Safety-net Primary Care Clinics and Psychiatric Emergency Department Visits

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Abstract

In this paper, I examine whether expanding access to safety-net primary care clinics (SNPCCs) has an impact on psychiatric emergency department (ED) utilization – defined as mental illness and substance use disorders, in California. Primary care physicians have assumed an increasingly important role in outpatient behavioral healthcare through screening, diagnosing, and prescribing medications. I leverage variation in travel distance to the nearest clinic in a zipcode area over the period 2005 to 2015 in a two-way fixed-effects regression. I find that one additional mile increase in travel distance leads to an increase of 0.13% in the number of psychiatric ED visits and the effects are primarily driven by female patients. My findings imply that delivering behavioral healthcare in SNPCCs can be a strategy to reduce unmet needs for behavioral healthcare among low-income groups. Policies designed to increase investments in safety-net primary care settings may have unintended benefits in reducing psychiatric ED utilization.

Keywords: Primary care; mental health; substance use; emergency department.

JEL codes: I10.

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1 Introduction

In the United States, mental health and substance use disorders (collectively referred to as 'psychiatric disorders') are common chronic conditions. Common mental health disorders (MHDs) are depression, anxiety, and mood disorders, and common substance use disorders (SUDs) are alcohol and opioid use disorders. According to the National Survey on Drug Use and Health (NSDUH) data, in 2019, over 61 million people had either any mental illness (AMI) or an SUD in the past year (NSDUH, 2019b). These conditions place a great burden on affected individuals, their families, and society through poor health, increased healthcare utilization, and worse employment outcomes. The annual economic burden of serious mental illness (SMI) and substance misuse is \$280 and \$896 billion in 2019, respectively (Kessler et al., 2008; National Institute of Drug Abuse, ND).

Although psychiatric disorders cannot be cured, these conditions can be effectively managed through appropriate outpatient care. Thus, psychiatric emergency department (ED) encounters are considered preventable (Weiss et al., 2016). Estimates from the Healthcare Cost and Utilization Project (HCUP) suggest that 12.5% of all ED visits in 2007 are related to psychiatric disorders and the rate has increased substantially since (Owens et al., 2011; Weiss et al., 2016). However, most EDs are ill-equipped to address the medical needs of a person in a mental health crisis (SAMHSA, 2020). Psychiatric boarding is a process of holding patients in EDs until an inpatient bed becomes available, which places large strains and costs on EDs. In 2008, 79% of ED medical directors reported that their hospital "boards" psychiatric patients, and 62% indicated that there are no psychiatric services involved with patient care while boarding (American College of Emergency Physicians, 2008).

While effective treatment options are available (American Psychiatric Association, 2006; Murphy and Polsky, 2016), less than half of individuals with AMI and only one-tenth of individuals with an SUD reported having received related treatment (NSDUH, 2019b). While there are many reasons for failure to receive treatment, shortages of mental healthcare and addiction medicine specialists are prevalent. Nearly 35% of counties have no licensed psychologists and nearly 60% do not have a single psychiatrist (Lin et al., 2016; New American Economy, 2017). Given the shortages and other reasons, primary care physicians have assumed an increasingly important role in outpatient behavioral healthcare through screening, diagnosing, and prescribing medications (Olfson et al., 2014; Olfson, 2016; Olfson et al., 2020; Wen et al., 2019).[1,2]

In this paper, I examine whether expanding local access to safety-net primary care clinics (SNPCCs) on psychiatric ED visits between 2005 and 2015 in California. Safety-net clinics deliver affordable health services to underserved populations, especially low-income and Medicaid enrollees. Furthermore, psychiatric disorders are most prevalent and difficulties in obtaining treatment are particularly high among low-income groups. For example, while Medicaid covered 14% of the general adult population, Medicaid covered 21% of adults with AMI, 26% of adults with SMI, and 17% of adults with SUDs in 2015 (Zur et al., 2017). Additionally, over one-third of US counties do not contain any outpatient mental health treatment facilities that accept Medicaid (Cummings et al., 2013). Psychiatrists are less likely than primary care physicians and other specialists to accept patients with Medicaid, even after Medicaid expansions (Bishop et al., 2014; Wen et al., 2019).

Whether local access to primary care changes ED utilization in general and for psychiatric conditions specifically is one of the key policy questions in curbing inappropriate use of ED services and containing healthcare costs. On one hand, improving access to primary care services could decrease inefficient ED use through timely managing symptoms in outpatient settings. Evidence on increasing access to primary care services via health insurance coverage suggests that overall ED visits, especially non-urgent visits

[1] Specialty providers such as psychiatrists and psychologists can additionally provide intensive psycho-pharmacological and psycho-social treatment (Olfson, 2016).

[2] For example, between 2010 and 2018, the rate of buprenorphine treatment, one of the three pharmacological treatments approved by the Food and Drug Administration (FDA) for opioid use disorder, prescribed by primary care providers increased from 12.9 per 10,000 people to 27.4. In contrast, the rates for psychiatrists and addiction medicine specialists increased from 8.7 to 12.0 (Olfson et al., 2020).

(Miller, 2012; Antwi et al., 2015), and ED visits for psychiatric disorders (Meara et al., 2014) decreased. Increasing convenient access to primary care providers was found to reduce ED visits (Dolton and Pathania, 2016; Pinchbeck, 2019). Incentivizing patients to visit their primary care physician was found to reduce non-urgent ED visits and improve mental health outcomes (Bradley et al., 2018; Bradley and Saunders, 2020).

On the other hand, improving access to primary care could increase the demand for ED care through improved communication or more detection and treatment of previously undetected medical problems. Additionally, finding the right psychotropic medication to treat psychiatric disorders often involves trial and error, and the side effects of some psychotropic medications can lead to adverse drug events resulting in emergency department visits and hospitalizations (Qato et al., 2018). Some studies of Medicaid expansion to low-income adults found that the expansion increased ED visits, including visits for primary care treatable conditions, and increased use of care in other settings (Taubman et al., 2014; Finkelstein et al., 2016; Nikpay et al., 2017; Woodworth, 2020). Studies on young adults aging out of parental or Medicaid insurance found that losing health insurance decreased ED visits (Anderson et al., 2012, 2014). Finally, past studies found that ED visits in general and for psychiatric disorders did not change after gaining health insurance coverage or incentivizing primary care providers to participate or increase participation in Medicaid (Pines et al., 2016; Maclean et al., 2018).

Using various datasets obtained from California's Office of Statewide Health Planning and Development (OSHPD), I estimate two-way fixed-effects regressions using zipcode-level psychiatric ED visits in total and separately for females and males. Psychiatric ED visits are defined as encounters with the chief cause of visits related to MHDs or SUDs. Additionally, I focus on visits for the uninsured and for which Medicaid and local safety-net programs were third-party payers. To measure treatment access, I utilize variations in travel distance to the nearest clinic, which is offered by clinic openings and closings. Furthermore, my preferred estimation specification includes county-by-year fixed-effects that flexibly control for potential confounders.

Overall, my within-zipcode analysis reveals that increases in travel distance to the nearest clinic lead to statistically significant increases in psychiatric ED utilization and the effects are primarily driven by female patients. My estimates suggest that a one-mile increase in travel distance leads to a 0.13% increase in the number of psychiatric ED visits. Scaling the effect size by 4, which is the average increase and reflects a 33.3% increase in travel distance over my study period, and comparing these estimates to the sample means imply that the average effect of an increase in travel distance is an increase of 0.5 ED visit in a zipcode area in a year. My results do not appear to be driven by reverse causality or confounding from unobservables and are robust to numerous sensitivity checks. Additionally, I provide evidence on the 'first stage' such that closing of an existing SNPCC leads to more psychiatric encounters at nearby SNPCCs. However, opening of an SNPCC does not crowd out other nearby SNPCCs in the short run, which suggests there could be potential unmet demand in the area where a new opening occurs. This asymmetry suggests that clinics affect care primarily by improving access.

My study is the first to investigate the impact of proximity to primary care clinics on behavioral healthcare outcomes. Previous work studied the effects of either expanding health insurance coverage or incentivizing primary care providers to participate or increase participation in Medicaid (Meara et al., 2014; Maclean et al., 2018). By using detailed data available at the zipcode-level on the universe of ED encounters and information on clinic openings, closings, and location, I provide evidence that there can be unintended benefits from proximity to SNPCCs on psychiatric emergency department utilization among low-income groups. My findings also complement previous economic research suggesting that proximity to healthcare providers matters (Buchmueller et al., 2006; Lu and Slusky, 2016, 2019; Lindo et al., 2020; Corredor-Waldron and Currie, 2021; Myers, 2021) and potential spillovers of access to behavioral healthcare on local communities (Swensen, 2015; Bondurant et al., 2018; Horn et al., 2021; Corredor-Waldron and Currie, 2021; Deza et al., 2022,?).

