Evictions and psychiatric treatment

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Abstract

Stable housing is critical for health, employment, education, and other social outcomes. Evictions reflect housing *instability* that is experienced by millions of Americans each year. Psychiatric disorders are proximate determinants of evictions. We estimate the effect of local access to psychiatric treatment on evictions. We combine data on the number of psychiatric treatment centers that offer outpatient and residential care within a county with eviction outcomes in a two-way fixed-effects framework. We find that ten additional psychiatric treatment centers in a county leads to a reduction of 2.1% in the eviction rate.

Keywords: Substance use; mental health; evictions; healthcare; access.

JEL codes: I10; I18; J20

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1 Introduction

Housing stability is a critical determinant of health and other economically important outcomes such as labor market performance, family structure, crime, and education. Indeed, a large interdisciplinary body of research shows that housing *instability* is associated with negative outcomes across these social domains (Hartman and Robinson, 2003). In particular, housing *instability* is associated with poor access to healthcare, worse physical and mental health, misuse of substances, mortality, and child neglect (Baggett et al., 2013; Desmond and Kimbro, 2015; Fowler et al., 2015; Tsai, 2015; Taylor, 2018; Vásquez-Vera et al., 2017; Bullinger and Fong, 2020; Hatch and Yun, 2020; Bradford and Bradford, 2020b).

Evictions are an extreme form of housing instability. According to the Princeton University Eviction Lab (2021), evictions are '...landlord-initiated involuntary moves that happen to renters.' That is, following an eviction, individuals and families must involuntarily leave their home and attempt to find another location in which to live. Securing future housing can be challenging as a previous eviction record can harm a renter's likelihood of being able to rent again. Thus, in addition to the immediate costs of an eviction, having been evicted can have persistent and negative effects on housing stability and well-being.

Evictions and associated costs are not uniformly distributed across the population. Instead, within the United States, the focus of our study, evictions disproportionately impact low-income people and minorities (Desmond, 2012; Eviction Lab, 2021). In 2013 the majority of all renting families and individuals living in poverty in the U.S. devoted over 50% of their income to housing, with nearly a quarter devoting at least 70%. These numbers are substantially higher than the 30% ceiling recommended by policymakers (Desmond, 2015). Over time, a larger proportion of renter income has been dedicated to housing, while there has been a simultaneous decrease in the number of new households receiving federal assistance and an increase in net rent (Schwartz, 2021). These forces create a setting in which widespread evictions among disadvantaged populations are plausible.

The U.S. annual eviction rate is nearly 3% implying that each year there are over 2.5M evictions (Eviction Lab, 2021). There is substantial heterogeneity across communities in the eviction rate (in addition to people as noted above). For example, in 2016 North Charleston, South Carolina had the highest recorded eviction rate in the country at 16.5%, over five times the national average.[1] The COVID-19 pandemic, and corresponding economic downturn, lead to a surge in renters unable to pay their rent: in May 2020, nearly one third of renters in the U.S. reported that they had little or no confidence that they could afford their next rent payment (Larrimore and Troland, 2020). The scale of COVID-19-related housing instability re-focused the attention of the public and policymakers on this crisis. For example, in attempts to prevent wide-spread evictions during the height of the COVID-19 crisis, governments at various levels adopted temporary policies prohibiting evictions for specific groups of renters.[2] While these policies potentially provide a short-run reduction in evictions at the height of a global pandemic, these policies do not speak to the broader American housing affordability crisis and its impacts on individuals, families, and communities.

Despite a long-standing interest in housing markets (Rosen, 1974; Horn et al., 2021), economists have only lightly examined evictions, either in terms of causes or consequences (Allen et al., 2019; Evans et al., 2019; Humphries et al., 2019; Bradford and Bradford, 2020b,a). The limited research activity may be attributable to an overall lack of comprehensive data on this outcome. Evictions are generally processed within local judicial systems and there is no national government data collection infrastructure that collates eviction outcomes. However, the Princeton University Eviction Lab has recently developed a publicly available and nearly national database tracking eviction outcomes. These data offer researchers the

[1] Sources: `https://www.statista.com/statistics/942681/eviction-rate-usa/` and `https://evictionlab.org/rankings/#/evictions`; last accessed May 15, 2021.

[2] See `https://www.phila.gov/fairhousingcommission/pages/default.aspx`, `https://www.cdc.gov/coronavirus/2019-ncov/covid-eviction-declaration.html`, and `https://www1.nyc.gov/content/tenantresourceportal/pages/eviction-moratorium-and-courthouse-closures`; all websites last accessed May 30, 2021. The federal government also prohibited evictions from Housing and Urban Development (HUD)-supported housing.

ability to study factors that lead to evictions in the U.S. at the (near) national level.

In this paper, we make use of Eviction Lab data to estimate the effect of substance use disorder (SUD) and mental health disorder (MHD) treatment access on eviction outcomes. We refer to SUD and MHD conditions collectively as 'psychiatric disorders.' These disorders are common and costly, with annual costs in the U.S. totally more than $1T (Insel, 2008; Kasunic and Lee, 2014).[3] Previous clinical research documents correlations between psychiatric disorders and evictions specifically and other measures of housing instability more generally (Fazel et al., 2008; Montgomery et al., 2013; Fazel et al., 2014; Aldridge et al., 2018; Martin et al., 2021).[4] While the reasons for evictions are myriad, psychiatric disorders are potentially proximate causes. For example, many psychiatric disorders are associated with worse employment outcomes (Ettner et al., 1997; Terza, 2002; Ettner et al., 2011; Banerjee et al., 2017), which may limit a renter's ability to pay rent, leading to an eviction. Impeded cognition can prevent an individual with a psychiatric disorder from performing normal activities. Examples include: a person with an SUD − during periods of elevated substance use − or an individual experiencing a psychotic episode may not be capable of paying their rent. Further, psychiatric disorders often cause disorganized thinking and actions that may lead to violations of lease terms. For example, being loud, acting in aggressive and threatening ways toward other renters or landlords, creating safety hazards, being under the influence of substances, having illicit drugs on the premises, or committing a crime (Swensen, 2015; Wen et al., 2017; Bondurant et al., 2018; Deza et al., 2022).

Our analysis examines the impact of access to psychiatric treatment on eviction outcomes. We focus on treatment as it is arguably more exogenous than psychiatric disorders themselves.[5] A large clinical and economic literature documents that a wide range of treat-

[3]Inflated by the authors from the original estimates to 2021 dollars using the Consumer Price Index.

[4]In our analysis of the 2019 Treatment Episode Dataset, which measures admissions to standalone SUD treatment, over 17% of patients admitted were homeless and nearly 19% resided in assisted living.

[5]For example, previous research shows that fear of an eviction can health to anxiety, depression, and general psychological distress, while individuals who are evicted are more likely to use substances (Bradford and Bradford, 2020a).

ment modalities are effective in reducing psychiatric disorders (Lu and McGuire, 2002; Ettner et al., 2006; Hunot et al., 2007; Cuijpers et al., 2011; Popovici and French, 2013; Mattick et al., 2014; Murphy and Polsky, 2016; Krebs et al., 2018).[6] Several recent economic studies show that enhancing access to such treatment improves management of psychiatric disorders (Swensen, 2015; Wen et al., 2017; Bondurant et al., 2018; Deza et al., 2022; Corredor-Waldron and Currie, 2019; Deza et al., 2021).[7] We proxy psychiatric treatment access with the number of standalone outpatient and residential facilities ('psychiatric treatment centers') within a county.[8] Data on psychiatric treatment centers are drawn from the U.S. Census County Business Patterns Database (CBP), which is based on Internal Review Service tax returns and captures the universe of establishments in the U.S.. We combine these establishment data with the number of completed evictions per county from the Eviction Lab database over the period 2000 to 2016. We estimate two-way fixed-effects models that leverage within-county variation in the number of psychiatric treatment centers over time.

Our findings suggest that ten additional psychiatric treatment centers per county leads to a 2.1% reduction in the eviction rate. Ten additional centers reflects a 17.1% increase in supply and suggests an eviction-center elasticity of -0.01.[9] We provide evidence on the 'first stage:' psychiatric disorders − which we proxy with deaths attributable to drug overdoses, fatal alcohol poisonings, and suicide − decline and admissions to treatment rise as

[6]Of relevance to our study, these studies document the effectiveness of the two modalities examined in this paper: standalone outpatient and residential treatment.

[7]These studies measure access in a broadly similar manner to our work (described next): the number of centers or offices within a county.

[8]We note that an alternative approach to measuring access could be to take the count of the number of providers, rather than centers. We have explored this possibility. Unfortunately, we cannot locate the number of, for example, psychiatrists or psychologists working in the centers we study at the county-level and over time. Standard sources for providers such as the Area Health Resource File pose challenges. First, the variables we require are not available for more than a handful of years at the county-level and our identification strategy requires access to provider counts in each year over many years. Second, we do not know the settings in which the providers work, for example, a psychologist could work in the centers we study or a private office, a hospital, a school, a correctional facility, or mainly other settings. Our interest is in understanding on access to psychiatric treatment center care impacts eviction outcomes. Therefore, we require information, at the county-level and over time, on care setting, leading us to select the center data.

