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Increasing healthcare usage among the homeless: evidence from Mobile Street Clinics in Brazil*

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July 30, 2025

Abstract

Homelessness is associated with an immense health burden and limited access to adequate healthcare. This paper studies the effects of Mobile Street Clinics on healthcare usage among people experiencing homelessness in Brazil. Exploiting unique administrative data in a staggered difference-in-differences setting, I find that Mobile Street Clinics strongly and persistently increase primary care usage and community-based ambulatory care usage among the homeless but do not improve healthcare continuity. These results provide first evidence for the effectiveness of homeless interventions in developing countries and have important policy implications for tackling the health burden of homelessness.

Keywords: homelessness, healthcare, mobile street clinics
JEL Classification: R20, I14, I18

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1 Introduction

Homelessness is an extreme form of poverty that affects around 150 million people worldwide (Habitat, 2020). Beyond being a social crisis, homelessness represents a public health emergency (Aldridge, 2020). It is associated with multiple adverse health conditions and highly increased mortality rates. In the US, for example, a homeless 40-year-old has the same mortality risk as a non-homeless 60-year-old (Meyer et al., 2023). Moreover, homeless individuals lack access to adequate healthcare even where it is freely available to everyone (Baggett et al., 2010). Several barriers, such as stigmatization and lack of trust, lead to an under-usage of ambulatory care and to an over-usage of less efficient and more expensive acute care (Kushel et al., 2001).

To tackle the health burden of homelessness, scholars and practitioners call for healthcare that is specifically targeted to the needs of the homeless population (Kerman & Stergiopoulos, 2024; Serchen et al., 2024). Such targeted healthcare should expand access to primary care, connect homeless patients to community-based ambulatory care, and foster healthcare continuity (Liu & Hwang, 2021). Evidence on which healthcare policies work, however, is sparse and limited to a few small-scale RCTs (Aubry et al., 2020; Kerman & Stergiopoulos, 2024; Wickham, 2020). Real-world evidence from large-scale policies remains a key gap in the literature for multiple reasons (Evans et al., 2021): existing policies are typically not implemented in a way that allows for causal identification; administrative data sets rarely contain information to differentiate between homeless and non-homeless patients; and potential changes in the homeless population are too small to be detected in population-level outcomes (Evans et al., 2021). The lack of evidence is especially pronounced for developing countries that host the majority of homeless people (Tipple & Speak, 2005) but where adequate data is particularly sparse (Carr-Hill, 2013).

I address this gap by providing the first large-scale evidence for the effectiveness of a healthcare policy that directly targets the homeless population in a developing country. I leverage the introduction of Mobile Street Clinics (henceforth MSCs) in major cities all over Brazil to estimate their effects on healthcare usage among the homeless. MSCs are healthcare teams that deliver targeted and low-barrier care directly on the street in hot spots of homelessness. While MSCs are employed in different countries and at different scales (Attipoe-Dorcoo et al., 2020), the Brazilian setting offers an exceptional opportunity to study their effectiveness. First, Brazil has a large and fast-growing homeless population whose needs have not been met by the country's free-of-charge healthcare system before the introduction of MSCs (Figueiredo et al., 2022; Natalino, 2023). Second, MSCs in

Brazil have been implemented in larger cities all over the country, allowing for causal identification in a difference-in-differences model. And third, the availability of high-quality ambulatory care data enables me to directly investigate the impacts on the homeless population.

Specifically, I use data on (i) primary care *on the street*, (ii) psycho-social care usage among the homeless, and (iii) the homeless' long-term tuberculosis care outcomes to assess the effects of MSC on primary care usage, community-based ambulatory care usage, and healthcare continuity. For identification, I exploit the step-wise introduction of MSCs across 81 different municipalities between 2015 and 2023 in a staggered Difference-in-Differences model, comparing never-treated or later-treated municipalities to early-treated municipalities (De Chaisemartin & d'Haultfoeuille, 2024). I assume that, in absence of MSCs, healthcare usage among the homeless in treatment municipalities would have followed the same trend as in control municipalities. Throughout the analysis, parallel pre-trends and additional robustness checks support the identification strategy.

My results show that MSCs strongly and persistently increase primary care usage on the street. On average, primary care on the street increases by around 520 services per 100,000 inhabitants after the introduction of the first MSC, relative to a pre-treatment mean of 50. Importantly, effects are not driven by a replacement of primary care *off* the street by primary care *on* the street but rather by an increase in total primary care usage. While the increase in primary care on the street is not surprising, it provides important insights: First, it confirms that MSCs are successful in lowering existing barriers to primary care usage on a large scale. Second, the striking effect size shows the enormous demand for primary care among the homeless.

To examine the type of primary care that MSCs deliver in more detail, I estimate effects separately for different health conditions. Effects are largest for conditions that are common among the homeless, such as alcohol use, drug use, and tuberculosis (Fazel et al., 2014). Healthcare related to chronic conditions, other infectious diseases, and reproductive health is also strongly affected. Given the complex health needs of the homeless population, the results by health conditions are particularly encouraging: They suggest that MSCs are able to address a wide range of different conditions and reach even the most excluded populations, such as homeless mothers (Santos et al., 2021).

Next, I look at the effects of MSCs on psycho-social care usage among homeless patients. In Brazil, psycho-social care is delivered in so-called psycho-social care centers, representing a community-based service that is not directly delivered by MSCs but that should be affected as a result of increased

primary care usage. I find that MSCs increase psycho-social care usage among the homeless by 11 services per 100,000 inhabitants, relative to a pre-treatment mean of 8. These effects show that MSCs are successful in connecting homeless patients to community-based care and, more broadly, suggest that targeted primary care can increase the usage of non-targeted downstream healthcare (Kerman & Stergiopoulos, 2024).

Finally, I investigate the effects of MSCs on healthcare continuity by looking at homeless patients' tuberculosis care outcomes. Tuberculosis care is informative about healthcare continuity because the successful treatment requires ongoing medication over the course of 6 months (Steffen et al., 2010). While the opening of the first MSC increases the detection of new tuberculosis cases among the homeless by around 35%, this increase is almost entirely driven by patients who drop out of treatment before being cured. This implies that MSCs are not sufficient to improve tuberculosis treatment adherence among the homeless and, more generally, suggests that targeted healthcare policies may have to be accompanied by other policies, such as monetary or non-monetary incentives, to improve healthcare continuity (Malotte et al., 2001).

In sum, my results draw a positive but nuanced picture. MSCs strongly increase primary care usage and community-based care usage among the homeless, while failing to improve healthcare continuity. Several robustness tests strengthen the causal interpretation of my main findings. Estimates are robust to different model specifications, estimators, and sample selection criteria. Importantly, increases in healthcare usage among the homeless cannot be explained by similar trends among the non-homeless, by simultaneous idiosyncratic increases in the homeless population, or by the expansion of related healthcare services.

My results contribute to different strands of literature. First, they directly add to the literature on interventions to improve healthcare usage among the homeless. Existing evidence comes mostly from RCTs with small sample sizes, short time frames, and low external validity (Christian et al., 2024; Fine et al., 2023; Kopanitsa et al., 2023; O'Toole et al., 2015; Sadowski et al., 2009). Studies investigating homeless interventions on a large scale focus on housing or financial assistance rather than on specific health policies and consistently fail to detect an effect on healthcare usage (Cohen, 2024; Downes et al., 2022; Kuehnle et al., 2023; Phillips & Sullivan, 2022). Healthcare interventions that are tailored to the demand of the homeless population may be more effective, but multiple literature reviews stress the lack of causal evidence on which policies work (Evans et al., 2021; Fazel et al., 2014; Hwang & Burns, 2014; Wickham, 2020). To the best of my knowledge, this study is

the first to investigate the effects of a country-wide healthcare policy that explicitly targets the homeless population.

Second, this study adds to the literature on homeless interventions more broadly by providing the first causal evidence from a developing country. While interventions in high-income settings are often successful and cost-effective in improving different socio-economic outcomes (Cohen, 2024; Corinth, 2017; Downes et al., 2022; Dwyer et al., 2023; Evans et al., 2016; Gubits et al., 2018; Kuehnle et al., 2023; Locks & Thuilliez, 2023; Palmer et al., 2019; Phillips & Sullivan, 2022, 2023; Stergiopoulos et al., 2015), interventions in developing countries face many additional challenges, such as particularly high levels of stigmatization, negative attitudes toward homeless individuals, and resource constraints (Speak & Tipple, 2006). My results provide evidence for the success of homeless interventions in resource-scarce settings.

Finally, this study adds to the literature on delivering healthcare to populations that are excluded for various reasons (Perreira & Pedroza, 2019; Watson, 2014). Multiple studies show the effectiveness of related policies to increase healthcare usage among vulnerable populations, such as ethnic minorities, poor households, or undocumented migrants (Aizer, 2003; Bailey & Goodman-Bacon, 2015; Currie, 2004; Finkelstein et al., 2012; Sabety et al., 2023). My results complement this literature by demonstrating the effectiveness of a policy that targets an extremely marginalized and burdened population.

This paper is organized as follows. In Section 2, I describe the institutional and conceptual background. In Section 3, I provide details on the data. In Section 4, I describe my empirical strategy. Results and robustness checks are presented in Sections 5 and 6. In Section 7, I discuss policy implications. Section 8 concludes.

2 Background

2.1 Homelessness and healthcare in Brazil

In line with global trends, homelessness in Brazil is growing rapidly. In 2023, Brazilian statistics included over 220,000 people living on the street, representing an increase of around 1,000% as compared to 2013 (Natalino, 2023). This large increase is a country-wide pattern, occurring simultaneously in all major municipalities (Figueiredo et al., 2022). Brazil's public healthcare system *SUS* (Sistema Único de Saúde), however, has long been unprepared to address the healthcare

needs of the growing homeless population (Vargas & Macerata, 2018). Even though SUS should ensure adequate and free-of-charge healthcare to everybody, the homeless still face large barriers to accessing primary and other sources of ambulatory care (Boccolini & de Souza Junior, 2016; de Menezes et al., 2022; Figueiredo et al., 2022). Some municipalities have been delivering healthcare that targets the homeless, for example by providing primary care directly on the street, but actions were typically ad-hoc and low in absolute numbers (C. C. d. Silva et al., 2015).

To address the specific healthcare needs of the homeless population, the National Primary Care Policy established MSCs as part of SUS in 2011 (de Menezes et al., 2022; Vargas & Macerata, 2018). Thereby, MSCs represent Brazil's first systematic and country-wide healthcare policy that targets the homeless (de Menezes et al., 2022). MSCs are primary care teams that actively go to homeless individuals and attend them on the street. Each MSC covers a specific geographic area within a municipality, operating at least 30 hours per week. MSC teams can consist of between 4 to 7 healthcare professionals and social workers, mostly community agents and nurses. The largest MSC teams also include physicians and odontologists (de Araujo Magalhães, 2018).

MSCs act as an entry point to the public healthcare system for the homeless, delivering the full range of primary care that is typically delivered in standard primary care units. In addition, MSCs have a strong focus on harm reduction related to alcohol and drug abuse (F. P. d. Silva et al., 2014). Ideally, MSCs should retain the majority of homeless patients within the primary care system, either by referring patients to standard primary care or by repeatedly attending them on the street. Patients who require more specialized care should be referred to other ambulatory or acute care providers. Thereby, MSCs are explicitly set up to work closely together with the public psycho-social care centers which provide community-based ambulatory care for mental illness, alcohol addiction, and drug addiction (Dias & Fontes, 2024; Vargas & Macerata, 2018).

Similar to other healthcare programs in Brazil, opening a MSC is voluntary for eligible municipalities. Eligibility depends on the municipalities' total and homeless populations, which together define the maximum number of MSCs that a municipality can apply for. Accounting for the growing number of homeless individuals, eligibility criteria have been changing over time and have become less restrictive. The last change occurred in 2021, entitling all municipalities with at least 100,000 inhabitants and/or at least 80 homeless individuals to apply for at least one MSC (Ministério da Saúde, 2024a, 2024b, 2024c).