2 Data and methods

2.1 Safety-net primary care clinic data

Clinics that focus on primary care services and are operated by nonprofit corporations are eligible for state licensure as primary care clinics.[3] These clinics focus on primary care services and offer a wide array of other services such as mental health, alcohol and drug treatment, and women's health services. Licensed primary care clinics obtain enhanced reimbursement from government health programs and have access to various funding sources for serving designated populations. These clinics include federally qualified health clinics (FQHCs), FQHC look-alikes, rural health centers, migrant health centers, free clinics, and other types of nonprofit community clinics and clinics serving specific populations. Licensed primary care clinics are also required to file annual utilization reports, which are called OSHPD Primary Care Clinic (PCC). Thus, for the purpose of this paper, I defined SNPCCs as all of those who filed the annual utilization reports.

The OSHPD-PCC data include information about the location and encounters by primary diagnosis types. Using this data, I create a list of all SNPCCs that ever filed reported between 2001 and 2019 and hand-collected all information in originally licensed date, the most recent license effective dates, and status dates obtained from the OSHPD facility search.[4] I exclude health centers that provide mainly dental health services or operated for less than 6 months. Thus, the final list includes 1,473 clinics that ever

[3]Private clinics, clinics operated by governmental entities (counties, cities, and tribal organizations), clinics operated as outpatient departments of hospitals, intermittent clinics (open less than 20 hours per week) operated by licensed primary care clinics, clinics run by teaching institutions, and student health services are not required a state license.

[4]https://lfis.oshpd.ca.gov/AdvSearch.

operated in CA between 2005 and 2015. Over the study period, Figure 1 shows that there are more openings than closings every year. As a result, the number of clinics operated in any given year has grown substantially from 772 to 1,205 over the same period.

Data from the OSPHD-PCC 2019 Pilot Table suggests that these clinics served almost 20% of the population in California, with a total of 24.6 million patient encounters. These clinics are funded mostly through California's Medicaid Program (known as Medi-Cal) reimbursement, which accounts for 53.8% of total revenue. Federal funds and grant programs account for 17% of the total revenue. Table 1 reports demographic characteristics of patient population compared to the overall population. Overall, these clinics served mostly females, younger individuals, and minority populations. Importantly, approximately 67% had family incomes at or below 200% of the federal poverty level. Patients with Medicaid as a payment source account for 60.4% of the patient population, and are followed by self-paying patients and patients receiving a sliding fee scale (patients paying a share of the overall treatment bill) or free care with 20.8%.

The primary geographic units for my analysis are zipcodes, as defined by the 2010 U.S. Census Bureau's ZIP Code Tabulation Areas (ZCTAs). ZCTAs aggregate census blocks to form real representations U.S. Postal Service (USPS) zipcode mail delivery routes. For most areas, the ZCTA code is the same as the USPS zipcode (Census Bureau, ND). Using data on coordinates of neighborhood centroids and clinic locations, I narrow down a list of clinics that are potentially the closest to each neighborhood centroid. I then calculate the travel distance from each neighborhood centroid to each of the clinic candidates, identified above, and obtain the minimum travel distance for each zipcode in each year. Variations in travel distance are driven by clinic openings and closings.

The average treatment effect that I estimate is local to the type of patients who seeks/stops treatment when a nearby SNPCC opens/closes but not otherwise. Thus, the 'compliers' are possibly patients with common, less severe, or disabling disorders to the extent that their health can be effectively treated in a primary care setting. The compliers may include individuals who take up new treatment when a clinic opens and/or individuals already receiving treatment but for whom the new clinic allows a better patient-provider match or is simply more affordable. These are the patients from whom my estimates are likely generated.

2.2 Emergency department data

To measure ED utilization, I use the 2005-2015 OSHPD Emergency Department data. This data contains all ED encounters, excluding those that resulted in a same-hospital admission. Thus, I combine the ED data with the OSHPD Inpatient Discharge data to create the universe of all ED encounters. Each encounter contains a single principle diagnosis, other secondary diagnoses, and their Clinical Classification Software (CCS) categories,[5] as well as information on patient's demographic characteristics, expected source of payment, and 5-digit postal zipcode of residence. I start my sample in 2005 because this is the first year that the data is available, and end the sample in 2015 because California adopted ICD-10 codes in quarter 4 of 2015.

Psychiatric visits are defined with the principle CCS categories for mental health conditions and illicit drug use disorders. The principal diagnosis is the chief cause of the encounter for care. I exclude dementia and intellectual disability/developmental disorders as these conditions are not generally treated in SA-MH clinics (Owens, Mutter and Stocks, 2006). Table 2 shows relevant CCS categories used in this study. I restrict the sample to encounters with Medicaid, local safety-net programs, and uninsured as expected sources of payment.[6] Due to the ACA Medicaid expansion, there was an increase in visits with Medicaid and a decline in visits with local safety net programs and insured. Thus I do not examine these groups separately. Using information patient's

[5]Clinical Classification Software is a tool developed as part of the Healthcare Cost and Utilization Project (HCUP) to group related International Classification of Disease (ICD9-CM) codes into broader categories.

[6]Uninsured includes self-paying, no charge, or charities as expected source of payment

residence, I collapse the data to obtain a balanced panel at the zipcode-year level. The final sample includes 1,749 zipcode areas spanning 14 years.

2.3 Empirical models

I estimate the effect of access to SNPCCs using a 'generalized difference-in-differences design', which exploits within-area variation over time while controlling for aggregate time-varying shocks. I implement this strategy using a Poisson regression using the following form:

$$Y_{z,c,t} = exp(\alpha_0 + \alpha_1 Distance_{z,c,t} + X_{z,c,t,}\beta + \alpha_z + \alpha_{c,t} + \epsilon_{z,c,t} \quad (1)$$

where $Y_{z,c,t}$ represents the number of ED visits for zipcode area z in county c in calendar year t. $Distance_{z,t}$ is the travel distance to the closest SNPCC measured in miles. The vector $X_{z,c,t,}$ includes travel distance to the closest hospital, and city-level unemployment rates, as well as indicators for the closest SNPCC being an FHQC or FHQC look-alike and being a rural center.[7]. α_z includes zipcode fixed-effects; $\alpha_{c,t}$ includes county-by-year fixed-effects; and $\epsilon_{z,c,t}$ is the error term. All analyses allow errors to be correlated within counties over time.

3 Results

3.1 Main results

Table 3 reports the Census 2010 demographic characteristics of zipcode areas with and without at least one SNPCC between 2005 and 2015. Areas with a clinic have a higher fraction of Hispanic, younger residents, poorer, and more densely populated

[7]The BLS provides unemployment rates for cities and towns with more than 25,000 population. I assign each zip code to the city with the most population. For cities with missing unemployment rates, I use the county-level unemployment rates (Buchmueller et al., 2006). `https://data.bls.gov/PDQWeb/la`.

than areas without a clinic. Areas with a clinic also experience higher psychiatric ED utilization. Interestingly, while the distance to the nearest clinic is over halved of that to the nearest hospital in areas with a clinic, they are slightly the same in areas without a clinic.

Table 4 presents estimates for α_1 in Equation 1. Each cell illustrates results from a separate regression where the dependent variables are the number of psychiatric ED visits in total and separately for females and males. I 'build' up my regression by progressively adding covariates. I begin estimation with a set of simple controls for differences across zipcode area and over time, in the form of area and year fixed-effects (column 1). I next add county-by-year fixed effects (column 2) to flexibly control for county-specific factors. Finally, I add time-varying control variables (column 3; preferred specification).

In the baseline regression controlling only for heterogeneity across zipcode areas and time, the coefficient estimates suggest there is a positive relationship between the outcomes of interest and travel distance. Accounting for the influence of county-specific factors in the form of county-by-year fixed effects greatly improves the precision of my estimates across all outcomes. My preferred specification additionally includes time-varying control variables and the inclusion of these variables leaves the estimates largely unchanged. Overall, this finding suggests that my results are not driven by a confounding factor.

Results for the total psychiatric ED visits are provided in Panel A. Overall, my estimates suggest that a one-mile increase in travel distance to the closest SNPCC leads to a 0.13% increase in ED visits. I next examine the effects separately for ED visits for females and males in Panels B and C, respectively. My estimates suggest that the effects of travel distance are concentrated among female patients with the effect size being 0.22%. I do not find statistically significant effects on ED visits by male patients. This pattern of results is perhaps unsurprising as women are the primary users of SNPCCs, accounting for 60.8% of the patient population.

To report the average effect of an increase in travel distance to the closest SNPCC, I scale the coefficient estimates by the average increase in travel distance. Over my time period, the average year-to-year increase is 4 miles, which is a 33% increase in the travel distance. Thus, comparing these coefficient estimates to the sample means and scaling these estimates by 4, the implied average effect is an increase of 0.5 psychiatric ED visit in a zipcode area in a year.

3.2 Assessing reverse causality

An important threat to the validity of my empirical strategy is the possibility that changes in the distance induced by clinic openings and closings might be driven by trends in ED outcomes. Such reverse causality, if present, could lead to a violation of parallel trends. To investigate this issue, I estimate an augmented version of Equation 1 that additionally includes 3 leads and 2 lag in the travel distance (i.e., distributed lead and lag model). I incorporate travel distance prior to 2005 and after 2015 in this analysis to retain my sample size and present my distributed lead and lag model results in a manner that is equivalent to an event study research design with a binary treatment variable (Schmidheiny and Siegloch, 2020). Thus, my final results include estimated coefficients for 4 leads, contemporary year, and 2 lag indicators with the 1-year lead being the omitted category. Results are shown in Figure 3. Overall, my estimates indicate substantial and immediate effects of an increase in travel distance and current ED visits being unaffected by future changes in travel distance.