[9]We use the treatment effect size for a single center (rather than ten centers) in our elasticity calculation.

the number of psychiatric treatment centers within the county increases. Our results do not appear to be driven by reverse causality, confounding from unobservables, or program induced migration, and are robust to numerous sensitivity checks. In sum, we offer the first plausibly causal evidence on the role of psychiatric outcomes in the eviction process. Our findings complement previous economic research suggesting that expanding access to psychiatric treatment, through insurance expansions or the number of providers within the local community, can have profound positive impacts on individuals with psychiatric disorders and their communities. Treatment provision could be used, alongside more standard policy levers, to promote housing stability and other economic and social goals.

The paper proceeds as follows. Section 2 provides a discussion of the eviction process, and psychiatric disorders and associated treatment. We present our main results and internal validity testing in Section 4. Heterogeneity analysis and sensitivity checking are reported in Section 5. Finally, Section 6 offers a conclusion and discussion.

2 Background

2.1 Evictions

Evictions generally begin when a landlord initiates legal action claiming that the renter is in violation of the lease agreement.[10] Violations can include failure to pay rent on time or in full, engaging in illegal activities on the property, damaging property, failure to maintain the property (e.g., not reporting maintenance or structural problems to management), frequent noise violations, violating lease-specific rules, and creating a health or safety hazard. Some leases include a 'no fault' clause which allows a landlord to evict a renter without cause.

Psychiatric disorders plausibly increase the probability that a renter violates their lease. As noted in Section 1, previous research establishes a strong correlation between psychiatric

[10]We focus on residential evictions, but we note that evictions can also occur in commercial settings.

disorders and measures of evictions specifically and housing instability more generally (Fazel et al., 2008; Montgomery et al., 2013; Fazel et al., 2014). For example, those with a psychiatric disorder may be less able to pay rent, either on time or at all, if impeded cognition leads to forgetting to pay rent or limits employment opportunities (Ettner et al., 1997; Terza, 2002; Ettner et al., 2011; Banerjee et al., 2017). Similarly, using illicit substances on the property is potentially more likely among those with an SUD, thus increasing the risk that a person with an SUD violates their lease. During a psychotic episode, those with an MHD may experience hallucinations or other sensory distortions that lead them to act in disorderly ways that may be perceived by others, including both landlords and tenants, as aggressive, dangerous, or threatening, which could lead to a lease violation.

While the regulations surrounding evictions vary across jurisdiction within the U.S., the general process proceeds as follows. Evictions are initiated by landlords. After some period of time has passed following a lease violation (if required by the jurisdiction), the landlord sends the renter a termination notice, most jurisdictions require that the notice be attached to the renter's door, hand-delivered, or sent by certified mail to the renter.[11] If the renter ignores the termination notice, the landlord files an eviction claim with the court.[12] There is often a filing fee of up to several hundred dollars that the landlord must pay. Once the eviction claim is filed, the process moves forward. A court date is set (generally in civil court, thus the renter is not guaranteed the right to an attorney) and both parties are required to appear. If the landlord does not appear in court, then the filing may be dismissed. On the other hand, if the renter does not appear, then the court is likely to find for the landlord and an eviction will be granted. If both parties appear, the judge hears the case and renders a decision. Appeals are possible as is the case with most legal proceedings. If the court finds for the landlord, an eviction order is set and the renter must vacate the property by a specific

[11] If the renter vacates the property after notification, this process is not considered an eviction but rather a voluntary departure.

[12] We examine this outcome, an eviction filing, in robustness checking.

date, and, in some cases, the renter may be required to pay the landlord for unpaid rent and other expenses associated with the eviction (e.g., damages to the premises). Contrawise, if the judge finds for the renter, no eviction occurs. If the renter refuses to vacate after a court order then the landlord must request (and pay for) the local sheriff or marshal to forcibly remove the renter and their possessions from the property. In our empirical analysis, we classify situations in which the renter vacates after the court order (either voluntarily or by the local sheriff or marshal) as an 'eviction.'[13]

The legal eviction process itself offers additional pathways through which a psychiatric disorder could impact an eviction proceeding (conditional on a filing). For example, a person with a psychiatric disorder may be less able to attend a court hearing or hire an attorney (as noted above, in most jurisdictions, an attorney is not guaranteed in an eviction proceeding), or to adequately defend their case, which would likely increase the probability of a completed eviction. We note that landlords are prohibited in all states from evicting a renter who is in residential treatment and thus not residing in the rented property.[14]

Our hypothesis is that increases in access to psychiatric treatment will prompt some individuals to take treatment (or locate treatment that is more effective for them, with effectiveness being patient-specific and involving nuanced factors such as patient-provider match quality), which will improve management of psychiatric disorders. Better managed psychiatric disorders will increase cognition and employment, and reduce crime, inappropriate and nuisance behaviors, and other activities likely to lead to a lease violation which will, in turn, reduce evictions. Therefore, our effects are local to those patients who take (effective)

[13]We do not observe if a tenant vacates their home due to an eviction letter only.

[14]If landlords were allowed to evict tenants receiving residential treatment, we would expect, all else equal, an *increase* in evictions as access to treatment raises. As we report in the manuscript, we document that evictions *decrease* as access to treatment rises. Thus, if some landlords (illegally) evict patients while they are receiving residential treatment, this behavior will bias our results toward zero. However, we note that if receiving treatment mechanically prevents evictions (for example, the renter cannot cause a noise violation if they are in treatment and not residing in the rented premises), then we might overstate the effect of treatment (through the causal channels we outline). To minimize such bias, we lag our treatment access variable by one year which extends beyond the average duration of residential treatment based on our analysis of the 2019 Treatment Episode Database (details available on request), as we describe in Section 3.3.

treatment when local access improves, but otherwise would not take (effective) treatment.

2.2 Psychiatric disorders and associated treatment

Psychiatric disorders are common. In 2019, 7.4% (20.3M) of American adults had an SUD, while 19.1% (47.6M) had an MHD (Substance Abuse and Mental Health Services Administration (2020)). As noted in Section 1, the costs to society of these conditions are high: more than $1T per year in the U.S. (Insel, 2008; Kasunic and Lee, 2014).[15] While treatment is arguably under-used – 10% of adults with an SUD and less than 50% of adults with an MHD receive treatment in any given year (Substance Abuse and Mental Health Services Administration, 2020) – clinical and economic literature documents the effectiveness and cost-effectiveness of a range of psychiatric treatment modalities (Lu and McGuire, 2002; Ettner et al., 2006; Hunot et al., 2007; Cuijpers et al., 2011; Popovici and French, 2013; Mattick et al., 2014; Murphy and Polsky, 2016; Krebs et al., 2018).

We examine two common psychiatric treatment modalities: care received in standalone outpatient and residential treatment centers, that is these centers do not include private practices.[16] The modalities we study accounted for 37% of total spending on SUD treatment ($15.5B) and 16% of total spending on MHD treatment ($38.1B) in 2020 (Substance Abuse and Mental Health Services Administration (2014)).[17] Further, patients receiving care in these settings likely have more severe disorders than those treated in less intensive settings which are described later in this section (Mee-Lee et al., 2013).

Services received in standalone outpatient facilities extend from less intensive care, such as counselling services (group, family, or individual), to more intensive treatment such as partial

[15]Inflated by the authors from the original estimates to 2021 dollars using the Consumer Price Index.

[16]We acknowledge that patients may have different ability to access alternative treatment modalities given varying resources, insurance, and so forth. For example, Medicaid-covered patients may be less able to access office-based care as many providers in these settings do not accept Medicaid and federal regulations limit the ability of Medicaid enrollees to access residential treatment (Wen et al., 2019; Maclean et al., 2021). If anything, we would expect that impeded access to the centers we study would attenuate our findings.

[17]In 2020, the U.S. spent $42B on SUD treatment and $238B on MHD treatment (Substance Abuse and Mental Health Services Administration, 2014).

hospitalization where the patient receives care that lasts multiple hours per day. Residential treatment involves 30- to 90-day stays where the patient resides in the center full-time. Treatment in these settings can involve a combination of psychotherapy (e.g., individual, family, or group cognitive behavioral therapy), medication (e.g., buprenorphine for opioid use disorder, antipsychotics such as aripiprazole for schizophrenia, and selective serotonin reuptake inhibitors for depression), and 'wrap-around' services, including connecting patients with social services, developing crisis management plans, social skills training, and vocational rehabilitation. There is overlap in the receipt of and components of SUD and MHD care, likely due in part to high comorbidity across the two conditions. For example, half of all individuals diagnosed with an MHD will also experience an SUD over their lifetime and vice-versa (Ross and Peselow, 2012; Kelly and Daley, 2013).

A prospective patient has a range of options from which to choose apart from standalone outpatient and residential treatment that we consider in our main analysis (we explore heterogeneity by modality in Section 5.1.1). Psychiatric care can be provided in office-based settings by psychiatrists, and non-physicians such as psychologists, psychiatric nurse practitioners, and social workers. Some psychiatric treatment can be delivered in primary care settings, which is often viewed as tertiary care. Primary care physicians can provide treatment (e.g., medications and counselling), screening and diagnosing, and referrals on to specialists. During crisis periods, patients may require hospitalization, care in this setting can include treatment available in other settings and be used to ensure patient safety, proper nutrition and sleep, and basic hygiene. Finally, the U.S. has developed a community mental health center system which focuses on delivering care to those with SUD and MHD within the community. The specific services offered by community mental health centers are determined by the level of patient need in the local area, as well as the overarching goal of this modality of care is that the community − rather than a single provider − provides care.[18]

[18]We note that SUD treatment can begin with detoxification, a process which often involves medication, through which the body rids itself of substances, this treatment modality is less salient for MHD. Further,

A non-trivial share of patients receiving care in the settings we consider may be mandated to treatment through the criminal justice system. For example, in the 2016 Treatment Episode Dataset (TEDS), an all-payer national database of admissions to stand-alone outpatient and residential SUD treatment,[19] 28% of admissions are referred through the criminal justice system (Substance Abuse and Mental Health Services Administration, 2016c). Thus, not all psychiatric care is voluntary, and instead may be required as part of a sentencing agreement. For instance, the U.S. criminal justice system has made use of involuntary commitment laws, which allow judges to mandate that convicted offenders receive psychiatric care within the modalities we study.[20] The fact that such treatment is involuntary does not necessarily imply that the treatment is ineffective. Criminology research suggests that these laws are effective in terms of reducing crime, presumably through improved psychiatric health, following (mandated) treatment (Kisely et al., 2017; Swartz et al., 2017).