Generally, the process of applying for and being granted federal funds to open a MSC can be

complicated and lengthy. Municipalities report bureaucratic application processes, difficulties in hiring the necessary healthcare professionals, and insufficient funds from the federal government as major barriers to the program (Medeiros & Cavalcante, 2018). This suggests that participation often depends on municipalities' underlying characteristics, such as administrative capacity and financial and human resources, rather than on immediate healthcare needs.

2.2 Conceptual framework and expected effects of Mobile Street Clinics

My analysis focuses on three important dimensions of healthcare usage that should be addressed by healthcare policies that target the homeless (Liu & Hwang, 2021): primary care usage, community-based care usage, and healthcare continuity. Because community-based care and healthcare continuity are broadly defined and difficult to measure, I focus on two closely related outcomes that are easily quantifiable and highly relevant for the homeless population. Specifically, I look at psycho-social care usage among the homeless to estimate the effects on community-based care, and at tuberculosis treatment outcomes to estimate the effects on healthcare continuity. Below, I outline the expected effects that MSCs should have on each of these three dimensions of healthcare usage.

The expected effects of MSCs are theoretically straightforward and go along different stages of healthcare utilization. The main goal of MSCs is to overcome the existing barriers to primary care by attending homeless individuals directly on the street. As a direct effect, MSCs should therefore increase primary care usage among the homeless population and address a wide range of different conditions (Fazel et al., 2014; Hwang & Burns, 2014). Next, increases in primary care usage should improve related downstream healthcare services. Importantly, MSCs should improve the integration of homeless patients into community-based care for mental health and substance abuse (Kerman & Stergiopoulos, 2024). Because MSCs in Brazil are explicitly set up to collaborate closely with local psycho-social care centers, one would expect large increases in psycho-social care usage among the homeless population. Finally, MSCs should improve healthcare continuity among the homeless population (Liu & Hwang, 2021). This is especially relevant for the treatment of conditions that require ongoing care, such as tuberculosis (Haddad et al., 2005). In Brazil, tuberculosis among the homeless is often undiagnosed and, even if diagnosed, homeless tuberculosis patients are twice as likely to abandon the treatment as compared to non-homeless patients (Silva Rodrigues et al., 2023). Therefore, MSCs should ideally increase both the number of detected and successfully treated tuberculosis cases.

While conceptually clear, whether or not the expected effects materialize is far from obvious. Anecdotal evidence points toward potential problems that may impede the successful operations of MSCs (Hallais & Barros, 2015). First, MSCs may not be able to match the healthcare needs of the homeless if existing barriers, such as stigmatization and lack of trust, prevail (Kerman & Stergiopoulos, 2024). Second, MSCs may simply replace primary care *off* the street with primary care *on* the street without increasing overall usage (Carrillo & Feres, 2019). Or third, healthcare workers may exert little effort to attend the homeless population, or may not be qualified to address their specific needs (Hallais & Barros, 2015). Improvements in downstream community care and healthcare continuity are especially hard to achieve. They require a high degree of initiative from the patients and strict treatment adherence – both of which are strongly susceptible to the living conditions of the homeless (Ranzani et al., 2016).

3 Data

I use different administrative data sets to either directly measure or closely approximate primary care, community-based psycho-social care, and tuberculosis care among the homeless. I combine these data sets with information on active MSCs at the municipality-by-year level. Because most outcome variables are available from 2015 onward, I limit the main analysis to the years 2015 to 2023. Where applicable, I provide results for additional time periods in the robustness section. All variables are transformed by 100,000 inhabitants using the population size from the 2010 census. Below, I describe the main data sources and give an overview of the key measures in my analysis.

3.1 Data sources

Mobile Street Clinics: Data on MSCs comes from Brazil's National Registry of Health Facilities (CNES). CNES is a registry of all healthcare professionals, teams, and facilities in Brazil, including all active MSCs per municipality, month, and year. For the main analysis, I create a binary treatment indicator that equals 1 for years in which municipalities have at least one MSC. Therefore, this study estimates the average effect of participating in the health policy (i.e., having at least one active MSC in a given year) rather than the effect of one additional MSC.

Primary healthcare utilization: To measure primary care usage among the homeless, I use data from Brazil's National Information System on Primary Health Care (SISAB). SISAB records

all public primary care services delivered per municipality and year, including services delivered through MSCs. While the dataset does not explicitly capture whether a patient is homeless or not, it records the locality where every service has been delivered. I make use of primary care services *on the street* to proxy for primary care usage among the homeless population. Primary care services can further be disaggregated by related health conditions (such as alcohol use, drug use, tuberculosis, diabetes, etc.).

Psycho-social care: To study the effects on community-based care, I use data on psycho-social care from Brazil's National Information System of Ambulatory Psycho-social Care (SIA-PS). The data set records all ambulatory care services provided in publicly funded psycho-social care centers. These centers are part of SUS and offer free-of-charge community-based care for mental health, alcohol, and drug problems (Dias & Fontes, 2024). The data set includes individual admissions, patients' municipality of residence, and a variable that directly captures whether a patient is homeless or not.

Tuberculosis: To investigate the effects on healthcare continuity, I use data on tuberculosis cases from Brazil's Notifiable Diseases Information System (SINAN). The data set records every diagnosed tuberculosis case in Brazil together with the treatment outcome, i.e., whether a patient completed the tuberculosis treatment successfully or not. It also contains patients' municipality of residence and a variable that directly captures whether a patient is homeless or not.

Official number of homeless individuals per municipality: Official numbers of homeless individuals in Brazil are based on the Cadastro Único (CadÚnico) data set that contains information on low-income individuals and households (Natalino, 2023). CadÚnico is a registry used for the administration of social programs and includes information on individuals' municipality of residence and self-reported homelessness. Despite suffering from measurement error (e.g., under-reporting of homelessness among females and underage individuals), it is considered the best available administrative data source to measure homelessness in Brazil (Natalino, 2023). The publicly available data captures the number of registered homeless individuals on a monthly level, without differentiating between specific individuals. Because the data cannot be aggregated on a yearly level, I use data from December of each year.

Auxiliary Data Sources: Geographic and demographic variables come from Brazil's Statistics Office IBGE. Data on municipalities' baseline characteristics, including health outcomes and socio-demographic variables, come from IEPS data.

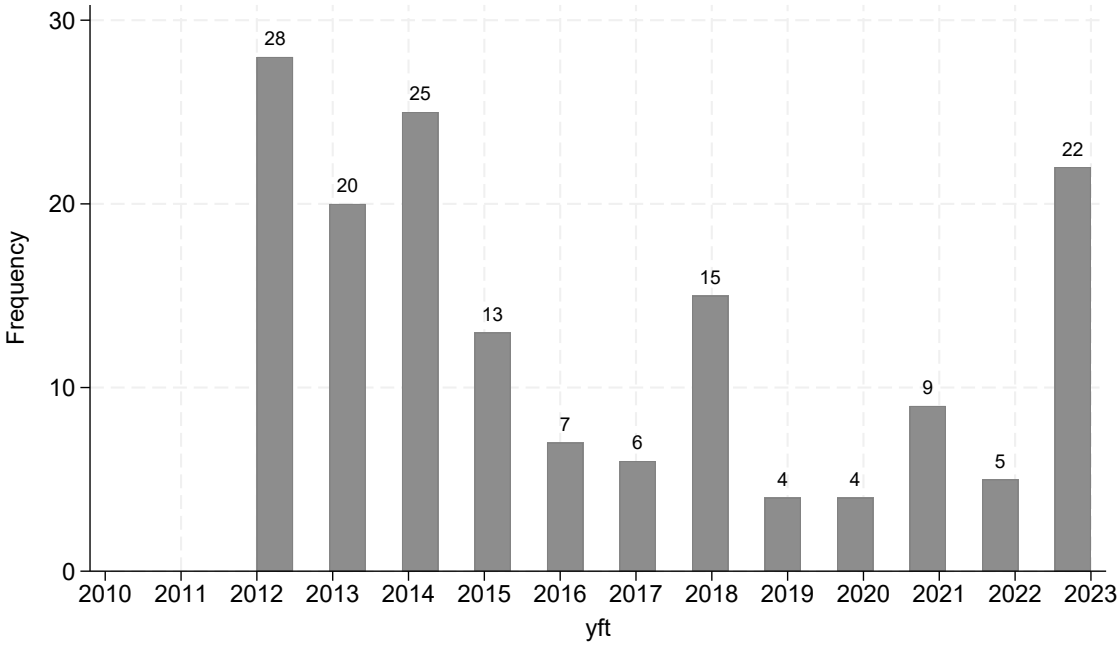


Figure 1: The figure shows the number of newly treated municipalities per year (i.e. municipalities that open at least one Mobile Street Clinic for the first time in a given year). Original data from CNES.

3.2 Descriptive statistics

Figure 1 shows the number of newly treated municipalities per year, with the first openings in 2012. Given that I restrict my analyses to the years 2015 onward, I have to disregard all treatment municipalities that opened their first MSC in 2015 or earlier. My working sample uses variation from 81 treatment municipalities (out of all 171 municipalities that participated in the program up to 2023) and 5,399 control municipalities.

While municipalities can open multiple MSCs, I use a binary treatment indicator that equals 1 if a municipality has at least one MSC in a given year. Figure 2 shows that this is a reasonable simplification: In my final sample, municipalities open, on average, 1.02 MSCs (with a maximum of 2 MSCs per municipality), corresponding to 0.61 MSCs per 100,000 inhabitants.[1] Note that treatment is non-absorbing and can turn from 1 to 0. In my sample, three municipalities leave the treatment at some point. All other municipalities remain treated after the opening of their first MSC.

Recall that joining or leaving the program is voluntary. Appendix Table A2 shows municipality-level

[1]Additionally, considering municipalities that opened MSCs before 2016 gives an average of 1.7 MSCs per municipality, corresponding to 0.47 MSCs per 100,000 inhabitants.

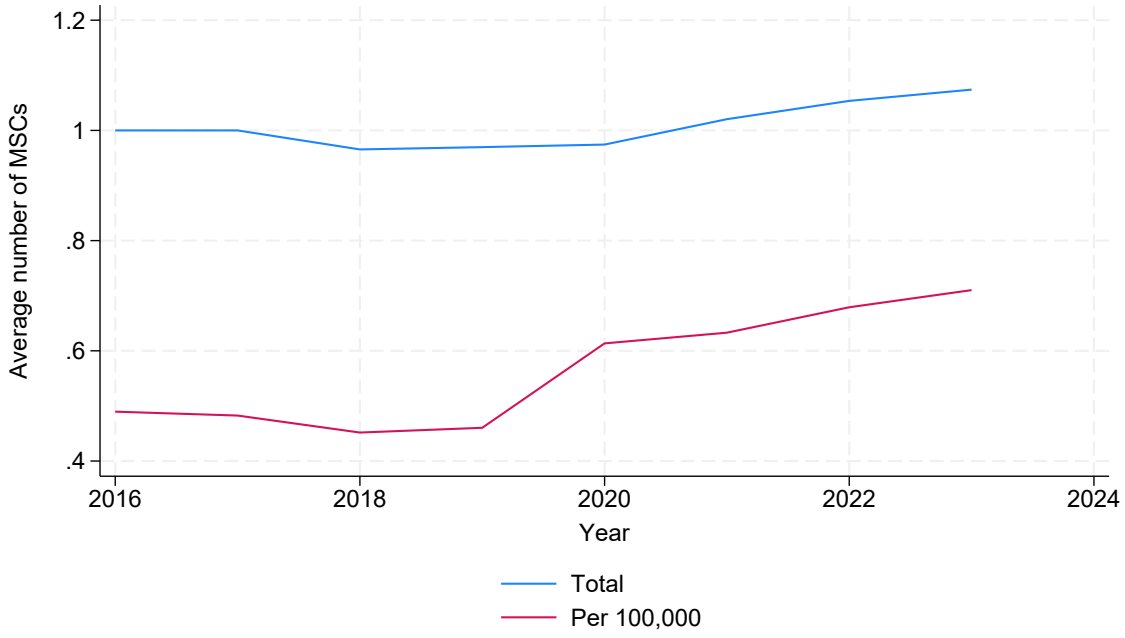


Figure 2: The figure shows the average number of MSCs per treatment municipality for all municipalities that have been treated from 2016 onward. The blue line shows the average absolute number per municipality, the red line shows the average number per municipality per 100,000 inhabitants. Original data from CNES.

baseline characteristics for control and treatment municipalities, revealing substantial variation between the groups. On average, municipalities that are larger, less vulnerable, and located in specific geographic areas are more likely to open at least one MSC. I account for these baseline differences in the empirical analysis by including different levels of fixed effects. Appendix Table A2 also shows differences between treatment municipalities that joined the program before 2016 (and that are excluded from the analysis) and treatment municipalities that joined in 2016 or later. Reassuringly, differences between the included and excluded treatment municipalities are mostly insignificant.