3.3 Psychiatric conditions including alcohol use disorder

I next examine the effects on psychiatric ED visits including alcohol use disorder (AUD). While AUD is the most common form of SUD and medications to treat AUD are available and approved by the FDA (i.e., acamprosate, disulfiram, naltrexone oral/long-acting injectable formulations; (SAMHSA, 2015)), medications are less likely to be the form of treatment among people who received alcohol use treatment. According to the 2019 NSDUH data, while people with AUD participated in self-help groups at the same rate (55%) as those with illicit drug use disorder, only 13.7% of those who received AUD treatment received medications for AUD. In contrast, 32.9% of those who received treatment for illicit drug use (i.e., not necessarily for opioid misuse) received medications for opioid misuse (NSDUH, 2019a). Results are reported in Figure 4. Overall, as expected, I see that the inclusion of AUD reduces the magnitude of coefficient estimates.

3.4 Spillovers onto nearby SNPCCs

I investigate how clinic openings and closings affect other clinics using the OSHPD-PCC data and estimate a stacked event study regression (Deshpande and Li, 2019; Cengiz et al., 2019). For any given opening (or closing), I take clinics that are within 1/3/5 miles of travel distance to the just-opened (closed) clinic as potentially treated clinics. I then restrict the treated clinics to those that (i) do not experience any openings and closings nearby three years prior to the opening (closing; i.e., the event), and (ii) are followed by openings (closings) or no events two years after the event. I then divide the data into 'timing groups' and clinics that experience openings or closings in the same year are in the same timing group. Thus, there are 6 timing groups during the study period 2005-2015. For each timing group, I create a control group consisting of clinics that are opened every year and do not experience any openings and closings within 5 miles of travel distance during the event window; thus holding the comparison group fixed for these analyses. Therefore, my sample is a balanced panel in event time. I then stack these datasets together into one long dataset and estimate the stacked event-study regressions separately for openings and closings. I implement this strategy using a Poisson regression evaluating the expected number of patient encounters with a principal diagnosis classified as psychiatric disorders with an exposure for the total encounters in a clinic. I include travel distance to the closest hospital and city-level unemployment rates as used in Equation 1, as well as clinic and county-by-year fixed-effects for each timing group. Standard errors are clustered around the county and are allowed to be correlated across timing groups.

Results are presented in Figure 5 for the effects of opening and closing of an SNPCC clinic in the upper and lower panels, respectively. There are several take-away points from this analysis. In the event of a closing, clinics within 3 miles experience an increase of 30 - 40% in patient encounters with psychiatric disorders. Comparing these estimates with the sample mean in treated clinics during the pre-event period of an average of 948 encounters with psychiatric disorders, this translates to an increase of 284-379 patient encounters with psychiatric disorders in a nearby clinic. Clinics within 1 mile seem to also experience an increase in patient encounters in the first year post-closures, however, I lack the power to detect any statistical significance. When defined treated clinics as other nearby clinics within 5 miles of travel distance to the closed clinic, I observed no patient spillovers post-closure.

In the event of a clinic opening, interestingly, I observe no changes in patient volumes with psychiatric disorders in nearby clinics in the first and second years post-openings. I observe there is a decrease of 10% ppts in patient volumes within 1 and 5 miles of travel distance to the 'just-opened' clinic, however, the coefficient estimates for clinics within one mile are not statistically significant. Comparing these estimates with the sample mean in treated clinics during the pre-event period of an average of 2,578 encounters with psychiatric disorders, this translates to a decrease of 258 patient encounters with psychiatric disorders in a nearby clinic starting in the third year post-opening. Overall, this pattern likely reflects unmet demand for psychiatric care or the stickiness of where patients receive care. It takes time for patients to switch from their previous source of care to a new clinic that just opened. However, when patients' source of care closes, some patients may delay getting care since it has become less convenient, or some may no longer have a usual source of care other than the ED. This asymmetry suggests that clinics affect care primarily by improving access.

4 Heterogeneity and robustness checking

4.1 Heterogeneity

Data from the OSPHD-PCC 2019 Pilot Table (Table 1) suggests that SNPCCs served mostly younger and minority populations. Thus, I examine heterogeneity in the effect of travel distance across subgroups by age, race, and ethnicity in Figure 6. Broadly, I find that the increase in ED visits is driven by all demographic groups; however, the effect size is larger for non-white and Hispanic groups.

Next, in Figure 7, I explore heterogeneity in the effect of travel distance by diagnosis types: mental health and drug use. I observe that my main results on total visits are driven by visits with mental health disorders. Additionally, for visits involving females, the effect of travel distance is driven by both mental health and drug use disorders, although the effect on drug use is not statistically significant.

My main specification exploits variation in travel distance stemming from both clinic openings and closings, which implicitly assumes a symmetric effect in travel distance. However, it is possible that the effects of increasing and decreasing travel distance are asymmetric. For example, a closure will force people to immediately switch providers whereas it may take time for patients to start using a new clinic when it opens. I next examine heterogeneity in the effect of increasing versus decreasing in travel distance by estimating 1 separately for increasing and decreasing. When considering increasing, my sample includes observations that experienced increases or no changes in distance, and excludes observations that ever experienced a decrease. Likewise, when considering decreasing, my sample includes observations that experienced decreases or no changes in distance, and excludes observations that ever experienced an increase. Results are reported in Table 5. Panel A shows the main results while Panels B and C show results for ‘increasing’ and ‘decreasing’ samples, respectively. For the total ED visits and visits involving female patients, I continue to find that changes in travel distance are positively associated with changes in ED visits, with increasing travel distance having larger effects. However, bootstrapping the difference in the effect sizes using a non-parametric bootstrap with 500 repetitions suggests that the difference is not statistically significant at the conventional level for all three outcomes. Thus, in no case, I can reject that the coefficient estimates for travel distance in Panels B and C are equal. I tentatively conclude that the relationship between distance and psychiatric ED visits is symmetric with respect to whether access is improving or worsening.

4.2 Robustness

I report a range of different specifications in Figure 8. My results are broadly stable across the sensitivity checks, although I lose precision in some specifications. First, I explore whether my findings are robust to alternative specifications holding my sample constant: replacing county-by-year fixed-effects with year fixed-effects and (i) county-level time-varying observable characteristics,[8] or (ii) county-specific linear trend; adding zipcode-level time-varying measures to better control for behavioral healthcare access and changes in economic activity;[9] and (3) including measures of clinic density within 10 miles.[10] This analysis of changing covariate sets offers an additional test of balance and suggests that my findings are not driven by unobservable variables. I note that coefficient estimates decline in magnitude and become imprecise in the specification

[8] I control for county-level demographic characteristics obtained from the National Cancer Institute’s Surveillance Epidemiology and End Results (SEER) program, poverty rates from the U.S. Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) program, and an indicator for Medicaid expansion.

[9] In particular, I control for the number of residential/outpatient treatment facilities, office-based mental health providers, and retail businesses obtained from the U.S. Census Bureau’s County Business Patterns (CBP): zipcode files.

[10] The measure of density is defined as the count of operating SNPCCs within 10 miles of travel distance of a zipcode centroid. This measure varies over time and a clinic can be counted multiple times across zipcodes. Alternatively, I create a measure that is within 5/15/30/60/90 and the magnitude of the coefficients on the distance variable remains largely unchanged across various measures of clinic density.

including county-specific linear time trends. However, the inclusion of county-specific linear trends can lead to over-controlling bias if the treatment variable leads to a change in outcome trends Meer and West (2016).

Next, I use two alternative measures of access: (i) travel time and (ii) weighted average travel distance to the three closest clinics. Of note, travel time and travel distance have highly correlated with the correlation between distance and time being 0.987 for all observations. Overall, coefficient estimates decline in magnitude and become imprecise for some outcomes. However, bootstrapping the difference between coefficient estimates for travel distance and travel time using a non-parametric bootstrap procedure with 500 repetitions, I find that the difference is not statistically different from zero for all three outcomes. Using the travel distance to the three closest clinics can account for the possibility that not everyone utilizes services at the closest clinic. While coefficient estimates become larger in magnitude, they also become imprecise. Thus, I conclude that my results are not meaningfully different when using alternative measures of access.

Furthermore, I alternatively estimate (i) an ordinary least squares (OLS) regression, where outcomes are defined as the natural log of the number of ED visits and data are weighted by relevant population using the 2010 census, and (ii) a negative binomial regression. In the weighted OLS specification, while my estimates are similar in magnitude to the results using a Poisson specification, the OLS estimates are imprecise. Using a negative binomial regression, my estimates are even more precise.