There are important differences in the financing of standalone outpatient and residential psychiatric treatment vs. general healthcare, and even other modalities of psychiatric treatment. For example, general healthcare is more heavily financed by private sources of payment compared to psychiatric treatment, and office-based psychiatric care generally relies on insurance and self-payment with little provision of 'charity' or free care. In 2015, private sources (e.g., private insurance and self-paying patients) accounted for 50% of general healthcare expenditures but just 43% of SUD treatment and 42% of MHD treatment (Substance Abuse and Mental Health Services Administration, 2019). In our own analysis of the 2016 National Survey on Drug Use and Health (NSDUH) (Substance Abuse and Mental Health Services Administration, 2016b), 22% of patients who reported care in psychiatric treatment centers received care at no charge (e.g., charity care offered by the center).

addiction medicine experts generally do not view detoxification as treatment *per se*, but instead as a precursor to such care (Center for Substance Abuse Treatment, 2006).

[19] TEDS also includes information on admissions to treatment received in a psychiatric wing of a general hospital and in a psychiatric hospital.

[20] In particular, this system has made use of outpatient care.

The financing for care received in psychiatric treatment centers influences the covariates we include in our regression models (Section 3.3). Insurance policies within the U.S. are primarily set at the federal- (e.g., Medicare and the Affordable Care Act) or state- (e.g., state-level regulation of private insurance policies or Medicaid eligibility) level. To account for such regulations, we control for state-by-year fixed-effects in our regression models. On the other hand, public funding through grants and contracts to support psychiatric treatment may be determined at both the state- and federal-level (for example, through recent federal acts aimed at improving access to and quality of psychiatric treatment, such as the 21st Century Cures Act of 2016 and the Substance Use-Disorder Prevention that Promotes Opioid Recovery and Treatment [SUPPORT] for Patients and Communities Act of 2018) and by more local-level factors (e.g., local government grants and contracts). While state-by-year fixed-effects will account for federal and state funding as noted above, we may be concerned about omitted variable bias from more local efforts to address psychiatric disorders and associated treatment. To control for these factors, in our main regression models we adjust for county-level demographics and county fixed-effects. We show that our results are robust to controlling for county-level health and social welfare expenditure proxies, which plausibly correlate with local-level public psychiatric treatment funding.[21]

3 Data and empirical strategy

3.1 Eviction data

We obtain data on eviction outcomes from the Princeton University-based Eviction Lab (Hepburn et al., 2020). These data represent the most comprehensive information on evic-

[21] We do not include these proxies in our main regression for two reasons. First, they are based on a survey of counties and we lose sample size when we include them in the regression model. Second, these variables could plausibly be impacted by the treatment centers we study. For example, counties may curtail or expand social expenditures when investments (by the county, state, or federal government) in psychiatric treatment centers increases. The former may occur if overall county budgets require cost reductions, while the latter may occur if investments in these outcomes are economic complements.

tions within the U.S. and are the only data that permit (nearly) nationwide analysis of the causes and consequences of evictions. The Eviction Lab collects information from court records, web scraping, and text parsing, and through partnerships with record collecting companies to create these data. Eviction information is validated by Lab administrators by comparison of overlapping data sources.

We examine county-level *completed* evictions (i.e., a judge finds in favor of the landlord and the renter is required by court order to vacate the property) in our main analysis. In a robustness check, we also examine eviction *filings*, that is when the landlord formally files an eviction claim in court. We report eviction *filings* in robustness checking due concerns about measurement issues with this variable (Goodspeed et al., 2020), however results are very similar across the two eviction variables and we do not have measurement error concerns in relation to the *completed* eviction variable. We convert eviction (completed and filing) counts to the rate per renter occupied houses in each county included in the sample.

We include data on completed evictions from 46 states and the District of Columbia over the period 2000 to 2016. We exclude four states (Alaska, Arkansas, North Dakota, and South Dakota) that have missing information on eviction outcomes and are therefore not included by the Eviction Lab in the data set (Bradford and Bradford, 2020b). Other individual counties have missing data for some years. Specifically, there are 12,076 (22.6%) county-years that have missing data.

3.2 Psychiatric treatment center data

We obtain data on psychiatric treatment from the County Business Patterns (CBP), a data product maintained by the U.S. Census Bureau (2022). The CBP data are based on tax returns completed each year by U.S. businesses and returned to the Internal Revenue Service (IRS). The U.S. Census receives a sub-set of aggregate-level data from IRS to create the CBP. We suspect that reporting quality in the CBP is high given the substantial costs to businesses of misreporting information on IRS tax returns. This activity is a felony crime that is punishable by fines and incarceration. In applying the U.S. tax code, the IRS conducts cleaning of the tax data to ensure that businesses pay correct taxes. See Deza et al. (2022) for a full discussion of CBP data quality.[22]

An establishment is defined by the U.S. Census as a 'single physical location at which business is conducted or services or industrial operations are performed.' The CBP data provides a point-in-time picture (the week of March 12 each year) of all establishments in the U.S. To classify establishments in the CBP over our study period, Census uses the North American Industry Classification System (NAICS) six-digit codes.[23] We consider two NAICS codes in our main analysis: standalone outpatient and residential psychiatric treatment centers (Swensen, 2015; Bondurant et al., 2018).

The specific six-digit NAICS codes are: 621420 (outpatient treatment) and 623220 (residential treatment). Our measure of psychiatric treatment is the number of centers in a county (i.e., the sum of NAICS codes 621420 and 623220 in each county/year pair). In our empirical models, outlined in Section 3.3, we lag centers by one year to allow for psychiatric treatment centers to open, access to care to improve, patients to receive treatment, management of psychiatric disorders to improve, and eviction outcomes to decline. This lag

[22]The IRS audits businesses that may have inaccurately reported tax information on tax forms. While the IRS does not release the algorithm that this Service applies to determine which businesses will be subject to an audit, one known factor is abnormal or outlier returns within an industry. On IRS tax forms businesses are required to provide the 'principal business code' (PBC) which corresponds to the activity that represents the majority of business revenue. Only one code is permitted per business. The PBC is used to classify a business and therefore the industry to which its returns will be compared. Tax experts encourage businesses to accurately report the PBC for this exact reason: being compared to businesses in a different industry raises the risk of being flagged as an outlier and hence an IRS audit. For example: 'Although the formula for flagging taxpayers for audits remains a secret, a portion of the determination comes from statistical comparisons of financial ratios derived from tax returns filed. The IRS has a large comparison base and uses anomalies as one of many triggers. Choosing the correct principal business code will help you file numbers comparable to your peers and may possibly reduce your chances of being audited.' (`https://smallbusiness.chron.com/principal-business-code-filing-taxes-1554.html`; last accessed May 10, 2021). The PBCs are recorded in the CBP as the six-digit NAICS industry codes that we use to isolate psychiatric treatment centers. Businesses are incentivized to accurately report their PBC (i.e., the NAICS code) as a means to avert an IRS audit, in addition to incentives related to avoiding fine and incarceration.

[23]Prior to 1998 the Census used four-digit Standard Industrial Classification codes. These codes are not fine enough to allow us to isolate psychiatric treatment centers from other healthcare centers.

structure is common within the economics literature (Swensen, 2015; Bondurant et al., 2018; Deza et al., 2022). Thus, we use the 1999 to 2015 CBP data.

We cannot separately isolate psychiatric treatment centers that provide SUD and MHD treatment in the CBP. However, as noted in Section 2.2, there is substantial co-morbidity in these conditions within patients. Further, based on our analysis of the 2016 National Survey of Substance Abuse Treatment Services (N-SSATS), a database used by the federal government to track SUD treatment received in standalone treatment centers, 46% of centers have a specific program for patients with a co-occurring MHD (Substance Abuse and Mental Health Services Administration, 2016a). For this reason, fully separating centers that provide SUD and MHD services is likely not feasible or even desirable.

We use the term 'access' when we refer to the number of centers per county. However, we realize that the number of centers captures at best one aspect of access to care, which is a much larger construct that encompasses ability to pay (e.g., income and insurance), cognition, ability to locate culturally appropriate care, and so forth, in addition to the number of accessible providers. However, geographic proximity to treatment has been shown to impact treatment use and management of psychiatric disorders (see Section 1), and thus does reflect an empirically important component of access.