Pre-treatment means for the main outcome variables are presented in Appendix Table A3 and show very low healthcare usage among the homeless at baseline. Note that pre-treatment means tend to be smaller for the treatment group because outcomes are divided by 100,000 inhabitants, and the treatment group consists of larger municipalities. Appendix Figures A1 to A2 plot the distribution of the main outcome variables.

4 Empirical strategy

4.1 Difference-in-differences model

To estimate the causal effect of MSCs on healthcare usage, I use a difference-in-differences model with variation in treatment timing that is robust to heterogeneous treatment effects and allows treatment units to leave treatment, following De Chaisemartin and d'Haultfoeuille (2024). The model computes dynamic event study estimates by comparing switchers, i.e., municipalities that experience a change in their treatment status between t and $t+1$, to municipalities with the same treatment status in t but that do not experience a change in their treatment status. For simplicity, I use a binary treatment indicator that takes the value of 1 if a municipality has at least 1 MSC in a given year, and zero otherwise. I provide additional results for a continuous treatment definition in the Appendix.

I estimate dynamic treatment effects using equation

$$y_{it} = \alpha_i + \lambda_t + \gamma_{rt} + \rho_{pt} + \sum_k \delta_k 1[t - E_i = k] + \epsilon_{it} \tag{1}$$

where E_i is the year in which municipality i experiences the first change in its treatment status, and $1[t - E_i = k]$ is an indicator for being k years from the treatment. $1[t - E_i = k]$ is negative for pre-treatment years (leads), positive for post-treatment years (lags), and 0 for the first treatment year. δ_k is the coefficient of interest, capturing placebo effects and dynamic effects relative to the municipalities' first treatment change. Given the binary treatment indicator, δ_k can be interpreted as the average effect of participating in the program across all municipalities that opened their first MSC between 2016 and 2023.

α_i and λ_t are municipality and year fixed effects. To control for potential region-specific or population size-specific trends, I include region-by-year fixed effects γ_{rt} and population-group-by-year fixed effects ρ_{pt}, restricting comparisons to municipalities in the same region and population group (Carrillo & Feres, 2019; Dias & Fontes, 2024; Goodman-Bacon & Cunningham, 2019). Moreover, I include not-yet-treated municipalities into the control group, which might represent counterfactual outcomes more accurately than never-treated municipalities alone (Callaway & Sant'Anna, 2021). Standard errors are clustered at the municipality level.

4.2 Internal validity and robustness checks

Identification relies on the standard no-anticipation and parallel-trends assumptions conditional on municipality and year fixed effects. That is, I assume that in the absence of MSCs, healthcare usage among the homeless in treatment municipalities would have followed the same trend as in control municipalities. Throughout the analyses, pre-treatment outcomes support the identifying assumptions. Still, one might be worried that estimated effects are driven by spurious time-varying trends rather than being caused by the opening of MSCs. For example, treatment municipalities might have experienced larger increases in their homeless population or implemented other related policies. To rule out spurious results, I explore several placebo outcomes related to municipalities' homeless population, healthcare supply, and healthcare usage. I also employ multiple alternative specifications in the difference-in-differences model (including different sets of fixed effects and municipality-level control variables) and different staggered estimators.

Evidence from the program implementation and from related healthcare programs in Brazil further backs the validity of the identification strategy. First, program participation seems to be driven by underlying and slow-changing municipality-level characteristics such as administrative capacity and financial resources (Medeiros & Cavalcante, 2018), which are controlled for by the municipality fixed effects. Second, evaluations of other Brazilian healthcare policies that relied on voluntary participation, such as the *More Doctors Program* or the introduction of psycho-social care centers, estimate credible causal effects using a difference-in-differences model and show that self-selection is of limited concern (Carrillo & Feres, 2019; Dias & Fontes, 2024).

Finally, I complement the year-level analysis of primary care usage with a bi-monthly analysis. The exact timing of opening a MSC depends on the approval of the federal government and is hard to predict for municipalities. It is therefore plausibly exogenous to municipalities, even if one may not be willing to rule out self-selection bias in the longer term. Results show that primary care usage on the street increases as an immediate result of MSCs and further support the validity of the research design and the causal interpretation of the results.

5 Results

Healthcare for the homeless population should (i) increase primary care usage, (ii) connect homeless individuals to downstream community-based care, and (iii) promote continuity of care (Liu &

Hwang, 2021). Using data on primary care, psycho-social care, and tuberculosis care, I provide results on each of these three dimensions of healthcare usage. The main results are presented in the form of event study graphs where red dots represent pre-treatment estimates and blue dots represent post-treatment estimates. All graphs show 95% confidence intervals that are clustered on the municipality level. Tables including exact point estimates and standard errors are presented in the Appendix.

5.1 Primary care usage

I start by investigating the effects of MSCs on primary care usage *on the street* in Figure 3 (see Appendix Table A4, Column 1 for more detail). In the first treatment year, $t = 1$, primary care usage on the street increases, on average, by 192 services per 100,000 inhabitants, relative to a pre-treatment mean of 50 for ever-treated municipalities. Treatment effects increase to 650 services per 100,000 inhabitants in $t = 2$ and remain relatively stable until 5 years after the opening of the first MSC.[2] Note that $t = 1$ combines municipalities that got treated earlier and municipalities that got treated later in that year. Taking together more and less affected municipalities can explain the attenuated effect. In line with the parallel trends assumption, pre-trends are close to zero and statistically insignificant. Moreover, pre-trends show no sign of anticipation. If the opening of a MSC was driven by self-selection based on differential growth in municipalities' homeless population, one might expect increases in primary care on the street already prior to the first treatment year. Reassuringly, this is not the case.

The increase in primary care usage on the street is not surprising but has important policy implications. First, it shows that MSCs are generally effective in making primary care accessible to the homeless population under real-world conditions, thereby confirming evidence from small-scale RCTs (Christian et al., 2024; Fine et al., 2023; Kopanitsa et al., 2023; O'Toole et al., 2015; Sadowski et al., 2009). Second, the size of the estimated effects indicates that MSCs work remarkably well in matching the homeless' demand for primary care. While estimates are large, the order of magnitude is not uncommon for successful healthcare interventions. RCTs investigating the effectiveness of outreach activities in the USA report increases in primary care usage of over 300% among illegal immigrants (Sabety et al., 2023) or homeless veterans (O'Toole et al., 2015). Large-scale healthcare policies can also have comparable effects. For example, Dias and Fontes (2024) find that the

[2]Using a continuous treatment definition yields a very similar picture to the binary treatment indicator, see Column 2 of Appendix Table A4.

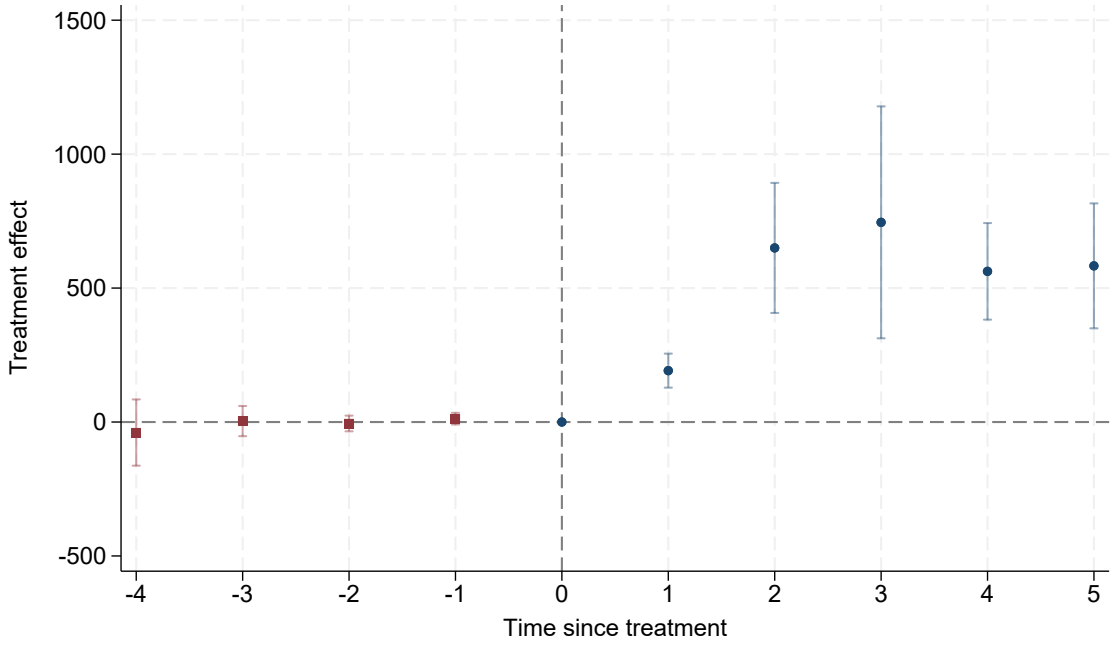
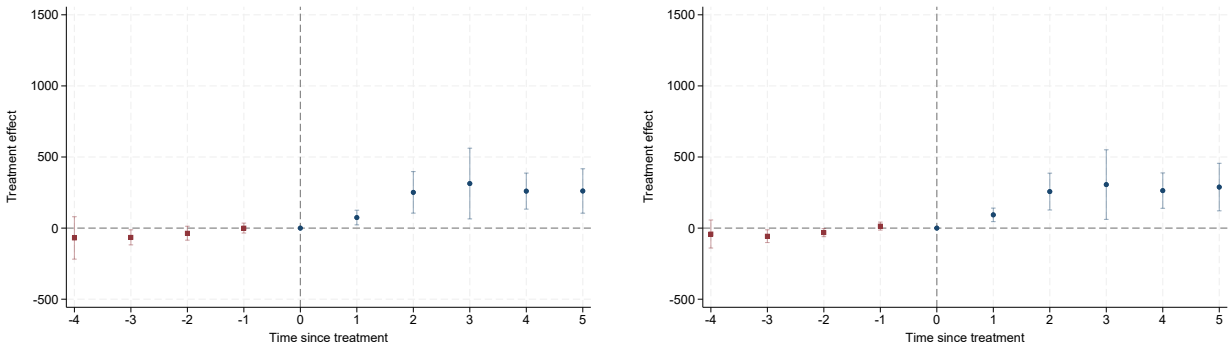


Figure 3: The graph shows event studies for the number of primary care services delivered *on the street*, following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SISAB.

opening of psycho-social care centers in Brazil increases the number of outpatient procedures by mental health professionals by over 100%. Given that homeless individuals represent an extremely disadvantaged group and that MSCs provide care with very low barriers to access, the large effects in Figure 3 are not implausible.