Second, I re-estimate my regression on a variety of different samples and my results are robust to (i) excluding zipcodes with 2010 census population estimates of less than 1000 residents, (ii) restricting zipcodes to those with travel distance ever within 50 miles, (iii) extending the sample period to include 2016-2018 data, and (iv) using quarterly data and clinic openings and closings re-defined at the quarter-year. I next sequentially exclude each county (a 'leave-one-out' analysis) to ensure that my findings are not driven by particular counties. My results are broadly robust as shown in Figure 9, although excluding San Bernardino county reduces precision.

Lastly, I conduct 2 falsification exercises. The first exercise involves placebo outcomes where dependent variables are psychiatric ED visits with private payers as a source of payment. The second exercise involves randomly re-shuffling travel distance across zipcodes, keeping constant the number of zipcodes in each county, 1,000 times, and obtaining 1,000 placebo t-statistics for each outcome. Results for the former exercise are presented in Figure 10 and show no effects of the travel distance on psychiatric ED visits for females, males, and total visits paid by private payers at the 5% confidence level. Results for the latter exercise are presented in Figure 11 where I plot the null distributions of the placebo t-statistics for each outcome. The solid lines denote the 5th and 95th percentiles of the distribution. The dashed line is the estimated t-statistics value from the actual regression. We can see that the estimated t-statistics are below the 5th percentile of the distribution for psychiatric ED visits for females and total ED visits, however, results for male patients are less conclusive. Overall, these falsification exercises indicate that my results are not driven by a spurious association.

5 Discussions

In this study, I examined changes in local access to SNPCCs on psychiatric ED utilization between 2005 and 2015. These clinics deliver primary care services as well as other services such as behavioral healthcare to low-income groups. I use travel distance to proxy local access and show that SNPCCs reduce psychiatric ED visits. Specifically, an additional one-mile increase in travel distance in a zipcode area leads to 0.13% increase in total visits, primarily driven by visits involving female patients. I find access to safety-net primary care clinics has limited effects on ED utilization by male patients. I additionally show that my findings are not driven by confounding factors or differential trends across zipcode areas and are robust to numerous sensitivity checks and placebo testings.

I provide evidence to support the hypothesis that expanded access to SNPCC is attributable to increased encounters with psychiatric diagnoses. Particularly, I find evidence of asymmetric effects in clinic openings and closures suggesting that clinics affect care primarily by improving access. I show that closings of an SNPCC lead to spillover onto nearby SNPCCs. When a new clinic opened, I find little evidence of crowdinging out in nearby clinics. This pattern likely reflects unmet demand for psychiatric care or the stickiness of where patients receive care. However, when patients' source of care closes, they may delay getting care since it has become less convenient, or they may no longer have a usual source of care other than the ER.

Given that psychiatric ED visits are preventable with adequate outpatient care, my findings suggest that SNPCCs have the potential to be welfare-improving. The magnitude is reasonable given my hypothesized compliers: a patient with a mental illness or substance use disorder who can be effectively treated in a primary care setting. To put my effect sizes in perspective, I compare my estimates to a prior study (Corredor-Waldron and Currie, 2021). The authors study the effects of access to SUD treatment facilities on drug-related ED visits in New Jersey and find that an additional mile increase in distance to SUD treatment centers increases SUD-related visits by 1.1%. Thus, my effect size of a 0.13% increase in ED visits driven by a one-mile increase to primary care clinics is reasonable in magnitude when comparing the expected increase in ED visits associated with a one-mile increase to SUD treatment clinics.

Reducing inappropriate use of ED services is important given the high cost and overcrowding of EDs. My estimates suggest that the implied average effect of an increase in travel distance is an increase of 875 (= 0.5*1749 ZCTAs) ED visits annually in California. Using the cost per ED visit attributable to a principal SUD diagnosis of $2,194 (converted to 2020 dollars; (Peterson et al., 2021)), this translates to the dollar value of ED visits incurred of $2M per year.

While my work does not directly look at sources of funding for safety-net care, it suggests an increased role for safety-net funding. My findings imply that delivering mental healthcare and SUD treatment in SNPCCs can be a strategy to reduce unmet needs for psychiatric care among low-income groups. Policies designed to increase investments in safety-net primary care settings may have unintended benefits in reducing psychiatric ED use.

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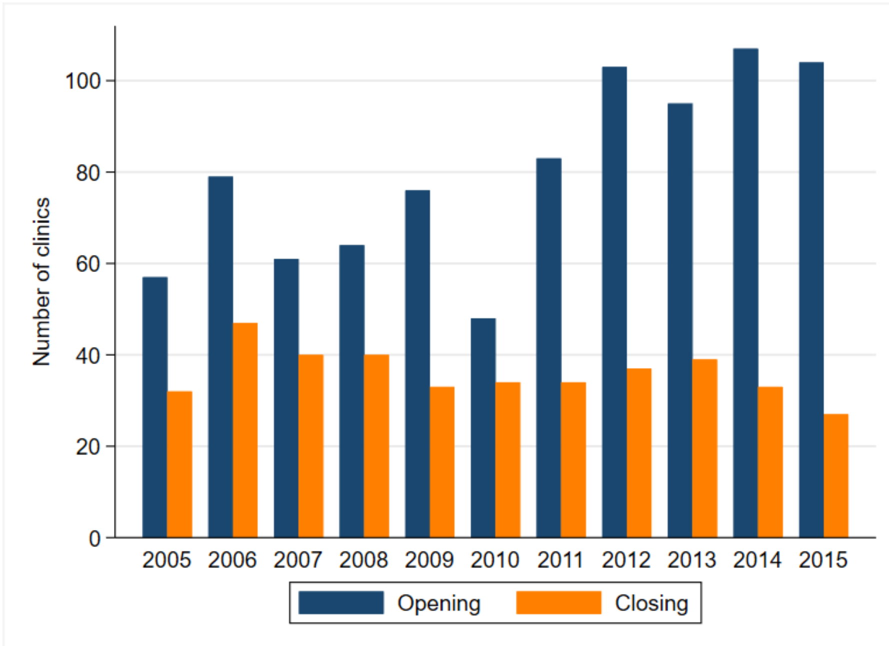
Figure 1: California satefy-net primary care clinics

Panel A: Timing of openings and closings



Panel B: Number of operating clinics

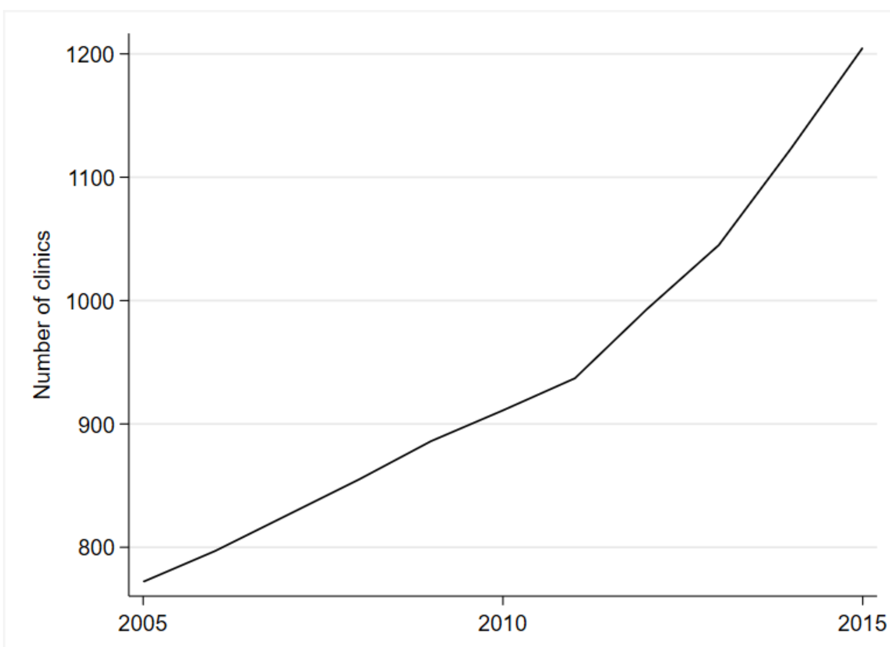
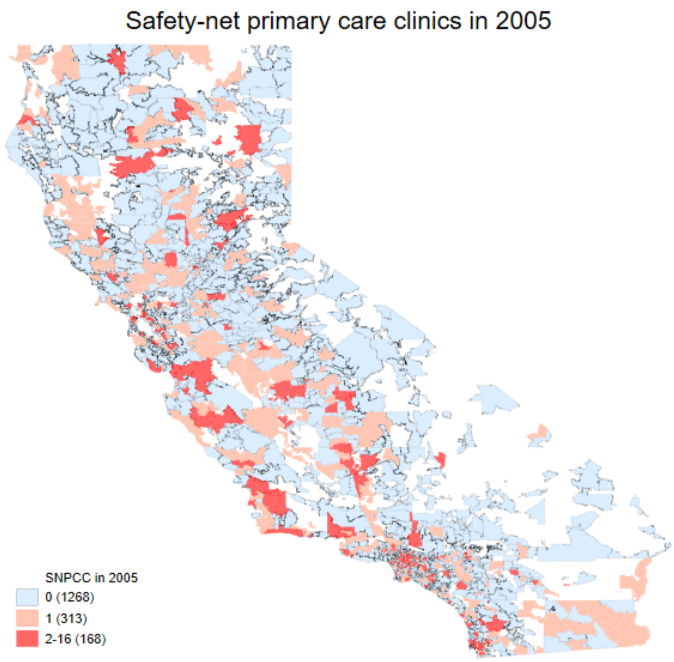


