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LOCAL ACCESS TO MENTAL HEALTHCARE AND CRIME

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ABSTRACT

We estimate the effect of local access to office-based mental healthcare on crime. We leverage variation in the number of mental healthcare offices within a county over the period 1999 to 2014 in a two-way fixed-effects model. We find that increases in the number of mental healthcare offices modestly reduce crime. In particular, ten additional offices in a county reduces crime by 1.7 crimes per 10,000 residents. These findings suggest an unintended benefit from expanding the office-based mental healthcare workforce: reductions in crime.

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1 Introduction

As part of the 1960s and 1970s de-institutionalization movement in the United States, state psychiatric hospitals closed and, among remaining hospitals, censuses declined (Lamb & Bachrach, 2001). The reduction in the number of Americans receiving treatment in psychiatric hospitals is staggering: 339 per 100,000 in 1955 and 22 per 100,000 by 2000 or a 94% decline (Lamb & Weinberger, 2005). Healthcare scholars suggest that public support for more humane treatment of the mentally ill, advancements in pharmacology (in particular, the anti-psychotic medication chlorpromazine [brand name Thorazine]; earlier treatment often relied on lobotomy and electroshock therapy), the high cost to government associated with financing long-term psychiatric hospitalization for large numbers of Americans, and changes in social welfare programs (e.g., Medicaid) were important drivers of de-institutionalization (Lamb & Bachrach, 2001; Yohanna, 2013). Hospital closures and reduced censuses lead to many mentally ill patients being displaced into the community.

As a result of de-institutionalization, concerns that individuals with mental illness were at elevated risk for crime, and therefore presented a danger to society, grew (Frank & McGuire, 2010). While advocates contended that those with mental illness did not pose an elevated crime threat, the limited data available at the time did not allow empirical testing of this hypothesis and public concerns remained. These concerns diminished as crime rates declined in the 1990s (Levitt, 2004). Recent violent attacks, particularly mass shootings, have been linked, at least anecdotally, to mental illness.[1] These events have revitalized public discussion of mental healthcare as a potential crime reduction tool.

While many modalities of mental healthcare improve patient outcomes (American Psychiatric Association, 2006; National Alliance on Mental Ilness, 2020; National Institute of Mental Health, 2020), there may be broader social benefits, including crime control. If mental healthcare has additional benefits, enhanced investment in such treatment by government may be warranted. Indeed, clinical studies document a robust correlation between mental illness and crime (Swanson et al., 2001; Frank & McGuire, 2010). For example, 50% of those incarcerated in jails and prisons have a mental illness (James & Glaze, 2006). Further, the number of mentally ill individuals housed in large U.S. incarceration facilities, such as the Los Angeles County Jail, Cook County Jail, and Rikers Island, exceeds the number of

[1] Please see the following news stories: https://www.vox.com/2019/8/5/20754770/trump-el-paso-dayton-speech-white-house-mental-illness-video-games-guns; https://www.syracuse.com/crime/2020/05/judge-orders-mental-evaluation-for-suspect-in-syracuse-train-station-shooting.html; and https://www.psychiatrictimes.com/article/mass-shooter-and-his-mental-functioning. All websites last accessed on July 18th, 2020.

individuals in any psychiatric institution in the country (Frank & McGuire, 2010). These correlations offer *prima facie* evidence that mental illness contributes to crime.

Criminal justice mental healthcare policies in the U.S. are mainly restricted to involuntary treatment. For instance, the criminal justice system has made use of involuntary commitment laws, which afford discretion to judges to mandate that convicted offenders receive mental healthcare. Such laws appear to be effective (Kisely, Campbell, & O'Reilly, 2017; Swartz, Bhattacharya, Robertson, & Swanson, 2017). Given that these laws focus on individuals required by the criminal justice system to enter treatment, rather than patients voluntarily seeking treatment, mental healthcare may be underutilized as a crime reduction policy.

While mental healthcare is valuable, there are shortages of providers. As recently as 2018, only 26% of the U.S. population's mental healthcare needs were met (Kaiser Family Foundation, 2018) and, in a given year, more than 50% of individuals meeting diagnostic criteria for mental illness do not receive any related treatment (Center for Behavioral Health Statistics and Quality, 2019). A commonly cited barrier to accessing mental healthcare treatment is inability to locate a provider (Center for Behavioral Health Statistics and Quality, 2019). Given this backdrop, expanding access to mental healthcare, by increasing the number of providers offering these services, may allow patients to receive care, manage their illness and associated symptoms, and, in turn, reduce crime.

This study is the first to explore the effect of access to office-based mental healthcare on crime. We hypothesize the following chain of events. Offices open and more patients take treatment, leading to improved mental health. Better mental health reduces crime through the likelihood of committing crime (e.g., better assessment of costs and benefits of one's actions, improved labor market opportunities, less need for substances) and the likelihood of victimization (e.g., less likely to be viewed as an easy target or to be homeless).

We estimate two-way fixed-effects models using county-level crime rates provided by the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting (UCR) program to construct measures of crime and the U.S. Census Bureau's County Business Patterns (CBP) 1999-2014. We identify spillover effects of mental healthcare to crime by exploiting variation in the county-level number of office-based mental healthcare providers. Our findings are in line with our hypothesized chain of effects. We find that ten additional offices in a county reduces crime by 1.7 crimes per 10,000 residents or 0.4%. We show that additional offices increase treatment-seeking and improve mental health.

This paper proceeds as follows. Section 2 reviews the related literature and provides a conceptual framework. Section 3 outlines our data and methods. Results are reported in section 4. Sensitivity analyses are reported in Section 5. Section 6 concludes.

2 Background, literature, and conceptual framework

2.1 Background

The epidemiology of many mental illnesses provides plausible mechanisms through which these conditions can affect crime. While discussing the specifics of each mental illness is beyond the scope of our study, we review several illnesses commonly treated in the office-based settings that we examine in our analysis (Stamm, Lin, & Christidis, 2018; National Alliance on Mental Ilness, 2020; National Institute of Mental Health, 2020) and their symptoms to offer intuition on the mental illness-crime link.

Mental illness is common: nearly 20% of the U.S. population meets diagnostic criteria for a mental illness (Center for Behavioral Health Statistics and Quality, 2019). Symptoms of psychotic disorders – a class of serious mental illnesses (e.g., schizophrenia) in which the affected individual has sensory experiences of things that do not exist and/or beliefs with no basis in reality – are hallucinations, delusions, and disordered thinking. Bipolar disorder causes oscillations in mood from emotional highs (mania) to lows (depression). Symptoms experienced during a mania phase include aggression and agitation, an exaggerated sense of self-confidence, poor decision-making, racing thoughts, and risk-taking behaviors. Antisocial personality disorder is characterized by aggressive and violent behavior, disregard for the safety and well-being of others, inability to feel empathy, and lack of remorse. Individuals with narcissistic personality disorder are arrogant, are unable to recognize the needs and feelings of others, believe that they are special and more important than others, and frequently take advantage of others. Those with paranoid personality disorder have relentless suspicion of people without reason and continuously feel that other people are 'out to get them.' These feelings lead to anger and acts of retaliation, hostility, hypersensitivity to criticism, and suspicion. These condition symptoms could contribute to crime through distorted assessments of situations and/or of costs and benefits of actions.

Even mental illnesses that are, anecdotally, less likely to be linked with crime can have criminogenic symptoms. For example, anxiety and depression are associated with aggression, delusions, disruptive behaviors, feeling helpless and worthless, incessant concern for personal safety and well-being without any evidence to support such unease, and irritation, all of which could potentially increase the propensity to commit crime.

Many mental illness impose side effects such as decision-making difficulties, headaches, fatigue, insomnia, memory loss, nausea and gastrointestinal difficulties, physical pain, and a sense of hopelessness and worthlessness that could reduce employment opportunities (Chatterji, Alegria, Lu, & Takeuchi, 2007; Chatterji, Alegria, & Takeuchi, 2011; Frijters, Johnston, & Shields, 2014; Banerjee, Chatterji, & Lahiri, 2017). The incentive to commit financially-motivated crimes may increase when legal employment options decline.

Mental illness may also raise the likelihood of developing a substance use disorder (SUD) as some individuals use alcohol and drugs to self-medicate their illness (Drake & Wallach, 1989; Levy & Deykin, 1989; Kilpatrick et al., 2003; Elliott, Huizinga, & Menard, 2012). An SUD can lead to crime through distorted decision-making, interacting with criminals when purchasing illicit drugs, and/or a need to secure funds to procure substances (Wen, Hockenberry, & Cummings, 2017; Bondurant, Lindo, & Swensen, 2018).

In addition to increasing the propensity to commit crime, many mental illnesses could also affect the probability of being victimized as the mentally ill may be viewed as 'easy' targets. Individuals with mental illness experience higher rates of victimization than the general population (Teplin, McClelland, Abram, & Weiner, 2005; Maniglio, 2009), plausibly because their symptoms leave them vulnerable. For instance, aggressive and disordered behavior may draw the attention of offenders (e.g., offenders may view aggressive behavior as a threat which requires retaliation). Those with mental illness are substantially more likely to be homeless than the general population (Fazel, Khosla, Doll, & Geddes, 2008), which plausibly increases opportunities for victimization.