While MSCs clearly increase primary care usage on the street, I am particularly interested in the effects on *total* primary care usage among the homeless. One might be concerned that MSCs lead to a substitution of primary care *off* the street by primary care *on* the street without actually increasing total usage. Typically, one would investigate potential substitution by looking at the effects on aggregate primary care usage, both on and off the street. In my setting, however, doing so would not be very informative. Primary care on the street only accounts for a fraction of all primary care, and an event study on aggregate outcomes would be highly underpowered. Instead, I look at aggregate primary care usage for health conditions that are particularly common among the homeless, but uncommon among the non-homeless. Specifically, I examine the effects on aggregate primary care usage related to alcohol use and drug use (both on and off the street), which are disproportionately prevalent among the homeless population (Fazel et al., 2014).



(a) Primary care for alcohol (all localities)

(b) Primary care for drugs (all localities)

Figure 4: The graph shows event studies for the number of all primary care services related to alcohol use (Panel a) and drug use (Panel b) following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SISAB.

Figure 4 plots the corresponding event studies (see Appendix Table A4, Columns 3 and 4 for more detail). Estimates strongly support that MSCs increased overall primary care usage among the homeless rather than shifting localities: The opening of the first MSC increases aggregate primary care usage related to alcohol use (Figure 4, Panel a) and drug use (Figure 4, Panel b), on average, by 218 and 228 consultations per 100,000 inhabitants. Considering that almost 1/3 of Brazil's homeless reported alcohol- or drug-related problems as one major reason for living on the street (Natalino, 2023), these point estimates fit well with the effects on primary care usage on the street.

5.1.1 Primary care usage on the street: heterogeneous effects by health conditions

To get a more detailed picture of the type of healthcare that MSCs provide, I look at heterogeneous effects by health conditions (Appendix Table A5). Increases in healthcare usage on the street are most pronounced for conditions that are common among the homeless, such as substance abuse and tuberculosis (Fazel et al., 2014), but also extend to chronic conditions and other infectious diseases. Reassuringly, estimates for alcohol and drug use *on the street* show a very similar pattern to estimates for aggregate alcohol and drug use but are smaller in absolute size. This again suggests that MSCs increase overall primary care usage among the homeless. Notably, MSCs also increase primary care on the street related to reproductive health, including pre- and post-natal care. Pregnant women who are homeless often face particularly strong barriers to accessing primary care, for example, due to fear of legal consequences (Milligan et al., 2002). The positive effect on reproductive healthcare suggests that MSCs reach even the most vulnerable people living on the street.

5.2 Community-based care: the case of psycho-social care

In addition to providing targeted primary care, MSCs should connect homeless patients to other downstream healthcare services, especially to community-based care for mental health and substance abuse (Kerman & Stergiopoulos, 2024; Liu & Hwang, 2021). Figure 5 plots event studies for the number of services delivered to homeless individuals in psycho-social care centers (Appendix Table A6, Column 1). On average, the introduction of the first MSC increases psycho-social care usage among the homeless by 11 visits per 100,000 inhabitants, relative to a pre-treatment mean of 8. Point estimates gradually increase over time and are jointly significant at the 1% level. Pre-trends are somewhat noisy but do not show any pattern that could explain the effect after the opening of the first MSC (Rambachan & Roth, 2023).

The data on psycho-social care also allows me to differentiate between referrals from different healthcare providers to psycho-social care centers. Looking specifically at homeless patients who have been referred from primary care (Appendix Table A6, Column 2) confirms the direct link between MSCs and psycho-social care usage. While estimated effects are noisier, they are broadly in line with Figure 5.

Overall, the results for psycho-social care usage show that MSCs are effective in connecting homeless patients to community-based care and, more generally, retaining them within the public healthcare system. This is especially relevant for homeless people with mental illnesses for whom community-based mental care may help to reduce chronic homelessness (Kerman & Stergiopoulos, 2024). Moreover, the results illustrate that targeted and non-targeted healthcare services should be seen as complements when designing healthcare policies for the homeless (Hwang & Burns, 2014).

5.3 Healthcare continuity: the case of tuberculosis

Conditions like tuberculosis require early detection and continuous care, which are particularly difficult to ensure for the homeless population (Jego et al., 2016; Silva Rodrigues et al., 2023). Looking at the effects on new tuberculosis diagnoses among the homeless in Panel (a) of Figure 6 shows an average increase of 0.35 per 100,000 inhabitants, relative to a sample mean of 1 (Appendix Table A6, Column 3). While imprecisely estimated, point estimates are jointly significant at the 5% level. These results are encouraging, given that under-detection remains a big challenge to ending tuberculosis, especially in developing countries (Alsdurf et al., 2016; Reid et al., 2019).

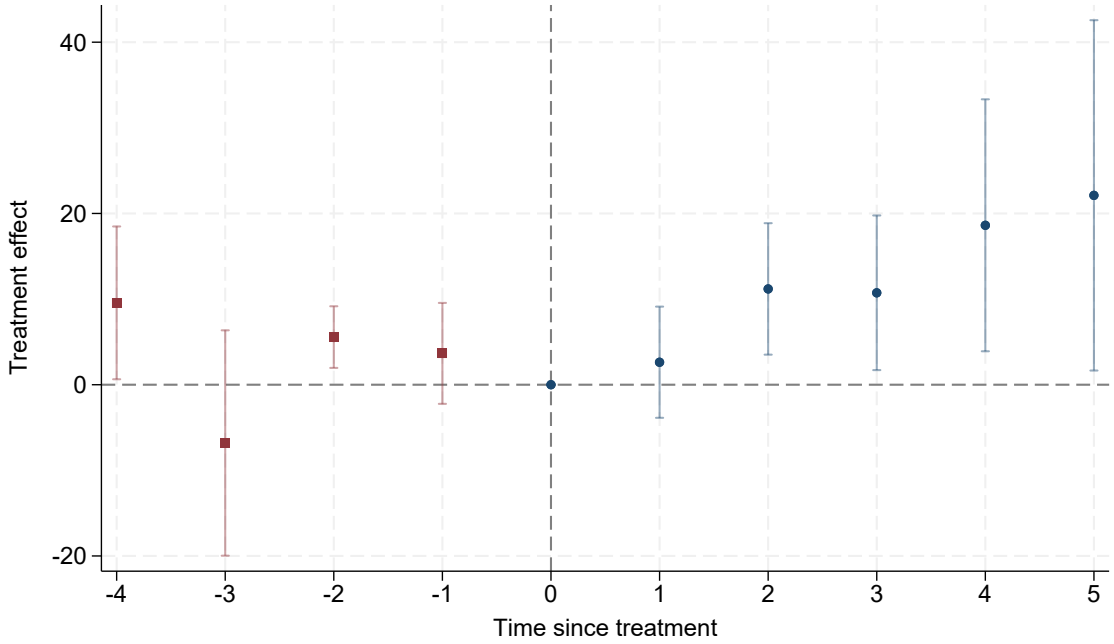
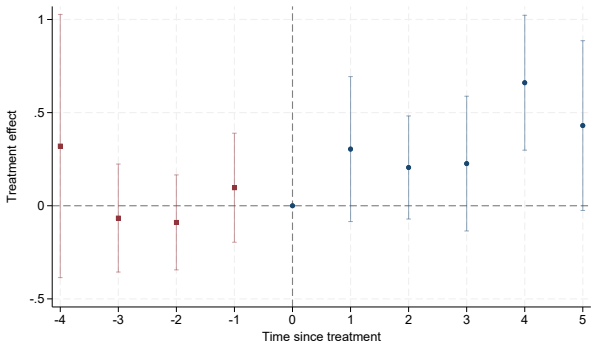


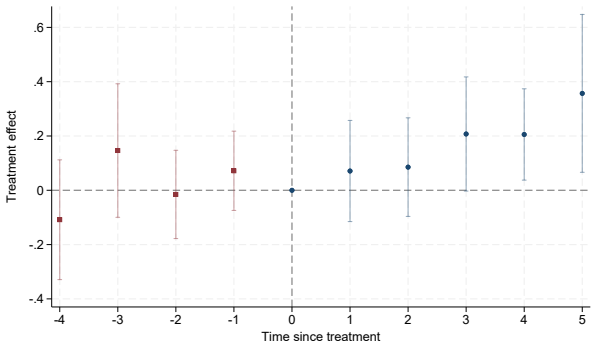
Figure 5: The graph shows event studies for the number of psycho-social care services at CAPS delivered to homeless patients, following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SIA-PS.

Turning to the treatment success of homeless tuberculosis patients, however, draws a more nuanced picture. Panel (b) of Figure 6 plots event study estimates for the number of homeless tuberculosis patients that abandon the treatment before completion (Appendix Table A6, Column 4). On average, drop-out increases by 0.16 cases per 100,000 inhabitants, whereas the number of homeless tuberculosis patients who complete the 6-month treatment remains unchanged (Figure 6, Panel (b); Appendix Table A6, Column 5).

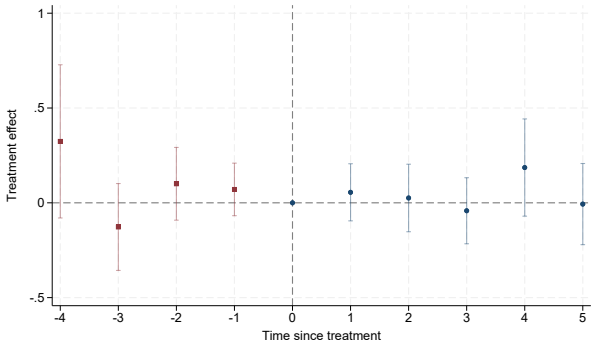
Results imply that the increase in tuberculosis detections is mostly driven by homeless patients who fail to complete the treatment. This is problematic, as unsuccessful tuberculosis treatment is often deadly and disproportionally prevalent among the homeless in Brazil (Silva Rodrigues et al., 2023; Steffen et al., 2010). More broadly, the findings for tuberculosis care suggest that MSCs face significant limitations in overcoming barriers to long-term and continuous care. They may have to be accompanied by more intensive outreach activities or by additional incentives, such as cash or in-kind transfers, that have often been proven cost-effective in increasing treatment adherence (Banerjee et al., 2010; Malotte et al., 2001).



(a) Tuberculosis diagnoses among homeless



(b) Abandoned tuberculosis treatment among homeless



(c) Successfully treated tuberculosis cases among homeless

Figure 6: The graph shows event studies for the number of diagnosed tuberculosis cases among the homeless (Panel a), the number of homeless tuberculosis patients that abandoned treatment before completion (Panel b), and the number of homeless tuberculosis patients that were successfully treated (Panel c), following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SINAN.

6 Robustness

6.1 Potential self-selection

Throughout the analyses, pre-treatment outcomes are in line with the parallel trends assumption. Still, one might still be worried that municipalities self-select into opening MSCs based on underlying trends that drive the increase in healthcare usage among the homeless. For example, MSCs may be opened by municipalities that experience particularly strong growth in their homeless population or that also expand other related healthcare and services. I perform several placebo estimations to rule out such spurious results.

Appendix Figure A4 shows event study estimates for the number of officially registered homeless individuals in CadÚnico – an imperfect, but the best available count of the homeless population. Based on this measure, there is no idiosyncratic increase in the number of homeless individuals in treatment municipalities. Next, Appendix Figure A5 plots event study estimates for the number of psycho-social care centers per municipality. If the expansion of MSCs occurred simultaneously with the expansion of psycho-social care services (Dias & Fontes, 2024), this may drive the observed pattern. Reassuringly, the opening of the first MSC is unrelated to the number of psycho-social care centers.