Figure 2: The number of satefy-net primary care clinics in California



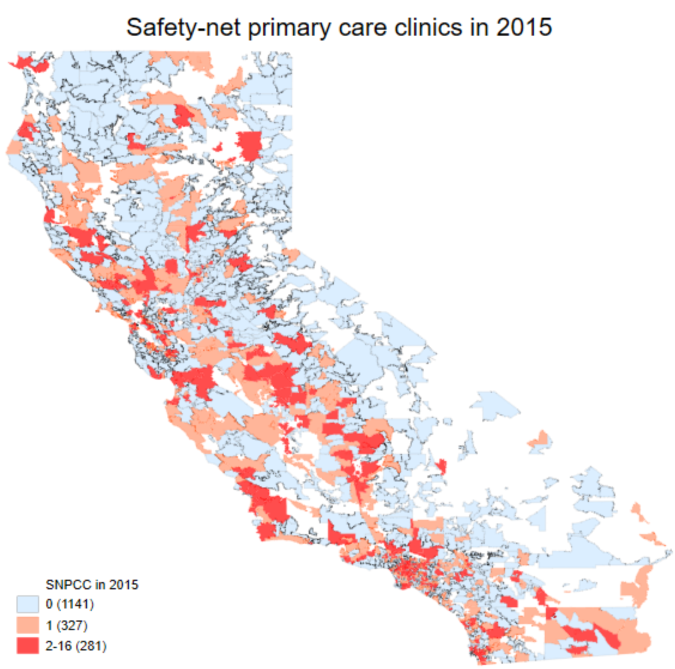
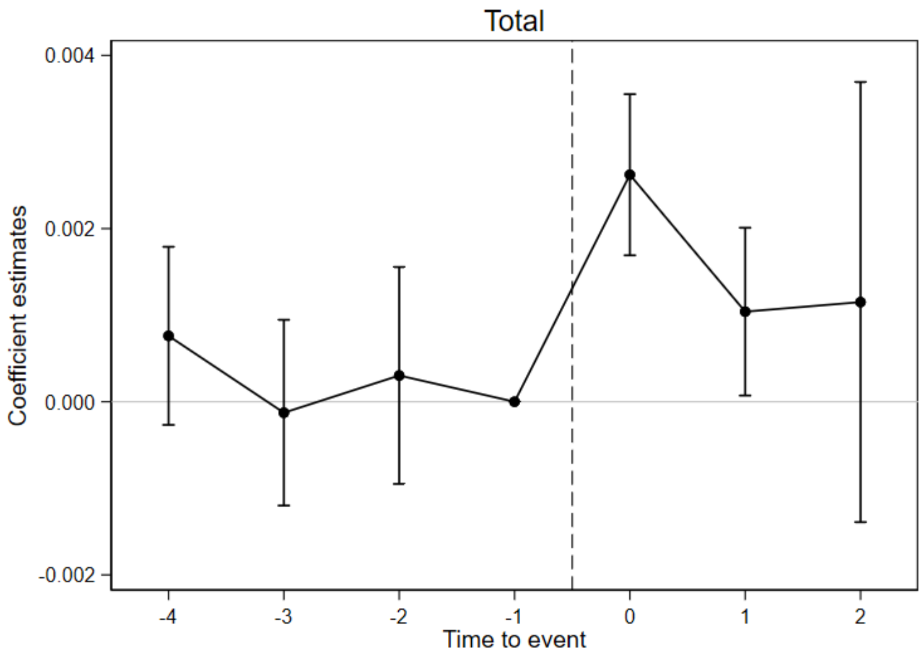
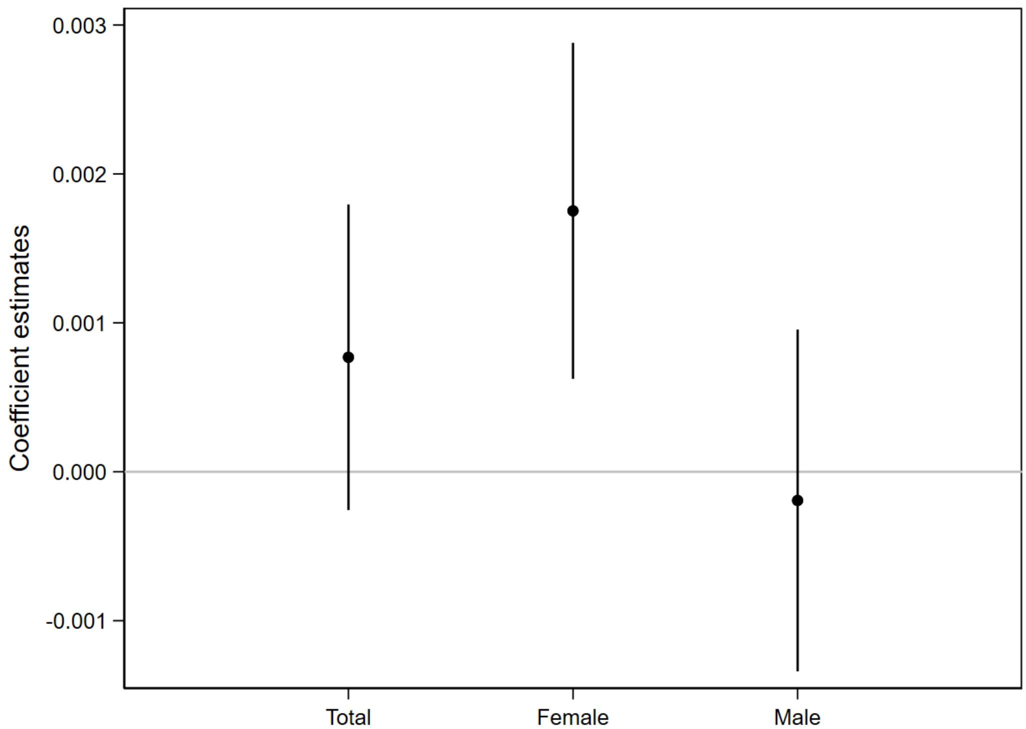


Figure 3: Effect of distance on psychiatric ED visits: Distributed lead and lag model



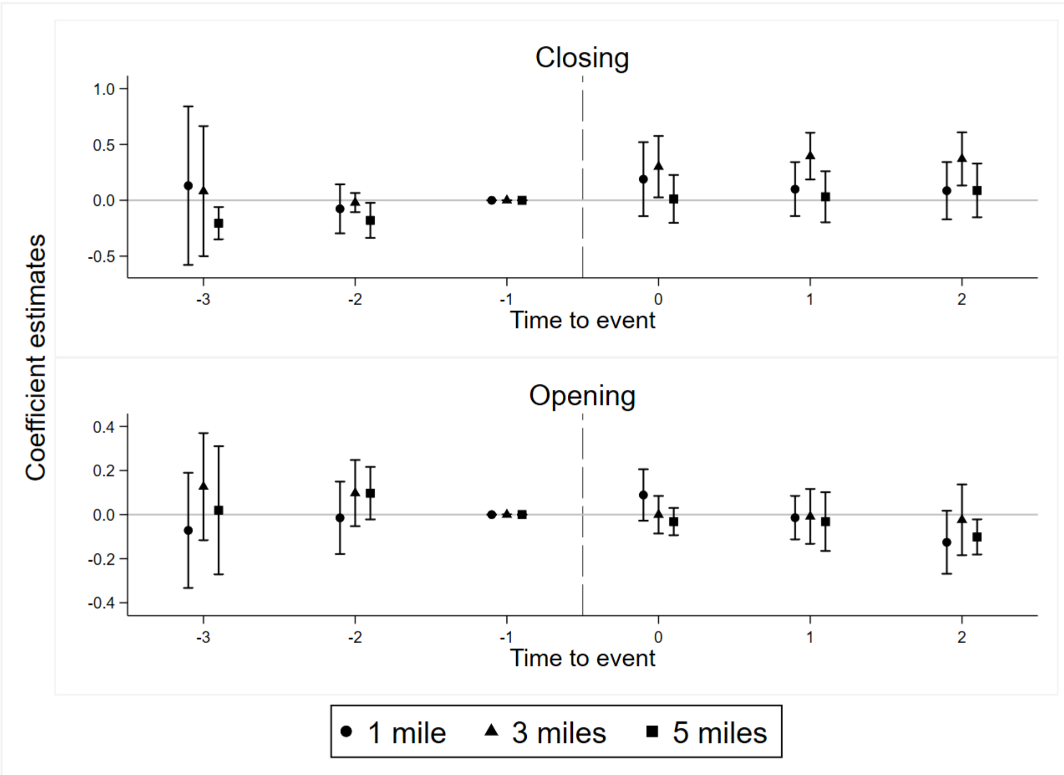
Notes: Estimates are based on a Poisson regression evaluating the number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. Estimates are based on an augmented version of Equation (1) that includes three leads, the contemporaneous number, and 2 lags of travel distance. All regressions include the full set of covariates. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 4: Effect of distance on psychiatric ED visits including alcohol use disorder