Overall, the epidemiology of mental illness suggests a correlation between these health conditions and a range of crime-related outcomes. The extent to which these correlations reflect a causal relationship is unclear. Mental illness and crime are likely driven by factors such as abuse, genetic pre-disposition, neglect, poverty, and trauma. These factors are rarely measured in datasets, preventing adequate adjustment for differences in regression models.

Office-based care, the modality we consider, includes a range of services that may reduce crime through improved mental health. We note that many mental illnesses cannot be cured and are better contextualized as a chronic condition that is managed, similar to diabetes. For example, most major mental illnesses can be treated with medications (e.g., Aripiprazole [brand name Abilify] for schizophreniaia and sertraline [brand name Zoloft] for depression) and/or through counseling services (e.g., cognitive behavioral therapy for anxiety and depression, talk therapy or psychotherapy for narcissistic personality disorder; indeed the predominant treatment for many personality disorders is talk therapy). We acknowledge that for many patients office-based care may not be appropriate and optimal care may vary across the lifecycle of the illness (e.g., periods in which more intensive care, for example a hospitalization, is required). Instead, we simply state that, at various points in the lifecycle of the condition, many mental illnesses can be treated in the office-based settings that we consider in our study.

2.2 Literature

Four quasi-experimental studies have examined the causal effect of mental healthcare on crime. Cuellar and Markowitz (2007) document that increased Medicaid spending by states on psychotropic prescriptions for stimulants and depression led to a reduction in violent crimes during the 1990s and 2000s. Marcotte and Markowitz (2011) show that the increased prescribing of psychotropics that occurred over the 1990s and 2000s decreased crime rates. Harcourt (2011) documents that institutionalization rates, in a prison or psychiatric hospital, lowered violent crime over the period 1934 to 2001. Finally, Landersø and Fallesen (2016) show very short-run declines in crime following a psychiatric hospitalization using administrative data from Denmark. The authors hypothesize that they capture mechanical incapacitation effects rather than a true reduction in crime.

While not focusing on mental healthcare *per se*, two recent studies show that increases in access to SUD treatment reduce crime (Wen et al., 2017; Bondurant et al., 2018). Given substantial co-morbidity across mental illness and SUD (Center for Behavioral Health Statistics and Quality, 2019), these findings are plausibly informative to our study as they suggest that expanding access to treatment reduces crime.

Our study contributes to this small literature by examining whether changes in access to office-based mental healthcare providers lead to changes in crime rates. Further, we consider a recent time period in the U.S. and use the universe of office-based mental healthcare providers, a modality of care that is becoming increasingly common.

2.3 Conceptual framework

We build a framework in which we can think through the relationship between access to office-based mental healthcare and crime. To do so, we leverage intuition offered by previous economic and sociological models of crime (Becker, 1968; Goldstein, 1985; Wen et al., 2017).

A crime that occurs in county j and in time t ($Crime_{i,k,j,t}$) that is committed by offender i against victim k is a function of mental illness symptoms experienced by the offender i ($Mental\ illness_{i,j,t}$) and the victim k in county j in time t ($Mental\ illness_{k,j,t}$). Crime rates are also influenced by other factors that affect offending and victimization propensities, $X_{1i,j,t}$ and $X_{1k,j,t}$. Finally, there are observed and unobserved factors that enhance or limit opportunities for crime that impact offenders and victims such as police presence and citizen actions in county j and time t: $P_{j,t}$. We can combine these factors in a crime rate production function outlined in Equation 1:

$$Crime_{i,k,j,t} = f(Mental\ illness_{i,j,t}, Mental\ illness_{k,j,t}, X_{1i,j,t}, X_{1k,j,t}, P_{j,t}) \quad (1)$$

We estimate the reduced form relationship between access to mental healthcare proxied by the offices of physicians and non-physicians specializing in mental healthcare in a county ('MH') and crime. We rewrite mental illness symptoms as a function of office-based mental healthcare providers in county j and in time *t-1* ($MH_{j,t-1}$), which affect mental illness symptoms of the potential offender i and victim k. Finally, $X_{2i,j,t}$ and $X_{2k,j,t}$ are factors that affect mental illness and associated symptoms of the potential offender and victim.

We can write the reduced form potential offending and victimization equations as follows:

$$Mental\ illness_{i,j,t} = g(MH_{j,t-1}, X_{2i,j,t}) \quad (2)$$

$$Mental\ illness_{k,j,t} = h(MH_{j,t-1}, X_{2k,j,t}) \quad (3)$$

After substituting Equations 2 and 3 into Equation 1, we have the reduced form equation for crime rates in county j and time t:

$$Crime_{i,k,j,t} = k(MH_{j,t-1}, X_{1i,j,t}, X_{1k,j,t}, X_{2i,j,t}, X_{2k,j,t}, P_{j,t}) \quad (4)$$

We assume that $X_{1i,j,t} = X_{1k,j,t} = X_{j,t}$ and that $X_{2i,j,t} = X_{2k,j,t} = X_{j,t}$. This simplification leads to the following crime production function in county j and time t:

$$Crime_{j,t} = l(MH_{j,t-1}, X_{j,t}, P_{j,t}) \quad (5)$$

Based on the established effectiveness of mental healthcare in treating mental illness, we hypothesize that, *ceteris paribus*, more office-based mental healthcare providers in a county will increase a prospective patient's access to treatment which will increase treatment uptake. Correspondingly, mental illness and associated symptoms will improve through the increased treatment receipt and, in turn, crime outcomes will fall. Thus, we expect to observe: $\partial Crime_{j,t}/\partial MH_{j,t-1} < 0$.

While there are other determinants of access to mental health treatment besides the number of offices in the local area (e.g., ability to pay, cognitive and social difficulties among those with mental illness, perceived stigma associated with mental illness and related treatment, transportation issues), the ability to find a provider within the local market is plausibly an important predictor of access.

We also acknowledge that there are other channels through which mental illness may influence crime. For example, individual-level variables that enter $X_{1i,j,t}$ and $X_{1k,j,t}$ such as the education or general health. As a particular example, if mental illness affects education quantity or quality (Solomon, 2018), this change can reduce employment opportunities through reduced marginal product and earned wage, leading to an increased propensity to commit crime. As another example, which may operate in the opposite direction, victims of crime may be less vulnerable to crime or (in the case of domestic violence) may be more likely to report the incident or leave the relationship as treatment options expand.[2]

Our empirical models will capture the overall effect of mental healthcare providers on county crime rates. We will not be able to isolate the relative importance of mental healthcare providers for offending and victimization. While these relationships are clearly important, we view our study as the first step in understanding the practical importance of local access to office-based mental healthcare providers as a tool to reduce crime rates.

3 Data and methods

3.1 Uniform Crime Reports

We use the UCR over the period 1999 to 2014. The UCR is compiled by the FBI to track criminal offenses known to police in the U.S. While we use the term 'crime' for brevity, we note that we capture crimes that are known to police officers which are a subset of all crimes. We use the County-Level Detailed Arrest and Offense Data (UCRC) prepared by the Inter-University Consortium for Political and Social Research.

The UCRC imputes missing data and includes a 'coverage' indicator to diagnose the amount of imputed data. We include observations with no more than 50% imputation

[2]We note the possibility that some offenders may be required to receive mental healthcare, including the modalities we study, as part of a sentence. Further, there is recent evidence that crime within the local area can impact mental health (Dustmann & Fasani, 2016). This pathway may suggest reverse causality: changes in crime influence mental health. We explore this possibility through the use of a distributed lag model and an event study later in the manuscript.

(Freedman & Owens, 2011), thereby excluding 2,962 observations (6% of the sample). We convert crime counts to the rate per 10,000 residents using population covered by the UCRC.

We examine changes in Part one crimes recorded in the UCRC: murder, manslaughter, rape, aggravated assault, robbery, burglary, larceny, and motor vehicle theft. We combine murder and manslaughter into one group and refer to the combined group as 'murder.' We construct aggregate measures of total, total violent (murder, rape, aggravated assault, and robbery), and total nonviolent (burglary, larceny, and motor vehicle theft) crimes. We focus on Part one crimes as they are most likely to be reported.[3]

3.2 Office-based mental healthcare providers

We use the number of establishments of physicians and non-physicians specializing in mental healthcare in each county to proxy local access to office-based care drawn from the U.S. Census Bureau's County Business Patterns (CBP) data. An establishment is: 'A single physical location where business is conducted or where services or industrial operations are performed.' In our study, an establishment is an office in which one or more physicians or non-physicians deliver mental healthcare. We refer to establishments as 'offices.'

CBP data include the near universe of establishments in the U.S. each year during the week of March 12th. These data have been utilized to study the effect of SUD treatment access on crime in recent economic studies (Swensen, 2015; Bondurant et al., 2018). We select establishments in the CBP with the following North American Industry Classification System codes to form a count of physician and non-physician offices in each county: 621112 (offices of physicians, mental health specialists) and 621330 (offices of mental health practitioners except physicians). Prior to 1998, the CBP did not include sufficiently fine information to allow identification of mental healthcare providers. We lag offices one year (Swensen, 2015; Bondurant et al., 2018). This lag structure allows time for an office to open, patients to access care, and mental illness and associated symptoms (including crime) to improve. Hence, we begin the study period in 1999. We have 45,577 county-year pairs.