The estimated effects do not coincide with larger municipality-wide trends in healthcare usage. Appendix Table A7 shows event study estimates for overall primary care usage, psycho-social care usage among the non-homeless, and detected tuberculosis cases among the non-homeless. While I do not have the statistical power to detect small changes in these outcome variables, the placebo regressions confirm that the strong increases in healthcare usage after the opening of the first MSC are unique to outcomes among the homeless.

Finally, I look at primary care usage on the street on a bi-monthly level to investigate whether the quasi-random opening date of a MSC has an immediate effect. Appendix Figure A6 shows that primary care usage on the street increases directly after the opening of the first MSC. Given that the exact opening date of a MSC is plausibly exogenous to municipalities, such immediate effects are unlikely to be driven by self-selection and further support a causal effect.

Taken together, the increases in healthcare usage among the homeless happen immediately after the opening of the first MSC and are not accompanied by similar trends in the number of registered homeless individuals, in the number of psycho-social care centers, or in healthcare usage among the

non-homeless. This evidence, together with parallel pre-trends, strongly supports the validity of my research design.

6.2 Different specifications

Given that the analysis relies on variation from only 81 treatment municipalities, one might be concerned that results are driven by analytical decisions – especially because estimated effects are very large (Button et al., 2013). I re-estimate my main results in the spirit of Simonsohn et al. (2020), using a range of different theoretically justifiable model specifications and sample criteria (Appendix Figures A7 to A9). For every outcome, I re-estimate equation 1 (i) using only municipality and year fixed effects, (ii) using municipality-profile-by-year fixed effects instead of population-category-by-year fixed effects, (iii) using state-by-year fixed effects instead of region-by-year and population-category-by-year fixed effects (iv) excluding municipalities that eventually leave the treatment, (v) excluding municipalities with less than 100,000 inhabitants in 2010, (vi) using only not-yet-treated municipalities as the control group, (vii) stopping the analysis in 2019 when Covid-19 started in Brazil, and (viii) controlling for baseline municipality characteristics (control variables include the number of medical doctors, the number of nurses, GDP per capita, per capita spending for Bolsa Familia, primary care coverage, and population size, all from 2010). While some of the point estimates become insignificant in specifications with reduced sample size, the overall pattern remains robust to different specifications.

6.3 Different estimators

Results are also robust to different estimators. Appendix Figures A10 and A11 plot event study estimates following Wooldridge (2021) and Wooldridge (2023) (using a poisson pseudo-maximum likelihood regression to account for the skewed outcome variables containing many zero values). Again, the overall picture remains unchanged.

7 Policy considerations

Because public funds for healthcare in developing countries are often limited, policymakers may be interested in the real-world importance of the estimated effects and in the cost-effectiveness of the intervention. Both are difficult to obtain with the available data, but approximate back-of-

the-envelope calculations can at least provide an indication of whether the estimated effects are of meaningful magnitude, and whether the program's funding is well spent.

Starting with the economic relevance, MSCs should ideally close the gap between the homeless populations' primary care demand and their primary care usage. Quantifying how much of this gap MSCs are able to reduce is difficult because (1) there is no benchmark value for the optimal number of primary care usage per homeless individual, and (2) there is no data that perfectly captures the number of homeless individuals per municipality in Brazil. Assuming that the ideal number of primary care usage among the homeless should be proportional to the usage among the average population (which is most likely a strong understatement of the reality as the health burden of homelessness exacerbates that of the average population), and taking the number of homeless individuals registered in the CadÚnico as a proxy for the total number of homeless individuals per municipality, gives the following back-of-the-envelope calculation:

Over the study period, the SISAB data set records, on average, 3.2 primary care services per year. According to CadÚnico, the average number of homeless individuals per municipality over the entire study period was 64 per 100,000 inhabitants, which should result in an approximate number of $64 * 3.2 = 205$ primary care services on the street per 100,000 inhabitants per municipality (assuming that all primary care usage among the homeless takes places on the street). The actual number of primary care usage on the street before the introduction of the first MSC, however, was only 56. The estimated ATT of 521 would imply very meaningful increases in primary care usage among the homeless. In fact, the ATT is substantially larger than the (very conservatively) estimated gap in healthcare usage between the homeless and non-homeless. This large difference can be explained by the actual number of homeless individuals and their healthcare needs being probably much larger in reality.

Next, the cost-effectiveness of healthcare interventions is typically calculated with the help of avoided hospital visits and avoided mortality. Due to lack of adequate data on hospitalizations and mortality among the homeless, such an approach is not feasible in this study. To still get a feeling of the program's cost dimension, I compare the average spending per service delivered in MSCs to the spending in standard primary care and hospital care. Especially hospital care is one major source of healthcare for the homeless, with admission rates, length-of-stay, and costs typically above those of the average population (Fazel et al., 2014; Hwang et al., 2013; Kushel et al., 2001).

According to the Ministry of Health, the total public spending for MSCs in 2021 was 49,043,600 R$

for 762,700 primary care services, resulting in an average cost of 64 R$ per service in a MSC (Rosa et al., 2022). This is about twice the cost of an average primary care service in 2021 (2,662,029,660 R$ for a total of 1,081,743,605 primary care services) but around 30 times lower than the cost of an average hospital service in 2021 (11,629,005 hospitalizations for a total of 22,373,669,991.24 R$). Following this simple back-of-the-envelope calculation, a 3% reduction in hospitalizations among the homeless alone would already set off the MSC program's costs.

Such a reduction is not implausible for multiple reasons. First, related studies typically find even larger reductions in hospital care, ranging from 7.5% to 30% (Dias & Fontes, 2024; Sadowski et al., 2009). Second, reductions typically extend to (and are often particularly pronounced for) emergency care, which is similarly common among the homeless and more costly than primary care (Kushel et al., 2001; Sabety et al., 2023; Sadowski et al., 2009). Third, multiple other benefits that are not easily quantifiable add to the potential benefits of MSCs: increases in primary care likely lead to the detection and control of other diseases (Bhalotra et al., 2019); the engagement of homeless patients in psycho-social care is central to addressing the root causes of homelessness (Kerman & Stergiopoulos, 2024); and anecdotal evidence emphasizes MSCs' social value to the homeless (Ferreira et al., 2016). Taken together, the program's costs are likely relatively moderate compared to its benefits.

8 Conclusion

In this study, I provide first large-scale evidence on the effects of Mobile Street Clinics (MSCs) on healthcare utilization among the homeless population in a developing country. Identification comes from municipality-level variation in the opening of MSCs following a government policy in Brazil. My results show that MSCs strongly increase primary care usage, community-based care usage, and the detection of tuberculosis cases among the homeless. However, MSCs are not able to improve healthcare continuity.

Effect sizes are substantial and meaningful for closing the gap in primary care usage between homeless and non-homeless individuals. Given the likely moderate costs relative to the program's benefits, MSCs represent a promising approach to overcoming barriers to healthcare utilization among the homeless. Additionally, my results suggest that targeted healthcare policies should complement non-healthcare-centered interventions, such as housing assistance or financial support, which, while improving different socio-economic outcomes among the homeless, have shown limited

impact on healthcare usage (Cohen, 2024; Downes et al., 2022; Phillips & Sullivan, 2022).

This study is especially informative for policymakers in developing countries that host the majority of the global homeless population (Tipple & Speak, 2005). Despite concerns about limited resources and high levels of stigmatization (Speak & Tipple, 2006), my findings demonstrate the potential effectiveness of homeless interventions in these contexts.

A question that remains unanswered is the potential impact on acute care, such as emergency care and hospitalizations. Ideally, MSCs should not only increase ambulatory care but also reduce avoidable acute care among the homeless (Fazel et al., 2014). Due to the absence of adequate data, evaluating these outcomes is left for future work.

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9 Appendix

9.1 Figures

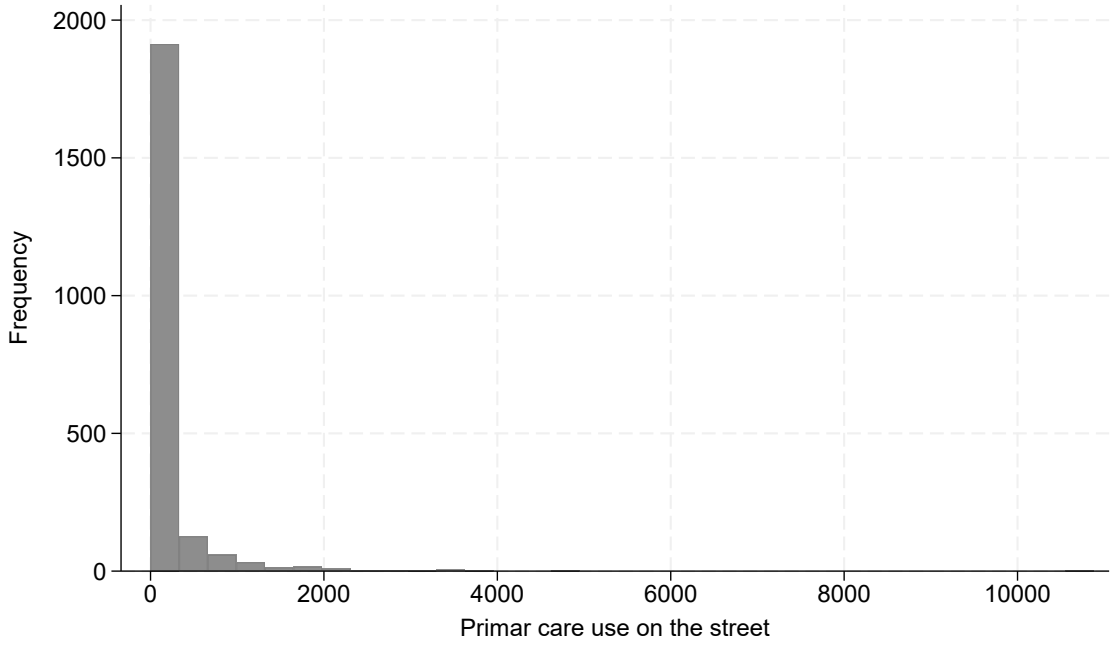


Figure A1: The graph plots the distribution of primary care usage on the street for the working sample. Outcomes per 100,000 inhabitants in 2010. Original data from SISAB.

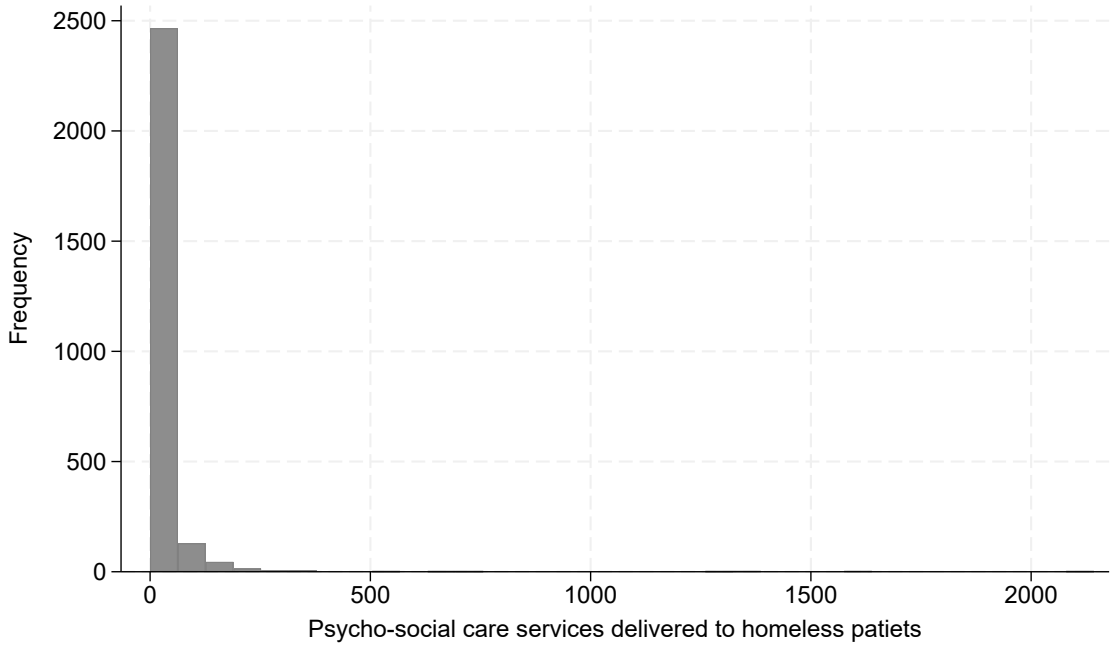


Figure A2: The graph plots the distribution of psycho-social care services delivered to homeless patients for the working sample. Outcomes per 100,000 inhabitants in 2010. Original data from SIA-PS.