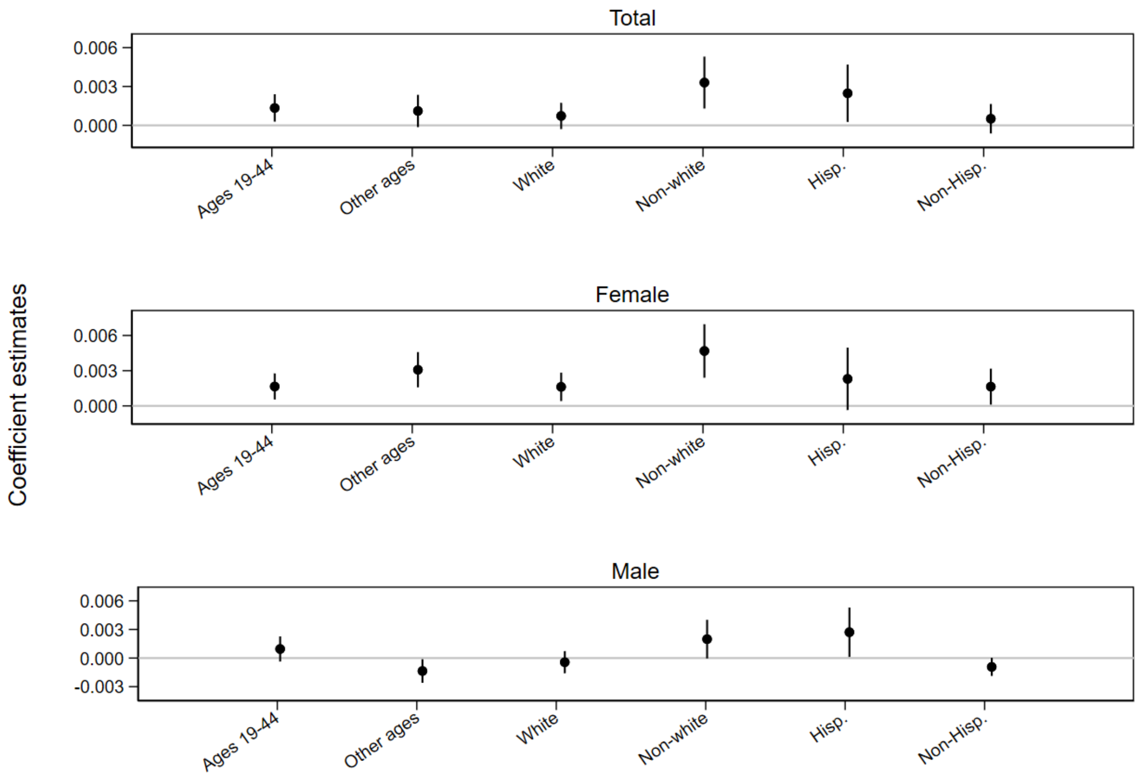
Notes: Estimates are based on a Poisson regression evaluating the number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. All regressions are estimated using Equation 1 and include the full set of covariates. Circles represent point estimates and 90% confidence intervals that account for within-county clustering are depicted by vertical lines.

Figure 5: Effect of clinic openings and closings on patient encounters with a psychiatric diagnosis in other nearby clinics



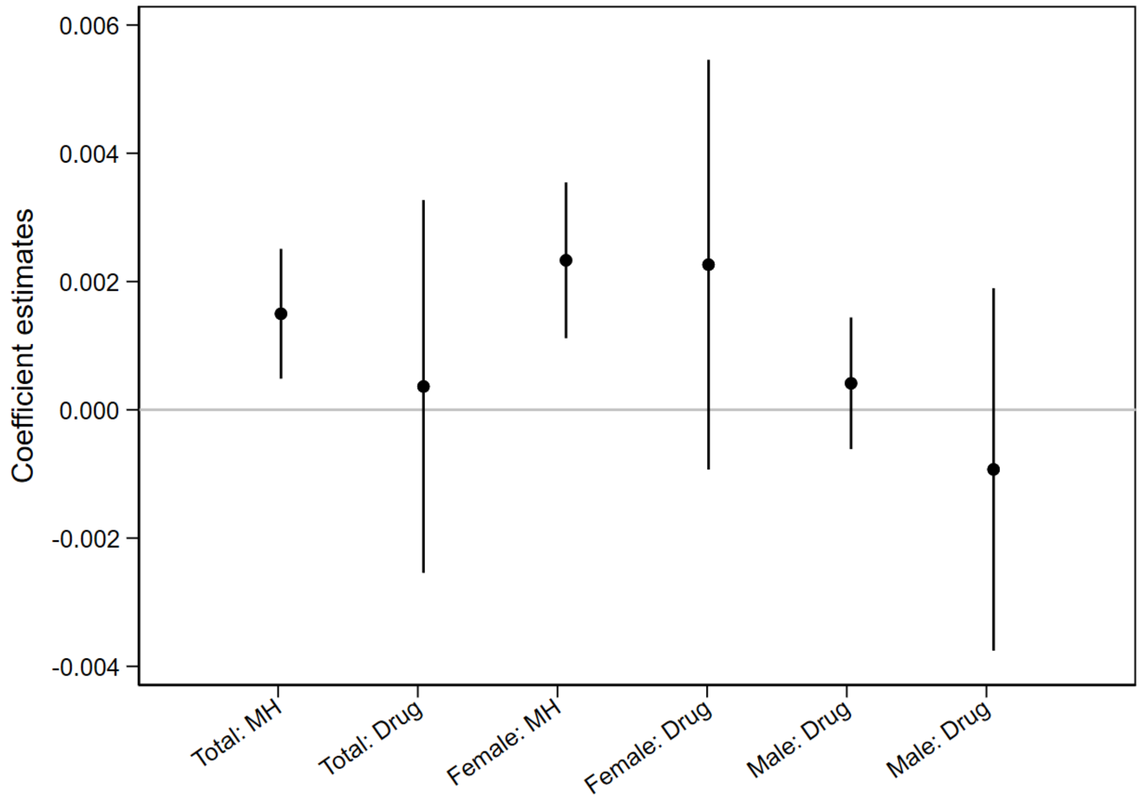
Notes: Notes: Data is obtained from the OSHPD-PCC 2005-2015. Estimates are based on a Poisson regression evaluating the expected number of psychiatric encounters with an exposure for the total encounters. The unit of observation is an SNPCC clinic in a county in a year. All regressions include clinic and county-by-year fixed-effects for each timing group, travel distance to the closest hospital, and city-level unemployment rates. Standard errors are clustered around the county and are allowed to be correlated across timing groups. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 6: Effect of distance on psychiatric ED visits: Heterogeneity by demographics



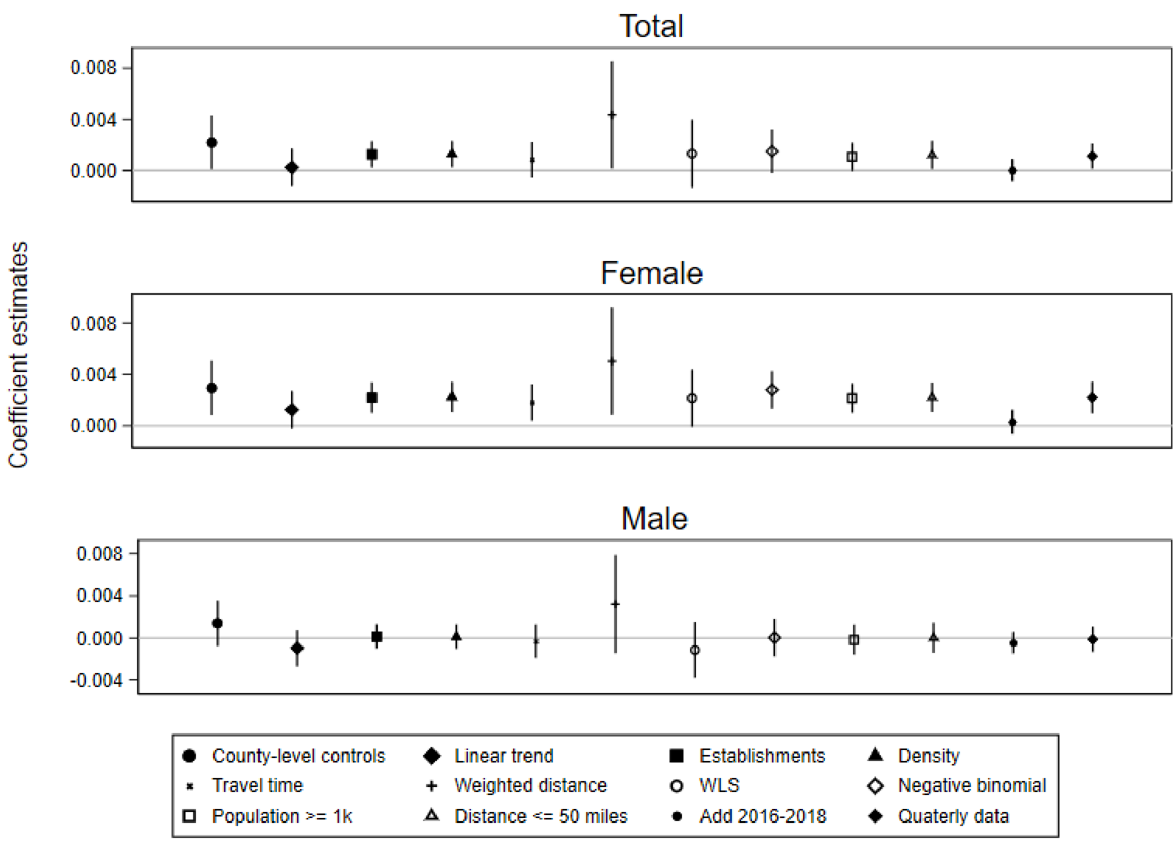
Notes: Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. All regressions are estimated using Equation 1 and include the full set of covariates. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 7: Effect of distance on psychiatric ED visits: Heterogeneity by diagnosis types