A patient seeking mental healthcare has a wide range of options from which to choose. We focus on one modality: office-based care. Other options include community mental health centers, hospitals, specialized outpatient facilities, and residential facilities. Office-based care for mental healthcare captures evaluation of the patient and associated health conditions,

[3] We are not stating that this focus fully eliminates under-reporting as we recognize that surveys of victims, for example the National Victimization Survey, reports that victims – in a survey setting – appear to under report crimes compared to other sources.

which includes treatment with behavioral interventions, counseling services, and prescription medications. We note that many mental illnesses – including anxiety and depression, and arguably more criminogenic illnesses such as anti-social personality, bipolar, paranoid, and psychotic disorders – can be treated in office-based settings (Stamm et al., 2018; National Alliance on Mental Ilness, 2020; National Institute of Mental Health, 2020).

There are several reasons why office-based care may be a particularly relevant, yet understudied, tool to mitigate crime. First, office-based providers play an increasingly important role in delivering mental healthcare. While in 1986 office-based care accounted for 24% of total mental healthcare expenditures, by 2014 this share had risen to 44%, an increase of 83% (Substance Abuse and Mental Health Services Administration, 2016). Second, many patients prefer to receive mental healthcare in general settings that we study rather than in specialized treatment facilities or psychiatric hospitals, thus office-based care may be more acceptable to patients which may improve treatment adherence. Third, office-based care has a relatively low variable cost. For example, a group counseling session with a physician costs $9.84 per patient while a day in a psychiatric hospital costs $999 (McCollister et al., 2017). Finally, from an empirical perspective, by examining office-based providers we are less concerned with confounding from incarceration effects, that is, when a patient is 'incarcerated' in residential or hospitalization treatment, crime is mechanically reduced.

The average treatment effect that we estimate in our empirical models is local to the type of patient who seeks treatment when an office-based mental healthcare provider opens in their county but not otherwise, and is likely to benefit, in terms of improved mental illness and reduced crime, from this access and the ensuing treatment use. We hypothesize that the 'compliers' are patients with relatively well-managed mental illness, to the extent that their health can be effectively treated in an office-based setting at some points in the lifecyle of the condition. We note that compliers may include individuals who take up new treatment when an office opens and/or individuals already receiving treatment but for whom the new office allows a better patient-provider match or simply better access (e.g., longer visits, shorter waiting times and/or travel times). These are the patients from whom our estimates are likely generated. The hypothesized complier foreshadows our modest effect sizes.

3.3 Empirical model

We estimate the following two-way fixed-effects regression model:

$$Crime_{i,s,t} = \beta_0 + \beta_1 MH_{i,s,t-1} + H_{i,s,t}\beta_2 + \lambda_i + \gamma_{s,t} + \mu_{i,s,t} \tag{6}$$

$Crime_{i,s,t}$ is a crime rate for county i in state s in year t. $MH_{i,s,t-1}$ is the number of office-based mental healthcare providers in the county lagged one year. $H_{i,s,t}$ is a vector of county-level characteristics (income, poverty rate, unemployment rate, and demographics). λ_i is a vector of county fixed-effects and $\gamma_{s,t}$ is a vector of state-by-year fixed-effects.[4] $\mu_{i,s,t}$ is the error term. We estimate least squares and cluster the standard errors around the county, and weight by the county population covered by the UCRC. We use variation in the number of mental healthcare provider offices to identify treatment effects. This variation is driven by the opening and closing of mental healthcare provider offices within a county.

Of note, controlling for demographics at the county-level allows us to account for potential compositional shifts that occur over time within a county that may lead to differential crime rates and access to office-based mental healthcare. County fixed-effects account for time-invariant characteristics of counties that may be correlated with both crime and access to office-based mental healthcare. The inclusion of state-by-year fixed-effects will account for state-specific shocks such as government-mandated changes in insurance coverage (public and private coverage for mental healthcare services is generally regulated at the state-level, for example, Medicaid expansions or adoption of laws that compel private insurers to cover mental healthcare treatment) and/or police expenditures. Similarly, the state-by-year fixed-effects will account for national-level changes in insurance coverage for mental healthcare services (for example, the Mental Health and Addiction Parity Act of 2010 and the Affordable Care Act [ACA], together these two Acts required most private insurance plans to cover mental healthcare service as of 2014), and economic, medical, or social factors that influence the national as a whole (e.g., new medications used to treat mental illness, stigma towards mental illness and associated treatment).

We chose to measure mental healthcare at the county level, rather than some other level of aggregation, for two reasons. First, we wish to facilitate comparison with previous, related studies that use the CBP to study the effect of access to healthcare on health and crime outcomes (Swensen, 2015; Bondurant et al., 2018). Second, the county arguably captures the geographic area in which individuals seek treatment and that is the relevant area for our study. For example, the zip-code is too small as most zip-codes do not have any office-based mental healthcare providers: only 20% have such a provider (authors' analysis of the CBP zip-code level data). More granular data is useful for other questions, for example, estimating the impact of healthcare providers on property values (Horn, Joshi, & Maclean, 2019). Alternatively, the state is arguably too large a market, for example, a resident in

[4] $\gamma_{s,t}$ subsumes year fixed-effects.

Amarillo Texas is unlikely to travel to Houston Texas for office-based mental healthcare. Indeed, most patients travel less than ten miles to seek mental healthcare (Schmitt, Phibbs, & Piette, 2003; Lindrooth, Lo Sasso, & Lurie, 2006; Rosenblum et al., 2011) which suggests that our use of the county is reasonable.

3.4 Identification

The identifying assumption of Equation 6 is outlined in Equation 7:

$$Cov(MH_{i,s,t-1}, \mu_{i,s,t} | H_{i,s,t}, \lambda_i, \gamma_{s,t}) = 0 \tag{7}$$

Put differently, the number of office-based mental healthcare providers per county is uncorrelated with the error term in Equation 6 after conditioning on county-level time-varying characteristics, county fixed-effects, and state-by-year fixed-effects. There are several threats to the validity of our empirical strategy which we next discuss and then investigate empirically in Section 4.4.

An important threat to the validity to our research design is reverse causality. Put differently, changes in crime may lead to changes in the number of office-based mental healthcare providers through demand-side effects. We do not suspect that mental healthcare providers observe changes in crime and then elect to open/close their offices. However, crime could indirectly prompt individuals to seek care through the actions of employers, family, or friends; the criminal justice system; and so forth, which, in turn, could increase demand for office-based services. We note that lagging our measure of mental healthcare access by one year partially addresses this concern. We formally explore reverse causality by estimating a distributed lag model following Swensen (2015) and Bondurant et al. (2018), and a local event study in the spirit of Cengiz, Dube, Lindner, and Zipperer (2019).

A second threat to the validity of our study is that changes in the number of office-based mental healthcare providers and changes in crime could both respond to a third unobserved (to the econometrician) factor. Of note, time-invariant unobservable factors will be captured by our county-level fixed-effects. An example of a time-varying unobserved factor could be public funds that increase policing (which could affect crime) and the generosity of public insurance (which could increase demand for mental healthcare providers' services). To the extent that these factors predominantly vary at the state-level, the state-by-year fixed-effects plausibly address this concern. Changes in the number of office-based mental healthcare providers and changes in crime could both respond to a third observable county-level confounder. For example, a positive shock in local economic conditions (which is not accounted for by our time-varying county-level controls), which could decrease incentives for financially motivated crimes while simultaneously increasing or decreasing demand for office-based mental healthcare providers. We explore the importance of observable confounders in two ways. (i) We regress the number of office-based mental healthcare providers on controls included in Equation 6 in order to assess balance across the 'treatment' and 'comparison' groups (Pei, Pischke, & Schwandt, 2018), or put differently we test the conditional independence assumption (CIA).[5] (ii) We report how the coefficient estimate on the office-based mental healthcare provider variable changes as, starting from a parsimonious baseline model that only controls for area and time fixed-effects, we progressively include covariates in Equation 6 (Altonji, Elder, & Taber, 2005).

Finally, a third threat to the validity of our study is that openings and closing of office-based mental healthcare providers may induce some residents to move to/away from a county. This behavior is a form of program-induced migration that can lead to bias in regression coefficient estimates (Moffitt, 1992).

4 Results

4.1 Characteristics of patients receiving office-based mental healthcare

Before proceeding to the main analysis, we first examine the characteristics of individuals who receive office-based mental healthcare. To do so, we draw data from the public use 2014 National Survey on Drug Use and Health (NSDUH). We select respondents ages 18 years and older who report receiving any mental healthcare in the office of a physician or therapist in the past year.[6] Table 1 reports demographics for the NSDUH sample (Panel A). For comparison, we also report characteristics of the sample that did not report receiving any mental healthcare (office-based or other modalities) in the past year. The two groups of respondents are broadly similar across age, insurance status, poverty, and education. However, there are non-trivial differences across sex, race/ethnicity, education, and labor

[5] All counties are to some extent treated, thus we are testing for balance across counties with greater (and lesser) treatment intensity.