3.3 Empirical model

This study aims to evaluate the relationship between local access to psychiatric treatment centers and eviction outcomes. We use variation in the number of centers, driven by openings and closings within a county and over time, to identify treatment effects. To this end, we estimate a two-way fixed-effect model using the following regression:

$$Eviction_{c,s,t} = \beta_0 + \beta_1 Center_{c,s,t-1} + X_{c,s,t}\beta_2 + \alpha_c + \alpha_{s,t} + \epsilon_{c,s,t} \tag{1}$$

where $Eviction_{c,s,t}$ is the eviction rate per renter occupied home in county (c) in state (s)

in year (t). $Center_{c,s,t-1}$ is the number of psychiatric treatment centers in the county, lagged one year. In our main specification we take the overall count of standalone outpatient and residential centers. We lag centers one year for reasons described in Section 3.2.

$X_{c,s,t}$ is a vector of time-varying county characteristics that are included to minimize omitted variable bias: population, employment, income, and sex, race, and age distribution.[24] α_c is a vector of county fixed-effects and $\alpha_{s,t}$ is a vector of state-by-year fixed-effects. $\epsilon_{c,s,t}$ is the error term. We weight the data by the county population and estimate least squares. Standard errors are clustered around the county. We convert coefficient estimates to relative effects by comparison with the sample mean.

As discussed in Section 2.2, governments provide a substantial amount of financing for the treatment modalities that we study. Including state-by-year fixed-effects in Equation 1 allows us to control for all time-varying changes in financing or regulations that occur at the state-or federal-level. County fixed-effects will account for time-invariant factors at this level of aggregation. However, bias attributable to time-varying county-level factors may remain a concern. We address this potential concern in Section 4.3.

Our analysis implicitly assumes that the county is the correct definition of the market for psychiatric care. This assumption is in line with previous research (Swensen, 2015; Bondurant et al., 2018; Deza et al., 2022; Corredor-Waldron and Currie, 2019; Deza et al., 2021). Clinical studies that assess how far patients travel to receive psychiatric care are generally in line with our market definition: over 60% of patients receive outpatient care opioid use disorder treatment within ten miles of their home (Rosenblum et al., 2011).

Recent research suggests that TWFE regression models can be biased due to heterogeneity in treatment effects across both time and treated units. To date, the majority of studies have explored binary or multi-valued treatments (de Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). Callaway

[24] These data are sourced from the Surveillance, Epidemiology, and End Results (SEER) Program (National Cancer Institute, 2021), (U.S. Department of Labor, 2021), and (U.S. Department of Labor, 2021).

et al. (2021) diagnose the issue with a continuous treatment and describe assumptions required for identification. In particular, Callaway et al. (2021) show that researchers must impose a 'stronger' version of parallel trends, that is that the path of outcomes for units with different doses of treatment would have been the same had both units received the same dose. Further, two additional assumptions are required: no treatment effect heterogeneity or dynamics. After making these assumptions the TWFE regression model will recover an estimate for the average causal response (ACR) parameter, that is the average change in outcome for an incremental change in treatment dose for all units. We make these assumptions and interpret our findings as estimates of the ACR parameter.[25]

3.4 Summary statistics

Table 1 reports summary statistics. There are an average of 58.65 psychiatric treatment centers per county over our study period. The average county-level eviction eviction rate is 2.86 respectively per renter occupied home.

Figure 1 reports trends in the eviction rate (top panel) and the total number of psychiatric treatment centers (bottom panel) over our study period (2000 to 2016). Eviction rates follow an inverse U-shape over the study period: this rate rose sharply over the early- to mid-2000s alongside the housing bubble, peaked in 2005, and then declined nearly monotonically through 2016. On the other hand, the number of psychiatric treatment centers trended upwards at relatively steady pace over the full period we consider, although early years of the study period appear to have experienced a more rapid increase.

We next report the characteristics of individuals who receive treatment in psychiatric treatment centers. To this end, we use data from the 2016 NSDUH (Substance Abuse and Mental Health Services Administration, 2016b). These data are collected and maintained

[25] Callaway et al. (2021) discuss how (even) stronger assumptions can be applied to allow recovery of a ACR on the treated parameter estimate. Researchers must assume no selection by units into treatment dose. We emphasize the ACR in our study to minimize assumptions, but realize that some readers may find an ACR on the treated of interest as well.

by the U.S. federal government for the purposes of generating the official U.S. statistics on mental health and substance use. We focus on adults 19 years and older. Results are reported in Table 2. There are notable differences across the two groups. In particular, individuals who report receiving psychiatric treatment in the past year are more likely to be below the federal poverty line (32% vs. 16%), receive public assistance (48% vs. 19%), have Medicaid coverage (41% vs. 15%), use tobacco products (60% vs. 34%), and use illicit drugs (46% vs. 21%). Individuals who report care in psychiatric treatment centers in the past year are less likely to report their health as very good or excellent: 32% vs. 60%. Overall, these summary statistics suggest that those who receive care in psychiatric treatment centers are less advantaged across than other individuals across a range of metrics.

4 Results

4.1 Evidence on the first stage

Before proceeding to our analysis on the effect of expanded access to psychiatric treatment centers on evictions, we attempt to provide evidence on the 'first stage.' We expect that, following an increase in the number of psychiatric treatment centers in a county, adverse outcomes associated with SUD and MHD will decline as management of these disorders improve. We consider psychiatric disorder proxies using restricted-use death certificate data obtained from the National Center for Health Statistics (Multiple Cause of Death data) (National Center for Health Statistics, 2022). We take the count of the number of deaths attributable to drug overdoses (all drugs, opioids, and benzodiazepines),[26] alcohol poisonings, and suicide.[27] We include deaths for those 19 years and older. We construct county-level death rates per 10,000 individuals. We estimate Equation 1 on our death certificate dataset.

[26]We focus on opioids and benzodiazepines fatal overdoses as the misuse of these substances is common and rising over our study period and are directly linked with common SUDs and MHDs.

[27]We use the following ICD 10 codes: X40-X45,X60-X65, X85, Y10-14 (total drug), T400-T404, T406 (opioids), T424 (benzodiazepines), T510-T514 (alcohol), and X60, X84 (suicide).

We note that drug overdose, alcohol poisoning, and suicide deaths are arguably 'blunt' or severe measures of psychiatric disorders. One benefit of using these measures is that they are objective and do not rely on self-reporting of psychiatric disorders (or associated symptoms), which may be under-reported in survey settings due to stigma, concerns about legal implications, and so forth among respondents. Further, we expect by focusing on severe measures of psychiatric disorders that we capture a lower-bound on the benefits of expanded access to psychiatric treatment centers. Put differently, if we observe effects for particularly severe measures of psychiatric disorders, then under reasonable assumptions, we would also expect improvements for less severe metrics.

Results are reported in Table 3. The pattern that emerges from this analysis is that, as the number of treatment centers increases within a county, deaths associated with psychiatric disorders decline. We observe that, ten additional psychiatric treatment centers per county leads to a reduction in the number of total drug and opioid overdose deaths by 0.028 (2.0%) and 0.012 (1.7%) per 10,000 residents, while the suicide death rate declines by 0.008 per 10,000 residents (0.7%). Coefficient estimates in the benzodiazepines and alcohol regression are negative, suggesting that these deaths also decline as treatment access improves, but do not rise to the level of statistical significance.

We also use data from the 2000-2011 N-SSATS to explore first stage effects (Substance Abuse and Mental Health Services Administration, 2016a). In the 2000-2011 N-SSATS, we have information on county and the annual number of admissions to stand-alone outpatient and residential treatment centers offering SUD and MHD treatment, thus mirroring the centers we examine. We aggregate the N-SSATS to the county-year level and estimate Equation 1. The coefficient estimate (standard error) on the lagged psychiatric treatment center variable is 76.4 (33.3). Comparing this estimate to the sample mean annual admissions (23,896.4) implies that ten additional centers increases the number of annual admissions by 764 per county or 3.2%.[28]

[28]We report the N-SSATS results in the text for brevity, but full results are available on request. Later

We view our analysis of death certificate and admissions data as providing suggestive evidence of our hypothesized causal chain of events: as local access to psychiatric treatment − as measured by the number of centers offering this care within a county − improves, treatment use rises and adverse outcomes associated with psychiatric disorders decline. We note that our findings are in line with recent work documenting that, as the number of psychiatric treatment centers increases in a county, adverse SUD-related outcomes decline (Swensen, 2015; Wen et al., 2017; Bondurant et al., 2018; Corredor-Waldron and Currie, 2019). With this evidence in hand, we proceed to our main analysis of eviction outcomes.

4.2 Regression analysis of eviction rates

Table 4 reports results for eviction rates. We build up the main model by progressively entering blocks of control variables. That is, we include county and year fixed-effects, and then add state-by-year fixed-effects (which subsume year fixed-effects), and county-level demographics. Table A1 reports a full set of coefficient estimates from our 'full' model that includes county fixed-effects, state-by-year fixed-effects, and county demographics. Coefficient estimates are stable across different sets of control variables (the untransformed estimated beta ranges from -0.005 to -0.009). We report results from the full model. Ten additional psychiatric treatment centers in a county leads to 0.06 fewer evictions per renter occupied home or 2.1% relative to the mean rate.