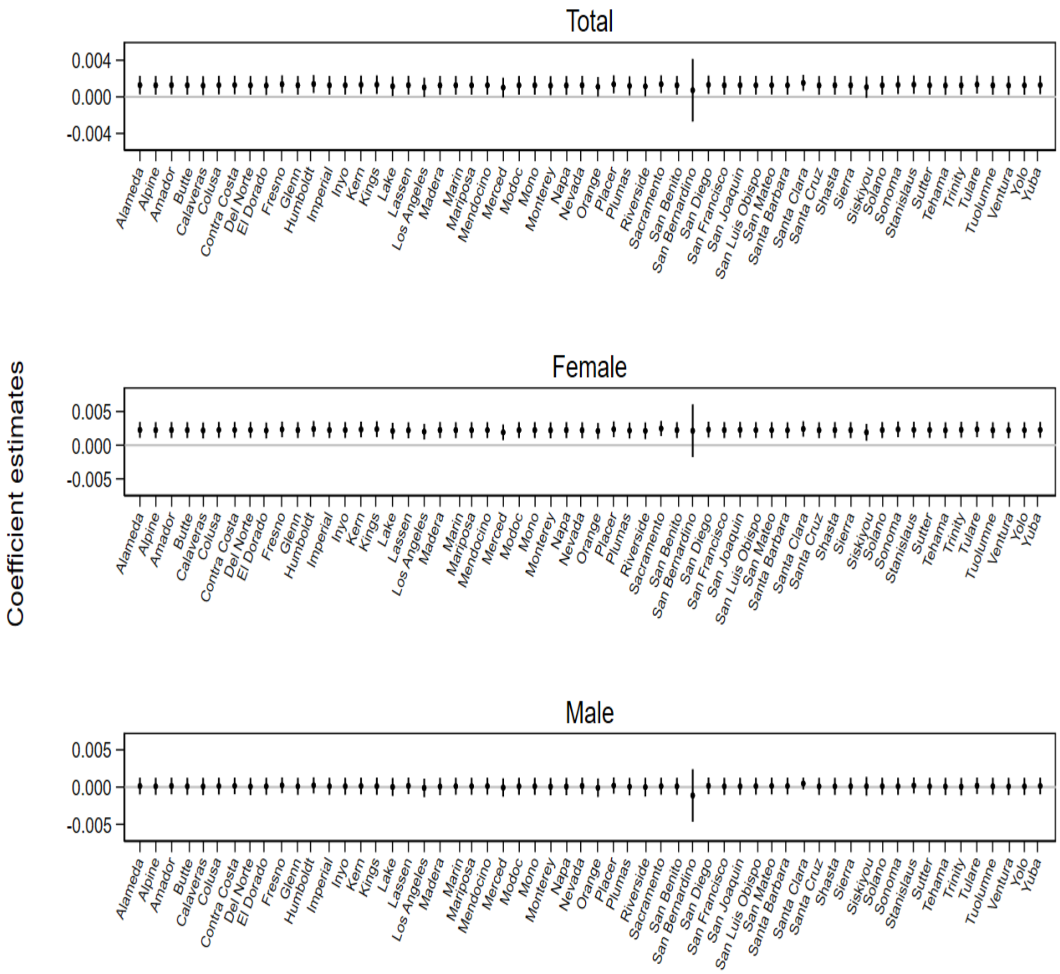
Notes: Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. All regressions are estimated using Equation 1 and include the full set of covariates. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 8: Effect of distance on psychiatric ED visits: Robustness check



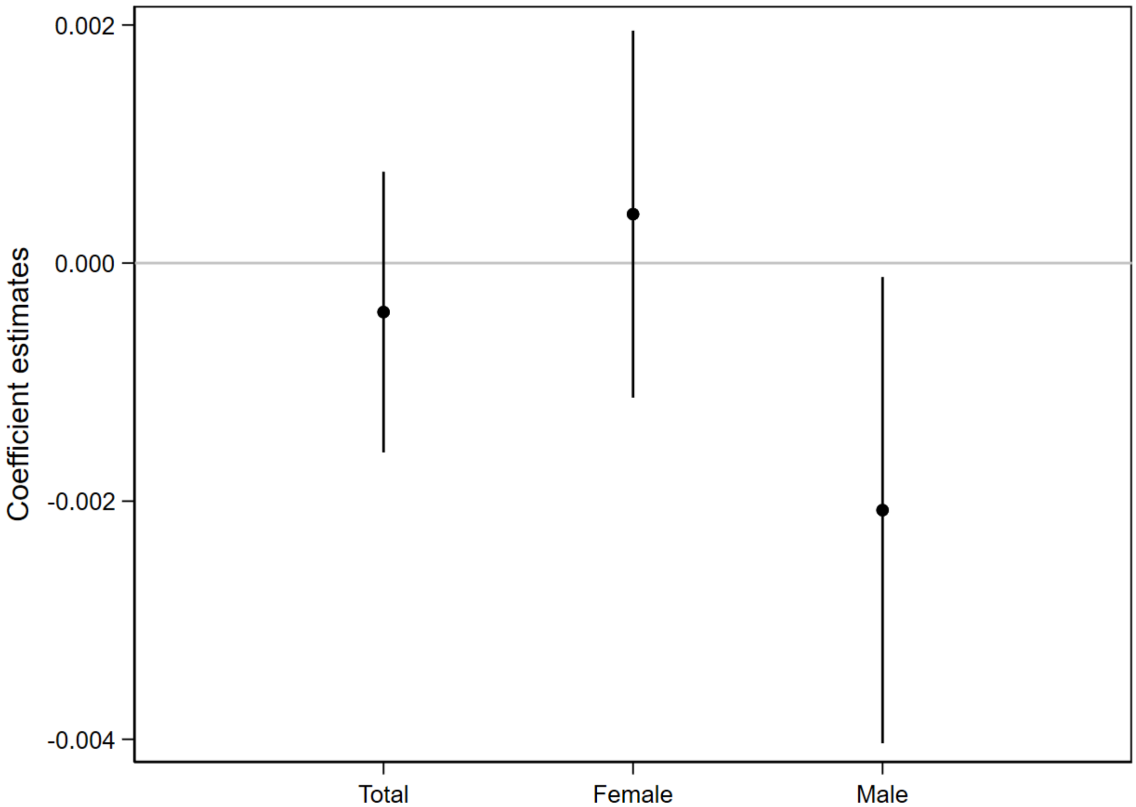
Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015 (unless otherwise noted). The unit of observation is a zipcode in county in a year unless otherwise noted. All regressions are estimated using Equation 1 and include the full set of covariates (unless otherwise noted). Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 9: Effect of distance on psychiatric ED visits: Leave-one-out



