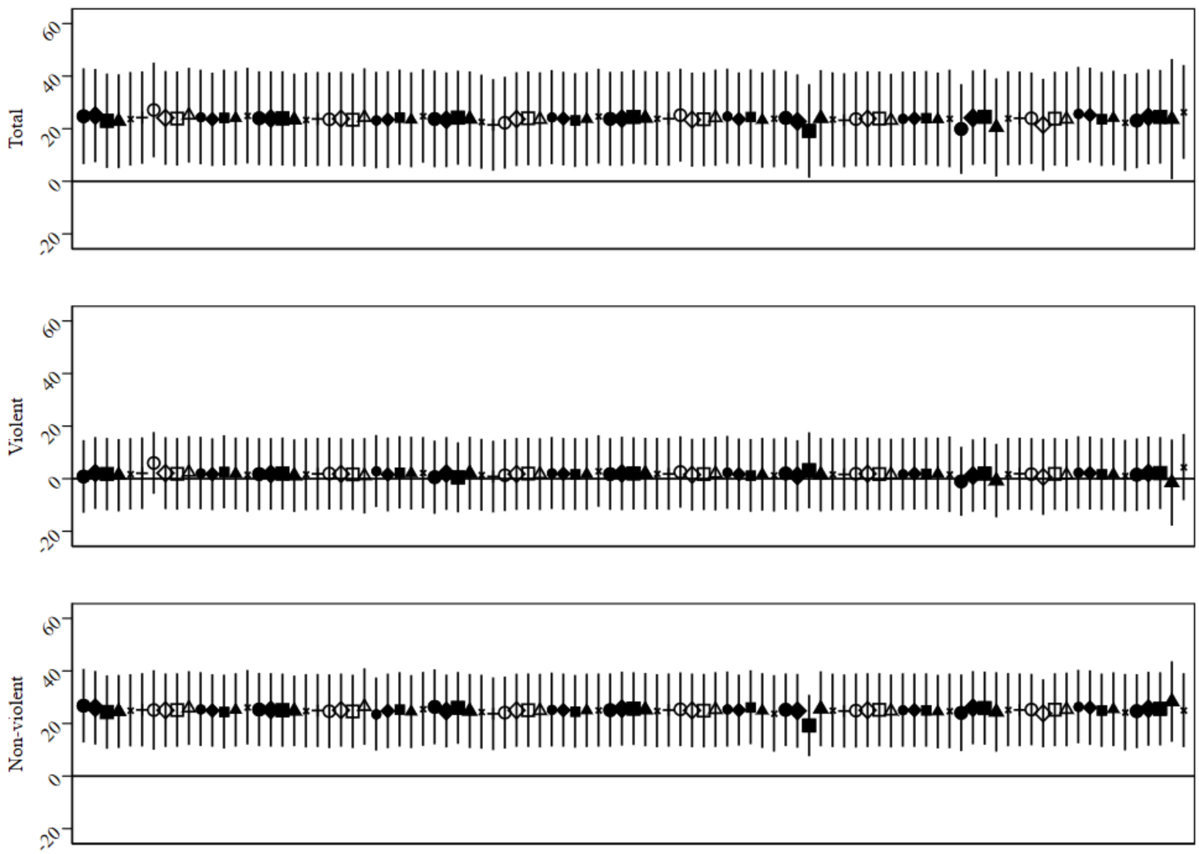
Notes: This figure plots coefficient estimates from separate a difference−in−differences regression of the variable reported on the x−axis on an interaction of exposure to the TennCare disenrollment and the post−period. Regressions include county fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is a county in a year. Data are weighted by the county population 21−64 years. Regressions estimated with OLS. Coefficient estimates are reported with circles and 95% confidence intervals that account for within−county clustering are reported with vertical lines.