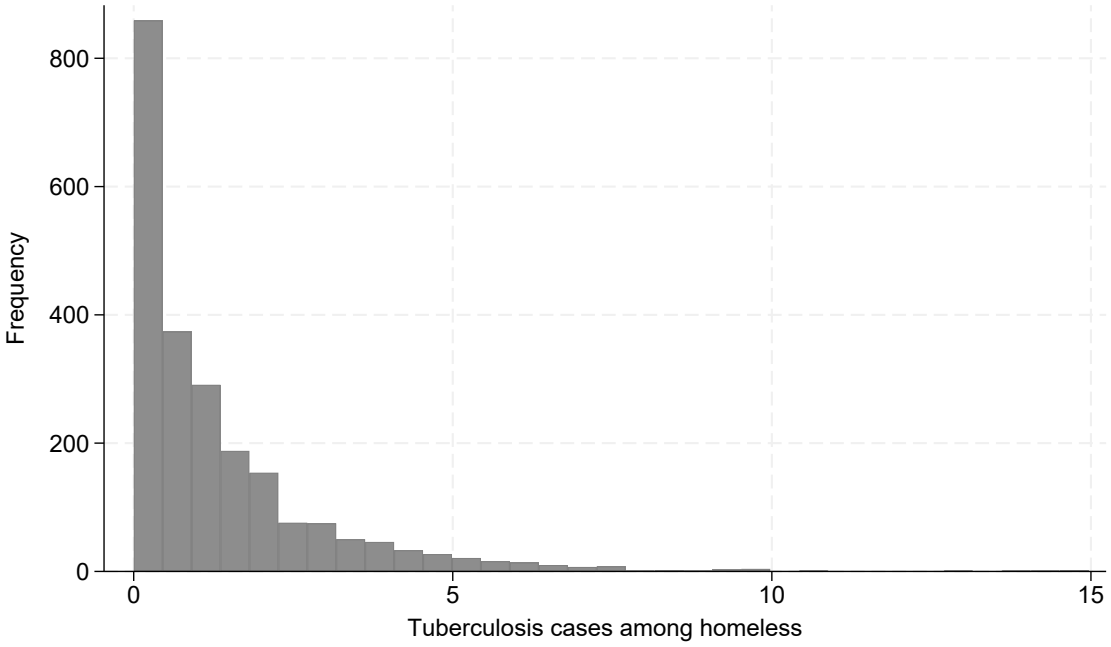


Figure A3: The graph plots the distribution of the number of diagnosed tuberculosis cases among he homeless for the working sample. Outcomes per 100,000 inhabitants in 2010. Original data from SINAN.

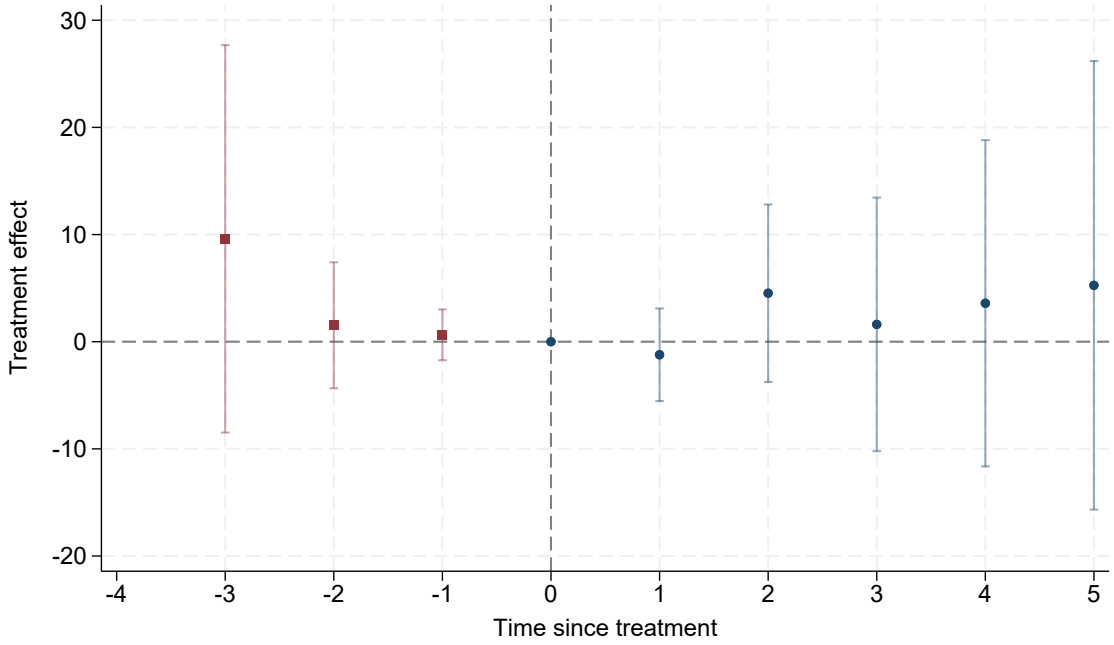


Figure A4: The graph shows event studies for the number of officially registered homeless individuals in the Cadastro Único, following equation 1, for the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and CadÚnico.

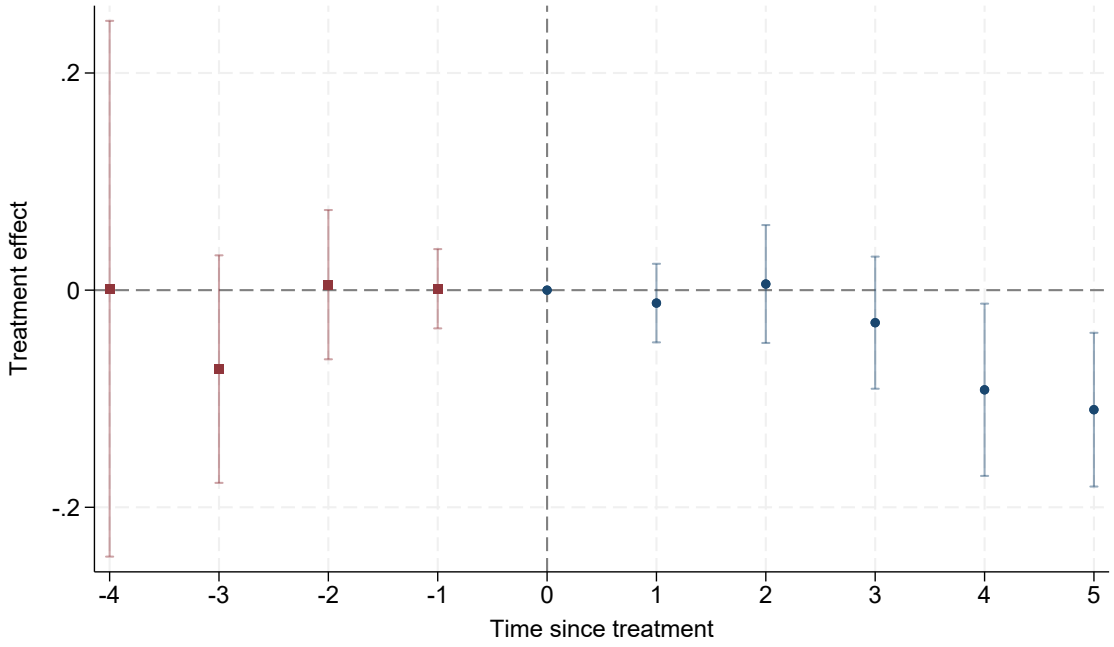


Figure A5: The graph shows event studies for the number psycho-social care centers, following equation 1, for the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES.

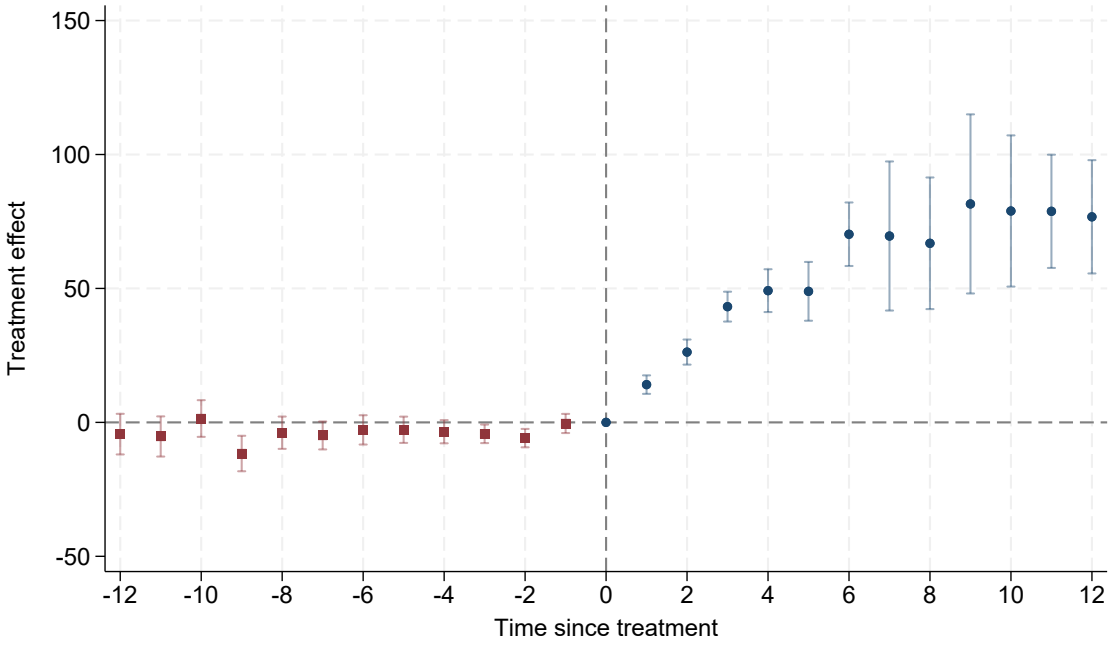


Figure A6: The graph shows event studies for the number of primary care services delivered *on the street* on a bi-monthly level, following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SISAB.