[6] Some patients receive treatment in multiple settings, for example a patient can receive treatment in an office-based setting and an inpatient setting in the past year. We do not exclude those respondents who report receiving treatment in multiple settings.

market participation. In particular, those who report office-based mental healthcare in the past year, relative to those who report no mental healthcare over this time horizon, are more likely to be female (68% vs 49%), white (80% vs. 63%), and to hold a college degree or higher (48% vs. 30%), and are less likely to report working in the past week (60% vs. 67%).

An informative concept for our study is how office-based mental healthcare is financed. Overall mental healthcare (i.e., office-based care and other modalities)[7] in the U.S. is less reliant on insurance payments than general healthcare. For example, Mark et al. (2016) show that in 2014 while 73% of general healthcare was financed through some form of insurance, this share was 65% for mental healthcare. There is heterogeneity in financing sources across different mental healthcare modalities. For example, the type of care that we study (office-based care) is financed differently than community mental health centers, psychiatric hospitals, or residential facilities; these modalities rely substantially on government grants and contracts, and public insurance. Office-based care is more likely to be financed by private health insurance or patients themselves. For example, psychiatrists are less likely than any other specialty to accept Medicaid (Wen, Wilk, Druss, & Cummings, 2019).

Table 1 Panel B reports how patients in the NSDUH report paying for office-based mental healthcare. These categories are not mutually exclusive and patients can use more than one source for payment. We show the most common means of paying for office-based mental healthcare are self-pay (47%) and private insurance (48%). Public insurance plays a smaller role in financing office-based care than overall mental healthcare treatment. In our sample, 13% and 7% report using Medicare and Medicaid respectively. Mark et al. (2016) show that in 2014 Medicare and Medicaid accounted for 15% and 25% of overall mental healthcare treatment spending. Only 4% of NSDUH respondents report receiving office-based mental healthcare for free while as much as 14% of total mental healthcare is provided without cost to patients (Mark et al., 2016).

As noted earlier in the manuscript, many of the policies that impact insurance coverage of mental healthcare treatment (public or private) vary at the state (e.g., requirements that private insurers or Medicaid cover mental healthcare benefits) or federal (e.g., Medicare, the Federal Employees Health Benefits Program, and the Mental Health Parity Act) level and are captured by our state-by-year fixed-effects. Thus, the within-county variation that we leverage in our empirical models is net of these factors and likely captures local characteristics, which we explore empirically in Section 4.4.2.

[7] We exclude informal care such as self-help as financing for this type of care is not available in government sources.

4.2 Summary statistics and crime trends

Summary statistics are reported in Table 2. The total crime rate per county is 360.0 per 10,000 residents; with 44.1 violent crimes and 315.9 nonviolent crimes per 10,000 residents. In terms of specific violent crimes, the rates per 10,000 residents are 0.52 murders, 2.95 rapes, 27.4 aggravated assaults, and 13.2 robberies. The rates per 10,000 residents for nonviolent crimes are: 69.4 burglaries, 213.4 larcenies, and 33.1 motor vehicle thefts. Figure 1 reports trends in crime rates over our study period in total, violent, and nonviolent crime rates. All three crime rates are declining modestly over our study period which is in line with previously established trends in these outcomes.

On average there are 122.0 mental healthcare provider offices per county, with 67.4 physician and 54.7 non-physician offices. The average year-to-year increase in offices that we observe in our data is nine, thus for ease of interpretation we discuss regression coefficient estimates scaled by ten. This increase reflects an approximately 8% change in the number of offices relative to the sample mean.

4.3 Baseline two-way fixed effects results

Table 3 reports selected regression results for the effect of county-level changes in the number of office-based mental healthcare providers on aggregate crime rates: total, violent, and nonviolent. Ten additional mental healthcare providers in the county reduces the total crime rate by 1.7 crimes per 10,000 residents or 0.5% (comparing the coefficient estimate with the sample mean, all relative effects are calculated in this manner). Violent and nonviolent crime rates decline following the opening of an office-based provider: ten additional offices in a county leads to 0.9 fewer violent crimes per 10,000 residents (2.0%) and 0.8 fewer nonviolent crimes per 10,000 residents (0.2%). The relative effect sizes are larger for violent crimes than nonviolent crimes as the baseline means are different: 44.1 violent crimes vs. 315.9 nonviolent crimes per 10,000 residents.

4.4 Identification testing

We examine several threats to the validity. We focus on total crime rates.

4.4.1 Parallel trends

We first explore the ability of our data to satisfy parallel trends. An obvious concern is that our findings reflect reverse causality: changes in mental illness lead to changes in the number of offices. Such reverse causality, if present, could lead to a violation of parallel trends. We note that we focus on crime and do not expect that increases in crime will influence the number of offices in a county directly. Further, we lag offices by one year, which should mitigate reverse causality concerns. However, we test parallel trends in two ways.

First, we estimate an augmented version of Equation 6 that includes two leads in the number of mental healthcare offices, the contemporaneous number of offices, and two lags in the number of offices, i.e., a distributed lag model (Swensen, 2015; Bondurant et al., 2018). Results indicate that crime rates are unaffected by future levels of office-based mental healthcare and only the one year lag is statistically distinguishable from zero, which provides suggestive evidence that the findings are not affected by reverse causality (Table 4).

Second, following Cengiz et al. (2019), who study a continuous treatment variable – the minimum wage – as we do, and estimate a 'local' event study. We locate a set of 'local' events which are defined as an increase in the number of offices in a county. We define local events as occurring in counties that experience such a change, and that (i) do not experience any change in the number of offices three years prior to the event and (ii) do not experience a change in the number of offices for three years after the event. We then select 'comparison' counties that do not experience any change in offices for this seven year 'event window.'[8] Results show no evidence of differential pre-trends (Figure 2).

4.4.2 Unobserved heterogeneity

While the state by year fixed effects addresses state-level confounders that could affect crime and the number of offices (e.g., resident preferences), we next probe the extent to which both changes in the number of offices and crime respond to a third county level confounder. We assess whether the number of office-based mental healthcare providers are predicted by our county-level covariates which could also predict crime (Pei et al., 2018). We find that the number of mental healthcare offices is predicted by the poverty rate and share of the county that is young and female (Table 5).

In addition to allowing a test of the CIA, the balance testing reported in (Table 5) also offers us an opportunity to examine what factors, not captured by county fixed-effects

[8]Seven years includes the three years pre-event, year of the event, and three years post-event.

and state-by-year fixed effects, can explain our source of variation. We observe that higher poverty rates are associated with fewer offices while the share of females ages 18-64 is positively correlated with the number of offices. The former suggests that relative income is important and demographics are as well.

Second, we explore the sensitivity of our estimates to different sets of control variables in the spirit of Altonji et al. (2005). We initially estimate a model with no time-varying controls (i.e., including only fixed-effects), and then sequentially add in each county-level control, re-estimate Equation 6, and report the relevant coefficient estimate (Table 6). Coefficient estimates are stable as we add controls and 95% confidence intervals overlap substantially.

While we would prefer to observe full balance in terms of our covariates across counties with different levels of treatment intensity, reassuringly the effect of office-based mental healthcare on crime remains largely unchanged if we include, or do not include, covariates for which there may be imbalance.

4.4.3 Program-induced migration

A third treat to validity is program-induced migration (Moffitt, 1992). In our context, for example, the opening of an office in a county may prompt individuals to move out of or into that county. We test for this behavior using data on past-year cross-county migration information available in the Current Population Survey (CPS) 1999-2014 (King et al., 2020). Specifically, we construct cross-county migration rates in each county and regress that outcome on the lagged number of office-based mental healthcare providers using Equation 6. We note that sample sizes are smaller than our main sample due to privacy-related suppression in the CPS. Results reveal no evidence that changes in the number of office-based mental healthcare providers influences such migration (Table 7).

4.4.4 Falsification

Finally, we conduct placebo testing. We randomly re-assign the office variable across counties and re-estimate our Equation 6 100 times, generating 'placebo estimates.' In particular, the randomization re-shuffles each cell (i.e., county-year) independently across counties and across years. If we are indeed capturing a 'true' effect of access to office-based mental healthcare, and not some other unobserved factor, we would expect our main estimate to be an outlier relative to all placebo estimates. We are unaware of any other factor that followed the same roll-out over U.S. counties. Our main coefficient estimate is an outlier from the placebo coefficient estimates (Figure 3).

4.4.5 Assessment of validity

We view these analyses as suggesting that a violation of parallel trends, reverse causality, unobserved heterogeneity, program-induced migration, or some other factor that followed the same staggered roll-out across counties as our office variable do not drive our findings.

4.5 Evidence on the first stage

The mechanism through which we expect that changes in local access to office-based mental healthcare lead to changes in crime is mental illness: additional office-based mental healthcare offices in a county allow more patients to receive care which, in turn, should reduce mental illness and crime. We test this hypothesis using data from several different sources. To study treatment, we follow Tefft (2011) and use Google search data (the Google Index), in particular we examine key words that suggest the search is related to office-based mental healthcare treatment. The Google Index captures the relative popularity of a search term, the index is computed as the quotient of the number of searches for any particular term divided by the total searches with the researcher-specified geographic area and time period. The Google Index ranges from zero to 100. Google data scientists conduct some data cleaning prior to releasing the data to researchers: low volume searches are assigned a zero value, duplicate searches are eliminated, and searches that involve special characters are removed.[9] These data are commonly used in economic studies (Tefft, 2011; Beheshti, 2019; Chalfin, Danagoulian, & Deza, 2019; Doleac & Mukherjee, 2019; Borup, Christian, & Schütte, 2020).