Figure A11: Effect of the TennCare disenrollment on crime rates using alternative samples and specifications: Uniform Crime Reports



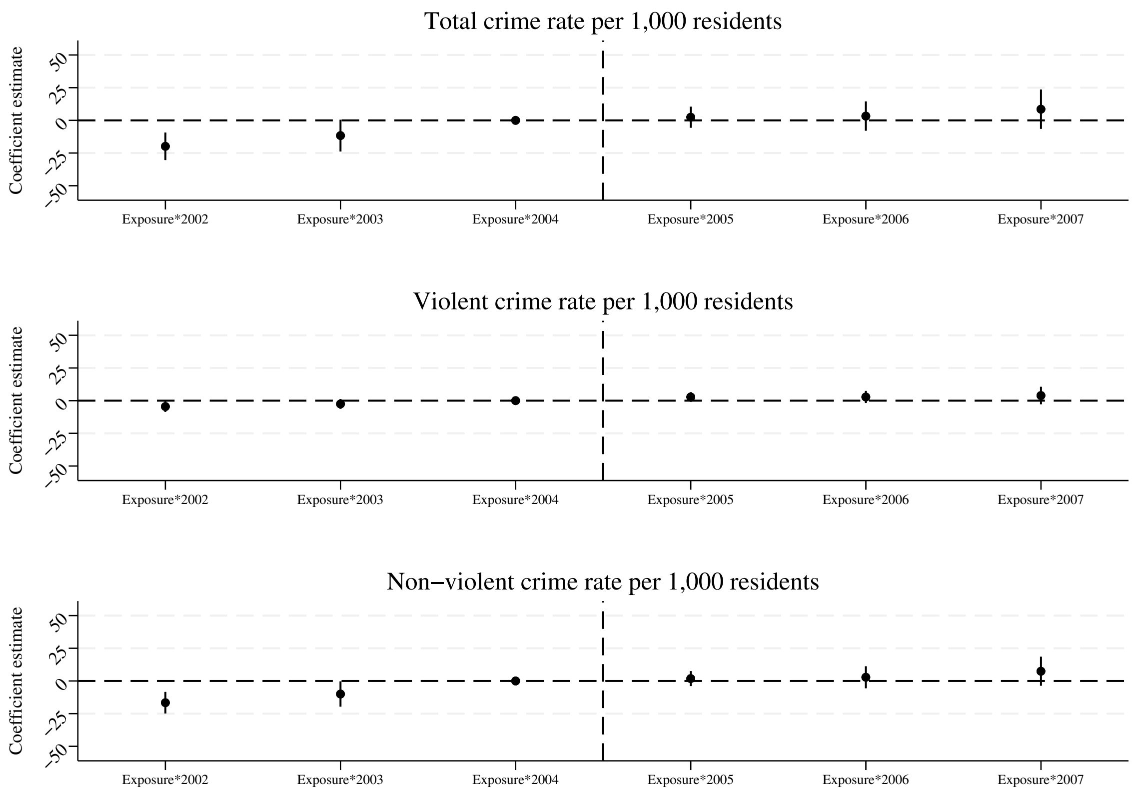
Notes: This figure plots coefficient estimates a difference−in−differences regression of crime rates on an interaction of exposure to the TennCare disenrollment and the post−period. The regression includes agency fixed−effect and urbanicity−by−year fixed−effects unless otherwise noted. The unit of observation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

Figure A12: Effect of the TennCare disenrollment on crime rates leaving one county out of the analysis sample at time: Uniform Crime Reports 2002−2007



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

Figure A13: Effect of the Missouri Medicaid contraction on crime rates using an event−study: Uniform Crime Reports 2002−2007



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

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

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

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

Table A2: Effect of the TennCare disenrollment on crime rates (no time−varying controls): Uniform Crime Reports 2002−-2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure × post	32.58***	3.19	31.56***
	(11.60)	(6.58)	(9.29)
β scaled to median county	6.19	0.61	6.00
Percent change (scaled β)	9.67	2.50	15.09
Median exposure	0.19	0.19	0.19
Pre−treatment mean	64.02	24.42	39.76
Observations	2682	2682	2682

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on exposure to the TennCare disenrollment and an indicator for the post−period. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is an agency in a county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 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.
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

Table A3: Effect of the TennCare disenrollment on specific crime rates: Uniform Crime Reports 2002−2007