The CBP employment information is heavily imputed by the U.S. Census to protect establishment privacy, to the extent that using this information is not advisable (Deza et al., 2022). However, recent work by Eckert et al. (2020) proposes a linear programming method taking advantage that sub-unit (e.g., counties) counts must 'add-up' to the unit total (e.g.,

years of the N-SSATS provide admissions information in broad categories and we choose not to incorporate those years of data into the study. Further, we do not have access to county-level data, only state- and nation-level in later years. We include all centers not located in a hospital with a primary focus of SUD treatment, MHD treatment, or a mix of both SUD and MHD treatment in our sample. We make these exclusions to match CBP centers as closely as possible.

state or nation) count to impute employment levels for each establishment. We use this information to construct county-level employment counts across the psychiatric treatment centers we study (more specifically, we take the total number of employees across all centers in the county), which potentially allows us to asses heterogeneity in center size. A limitation of these data, which are novel and important, is that we cannot determine the jobs that establishment workers do, thereby we treat a maintenance worker and a psychologist equivalently when this treatment may be inappropriate. We estimate Equation 1 using employment counts (where employment is measured in the centers we study) rather than center counts.

Results are similar in sign and significance to our main findings. An additional 100 psychiatric treatment center employees (the mean is 1,247) per county leads to an 0.6% reduction in the eviction rate (un-transformed beta = -0.00016, p-value $<$ 0.000). We note that effects may be diluted as we combine all types of employees, both those that deliver psychiatric treatment (e.g, psychiatrists and psychologists) and those that do not (e.g., maintenance staff and food service workers).

4.3 Internal validity

We next probe three potential threats to identification: (i) reverse causality and differential pre-trends, (ii) unobserved confounding, and (iii) endogenous migration. Our results from this analysis provide suggestive evidence that our design is internally valid.

4.3.1 Differential pre-trends

One concern with our analysis is that differential trends between counties that do experience and do not experience changes in the number of psychiatric treatment centers. Evictions do not appear *ex ante* to be obvious determinants of the number of psychiatric treatment centers, and lagging centers one year in Equation 1 plausibly minimizes such concerns. However, we probe this hypothesis more formally in our data.

To do so, we follow Cengiz et al. (2019) and estimate a 'local event study.' This model is akin to a canonical event study with a binary treatment variable.[29] However, because our treatment variable (number of psychiatric treatment centers per county) is continuous, we must make some adjustments. We define an event as an increase in the number of centers in a county. The event window is defined as four years pre-event, year of the event, and four years post-event. The treatment group for an increase must have no change in the number of centers in the four years pre-event. We 'stack' the local events and estimate the local event study on the stacked data set, and we use separate fixed-effects (county and state-by-year) for each event. We include time-varying county control variables (which imposes the restriction that the effects of these controls on the outcome are homogeneous across events), but results are not appreciably different if we remove controls. The omitted category is the year prior to the local event. Standard errors are clustered at the level of the county.[30]

Local event study results are reported in Figure 2. We observe no evidence of differential pre-trends between counties that experience, and do not experience, an event. Following an increase in the number of centers in a county, we see a decrease in eviction rates that continues across the four years of the post-event period.

As an additional attempt to explore possible differential pre-trends and reverse causality, we estimate a variant of Equation 1 that adds four 'leads' (four, three, two, and one year in advance) and the contemporaneous year value in the number of centers in the spirit of Swensen (2015) and Bondurant et al. (2018). Results are summarized here for brevity, but are available on request. None of the leads nor the contemporaneous value is statistically significant and the lag value carries a negative sign that is statistically distinguishable from zero and is similar on sign to our main finding (Table 4).

[29]This estimator is also referred to as a stacked event study or stacked difference-in-differences model. In the local event study, we use the 1998 through 2016 CBP data in these analyses to maximize sample size. Beginning in 2017, Census suppresses county-NAICS cells with less than three establishments and for this reason we do not use future years.

[30]We must exclude some counties to construct our local event study analysis sample. Our local event study sample includes 1,569 counties.

4.3.2 Unobserved confounding

Using intuition offered by Altonji et al. (2005), we first estimate a baseline regression model that controls for the number of psychiatric treatment centers and fixed-effects (county and state-by-year), and progressively add covariates into the regression model.[31] If coefficient estimates are stable across different sets of controls, this finding suggests that our results are not driven by unobservables. Additionally, we estimate models that control for local government health expenditures (which we proxy with payroll for health and social service expenditures (Kaplan, 2021)). The purpose of estimating this additional specification is to explore the robustness to county-level factors that may predict both eviction outcomes and psychiatric treatment centers. Expenditures proxy for county-level financial support for psychiatric treatment centers. This specification is not our primary model as the expenditure variables only available for a sub-set of counties, as they are drawn from a sample of counties.

Broadly, our results from these analyses support the validity of our main findings. Our results are robust across specifications with sequentially richer sets of observable controls (Table 5). In particular, including proxies for local government expenditures on health and social investments does not substantially alter our results.

Next we test for conditional balance following Pei et al. (2019). To implement this test, we regress the number of psychiatric treatment centers on all other right hand variables included in Equation 1. If we observe conditional balance across counties with different levels of psychiatric treatment centers (i.e., treatment exposure), then this finding can offer suggestive evidence that other factors (which we do not measure) are also balanced. Results are reported in Table 6. We find that counties with larger populations and higher shares of the population ages 20 to 59 years (relative to the omitted age group, 60 years and older) have larger number of centers. Otherwise, the counties with higher (vs. lower) numbers of centers appear broadly balanced. Our results (reported in Table 5) are not sensitive to

[31] We realize that this exercise could be viewed as somewhat repetitive of the analysis reported in Table 4, but we wish to explore the importance of each covariate block.

including or excluding covariates, including those that appear to display imbalance.

Finally, we implement a method proposed by Oster (2019) to further explore the potential importance of unobservables. The author recommends not only considering coefficient stability as included covariates are changed, but also how much variation in the outcome (eviction rate in our setting) is explained by the included covariates. That is, if the 'best' possible model (i.e., one that includes all relevant unobservables) does not explain substantially more variation in the outcome than the actual model estimated by the researcher, then the scope for omitted variables to contaminate regression coefficient estimates is plausibly minimal. Oster proposes a ratio (δ) of the importance of the observed variables (i.e., those included by the researcher) to the importance of the unobserved variables in the best model, as defined above, required to push the estimated parameter (that is the coefficient estimate on lagged psychiatric treatment center variable in Equation 1) to specific value. We implement this test, selecting a value of zero (a common null hypothesis) for the parameter estimate. If the estimated δ is less than zero (in absolute value), Oster interprets this finding to imply that there is limited scope for omitted variables to lead to substantial bias in the estimated regression coefficients. We estimate that δ is -0.410, which suggests that omitted variables are unlikely to drive our findings.

4.3.3 Endogenous migration

A final threat to validity that we investigate is the possibility of 'program induced migration' (Moffitt, 1992). That is, the opening and closing of psychiatric treatment centers may prompt people to move away from (or possibly towards) these centers, this pattern of results will lead to a violation of the stable unit treatment value assumption required for TWFE models to recover causal estimates. To test for this behavior, we use across-county migration data from the Annual and Social Economic Supplement to the Current Population Survey (CPS) 2000 to 2016 (Flood et al., 2020). We construct a measure for a past year move across county lines and regress this measure on the number of psychiatric treatment centers using Equation 1. Our sample size declines as the CPS suppresses county identifiers for smaller (typically more rural) counties due to privacy concerns. Hence, this analysis focuses on more urban counties and is at best able to offer suggestive evidence.

We find no evidence that the changes in the number of psychiatric treatment centers prompts individuals to migrate across county lines (Table 7). The coefficient estimate on the number of psychiatric treatment centers is not statistically distinguishable from zero and is small in magnitude. This null finding is in line with a recent study showing that changes in the number of psychiatric treatment centers has no statistically significant impact on residential property values (Horn et al., 2021) within the local area, which suggests that consumers do not view such centers as a dis-amenity on average.

5 Heterogeneity and robustness

5.1 Heterogeneity

5.1.1 Psychiatric treatment provider type

We study the effect of two different types of psychiatric treatment centers in our main analysis: standalone outpatient and residential centers. While both types of centers offer psychiatric treatment, there are potential differences in terms of treatment and patients. For example, patients in residential treatment may have more severe psychiatric disorders than those receiving outpatient care and Medicaid patients may have less ability to access residential treatment due to federal legislation (e.g., Institutions for Mental Disease Exclusion).[32]

To study heterogeneity in effects across psychiatric treatment centers, we estimate Equa-

[32]Recently, some state Medicaid programs have been granted waivers to the Institutions for Mental Disease Exclusions, which prevents federal funds from being used to pay for enrollee treatment in these Institutions (Maclean et al., 2021). However, these changes generally occurred after our study period and are captured by our state-by-year fixed effects.

tion 1 using counts of (i) outpatient and (ii) residential treatment centers. We also add to this analysis additional providers who treat psychiatric disorders but in different settings: office-based physicians specializing in psychiatric treatment (e.g., psychiatrists), office-based non-physicians specializing in psychiatric treatment (e.g., psychologists, psychoanalysts, and social workers), general physicians, and a catch-all category of providers that potentially offer psychiatric treatment of crisis centers, self-help treatment (e.g., Narcotics Anonymous), various counselling services (e.g., marriage), and welfare services.[33] Comparable with our main treatment variables, we construct counts of these establishments in each county and enter them sequentially in Equation 1. While these alternative settings are not the focus of our study, we wish to compare effects across different modalities and shed light on the potential for various types of treatment and providers to impact eviction outcomes.