We generate Google search trends for each state and year separately over our study period, while ideally we would prefer to measure searches at the county-year level, such data have substantial missingness and thus meaningful analysis are not possible (full details available on request). Thus, we note that there may be some measurement error in the definition of the healthcare market. We include the following search terms: clinical psychologist, psychiatrist, psychoanalyst, psychologist, psychotherapist, and social worker. We select these search terms as the overlap with the type of healthcare providers likely to work in the office-based settings we measure in the CBP. Results, reported in Table 8 Column 1, suggest that searches for office-based mental healthcare providers increase as the number of offices rises. This pattern of results is in line with the hypothesis that as access increases in the local healthcare market, likely patients search online to learn more about such providers. This behavior suggests that patients become more interested in treatment and, in turn, take-up treatment.

[9] Please see the Google website for full details: https://support.google.com/trends/answer/4365533?hl=en (last accessed July 18, 2020).

Next, we consider measures of mental illness. To do so, we draw data on suicides from the Centers for Disease Control and Prevention's Public Use National Vital Statistics System (NVSS) Underlying Cause of Death public use files (ICD-10 codes U03, X60 to X84, and Y87.0). Cells with less than ten deaths are suppressed for privacy by the data provider. We therefore impute a value of five for such cells but results are robust to imputing a value of zero (lowest possible value) and nine (highest possible value). We convert the deaths to annual rate per 10,000 adults. We also use data on adults (18+) meeting diagnostic criteria for any mental illness (AMI) in the public use NSDUH state-level averages; unfortunately public data are not available at the county-level and thus we likely mis-characterize the market in which individuals seek care. We find that an additional ten offices in a county and state reduces the suicide rate by 0.4% and AMI rate by 0.1% (Table 8 Columns 2 and 3).

Collectively, we view our analysis of Google Index, NVSS, and NSDUH to support our hypothesized causal pathway from changes in mental healthcare providers to crime. That is, as the number of office-based mental healthcare providers in the local area increases, treatment uptake rises and mental illness improves.

4.6 Cost-adjusted crime rates

Our results treat the crimes equivalently in the sense that one additional homicide and one additional burglary are considered identically. This assumption is not likely true as different crimes are more and less costly in terms of criminal justice system and victim costs. Chalfin and McCrary (2018) point out that the benefits from reductions in property crime are not sufficient to justify the expense of additional police officers. Alternatively, even relatively small reductions in violent crimes are sufficient to justify additional investments. Given heterogeneity in costs, we next estimate a cost-adjusted version of our main regression model following Chalfin and McCrary (2018).

Accounting for differences in social costs across crime types does not qualitatively alter our main findings (Table 9). An additional ten offices per county leads to a 2.1% reduction in the expected cost of total crimes per capita, a 2.2% reduction in the expected cost of violent crime per capita, and a 0.9% reduction in the expected cost of nonviolent crime per capita. We note that relative effect sizes are larger after adjusting for crime costs.

4.7 Heterogeneity

4.7.1 Heterogeneity by type of crime

We consider broad categories of violent and non-violent crime, but these groupings may mask differences in the responsiveness to treatment. We examine heterogeneity by specific types of violent and non-violent crimes (Tables 10 and 11) to allow for differential responsiveness to treatment. In terms of violent crimes, an additional ten offices in a county reduces murder rates by 2.5%, aggravated assault rates by 2.2%, and robbery rates by 2.0%. Turning to nonviolent crimes, rates of burglaries and motor vehicle thefts decline by 0.3% and 1.8% respectively when the number of offices in a county increases by ten.

4.7.2 Heterogeneity by mental healthcare providers

We replace overall mental healthcare provider offices with two variables that separately consider offices of physicians and offices of non-physicians. The two providers types deliver somewhat distinct types of treatment which may have differential effects on crime. For instance, physicians are better able to prescribe medications (i.e., generally only those providers holding an MD or DO can prescribe medications) than non-physicians.[10] Medications have known side effects (e.g., aggression, lethargy) which may *increase* the propensity to commit crime or of victimization. Non-physicians rely more on non-medication forms of treatment (e.g., cognitive behavioral therapy, group therapy, and family therapy). Further, non-physicians (e.g., social workers) are more likely to provide support or 'wrap-around' services such as education assistance, employment, and social service. The profile of the marginal patient seeking care with a physician and non-physician may also differ, leading to differential effects on crime. Although the CBP has limited information on the number of employees working in an establishment,[11] the offices of non-physicians are larger than physician offices (1.7 times) suggesting that these offices have differential scope to treat patients.

Our findings appear to be driven by non-physicians (Table 12). Coefficient estimates on the number of physician offices, while not precise, carry *positive* signs. On the other hand, the coefficient estimates on the non-physicians are similar to our main findings: an additional ten non-physician offices reduces total crime rates by 0.6%, violent crime rates by 2.4%, and

[10] We note that psychiatric nurse practitioners can potentially prescribe medications. Such providers could be listed under the non-physician code but we suspect that most are coded as 621399 (offices of all other miscellaneous health practitioners). We do not consider this code as it includes a wide range of providers, most unrelated to mental healthcare (e.g., denturists, dietitians, midwives).

[11] Over 70% of the employment data is imputed and the data lack any employee job details.

nonviolent crime rates by 0.4%.

In the bottom panel of Table 12, we include an interaction term between the two provider types in the regression model. While the main effects are not appreciably different (the main effects for non-physicians are large but 95% confidence intervals overlap with the confidence interval associated with the comparable estimate in the non-interacted model), the interaction term is *positive* which suggests that there may be declining marginal productivity for non-physicians as the number of physicians increases. We note that the interaction term coefficient estimate is not precise in the violent crime specification.[12]

4.7.3 Heterogeneity by baseline county demographics

Counties may experience differential effects of office-based mental healthcare providers based on their characteristics. For example, more urban areas may have more opportunities for crime (e.g., greater homeless populations) and may therefore receive greater benefit from additional offices, on the other hand such localities may have higher poverty rates and thus individuals maybe less likely to receive care in the settings we study. Further, high crime areas may have more individuals who could benefit from treatment in terms of reducing crime. Finally, higher income areas may have the financial resources to receive mental healthcare treatment, but may also be less likely to have residents that commit crimes.

To explore these possibilities, we examine heterogeneity by county-level characteristics (all measured in 1998, thus prior to our study period): (i) population density proxied by the population per square mile of land area,[13] (ii) total crime rates, and (iii) personal income. We note that the total sample size of the sub-samples is less than our overall sample size, we lose sample because we do not rely on a balanced panel of counties.

The effect of office-based mental healthcare provider offices appears to be larger in counties with lower population density; indeed coefficient estimates are more precisely estimated and larger in less dense population areas (Table 13). Table 14 reports coefficient estimates for counties with above and at/below the mean total crime rate. While the coefficient estimates differ in absolute size, the relative effect sizes are similar. Finally, considering heterogeneity by average personal income (Table 15), coefficient estimates, both in absolute and relative terms, are larger among lower income counties. For instance, an additional ten office-based

[12]Based on these findings, our results appear to be driven by non-physicians. We have re-estimated all regressions using only non-physicians to define our measure of local access to office-based mental healthcare. Findings are similar to those reported in the manuscript, but are somewhat larger in magnitude (although 95% confidence intervals overlap so we are reluctant to overstate differences). Results are available on request.

[13]Population density is measured in 2000. We could not locate this information for 1998.

mental healthcare providers reduces total crime rates by 0.29% in counties with incomes above the sample mean and 8.61% in counties with incomes at or below the sample mean. We note that while coefficient estimates differ across some sub-samples, many of the 95% confidence intervals overlap, thus we are reluctant to place too much emphasize heterogeneity by county-level characteristics.

5 Robustness

We next report several sensitivity analysis. First, we estimate different specifications and samples. We remove population weights, exclude state-by-year fixed-effects, estimate a first-difference model, examine crime counts, apply an inverse hyperbolic sine to the crime rates, and control for general physicians to capture broader access to healthcare (Appendix Table A1).[14] We exclude counties with no office-based mental healthcare providers, exclude years in which the ACA was effective (2010-2014), and use the Quarterly Census of Employment and Wages to construct our office count (Appendix Table A2).[15] We also aggregate the data to the state and core-based statistical area (CBSA) (Table A3), and we use a quadratic in the number of offices (Table A4).

6 Discussion

In this study we provide the first evidence on the effect of office-based mental healthcare local access on crime. Our findings suggest that increases in office-based mental healthcare providers reduce crime rates. An additional ten mental healthcare provider offices in a county leads to a 0.5% reduction in the overall county crime rate. We provide evidence that mental illnesses decline as the number of office-based mental healthcare increases within a county, suggesting that crime declines are driven by improved mental health.

These findings suggest that increasing access to office-based mental healthcare providers have positive, albeit modest, spillover effects to crime. The magnitude is reasonable given

[14] We lose some precision in the total and non-violent crime specifications when we include general physicians in the regression model. We suspect that the drop in precision is attributable to collinearity between the healthcare variables. The correlation is over 0.95.