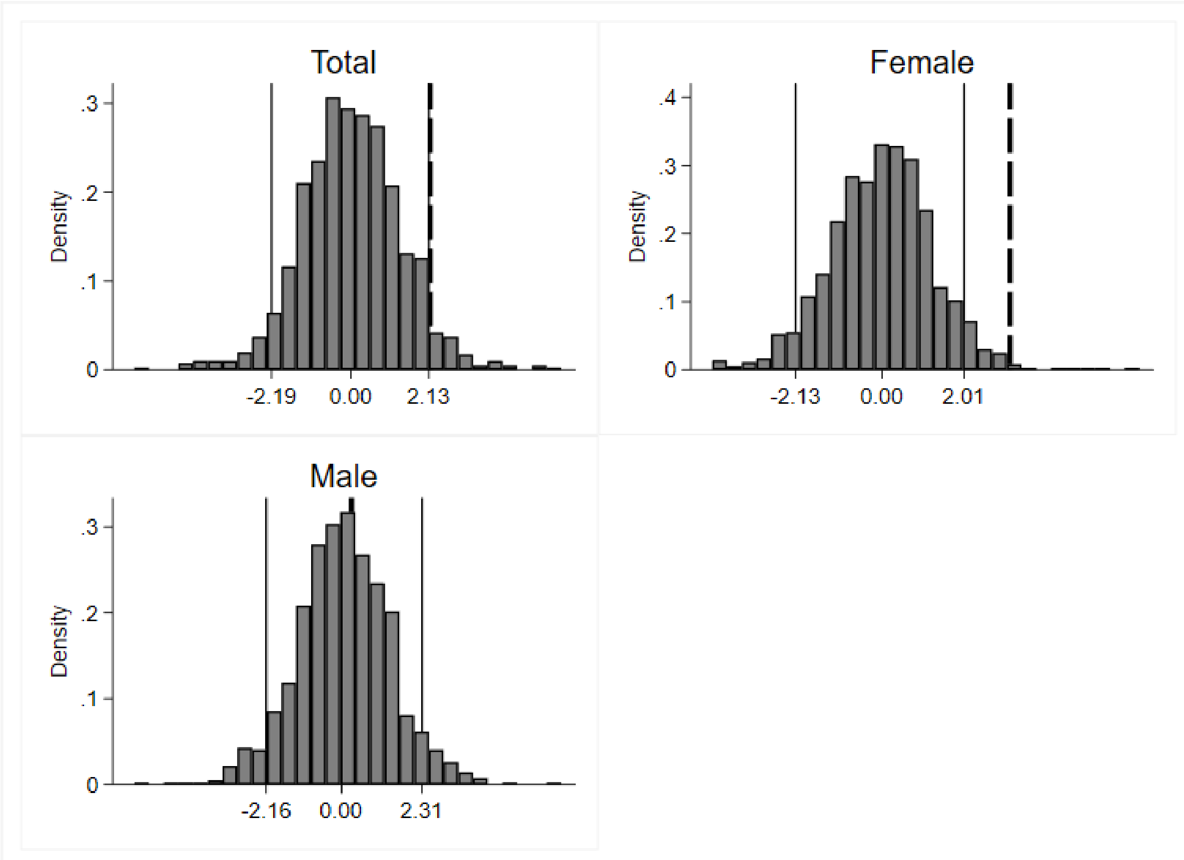
Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. All regressions are estimated using Equation 1 and include the full set of covariates. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 10: Effect of distance on psychiatric ED visits: Placebo outcomes



Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. All regressions are estimated using Equation 1 and include the full set of covariates. Circles represent point estimates and vertical lines depict 90% confidence intervals that account for within-county clustering.

Figure 11: Effect of distance on psychiatric ED visits: Placebo distance



Notes: I randomly re-shuffle travel distance across zipcodes and time, keeping constant the number of zipcodes in each county. I repeat this procedure 1,000 times and obtain the null distribution of the placebo t-statistics for each of the three outcomes. All regressions are estimated using Equation 1 and include the full set of covariates. The x-axis reports the t-statistic value. The solid lines denote the 5th and 95th percentiles of the distribution. The dashed line is the estimated t-statistics from the actual regression.

Table 1: Characteristics of patient population in 2019

	Patient population	California	U.S.
Total encounters	24,638,761	-	-
Population	7,454,009	-	-
Pct. Male	39.1	49.7	49.2
Pct. Female	60.9	50.3	50.8
Pct. White	61.1	73.9	77.7
Pct. Other race	38.9	26.1	22.3
Pct. Hispanics	52.8	39.4	18.5
Pct. Non-Hispanics	47.2	60.6	81.5
Pct. Ages 19 and under	32.8	22.7	24.9
Pct. Ages 20 to 34	25.4	22.5	20.6
Pct. Ages 35 to 44	12.6	15.3	12.7
Pct. Ages 45 to 64	21.3	25.2	25.4
Pct. Ages 65 and above	7.9	14.8	16.5
Federal poverty line			
Income below 200% FPL	66.8	22.5	22.7
Unknown	29.0	-	-
Patient coverage (%)			
Medicaid	60.4	-	-
Self-Pay/Sliding Fee/Free	20.8	-	-
Private	8.1	-	-
Medicare	6.4	-	-
Other payers	4.3	-	-
Encounters by payment source (%)			
Medicaid	64.0	-	-
Self-Pay/Sliding Fee/Free	10.0	-	-
Private	7.2	-	-
Medicare	8.5	-	-
Other payers	10.3	-	-

Notes: Patient population comes from OSHPD-PCC 2019 Pivot Table. General population demographics comes from the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute. Poverty status for the general population comes from the 2019 American Community Survey: 1-year estimates.

Table 2: Clinical classification software mental health and SUD categories

Code	Condition
650	Adjustment disorders
651	Anxiety disorders
652	Attention-deficit, conduct, and disruptive behavior disorders
653	Delirium, dementia, and amnestic and other cognitive disorders
654	Developmental disorders
655	Disorders usually diagnosed in infancy, childhood, or adolescence
656	Impulse control disorders, NEC
657	Mood disorders
658	Personality disorders
659	Schizophrenia and other psychotic disorders
660	Alcohol-related disorders
661	Substance-related disorders
662	Suicide and intentional self-inflicted injury
663	Screening and history of mental health and substance abuse codes
670	Miscellaneous mental health disorders

Table 3: Summary statistics: 2005-2015

	Full Sample	With a clinic	W/o a clinic
A: Number of zipcode areas	1,749	655	1,094
B: Number of clinics ever operated	0.84	2.25	0.00
C: Demographics			
Pct. Male	50.72	50.16	51.06
Pct. Female	55.14	54.89	55.30
Pct. Non-Hispanic white	54.28	41.13	62.16
Pct. Non-Hispanic black	4.01	5.55	3.08
Pct. Non-Hispanic other race	13.06	13.76	12.64
Pct. Hispanics	28.65	39.56	22.12
Pct. Ages 19 and under	25.38	27.47	24.12
Pct. Ages 20 to 34	19.42	22.07	17.84
Pct. Ages 30 to 44	12.71	13.43	12.28
Pct. Ages 45 to 54	18.58	16.89	19.60
Pct. Ages 55 to 64	15.82	13.21	17.39
Pct. Ages 65 and above	13.95	11.99	15.13
Population	21,253	34,638	13,239
Population per square miles	3,277	5,511	1,940
Per-capita income ($2019)	38,127	34,330	40,478
D: Relevant variables			
Total psychiatric ED visits	100	190	40
Psychiatric ED visits for females	50	90	20
Psychiatric ED visits for males	50	100	20
Travel distance to the nearest SNPCC	12.14	5.30	17.07
Travel distance to the nearest hospital	12.73	8.40	15.85
The nearest clinic is a FHQC	0.34	0.34	0.34
The nearest clinic is a RHC	0.02	0.01	0.03
Unemployment rate (%)	8.93	8.93	8.93
N	19,239	8,063	11,176

Notes: Panel C presents demographic information from the 2010 decennial census and per-capita income (5-year estimate) from the American Community Survey 2015-2019. Panel D includes relevant variables used in the regression. Distance is measured in miles. Averages of psychiatric ED visits are rounded to nearest ten to avoid disclosing small cell sizes. FHQC stands for federally health qualified health center. This variable also includes FQHC look-alikes. RHC stands for rual health center.

Table 4: Effect of distance on psychiatric ED visits

	(1)	(2)	(3)
Panel A: Total			
Distance	0.00235	0.00133**	0.00126**
	(0.00163)	(0.00064)	(0.00062)
Panel B: Female			
Distance	0.00297*	0.00234***	0.00224***
	(0.00154)	(0.00076)	(0.00072)
Panel C: Male			
Distance	0.00161	0.00015	0.00010
	(0.00179)	(0.00069)	(0.00070)
ZCTA and year FEs	Yes	Yes	Yes
County-by-year FEs	No	Yes	Yes
Control variables	No	No	Yes
N	19,239	19,239	19,239

Notes: Estimates are based on a Poisson regression evaluating the expected number of psychiatric ED visits in California from 2005-2015. The unit of observation is a zipcode in county in a year. Standard errors (in parentheses) allow to be correlated within counties over time. ***, **, and * represent statistical significance at the .01, .05, and .10 level, respectively.

Table 5: Effect of distance on psychiatric ED visits: Testing for asymmetry

	Total	Female	Male
Panel A: Full sample			
Distance	0.0013**	0.0022***	0.0002
	(0.0006)	(0.0007)	(0.0007)
N	19,239	19,239	19,239
Panel B: Areas experienced increases or no changes in distance			
Distance	0.0029	0.0056***	-0.0003
	0.0027	0.0015	0.0039
N	9,251	9,251	9,251
Panel C: Areas experienced decreases or no changes in distance			
Distance	0.0016***	0.0028***	0.0002
	0.0006	0.0009	0.0009
N	12,804	12,804	12,804

Notes: Estimates are based on a Poisson regression evaluating the expected number of ED visits related to MH in California from 2005-2015. Each cell is a separate regression. All regressions are estimated using Equation 1 and include the full set of covariates. Standard errors (in parentheses) allow to be correlated within counties over time. ***, **, and * represent statistical significance at the .01, .05, and .10 level, respectively.