Results are reported in Figure 3. Our findings are similar for outpatient and residential centers that we consider in our main analysis, as access to both center types increases eviction outcomes decline. However, we observe no change in evictions when access to office-based physicians specializing in mental healthcare increases, but eviction outcomes decline as access to the remaining three provider types improve. Effect sizes are much smaller for the non-center-based providers than those we estimate for outpatient and residential centers, but these findings suggest that access to psychiatric treatment more broadly defined potentially confers benefits to individuals on the margin of facing eviction.

We suspect that the null finding for office-based physicians specializing in mental healthcare (e.g., psychiatrists) is attributable limited treatment of lower income patients who are at most risk for eviction. For example, Wen et al. (2019) show that psychiatrists are less likely than any other physician speciality to accept Medicaid, a public insurance program that predominately covers lower income Americans. Put differently, such providers are less

[33]The six digit NAICS codes are as follows: 621112 (offices of physicians specializing in psychiatric treatment), 621330 (offices of non-physicians specializing in psychiatric treatment), 621111 (offices of general physicians), and 624190 (catch all for various services potentially related to psychiatric treatment).

likely to treat lower income patients who are at elevated risk for eviction.

5.1.2 Urbanicity

We next report results by county urbanicity. More specifically, we classify each county as urban or non-urban based on the 2013 U.S. Department of Agriculture (USDA) Rural-Urban Continuum Codes (Economic Research Service, 2021).[34] There are differences in terms of evictions and access to psychiatric treatment centers by urbanicity, suggesting that there may also be heterogeneous effects. For example, access to psychiatric treatment is more limited in rural areas than in metropolitan and urban areas (Bureau of Health Workforce, 2021): in 2021, rural communities accounted for 58.4% of all Designated Mental Health Professional Shortage Areas in the U.S. However, rents are generally lower in rural vs. urban areas, and thus *ex ante* the relative strength of the relationship across these settings is not obvious.

Stratifying by urbanicity (Figure 4), our findings for the overall sample appear to be driven by urban counties. Coefficient estimates are only statistically different from zero in the urban sample and are very similar to our main findings based on all counties.[35]

5.2 Robustness

We next estimate a serious of robustness checks. Our results are robust and we summarize the analysis we have conducted. Robust checking is reported in Figure 5. Results based on Equation 1 using our main sample are reported for comparison.

We first estimate unweighted regression. Second, we change the covariates included in Equation 1, holding the analysis sample constant. We use exclude economic controls, exclude demographic controls, include only county and year fixed-effects, drop county fixed-effects, and use different lag structures for centers (i.e., use two and three year lags).

[34] Codes two through seven are defined as urban counties and all others as non-urban

[35] The Eviction Lab data do not include demographic information on evicted individuals. Hence, we are not able to study individual-level heterogeneity.

Third, we hold the regression model constant and alter our study period to exclude effects from potentially important policy and economic changes that occurred over our study period. We exclude counties with no treatment centers; years in which the Affordable Care Act, a major transformation of the U.S. healthcare delivery system (Oberlander, 2010), is in effect (2010 to 2016); and drop the years of the Great Recession (2008 to 2010) as this economic downturn substantially reduced employment and income, thus potentially impacting eviction outcomes and psychiatric disorders (Hollingsworth et al., 2017).

Fourth, we cluster our standard errors at higher levels of aggregation: core-based statistical areas (CBSA) and states. We want to allow for the possibility that counties with a CBSA or state may experience similar economic or policy environments (e.g., shared insurance or housing regulations), leading to serially correlated errors.[36] Fifth, we re-define our center measure to include all providers that could offer psychiatric treatment (office-based psychiatric providers, office-based physicians, and 'other' providers delivering psychiatric treatment). Sixth, we use the county population (rather than the renter population) as the denominator in our eviction rate variable.

Finally, we examine a second measure of eviction: eviction *filings* per renter occupied home (Table 8).[37] A filing occurs when landlord perceives that a renter has violated terms of the lease agreement, while a completed eviction also incorporates a renter's ability to effectively navigate the justice system and a (potentially) objective view of the legitimacy of the eviction filing as a judge oversees the proceedings and renders a decision. An eviction likely imposes a more severe burden on the evicted person, that person must leave their home, but filings are more common (there are on average 6.34 filings per renter occupied

[36]Interestingly, our estimated standard errors are smaller when we cluster at the state (vs. the county) level. As noted by Angrist and Pischke (2008), while standard errors tend to increase at higher levels of aggregation, the relative size is context-specific. For example, Baltimore, MD and Philadelphia, PA may be impacted by more correlated shocks than Philadelphia, PA and Altoona, PA.

[37]The sample size for eviction filings is somewhat different from the completed eviction sample size. The difference in sample size is attributable to differences in missingness across the two variables. Full details available on request.

home vs. 2.86 evictions per renter occupied home in our sample of counties) and may capture 'attempted' evictions that may be unsuccessful if the case is not legitimate. Results are very similar to our completed eviction findings: we find that ten additional centers per county leads to a 1.4% decline in eviction filings (vs. 2.1% for completed evictions). Comparing our findings across the two measures (filings and completed evictions) offers us suggestive evidence that those with psychiatric disorders are not disproportionately subject to illegitimate eviction filings. Put differently, we do not observe much larger effects for filings than we do for completed evictions (indeed filing effects are smaller in relative terms than completed eviction findings). Alternatively, one could view our findings (effect sizes are larger for completed evictions than filings) to imply that the court proceedings pose additional barriers to those with psychiatric disorders. However, examination of the 95% confidence intervals suggest more similar effects across the two outcomes, hence we raise these arguments as possibilities only. Additionally, as note earlier, we do not emphasize this result as we are somewhat concerned about data quality (Goodspeed et al., 2020).[38] Note that these quality issues have not been raised for our primary measure (completed evictions).

6 Conclusion

The United States is in the midst of a housing crisis, both in terms of overall affordability and in terms of evictions (Eviction Lab, 2021). Each year, 3% of households experience a completed eviction − or 2.5M evictions annually. Those who are evicted tend to move to lower-income and higher crime areas, and to homes that are of lower quality (e.g., that do not have adequate heat), and face challenges in renting in the future (Goodspeed et al., 2020). In sum, evictions are persistently harmful to individuals, families, and communities, and disproportionately impact vulnerable demographic groups: those living in poverty as

[38] The key concern raised by Goodspeed et al. (2020) is that the Eviction Lab methodology for collecting eviction filings, which relies on data from a third-party vendor, may lead to heterogeneous under-counting of filings across counties. We note that Goodspeed et al. (2020) consider just one state, Michigan.

well as minority populations (Eviction Lab, 2021).

There is scant economic research on evictions, either in terms of causes or consequences (Allen et al., 2019; Humphries et al., 2019; Bradford and Bradford, 2020b,a; Evans et al., 2019). We add to this small literature by examining the role of psychiatric disorders in eviction outcomes over the period 2000 to 2016. In particular, we study how access to psychiatric treatment impacts eviction filing and completed eviction rates within a county. Clinical and economic evidence suggests that many modalities of psychiatric treatment are effective, and symptoms of many common psychiatric disorders (e.g., disorganized thinking, hallucinations, using substances, crime commission, violence) may increase the likelihood of an eviction. Further, a series of recent economic research suggest that expanded access of such treatment improves psychiatric disorders and reduces social costs (Swensen (2015); Bondurant et al. (2018); Deza et al. (2022); Corredor-Waldron and Currie (2019)).

Our study builds on these related lines of research. We document that expanding access to psychiatric treatment centers offering residential and outpatient care reduces eviction outcomes. In particular, we find that ten additional psychiatric treatment centers in a county leads to a reduction of 2.1% in the eviction rate. Ten additional centers reflect a 17.6% increase in supply for the average county in our sample and suggests an eviction-center elasticity of -0.01 (using one center in this elasticity calculation). Each year there are 2.5M evictions in the U.S., thus our findings imply that adding ten centers per county could reduce the total number of evictions by 52,500 annually.[39] These findings are robust to numerous sensitivity checks and are not attributable to differential pre-trends between counties that do and do not experience an increase in the number of centers.

We can compare our findings to the effectiveness of state-wide prohibition of eviction filings in small claims court (instead, such filings much occur in the, more costly to the landlord, standard court), a common state policy to reduce evictions (30 states had such

[39]We note that, due to limited coverage in the Eviction Lab data, we do not include all counties in our sample. Hence, we are extrapolating our findings to these counties in our calculation.

a law in place by the end of our study period). Bradford and Bradford (2020a) show that following state prohibition on eviction filings in small claims court, the county-level eviction rate falls by 6.9%. We show that ten additional psychiatric treatment centers per county leads to a decline of 2.1% in the county-eviction rate. Our findings suggest that investments in psychiatric treatment, in particular standalone residential and outpatient centers, compare favorably in terms of reducing evictions to commonly used state (or county) policy levers.

We can also contrast our findings to the literature that examines to what extent access to psychiatric treatment has spillover effects on other socially valuabe outcomes, in particular crime. For example, using the same CBP data that we leverage here, Bondurant et al. (2018) show that ten additional psychiatric treatment centers per county reduces crime rates by 3%, that is a very similar size as to our findings for evictions.[40]

Taken in this light, the effects we estimate from a non-standard policy tool − indeed one that, to the best of our knowledge, is not generally leveraged to address eviction outcomes − appears to compare favorably with a more standard policy. The effects we observe for evictions are in addition to directly targeted outcomes (i.e., psychiatric disorders) and can therefore be considered a positive spillover.