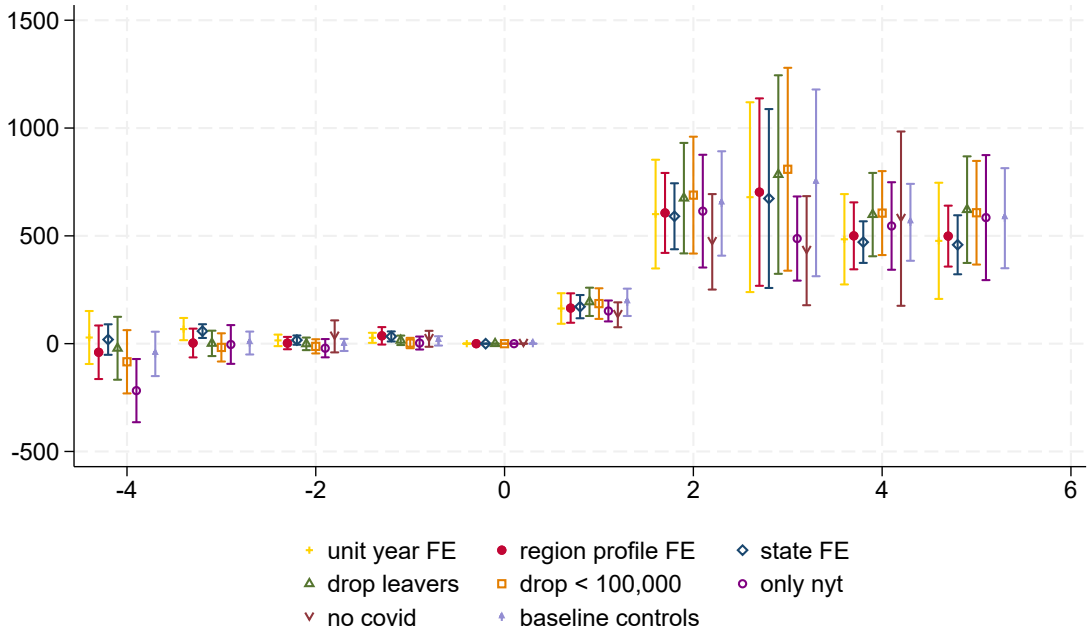


Figure A7: The graph shows event studies for the number of primary care services delivered on the street for different regression specifications. Outcomes per 100,000 inhabitants. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SISAB.

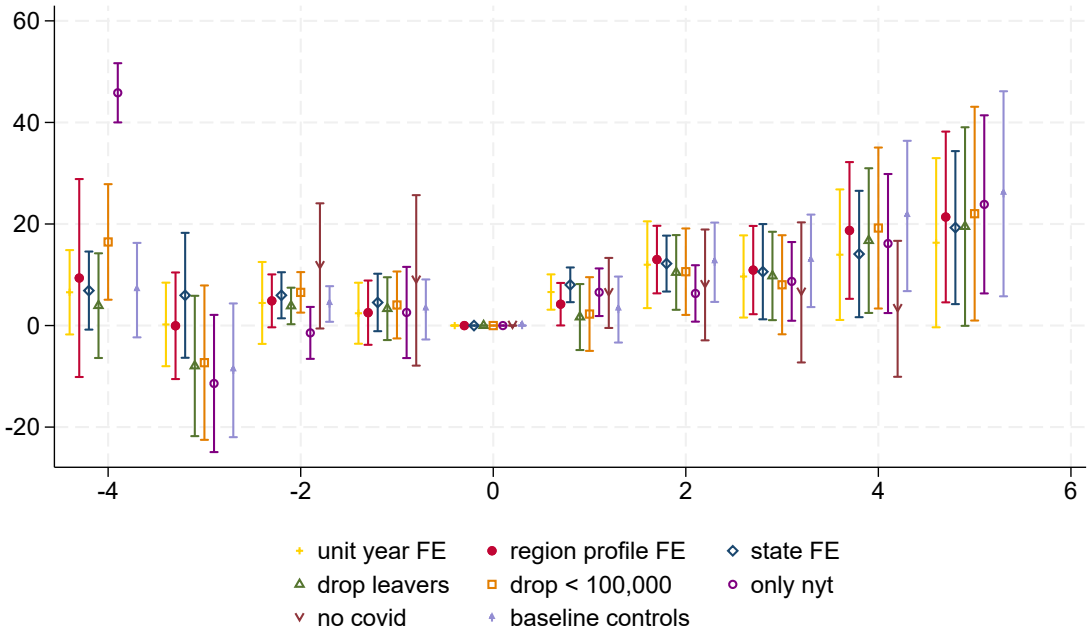


Figure A8: The graph shows event studies for the number of psycho-social care services at CAPS delivered to homeless patients for different regression specifications. Outcomes per 100,000 inhabitants. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SINAN.

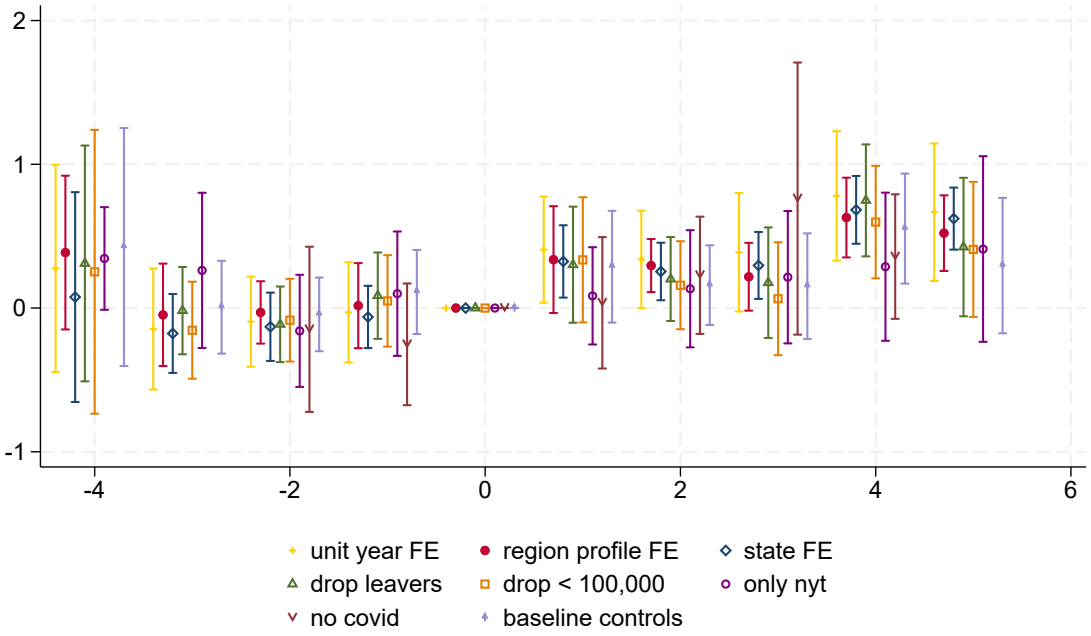
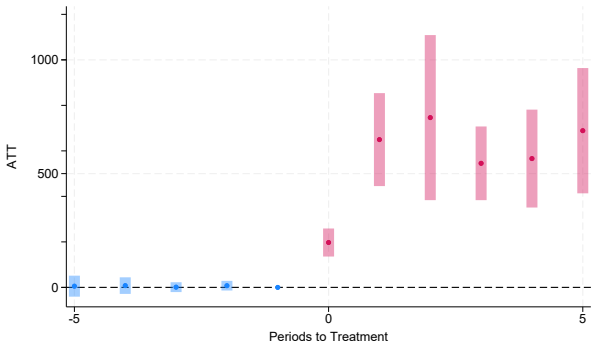
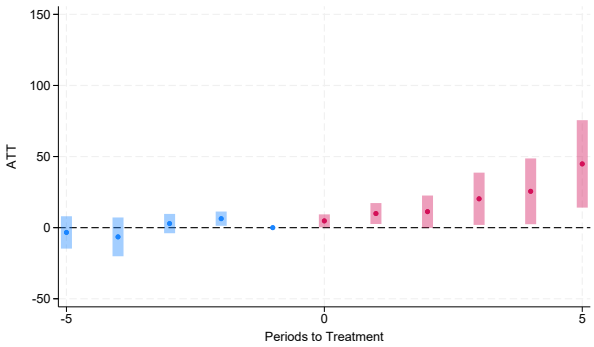


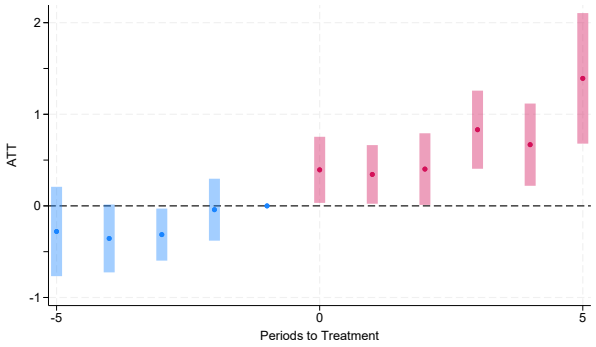
Figure A9: The graph shows event studies for the number of diagnosed tuberculosis cases among the homeless for different regression specifications. Outcomes per 100,000 inhabitants. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES and SIA-PS.



(a) Primary care usage on the street

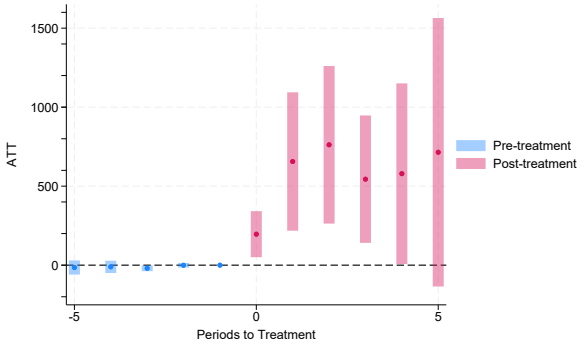


(b) Psycho-social care usage among homeless

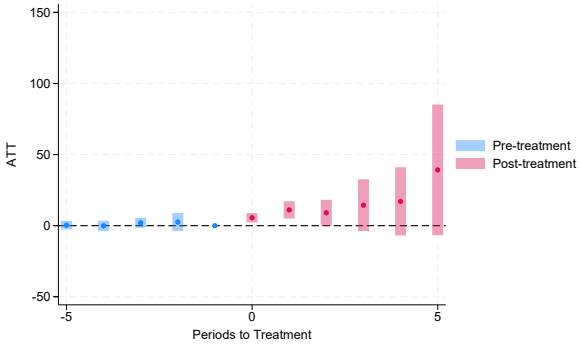


(c) Diagnosed tuberculosis cases among homeless

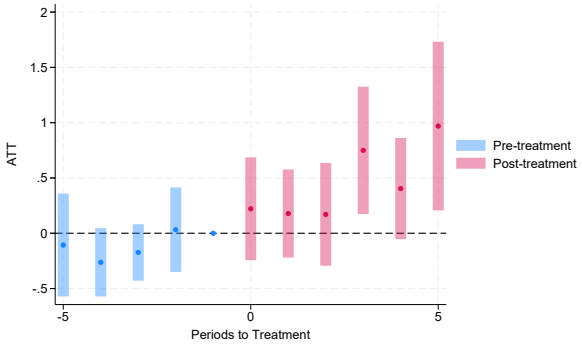
Figure A10: The graph shows event studies for the main outcome variables using the estimator proposed by Wooldridge (2021). Outcomes per 100,000 inhabitants in 2010. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES, SISAB, SIA-PS, and SINAN.



(a) Primary care usage on the street



(b) Psycho-social care usage among homeless



(c) Diagnosed tuberculosis cases among homeless

Figure A11: The graph shows event studies for the main outcome variables using the estimator proposed by Wooldridge (2023). The poisson-pseudo maximum likelihood estimator accounts for skewed outcome variables with many zeros. Event study estimates include 95 percent confidence intervals, where standard errors are clustered at the municipality level. Original data from CNES, SISAB, SIA-PS, and SINAN.