	Panel A: Violent crime			
Outcome:	Murder	Rape	Robbery	Agg. Assault
Exposure × post	-0.06	-0.17	-0.20	2.61
	(0.04)	(0.11)	(0.22)	(6.83)
β scaled to median county	-0.01	-0.03	-0.04	0.50
Percent change (scaled β)	-25.00	-9.68	-7.27	2.13
Median exposure	0.19	0.19	0.19	0.19
Pre−treatment mean, high exposure counties	0.04	0.31	0.55	23.42
Observations	2682	2682	2682	2682
	Panel B: Non-violent crime			
Outcome:	Burglary	Theft	MV theft	Arson
Exposure × post	0.19	26.06***	0.52	-0.13
	(2.93)	(7.87)	(0.83)	(0.19)
β scaled to median county	0.04	4.95	0.10	-0.02
Percent change (scaled β)	0.43	19.00	3.46	-8.70
Median exposure	0.19	0.19	0.19	0.19
Pre−treatment mean, high exposure counties	9.30	26.05	2.89	0.23
Observations	2682	2682	2682	2682

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on exposure to the TennCare disenrollment and an indicator for the post−period. Agg. = aggravated. MV = motor vehicle. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is an agency in county in a year. Data are weighted by the population served by the agency. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 Medicaid coverage rate). Regressions estimated with OLS. Standard errors are clustered around the county and reported in parentheses.
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

Table A4: Effect of TennCare disenrollment on the cost of crime rates: Uniform Crime Reports 2002−2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure × post	-488.00	-497.81	13.71
	(429.25)	(421.13)	(8.98)
β scaled to median county	-92.72	-94.58	2.60
Percent change (scaled β)	-6.82	-7.23	5.24
Median exposure	0.19	0.19	0.19
Pre−treatment mean, high exposure counties	1359.79	1308.56	49.58
Observations	2682	2682	2682

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on exposure to the TennCare disenrollment and an indicator for the post−period. The regression includes time−varying county demographics, agency fixed−effects, and urbanicity−by−year fixed-effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Tennessee pre−disenrollment (median exposure = 0.19 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.
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

Table A5: Effect of the TennCare disenrollment on crime rates comparing Tennessee to other Southern and all other states: Uniform Crime Reports 2002−2007

	Panel A: Comparing Tennessee to other Southern states		
Outcome:	Total crime	Violent crime	Non−violent crime
Tennessee × post	1.76**	0.75	1.01**
	(0.78)	(0.58)	(0.44)
Observations	23610	23610	23610
Pre−treatment mean, TN	59.213	22.785	36.428
Bootstrap p−value	0.025	0.199	0.019
	Panel B: Comparing Tennessee to all other states		
Outcome:	Total crime	Violent crime	Non−violent crime
Tennessee × post	2.21***	0.99*	1.23***
	(0.71)	(0.56)	(0.40)
Observations	74472	74478	74478
Pre−treatment mean, TN	59.213	22.785	36.428
Bootstrap p−value	0.002	0.075	0.001

Notes: Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on an interaction between the state of Tennessee and an indicator for the post−period. The regression includes time−varying characteristics, agency fixed−effects, and urbanicity−by−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. Standard errors reported in parentheses are clustered around the county and calculated using a paired (nonparametric) bootstrapping procedure. Reported p-values are calculated using the wild bootstrap to account for small number of state clusters (Roodman et al., 2019).
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.

Table A6: Effect of the Missouri Medicaid contraction on crime rates: Uniform Crime Reports 2002−2007

Outcome:	Total crime	Violent crime	Non−violent crime
Exposure × post	10.92**	4.60*	9.19**
	(5.42)	(2.51)	(3.99)
β scaled to median county	1.97	0.83	1.65
Percent change (scaled β)	3.95	5.44	4.74
Median exposure	0.18	0.18	0.18
Pre−treatment mean, high exposure counties	49.82	15.26	34.82
Observations	3258	3258	3258

Notes: This table reports coefficient estimates from a difference−in−differences regression of crime rates on exposure to the Missouri Medicaid contraction and an indicator for the post−period. The regression includes time−varying county−level covariates, agency fixed−effects, and urbanicity−by−year fixed−effects. The unit of observation is an agency in county in a year. The scaled β reports the predicted effect size for the median Medicaid−exposed county in Missouri pre−disenrollment (median exposure = 0.18 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.
***, **, and * = statistically different from zero at the 1%, 5%, and 10% level, respectively.