This study has limitations. We are not able to study all eviction outcomes. Further, we do not know the specific reasons that lead to the eviction and we are unable to study heterogeneity across individuals as the Eviction Lab data do not provide demographics for the evicted. Future work, using different data sources, could explore these questions. We view our work as a step in understanding the causal relationships between psychiatric disorders and eviction outcomes specifically, and housing stability more broadly.

Our work documents a previously undocumented benefit of access to psychiatric treatment: reduced eviction filings and completed evictions. This relationship is important as the U.S. is currently in the midst two epidemics: (i) a psychiatric disorder epidemic char-

[40]See Table 2, Column (5) in that paper.

acterized by substance use and mental illness, and (ii) a housing affordability epidemic that disproportionately impacts lower income groups that are at elevated risk for psychiatric disorders. Our findings suggest that policies targeting the psychiatric disorder epidemic may yield positive spillovers: promoting housing stability by reducing evictions. These benefits could occur alongside general improvements in health and other benefits that impact individuals privately and society more broadly such as improved labor market outcomes, reduced crime, stronger families, better credit scores, and so forth.

7 Tables and Figures

Table 1: Summary statistics.

Variable:	Mean	S.D.	Min.	Max.	N
Centers	58.65	105.73	0.00	622.00	39364
County evictions	4612.42	7541.90	0.00	47716.00	39364
County eviction rate	2.86	2.32	0.00	24.16	39364
County poverty rates	14.27	5.15	2.50	53.00	39364
County median income (in 10,000's)	5.04	1.32	1.64	13.46	39364
County population (per 100,000)	12.43	21.30	0.00	101.21	39364
Percent female	0.51	0.01	0.28	0.57	39364
Percent Black	0.13	0.13	0.00	0.86	39364
Percent Native American/Indigenous	0.01	0.03	0.00	0.86	39364
Percent Asian/Pacific Islander	0.05	0.06	0.00	0.72	39364
Percent Hispanic	0.16	0.17	0.00	0.96	39364
Percent ages 0-19	0.27	0.03	0.08	0.46	39364
Percent ages 20-59	0.55	0.03	0.27	0.75	39364

Note: Unit of observation is a county in a state in a year. Data are weighted by the county population.

Table 2: Demographics of individuals with and without psychiatric treatment in the past year: NSDUH 2016.

Sample:	No Treatment in PY	Treatment in PY
19 to 34 years	0.36	0.39
25 to 64 years	0.64	0.61
Male	0.49	0.46
Female	0.51	0.54
White race	0.61	0.70
Black race	0.12	0.12
Other race	0.087	0.065
Hispanic	0.18	0.12
Below the federal poverty level	0.16	0.32
Assistance program acceptance	0.19	0.48
Any health insurance	0.88	0.89
Private insurance	0.68	0.38
Medicaid or CHIP insurance	0.15	0.41
Medicare insurance	0.044	0.16
Military insurance	0.037	0.081
Very good or excellent health	0.60	0.32
Tobacco product use in the past year	0.34	0.60
Alcohol use in the past year	0.74	0.72
Illicit drug use in the past year	0.21	0.46
Observations	36187	993

Note: Unit of observation is a respondent. Column 1 includes means from counties with no standalone psychiatric treatment centers in the past year. Column 2 includes means from counties with at least one standalone psychiatric treatment centers in the past year. PY = past year.

Table 3: Effect of local access to psychiatric treatment on mortality outcomes.

Outcome:	All Drug	Opioid	Benzo	Alcohol	Suicide
Centers (lagged)	−0.0282***	−0.0118**	−0.0018	−0.0009	−0.0079***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Mean of Dependent Variable	14.39	7.07	1.79	1.46	11.74
Observations	39327	39327	39327	39327	39327
County Fixed-Effects	Yes	Yes	Yes	Yes	Yes
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Note: Unit of observation is a county in a state in a year. All models estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of local access to psychiatric treatment on eviction outcomes.

Outcome:	Eviction Rate	Eviction Rate	Eviction Rate
Centers (lagged)	−0.009***	−0.005***	−0.006***
	(0.00)	(0.00)	(0.00)
Mean of Dependent Variable	2.86	2.86	2.86
Observations	39364	39364	39364
County Fixed-Effects	Yes	Yes	Yes
State-by-Year Fixed-Effects	No	Yes	Yes
Controls	No	No	Yes

Note: Unit of observation is a county in a state in a year. All models estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of local access to psychiatric treatment on the completed eviction rate: Progressively add in covariates.

	(1) Eviction Rate	(2) Eviction Rate	(3) Eviction Rate	(4) Eviction Rate	(5) Eviction Rate
Centers (lagged)	−0.009***	−0.005***	−0.005***	−0.006***	−0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
County poverty rates			0.000	0.001	0.005
			(0.01)	(0.01)	(0.02)
County median income (in 10,000's)			−0.130*	−0.139*	−0.124
			(0.08)	(0.08)	(0.10)
County population (per 100,000)				0.049	0.066
				(0.08)	(0.08)
Percent female				−2.218	0.650
				(7.31)	(14.52)
Percent Black				−3.361	−5.644
				(4.47)	(5.35)
Percent Native American/Indigenous				21.898**	24.073
				(10.22)	(19.51)
Percent Asian/Pacific Islander				−2.741	2.777
				(4.11)	(4.66)
Percent Hispanic				−2.595	−3.508
				(2.69)	(3.23)
Percent ages 0-19				3.747	9.119*
				(3.72)	(5.52)
Percent ages 20-59				1.953	8.230
				(4.04)	(6.11)
Payroll for fulltime and partime streets and highways					0.000
					(0.00)
Payroll for fulltime and partime police officers					0.000
					(0.00)
Payroll for elementary and secondary instruction					0.000
					(0.00)
Constant	3.355***	3.163***	3.821***	3.151	−3.259
	(0.09)	(0.08)	(0.44)	(5.44)	(9.94)
Mean of Dependent Variable	2.86	2.86	2.86	2.86	2.86
Observations	39348	39338	39338	39338	16013
State-by-Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
County Fixed-Effects	No	Yes	Yes	Yes	Yes
Economic Controls	No	No	Yes	Yes	Yes
Demographic Controls	No	No	No	Yes	Yes
Local Payroll Controls	No	No	No	No	Yes

Note: Unit of observation is a county in a state in a year. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Test of covariate balance.

Variable:	Centers (lagged)
County poverty rates	−1.408
	(0.86)
County median income (in 10,000's)	−2.165
	(4.20)
County population (per 100,000)	5.688*
	(3.22)
Percent female	159.774
	(100.02)
Percent Black	−51.701
	(103.99)
Percent Native American/Indigenous	531.624
	(418.89)
Percent Asian/Pacific Islander	−170.132
	(354.26)
Percent Hispanic	−289.219
	(241.19)
Percent ages 0-19	−609.252
	(431.53)
Percent ages 20-59	488.376**
	(207.95)
Mean of Dependent Variable	57.46
Observations	39364
State-by-Year Fixed-Effects	Yes
County Fixed-Effects	Yes
Robust Standard Errors	Yes

Note: Unit of observation is a county in a state in a year. Data are weighted by the county population. The regression coefficient estimates and associated standard errors are generated from the same specification. Standard errors are reported in parentheses and account for within county clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of local access to psychiatric treatment on migration outcomes: Current Population Survey.

Outcome:	Migration Rate
Centers (lagged)	0.000
	(0.00)
Mean of Dependent Variable	0.04
Observations	3131
State-by-Year Fixed-Effects	Yes
County Fixed-Effects	Yes
Controls	Yes

Note: Unit of observation is a county in a state in a year. All models estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering.

* p < 0.1, ** p < 0.05, *** p < 0.01.

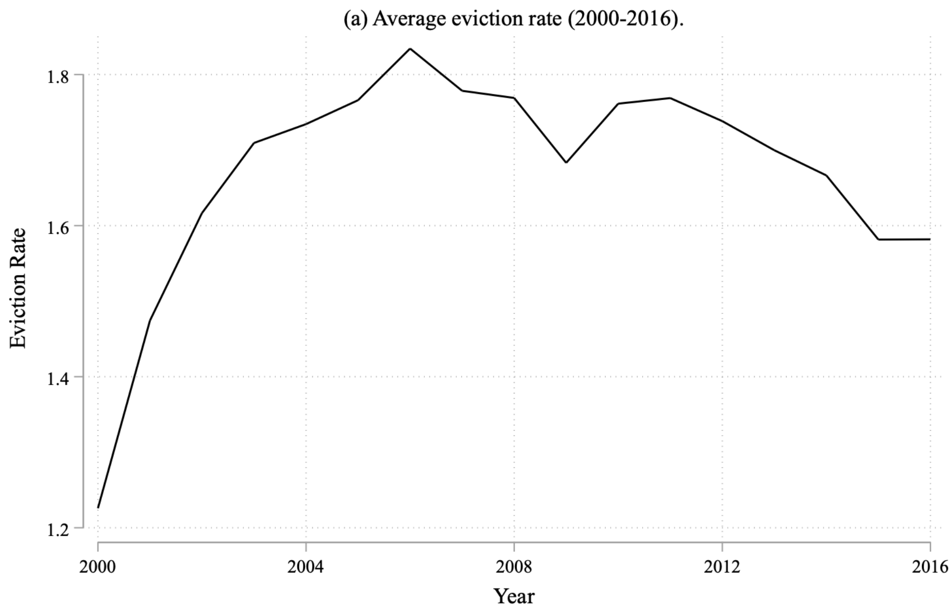
Table 8: Effect of local access to psychiatric treatment on eviction filings.