9.2 Tables

Table A1: Data Aggregation Details

Aggregation	**Includes**	**Data Source**
Chronic conditions	Asthma, Diabetes, Chronic obstructive pulmonary disease, Hypertension, Cardiovascular disease, Obesity, Malnutrition	SISAB
Infectious conditions	Dengue, Sexually transmitted diseases, Hansen's disease	SISAB
Mother and child health	Prenatal care, Childcare, Childcare 6 weeks, Sexual and reproductive health	SISAB
Cancers	Breast cancer screening, Colon and uterus cancer screening	SISAB

Table A2: Municipality characteristics

Variable	(1) Never treated Mean/(SE)	(2) Treated after 2015 Mean/(SE)	(3) Treated before 2016 Mean/(SE)	Pairwise t-test (1)-(2)	(2)-(3)
Region					
North	0.081	0.111	0.067	-0.031	0.044
	(0.004)	(0.035)	(0.026)		
North-East	0.325	0.222	0.222	0.103**	0.000
	(0.006)	(0.046)	(0.044)		
Centre-West	0.084	0.099	0.089	-0.015	0.010
	(0.004)	(0.033)	(0.030)		
South	0.217	0.123	0.133	0.093**	-0.010
	(0.006)	(0.037)	(0.036)		
South-East	0.294	0.444	0.489	-0.150***	-0.044
	(0.006)	(0.056)	(0.053)		
Municipality profile					
Capital	0.000	0.025	0.278	-0.025***	-0.253***
	(0.000)	(0.017)	(0.047)		
Biggest 100	0.011	0.259	0.167	-0.248***	0.093
	(0.001)	(0.049)	(0.040)		
Metropolitan area	0.086	0.198	0.289	-0.111***	-0.091
	(0.004)	(0.045)	(0.048)		
20% poverty	0.315	0.037	0.033	0.278***	0.004
	(0.006)	(0.021)	(0.019)		
Other	0.587	0.481	0.233	0.105*	0.248***
	(0.007)	(0.056)	(0.045)		
Population category (2010)					
>100k	0.026	0.889	0.956	-0.863***	-0.067
	(0.002)	(0.035)	(0.022)		
50k-100k	0.061	0.099	0.033	-0.038	0.065*
	(0.003)	(0.033)	(0.019)		
20k-50k	0.200	0.000	0.011	0.200***	-0.011
	(0.005)	(0.000)	(0.011)		
10k-20k	0.255	0.012	0.000	0.243***	0.012
	(0.006)	(0.012)	(0.000)		
5k-10k	0.227	0.000	0.000	0.227***	.n
	(0.006)	(0.000)	(0.000)		
<5k	0.231	0.000	0.000	0.231***	.n
	(0.006)	(0.000)	(0.000)		
N	5399	81	90		

Notes: Municipality averages for the year 2010. Significance: ***=.01, **=.05, *=.1. Column 1 includes all never-treated municipalities, column 2 includes treatment municipalities that opened their first MSC after 2015, and column 3 includes treatment municipalities that opened their first MSC before 2016 and are thus excluded from the main analyses. Data from IBGE.

Table A3: Mean outcome variables before treatment

	(1) Total sample		(2) Control		(3) Treatment	
Variable	N	Mean	N	Mean	N	Mean
Primary care						
All	48,585	746,000	48,167	750,000	418	290,000
Alcohol	48,112	389.8	47,704	391.9	408	144.7
Drugs	48,112	165.70	47,704	166.3	408	100.9
Primary care on the street						
All	48,585	145.4	48,167	146.3	418	50.4
Alcohol	48,585	0.7	48,167	0.7	418	0.3
Drugs	48,585	0.3	48,167	0.3	418	0.1
Tuberculosis	48,585	0.1	48,167	0.1	418	0.1
Chronic	48,585	24.8	48,167	25	418	10.2
Infectious	48,585	1	48,167	1	418	0.8
Maternal	48,585	16.8	48,167	16.9	418	5.7
Cancer	48,585	1.1	48,167	1.2	418	0.7
Psycho-social care (homeless)	49,011	14.3	48,591	14.3	420	8.1
Tuberculosis diagnoses (homeless)	49,011	0.4	48,591	0.4	420	1.2
Tuberculosis drop-out (homeless)	49,011	0.1	48,591	0.1	420	0.4
CadÚnico (homeless)	43,612	11.8	43,192	11.4	420	43

Notes: The table shows municipality-year pre-treatment means. For control municipalities, all years are considered. For treatment municipalities, only years before treatment are considered. All outcomes are measured per 100,000 inhabitants based on municipalities' population in 2010. Data from CNES, SISAB, SIA-PS, SINAN, and Cadastro Único.

Table A4: Effects of MSCs on primary care usage

	(1) On the street	(2) On the street, cont.	(3) Total alcohol	(4) Total drugs
Effect 1	191.9***	191.6***	74.27**	93.19***
	(32.42)	(7.025)	(26.27)	(24.29)
Effect 2	649.9***	655.3***	251.5***	256.9***
	(123.9)	(6.487)	(74.51)	(66.07)
Effect 3	745.5***	751.4***	313.4*	306.0*
	(220.9)	(10.74)	(126.8)	(124.9)
Effect 4	562.4***	561.9***	260.2***	263.6***
	(91.97)	(18.26)	(64.67)	(63.48)
Effect 5	583.0***	583.0***	261.1**	288.6***
	(119.0)	(21.59)	(79.64)	(85.22)
Placebo 1	12.52	12.78*	0.228	14.19
	(11.15)	(5.399)	(17.82)	(14.36)
Placebo 2	-5.412	-4.989	-35.91	-31.73*
	(14.93)	(6.592)	(24.97)	(14.48)
Placebo 3	3.561	1.247	-64.92*	-56.75*
	(28.76)	(12.03)	(27.01)	(22.91)
Placebo 4	-39.28	-21.35	-69.00	-41.48
	(63.12)	(19.06)	(76.09)	(50.31)
Average total effect	520.9***	778.1***	217.8***	227.9***
	(80.72)	(14.51)	(50.04)	(47.11)

Notes: The table shows event study coefficients for different primary care outcomes, following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 residents in 2010. Standard errors in brackets and clustered at the municipality level. Significance: ***=.01, **=.05, *=.1. Original data from CNES and SISAB.

Table A5: Effects of MSCs on primary care on the street by health conditions

	(1) Alcohol	(2) Drugs	(3) Tuberculosis	(4) Chronic	(5) Infectious	(6) Birth	(7) Cancer
Effect 1	54.31***	43.56**	1.255*	17.12***	3.358*	12.99***	0.261
	(15.85)	(14.82)	(0.519)	(4.417)	(1.394)	(2.725)	(1.444)
Effect 2	251.4***	213.8***	7.075**	37.36***	24.90*	62.98	-1.187
	(66.60)	(60.44)	(2.634)	(9.360)	(12.10)	(32.62)	(1.931)
Effect 3	296.2*	246.0*	8.795***	60.50*	14.29*	27.45***	-1.148
	(128.6)	(119.4)	(2.191)	(25.07)	(6.390)	(5.905)	(1.765)
Effect 4	167.9***	128.1***	3.624***	32.05***	4.147***	23.52***	-1.146
	(37.52)	(33.42)	(0.831)	(8.220)	(1.181)	(6.253)	(2.137)
Effect 5	184.9***	151.5**	13.70	37.58***	9.947	20.57***	-1.725
	(44.87)	(49.86)	(8.262)	(10.91)	(5.660)	(5.351)	(2.715)
Placebo 1	0.0803	0.000914	0.00443	2.801	0.336	-2.327	0.465
	(0.446)	(0.329)	(0.0469)	(2.946)	(0.562)	(1.920)	(1.623)
Placebo 2	-0.0477	-1.316*	-0.261***	3.872	-0.410	-1.383	-2.290
	(1.134)	(0.617)	(0.0388)	(4.728)	(0.239)	(2.268)	(2.036)
Placebo 3	-0.809	-1.286	-0.300**	-4.439	0.100	2.274	0.981***
	(1.928)	(1.579)	(0.104)	(4.924)	(0.373)	(3.621)	(0.291)
Placebo 4	-16.20*	-15.22*	1.891***	-0.317	1.017	9.340	3.180***
	(7.387)	(6.360)	(0.170)	(8.678)	(0.621)	(6.204)	(0.676)
Average total effect	183.4***	150.9***	6.098***	35.89***	11.47**	30.23***	-0.816
	(41.65)	(38.04)	(1.572)	(7.617)	(3.913)	(8.429)	(1.799)

Notes: The table shows event study coefficients for primary care usage on the street by health condition, following equation 1, covering the years 2015 to 2023. Outcomes per 100,000 residents in 2010. Standard errors in brackets and clustered at the municipality level. Significance: ***=.01, **=.05, *=.1. More detail on the different condition categories in Table A1. Original data from CNES and SISAB.

Table A6: Effects of MSCs on psycho-social care and tuberculosis care among the homeless

	(1) Psycho-social	(2) Psycho-social, referred	(3) Tub diagnosis	(4) Tub treatment incomplete	(5) Tub treatment complete
Effect 1	2.627	1.261	0.304	0.0710	0.0554
	(3.314)	(0.941)	(0.199)	(0.0950)	(0.0768)
Effect 2	11.19**	3.367	0.205	0.0853	0.0255
	(3.917)	(2.296)	(0.141)	(0.0927)	(0.0909)
Effect 3	10.73*	6.947*	0.226	0.207	-0.0419
	(4.607)	(3.517)	(0.185)	(0.107)	(0.0889)
Effect 4	18.62*	9.119*	0.660***	0.206*	0.186
	(7.507)	(4.621)	(0.185)	(0.0858)	(0.131)
Effect 5	22.11*	12.23	0.430	0.357*	-0.00674
	(10.44)	(6.366)	(0.233)	(0.148)	(0.109)
Placebo 1	3.660	3.853	0.0968	0.0717	0.0706
	(3.008)	(2.816)	(0.149)	(0.0745)	(0.0707)
Placebo 2	5.563**	2.593*	-0.0893	-0.0152	0.100
	(1.837)	(1.010)	(0.130)	(0.0829)	(0.0979)
Placebo 3	-6.807	-4.846	-0.0661	0.146	-0.127
	(6.715)	(5.995)	(0.148)	(0.125)	(0.117)
Placebo 4	9.561*	11.73***	0.321	-0.108	0.324
	(4.552)	(2.411)	(0.360)	(0.113)	(0.206)
Average total effect	11.32**	5.577	0.350*	0.162*	0.0440
	(4.294)	(2.921)	(0.142)	(0.0730)	(0.0798)

Notes: The table shows event study coefficients for different downstream outcomes, following equation 1. Outcomes per 100,000 residents in 2010. Standard errors in brackets and clustered at the municipality level. Significance: ***=.01, **=.05, *=.1. Original data from CNES, SIA-PS, and SINAN.

Table A7: Effects of MSCs on overall primary care, psycho-social care among the non-homeless, and tuberculosis diagnoses among the non-homeless

	Overall primary care	Psycho-social non-homeless	Tuberculosis cases non-homeless
	(5)	(2)	(5)
Effect 1	36704.7*	25.18	1.364
	(17092.1)	(76.84)	(1.200)
Effect 2	130.8	-30.37	2.298
	(19228.2)	(79.77)	(1.320)
Effect 3	-3308.4	-114.4	0.843
	(18635.0)	(102.4)	(1.558)
Effect 4	6841.1	-201.7	0.358
	(28570.3)	(141.1)	(1.843)
Effect 5	18251.2	-247.5	-1.383
	(36751.4)	(180.2)	(2.171)
Placebo 1	-23896.9	-62.79	0.380
	(12409.1)	(83.99)	(1.113)
Placebo 2	-48362.9**	47.21	1.072
	(15016.3)	(105.0)	(1.189)
Placebo 3	4871.2	101.7	-3.645**
	(22178.0)	(147.8)	(1.292)
Placebo 4	4694.6	271.4	-7.390***
	(72768.9)	(189.7)	(1.471)
Average total effect	14734.2	-85.47	1.003
	(16974.2)	(82.20)	(1.140)

Notes: The table shows event study coefficients for overall primary care (on and off the street), psycho-social care among the non-homeless, and tuberculosis diagnoses among the non-homeless, following equation 1. Outcomes per 100,000 residents in 2010. Standard errors in brackets and clustered at the municipality level. Significance: ***=.01, **=.05, *=.1. Original data from CNES, SISAB, SIA-PS, and SINAN.