[15] We prefer the CBP for the following reasons. (i) We can use data beginning in 1999 in CPB vs. 2002 in QCEW. (ii) CBP is more commonly used in the related literature and we wish to facilitate comparison. (iii) The QCEW does not include proprietors and therefore likely under-counts many of the providers that we seek to study (`https://www.bls.gov/cew/overview.htm`; last accessed July 18th, 2020). (iv) CBP excludes most establishments with government employees but this restriction does not pose a problem when studying office-based mental health providers as these providers are generally not government-owned.

our hypothesized complier: a patient whose mental illness can be effectively treated in office-based settings. The costs of crime to society are extremely high, thus even modest declines in the number of crimes may be valuable. For instance, the value of one averted murder is $10.9M (McCollister et al., 2017).[16] Policymakers seeking to reduce crime may wish to consider enhanced investments in this modality of mental healthcare, for instance, subsidies or tax credits to mental healthcare providers who open in areas with high crime rates.

Our study has limitations. We consider only one dimension of mental healthcare treatment access: the number of office-based providers in a county. Also, our estimates have an intent-to-treat (ITT) interpretation. While the ITT is arguably informative from a policy perspective, information on the treatment-on-the-treated (TOT) estimate is also of interest.

Our study adds to a small but growing literature which suggests that supportive, rather than punitive, policies are effective in reducing crime related to behavioral health conditions. Wen et al. (2017) exploit changes in state Medicaid Health Insurance Flexibility and Accountability (HIFA) waivers to non-traditional populations (low-income, childless adults) that cover SUD treatment to study the effect of SUDs on crime. The authors document that improved access to SUD treatment through waivers reduces crime, in particular robbery, aggravated assault, and larceny. Using a similar identification to the one we employ, Bondurant et al. (2018) evaluate the extent to which expanding access to specialty SUD treatment facilities, measured by opening and closings of such facilities, affect crime. The authors show that the increased numbers of SUD treatment facilities in a county reduce violent and financially motivated crimes with the county, in particular murder. Overall, these studies suggest that expanding the behavioral healthcare workforce can have both direct health benefits and indirect crime-control benefits to society.

[16]Inflated by the authors to 2020 dollars using the Consumer Price Index.

Table 1: NSDUH demographics 2014

Sample:	Office-based mental healthcare in past year	No mental healthcare in past year
Panel A: Demographics	–	–
18-20 years	0.052	0.057
21-25 years	0.086	0.094
26-34 years	0.15	0.16
35+ years	0.71	0.69
Male	0.32	0.51
Female	0.68	0.49
White	0.80	0.63
Black	0.053	0.13
Other race	0.054	0.082
Hispanic	0.091	0.17
Less than high school	0.068	0.14
High school	0.19	0.29
Some college	0.26	0.27
College degree	0.48	0.30
Work in the past week	0.60	0.67
Any health insurance	0.93	0.87
No health insurance	0.066	0.13
Medicaid	0.13	0.11
Medicare	0.21	0.20
Private insurance	0.73	0.67
Other insurance	0.48	0.35
Below federal poverty line	0.13	0.15
Family income < \$20k	0.17	0.18
Family income 5k - < \$50k	0.25	0.31
Family income \$50k - < \$75k	0.15	0.17
Family income > \$75k	0.42	0.35
Panel B: Mental healthcare treatment payment source		
Self-pay	0.47	–
Private insurance pay	0.48	–
Medicare pay	0.13	–
Medicaid pay	0.073	–
Other pay	0.100	–
Free care	0.038	–
Observations	2033	35221

Notes: The data set is the NSDUH 2014. The unit of observation is a survey respondent. Observations are weighted by NSDUH-provided survey weights.

Table 2: Summary statistics 1999-2014

Variable:	Mean/proportion
County crime rates per 10,000 residents	
Total	360.0
Violent	44.1
Nonviolent	315.9
County mental healthcare provider offices	
Physicians & non-physicians	122.0
Physicians	67.4
Non-physicians	54.7
County characteristics	
Per capita income	43673.0
Poverty rate	13.9
Unemployment rate	6.45
White	0.87
African American	0.13
Population 0-17 years	0.25
Population 18-64 years	0.63
Population 65+ years	0.12
Male	0.51
Female	0.49
Observations	45577

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. Observations are weighted by the population covered by the UCR data.

Table 3: Effect of office-based mental healthcare providers on aggregate crime rates: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.1674***	-0.0886***	-0.0788**
	(0.0421)	(0.0078)	(0.0400)
Observations	45577	45577	45577

Notes: The dataset is the combined UCRC and CBP 1999-2014. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics (see Section 3.3), state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 4: Effect of office-based mental healthcare providers on aggregate crime rates using a distributed lag model: 1999-2014

Outcome:	Total crime rate
Mean	357.0
Two year lag in offices of mental healthcare providers	-0.0828
	(0.0736)
One year lag in offices of mental healthcare providers	-0.1056**
	(0.0413)
Contemporaneous offices of mental healthcare providers	-0.0327
	(0.0556)
One year lead in offices of mental healthcare providers	-0.0441
	(0.0452)
Two year lead in offices of mental healthcare providers	0.1056
	(0.0941)
Observations	43180

Notes: The dataset is the combined UCRC and CBP 1999-2014. The sample size is smaller than the main sample as we lose one year of data by including leads and lags (CPB data are only available as of 1998 at the six-digit occupation coding level). The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics (see Section 3.3), state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 5: Effect of controls on number of mental healthcare provider offices: 1999-2014

Outcome:	Offices of mental healthcare providers
Mean	122.0
County-level controls	
Per capita personal income	0.0011
	(0.0008)
Poverty rate	-1.8056*
	(1.0854)
Unemployment rate	0.8661
	(2.0935)
African American	-63.0616
	(113.4604)
Males 0-17 years	-171.8764
	(450.0190)
Females 0-17 years	-632.6301
	(889.9781)
Males 18-64 years	226.6462
	(179.8463)
Females 18-64 years	1661.3863***
	(610.7289)
F-test of joint significance	3.43
(p-value)	(0.0006)
Observations	45577

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level. 95% confidence interval is reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 6: Effect of office-based mental healthcare providers on aggregate crime rates using different sets of control variables: 1999-2014

Outcome:	Total crime rate
Mean	360.0
Model includes fixed-effects only	-0.2011***
	(0.0538)
Include county-level controls	
Added control variable: Per capita personal income	-0.2116***
	(0.0527)
Added control variable: Poverty rate	-0.2232***
	(0.0503)
Added control variable: Unemployment rate	-0.2243***
	(0.0495)
Added control variable: Share African American	-0.2245***
	(0.0498)
Added control variable: Age controls	-0.1971***
	(0.0440)
Added control variable: Share female	-0.1674***
	(0.0421)
Observations	45577

Notes: Each row reflects the coefficient estimated in a regression that includes the listed variable and all variables reported in the preceding rows. The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the county population. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 7: Effect of office-based mental healthcare providers on migration rates: 1999-2014

Outcome:	Past year cross-county migration rate
Mean	0.0430
Offices of mental healthcare providers	0.0000
	(0.0000)
Observations	3953

Notes: The data set is the combined ASEC-CPS and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. The sample size is smaller than the main sample due to suppression of counties in the ASEC-CPS. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the county population. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 8: Effect of office-based mental healthcare providers on mental healthcare take-up and mental illness

Outcome:	Search rate	Suicide rate	Any AMI
Mean	295.3	360.0	0.181
Offices of mental healthcare providers	0.0753***	-0.0005**	-0.00002**
	(0.0215)	(0.0001)	(0.00001)
Observations	450	45577	350
Data source	Google Index	NVSS	NSUDH
Years	2004-2014	1999-2014	2002-2014

Notes: Office-based mental healthcare providers are lagged one year. The unit of observation is a state in a year in the Google Index and NSDUH data. The unit of observation is a county in a state in a year in the NVSS data. We note that Google Index and NSDUH data are not available in all years of our main study period (1999-2014). All models estimated with least squares and control for state characteristics, state fixed-effects, and year fixed-effects in the Google Index and NSDUH analysis. Google Index search terms include: clinical psychologist, psychiatrist, psychoanalyst, psychologist, psychotherapist, and social worker. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects in the NVSS analysis. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the state level and are reported in parentheses in the Google Index and NSDUH data. Standard errors are clustered at the county level and are reported in parentheses in the NVSS data. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 9: Effect of office-based mental healthcare providers on cost-adjusted crime rates: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Mean	$573.4	$529.52	$43.9
Offices of mental healthcare providers	-1.2093***	-1.1708***	-0.0385***
	(0.1128)	(0.1130)	(0.0106)
Observations	45577	45577	45577

Notes: The dataset is the combined UCRC and CBP 1999-2014. Crime rates are cost-adjusted following Chalfin and McCrary (2018): murder ($7M), rape ($142,020), robbery ($12,624), aggravated assault ($38,924), burglary ($2,104), larceny ($473), and motor vehicle theft ($5,786). The interpretation of the coefficient estimates is a change in the crime-rate costs. Office-based mental healthcare providers are lagged one year in all regressions. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics (see Section 3.3), state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 10: Effect of office-based mental healthcare providers on specific violent crime rates: 1999-2014