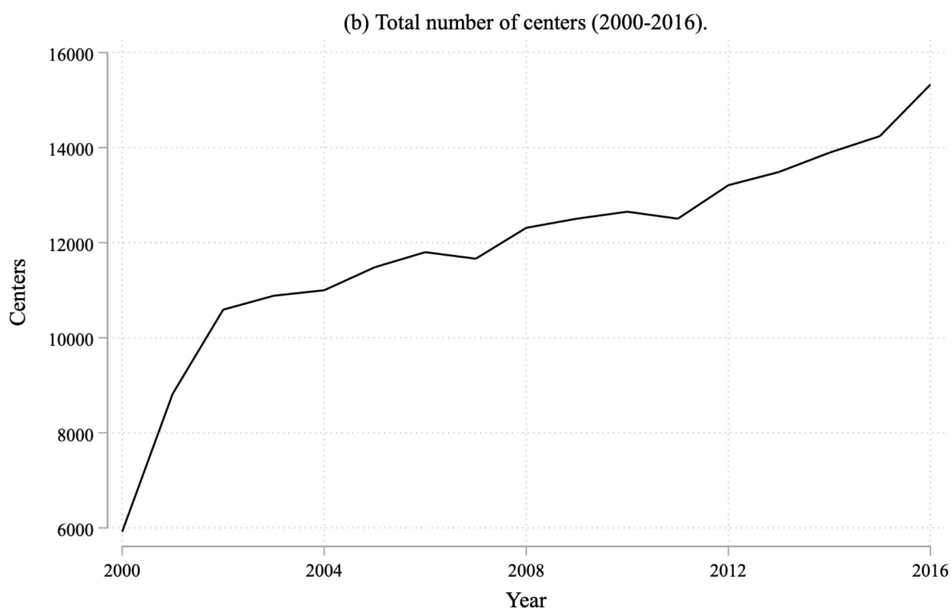
Outcome:	Filing Rate
Centers (lagged)	−0.009***
	(0.00)
Mean of dependent variable	6.34
Observations	39364
State-by-year fixed-effects	Yes
County fixed-effects	Yes
Controls	Yes

Note: Unit of observation is a county in a state in a year. All models estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering.

* p < 0.1, ** p < 0.05, *** p < 0.01.

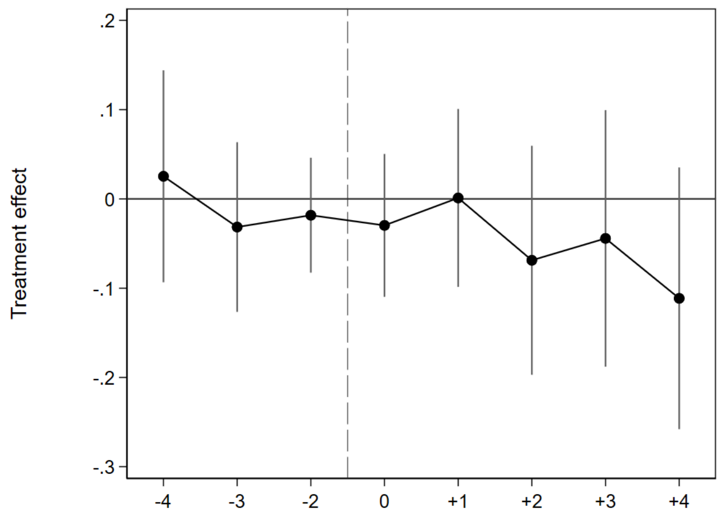
Figure 1: Trends in eviction rates and local access to psychiatric treatment.





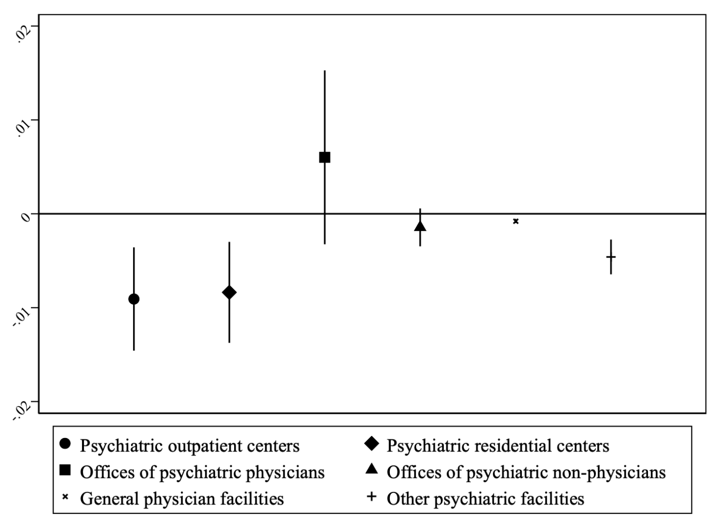
Note: Unit of observation is the year. Data are weighted by the county population.

Figure 2: Effect of local access to psychiatric treatment center using a local event study.



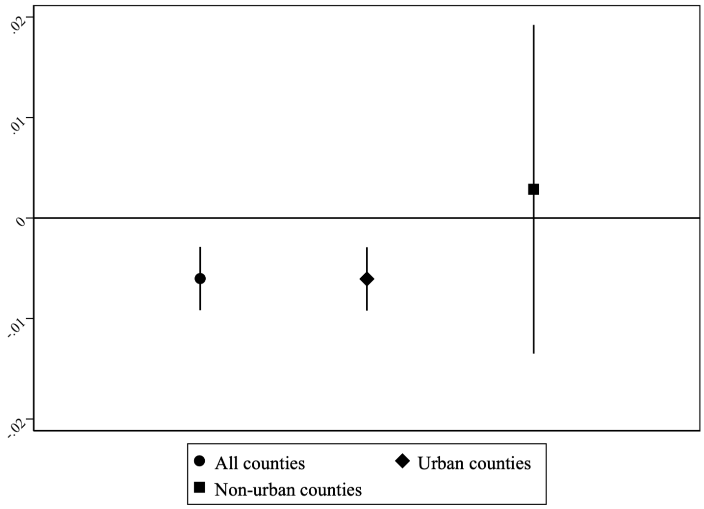
Note: Unit of observation is a county in a state in a year. Model is estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. 95% confidence intervals that account for within county clustering are reported with vertical line. The omitted period is -1.

Figure 3: Effect of local access to psychiatric treatment on eviction outcomes: Heterogeneity by provider type.



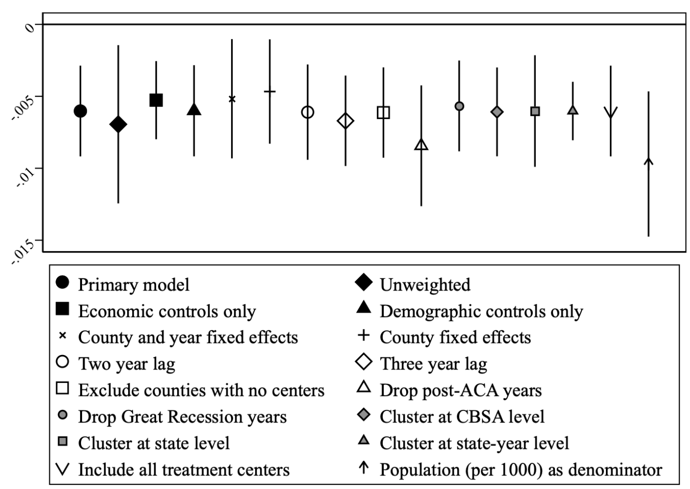
Note: Unit of observation is a county in a state in a year. Models are estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. 95% confidence intervals that account for within county clustering are reported with vertical line.

Figure 4: Effect of local access to psychiatric treatment on eviction outcomes: Heterogeneity by urbanicity.



Note: Unit of observation is a county in a state in a year. Models are estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. 95% confidence intervals that account for within county clustering are reported with vertical line.

Figure 5: Effect of local access to psychiatric treatment on eviction outcomes: Alternate specifications and samples.



Note: Unit of observation is a county in a state in a year. Models are estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. 95% confidence intervals that account for within county clustering are reported with vertical line.

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8 Appendix

Table A1: Effect of local access to psychiatric treatment on eviction outcomes: Full set of coefficient estimates.

Outcome:	Eviction Rate
Centers (lagged)	–0.006***
	(0.00)
County poverty rates	0.001
	(0.01)
County median income (in 10,000's)	–0.139*
	(0.08)
County population (per 100,000)	0.049
	(0.08)
Percent female	–2.218
	(7.31)
Percent Black	–3.361
	(4.47)
Percent Native American/Indigenous	21.898**
	(10.22)
Percent Asian/Pacific Islander	–2.741
	(4.11)
Percent Hispanic	–2.595
	(2.69)
Percent ages 0-19	3.747
	(3.72)
Percent ages 20-59	1.953
	(4.04)
Constant	3.151
	(5.44)
Mean of Dependent Variable	2.86
Observations	39364
State-by-Year Fixed-Effects	Yes
County Fixed-Effects	Yes
Controls	Yes

Note: Unit of observation is a county in a state in a year. All models estimated with weighted least squares and control for county demographics, county fixed-effects, and year fixed-effects. Data are weighted by the county population. Standard errors are reported in parentheses and account for within county clustering.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.