Outcome:	Murder	Rape	Agg. assault	Robbery
Mean	0.52	2.95	27.4	13.2
Offices of mental healthcare providers	-0.0013***	-0.0006	-0.0598***	-0.0269***
	(0.0001)	(0.0005)	(0.0057)	(0.0030)
Observations	45577	45577	45577	45577

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 11: Effect of office-based mental healthcare providers on specific nonviolent crime rates: 1999-2014

Outcome:	Burglary	Larceny	Motor vehicle theft
Mean	69.4	213.4	33.1
Offices of mental healthcare providers	-0.0193*	0.0000	-0.0595***
	(0.0102)	(0.0263)	(0.0166)
Observations	45577	45577	45577

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 12: Effect of office-based mental healthcare providers on aggregate crime rates, heterogeneity by mental illness provider type: 1999-2014

Outcome:	Total	Total violent	Total nonviolent
Mean	360.0	44.1	315.9
Do not interact provider types			
Offices of physicians	0.3408	0.0655	0.2753
	(0.2946)	(0.0627)	(0.2469)
Offices of non-physicians	-0.2307***	-0.1078***	-0.1229**
	(0.0557)	(0.0084)	(0.0510)
Observations	45577	45577	45577
Interact provider types			
Offices of physicians	0.2849	0.0667	0.2182
	(0.3083)	(0.0635)	(0.2602)
Offices of non-physicians	-0.5298***	-0.1012***	-0.4286***
	(0.1701)	(0.0314)	(0.1451)
Interaction	0.0006**	-0.0000	0.0006**
	(0.0003)	(0.0001)	(0.0003)
Observations	45577	45577	45577

Notes: The specification includes both offices of physicians and offices of non-physicians. In the top panel, the two provider variables are not interacted. In the bottom panel, the two provider type variables are interacted. The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 13: Effect of office-based mental healthcare providers on aggregate crime rates, interact with baseline population density: 1999-2014

Outcome:	Total	Total violent	Total nonviolent
> mean baseline population density			
Mean	396.3	52.1	344.2
Offices of mental healthcare providers	-0.0663	-0.0772***	0.0109
	(0.0610)	(0.0107)	(0.0552)
Observations	5029	5029	5029
≤ mean baseline population density			
Mean	314.6	33.2	281.3
Offices of mental healthcare providers	-1.0170**	-0.0501	-0.9669**
	(0.4358)	(0.0471)	(0.4037)
Observations	31441	31441	31441

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. Baseline population densities are measured in 1998. The sample size is smaller than the main sample as the county must appear in the data in 1998. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 14: Heterogeneity in the effect of office-based mental healthcare providers on aggregate crime rates by baseline total crime rates: 1999-2014

Outcome:	Total	Total violent	Total nonviolent
> mean baseline total crime rate			
Mean	466.0	58.8	407.2
Offices of mental healthcare providers	-0.0999	-0.0952***	-0.0047
	(0.1365)	(0.0284)	(0.1190)
Observations	12252	12252	12252
≤ mean baseline total crime rate			
Mean	62.5	15.3	55.1
Offices of mental healthcare providers	-0.1188***	-0.0340***	-0.0848**
	(0.0397)	(0.0055)	(0.0392)
Observations	24218	24218	24218

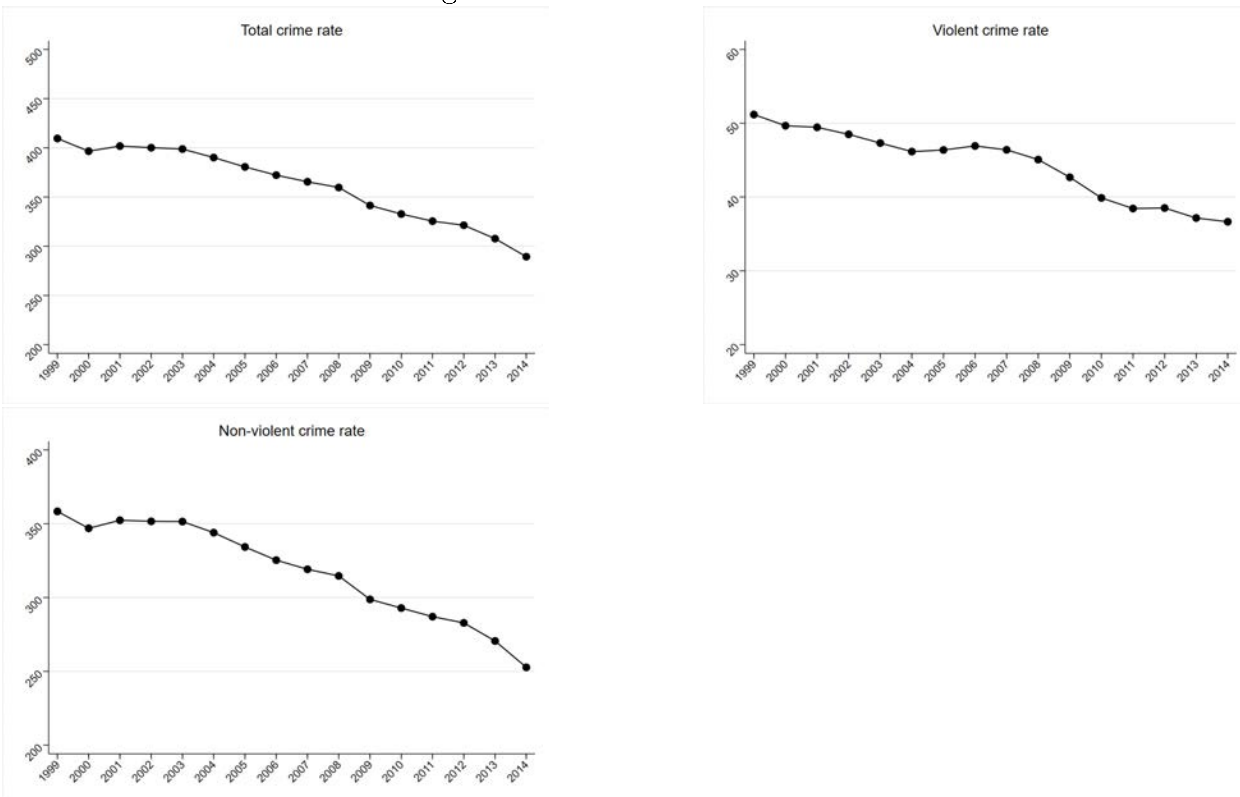
Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. Baseline total crime rates are measured in 1998. The sample size is smaller than the main sample as the county must appear in the data in 1998. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level. 95% confidence interval is reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table 15: Heterogeneity in the effect of office-based mental healthcare providers on aggregate crime rates by baseline personal income: 1999-2014

Outcome:	Total	Total violent	Total nonviolent
$>$ mean baseline personal income			
Mean	372.8	46.5	326.3
Offices of mental healthcare providers	-0.1068**	-0.0811***	-0.0257
	(0.0424)	(0.0088)	(0.0389)
Observations	22392	22392	22392
$\leq$ mean baseline personal income			
Mean	324.1	36.9	287.1
Offices of mental healthcare providers	-2.8006***	-0.2819**	-2.5187***
	(0.8591)	(0.1160)	(0.8157)
Observations	14078	14078	14078

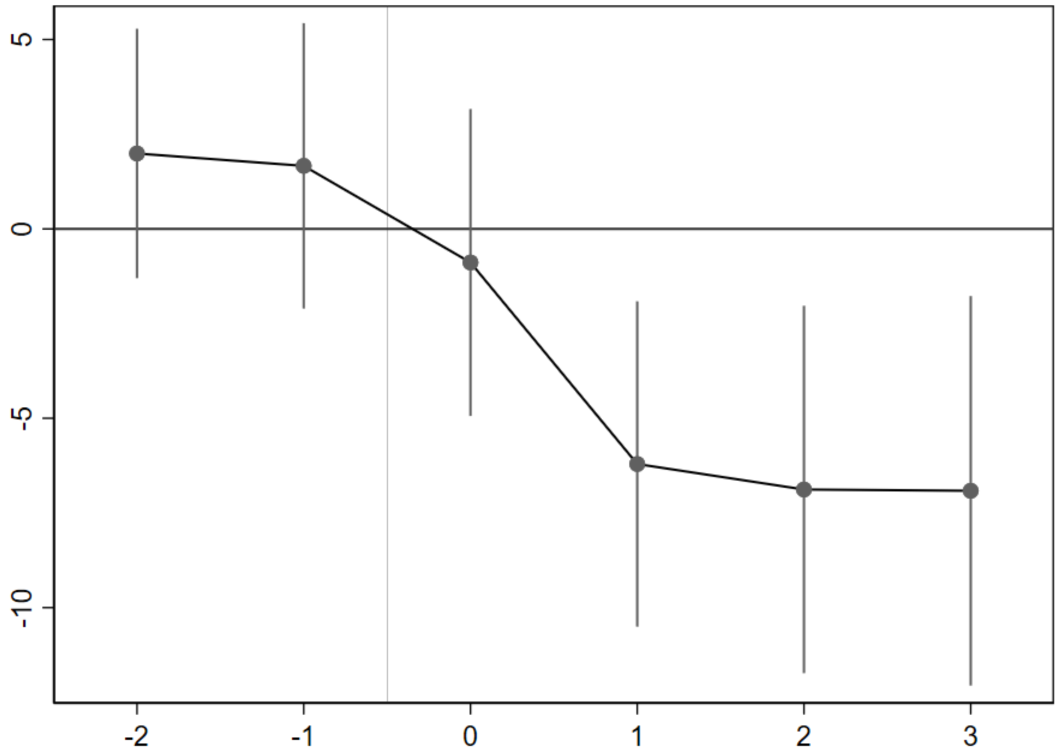
Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. Baseline personal income is measured in 1998. The sample size is smaller than the main sample as the county must appear in the data in 1998. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level. 95% confidence interval is reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Figure 1: Trends in crime rates



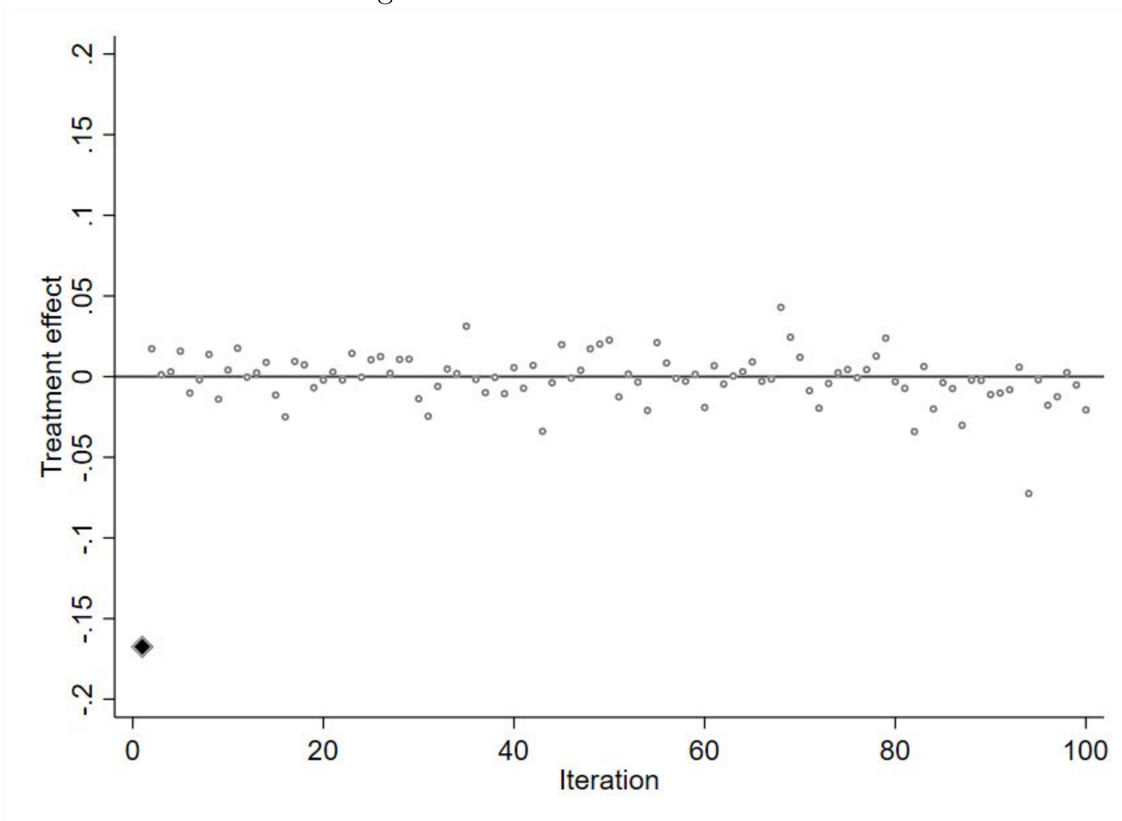
Notes: The data set is the UCRC 1999-2014. Data are aggregated to the year level using population weights. The sample mean values of total, violent, and non-violent crimes per 10,000 residents are 360.0, 44.1, and 315.9 respectively.

Figure 2: Local event study: Total crime rates



Notes: The dataset is the combined UCRC and CBP 1999-2014. The unit of observation is a county in a state in a year. The outcome variable in all models is the total crime rate per 10,000 residents in the county. All models estimated with least squares and control for county characteristics (see Section 3.3), state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. The sample mean values is 360.0 total crimes per 10,000 residents. 95% confidence intervals account for within county clustering and are reported with vertical lines. See Section 4.4 for details on the analysis and specifications.

Figure 3: Falsification: Total crime rates



Notes: The dataset is the combined UCRC and CBP 1999-2014. The unit of observation is a county in a state in a year. The outcome variable in all models is the total crime rate per 10,000 residents in the county. All models estimated with least squares and control for county characteristics (see Section 3.3), state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. The sample mean values is 360.0 total crimes per 10,000 residents. The black diamond represents our main coefficient estimate and the gray cirlces represent the 100 placebo coefficient estimates. See Section 4.4 for details on the analysis and specifications.

Table A1: Effect of office-based mental healthcare providers on aggregate crime rates, using different specifications: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Unweighted			
Mean	244.9	26.1	218.7
Offices of mental healthcare providers	-0.6758***	-0.1199***	-0.5559***
	(0.1803)	(0.0180)	(0.1722)
Observations	45577	45577	45577
Drop state-by-year fixed-effects			
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.0593	-0.0668***	0.0075
	(0.1188)	(0.0133)	(0.1081)
Observations	45577	45577	45577
First-differences model			
Mean	244.3	26.1	218.2
Offices of mental healthcare providers	-0.0011	-0.0220***	-0.0576
	(0.0333)	(0.0033)	(0.2383)
Observations	42521	42521	42521
Crime counts, control for population			
Mean	43037.4	6673.2	36364.2
Offices of mental healthcare providers	-232.5410***	-88.0923***	-144.4487***
	(39.0182)	(13.6307)	(25.8937)
Observations	45577	45577	45577
Logarithm of crime rate			
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.0012**	-0.0019***	-0.0010*
	(0.0005)	(0.0004)	(0.0005)
Observations	45577	45577	45577
Inverse hyperbolic sine of crime rate			
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.0008***	-0.0017***	-0.0006*
	(0.0003)	(0.0003)	(0.0003)
Observations	45577	45577	45577
Control for general doctors			
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.1015	-0.0427**	-0.0588
	(0.0838)	(0.0190)	(0.0696)
Observations	45577	45577	45577

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects unless otherwise noted. Observations are weighted by the population covered by the UCRC data unless otherwise noted. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table A2: Effect of office-based mental healthcare providers on aggregate crime rates, using different samples: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Exclude counties with no offices			
Mean	241.0	26.8	214.2
Offices of mental healthcare providers	-0.1405***	-0.0844***	-0.0561
	(0.0415)	(0.0082)	(0.0389)
Observations	23919	23919	23919
Exclude ACA years (2010-2014)			
Mean	382.4	47.1	335.3
Offices of mental healthcare providers	-0.2820***	-0.1301***	-0.1518***
	(0.0633)	(0.0197)	(0.0574)
Observations	30523	30523	30523
Use QCEW 2002-2014			
Mean	351.3	42.9	308.4
Offices of mental healthcare providers	-0.1294	-0.0570***	-0.0724
	(0.1315)	(0.0209)	(0.1169)
Observations	37771	37771	37771

Notes: The data set is the combined UCRC and CBP 1999-2014 unless otherwise noted. Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects unless otherwise noted. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table A3: Effect of office-based mental healthcare providers on aggregate crime rates, aggregate to the state and CBSA: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Aggregate data to the state			
Mean	271.1	30.7	240.5
Offices of mental healthcare providers	-0.0423	-0.0157***	-0.0266
	(0.0293)	(0.0035)	(0.0262)
Observations	800	800	800
Aggregate data to the CBSA			
Mean	335.4	37.4	298.0
Offices of mental healthcare providers	-0.8924**	-0.0977***	-0.7947**
	(0.3534)	(0.0250)	(0.3447)
Observations	14111	14111	14111

Notes: The data set is the combined UCRC and CBP 1999-2014. Office-based mental healthcare providers are lagged one year. The unit of observation is a state or CBSA in a year. State-level models estimated with least squares and control for state characteristics, state fixed-effects, and year fixed-effects. CBSA-level models estimated with least squares and control for CBSA characteristics, CBSA fixed-effects, and state-by-year fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the state or CBSA level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

Table A4: Effect of office-based mental healthcare providers on aggregate crime rates allowing for a quadratic in offices: 1999-2014

Outcome:	Total crime	Violent crime	Nonviolent crime
Mean	360.0	44.1	315.9
Offices of mental healthcare providers	-0.3400**	-0.0706**	-0.2694**
	(0.1609)	(0.0317)	(0.1370)
Offices of mental healthcare providers	0.0001	-0.0000	0.0001*
squared	(0.0001)	(0.0000)	(0.0001)
Observations	45577	45577	45577

Notes: Office-based mental healthcare providers are lagged one year. The unit of observation is a county in a state in a year. All models estimated with least squares and control for county characteristics, state-by-year fixed-effects, and county fixed-effects. Observations are weighted by the population covered by the UCRC data. Standard errors are clustered at the county level and are reported in parentheses. ***,**,* = statistically different from zero at the 1%,5%,10% level.

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