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Abstract

A core challenge for healthcare systems is ensuring timely care for critical conditions while efficiently managing lower-complexity cases. Hospitals, often overburdened by both, struggle to balance these demands and allocate resources effectively. Many countries have responded by introducing alternative 24/7 facilities to relieve hospital strain and improve patient outcomes, yet evidence on their impact remains limited. We evaluate the introduction of freestanding Emergency Care Centers (UPAs) within Brazil's publicly funded health system, leveraging rich administrative data. We find that UPAs reduced hospital outpatient procedures by 30% and hospital admissions for ambulatory-sensitive conditions by 24–37%, enabling hospitals to focus on more complex cases, such as surgeries and obstetric admissions, which increased by 25%. We see a 13% reduction in inpatient mortality, particularly in intensive care and for conditions best suited to hospital treatment. While some deaths were displaced to UPAs, there was a decline in population-level mortality of 1.8%, albeit this is not statistically significant. Our findings show how an intermediate tier of emergency care reshapes patient sorting, alleviates hospital congestion, and improves hospital performance in an overstretched public health system.

JEL: I11, I15, I18.

Keywords: emergency care; urgent care; hospital performance; population health; displacement effects; mortality.

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1 Introduction

Hospitals play a central role in the healthcare system, handling the majority of emergency care cases (Samadbeik et al., 2024; Morley et al., 2018). However, they are increasingly overwhelmed by low complexity cases that reflect gaps in primary and outpatient care services, and that divert resources away from the more critical and complex cases that hospitals are designed to handle (Cowling et al., 2013; WHO, 2010; Currie and Slusky, 2020). Policymakers have responded by strengthening ambulatory care and other non-hospital services, yet there is limited evidence on whether these strategies effectively alleviate pressure on hospitals, enhance their performance, and lead to better population-level outcomes (Weinick et al., 2010). In an era of constrained resources and growing healthcare needs, understanding how such reforms affect hospitals and patient outcomes is important.

This paper assesses the impact of opening Emergency Care Centers (Unidades de Pronto Atendimento, hereafter UPA) in the state of Rio de Janeiro, Brazil, starting in 2007. UPAs are free-standing, 24/7 facilities that provide intermediate emergency care, bridging primary care and hospital services. Equipped with X-rays, electrocardiography, labs, and observation beds, they provide care for acute and chronic conditions (including heart attacks and strokes), first aid for trauma and surgical cases, and consultations for lower-severity issues (Konder and O'Dwyer, 2016). Their creation aimed to achieve two primary goals: (1) to expand the availability of emergency care by reducing the average distance to emergency units, and (2) to reduce the burden on hospitals, allowing them to focus on more complex cases requiring specialist care. If these goals were met, we would expect to see improvements in both hospital performance and population health outcomes. This paper examines whether these expectations materialized.

Our analysis proceeds in two stages. First, we study hospital-level outcomes, and define treatment as the opening of an UPA in the catchment area of the hospital. We geocoded the location of all hospitals and UPAs and identified the exact opening dates of each UPA in Rio de Janeiro between 2005 and 2016, after which growth in UPAs in Rio plateaued.[1] We then compare the evolution of outcomes between treated and untreated hospitals. In the second stage, we analyze city-level (municipal) outcomes, where treatment is defined as the opening of the first UPA within the municipality. For both analyses, we track outcomes for ten quarters before and sixteen quarters after UPA openings.

Hospital-level outcomes include outpatient procedures, inpatient admissions, and hospital mortality. We classify admissions and deaths based on whether they are amenable to ambulatory or emergency care, using established classifications from Alfradique et al. (2009) and Vashi et al. (2019). This classification allows us to identify the conditions most likely affected by UPA openings, helping to ensure that observed effects are attributable to the intervention rather than other factors.[2] We further explore how the impact of UPA openings on hospitals varies by type of admission, distinguishing between surgical, clinical, and intensive-care treatments. At the city level, we analyze deaths by cause and location to assess whether the decline in hospital deaths is offset by increases elsewhere, such as at home, on the streets, or within UPAs themselves, providing a comprehensive view of the

[1]While UPAs were implemented nationwide, we restrict our analysis to the state of Rio de Janeiro. This choice reflects both the state's pioneering role in the conception and early implementation of the UPA model and the fact that this focus allows us to devote effort to carefully constructing detailed and consistent data. For Rio de Janeiro, we conducted a comprehensive geocoding of all health establishments, ensuring precise spatial coordinates that were essential for defining treatment status and calculating distances. We also linked multiple administrative sources and constructed the exact opening and closure dates of UPAs and hospitals.

[2]Specifically, if the results are driven by the UPA openings, we expect a diversion of cases that are manageable through ambulatory or emergency care, while more severe conditions remain in hospitals.

broader population-level impact. To account for the staggered rollout of UPAs and potential treatment heterogeneity, we employ difference-in-differences event studies following de Chaisemartin and D'Haultfoeuille (2022). Identification relies on the assumption that the timing of UPA openings is idiosyncratic, and tests of pre-policy coefficients support this assumption.

We start by documenting that UPA openings substantially improved access to emergency care, reducing the median distance to the nearest emergency unit by 27%. By the end of the rollout, UPAs had become the closest emergency facility for 50% of the population, highlighting their role in decentralizing emergency services.

We find that UPAs played a significant role in reducing pressure on hospitals, as evidenced by a 30% reduction in outpatient procedures and significant decreases in inpatient admissions for ambulatory-sensitive conditions, alongside no change in admissions for non-ambulatory conditions (e.g., cancer and viral pneumonia). Admissions for conditions manageable by ambulatory care alone (e.g., gastroenteritis) fell by 38%, and admissions for conditions sensitive to both ambulatory and emergency care (e.g., asthma) dropped by 24%. Together, these conditions accounts for a quarter of all hospital inpatient admissions at baseline, highlighting the substantial portion of the hospital caseload that could be redirected to UPAs. Overall, the evidence is that UPAs effectively handled and diverted less severe cases away from hospitals.

Further analysis of admissions by type reveals a notable shift in hospital focus, with a 25% increase in surgical and obstetric admissions and a 27% reduction in clinical and other types of admissions. This is consistent with hospitals increasing their focus on advanced care (such as surgeries and complex interventions), facilitated by the reduced load of less severe cases. Thus UPAs not only eased hospital caseloads but also enhanced hospital delivery of specialized and high-complexity care.

Next, we examine whether the observed reduction in hospital caseload translated into improved hospital performance. Inpatient mortality (conditional on admission) fell by 0.8 percentage points, a 13% reduction from baseline levels. The most pronounced declines occurred among conditions not amenable to ambulatory care and within intensive care units, consistent with other indications that UPA opening allowed hospitals to better manage potentially high-risk patients.

To understand the mechanisms behind these performance gains, we further analyzed how hospital resources were reallocated after UPA openings. We observed a shift in hospital operations, with health professionals dedicating more hours to inpatient services rather than ambulatory and administrative tasks. Additionally, hospitals experienced an 11% increase in the availability of medical and infrastructure equipment, supporting their ability to meet the needs of patients. This reallocation of both human and physical resources will have plausibly contributed to the observed improvements in hospital outcomes.

While UPAs have clearly reduced hospital caseloads and inpatient mortality, the broader policy objective is to improve overall population health. Using city-level vital statistics disaggregated by cause and location, our analysis confirms a significant reduction in hospital deaths by 19.7 per 100,000 people following UPA openings. However, some deaths were displaced to UPAs, with 14.5 deaths per 100,000 occurring there. When accounting for deaths at home, on the street or in other health facilities, the net reduction was 3 deaths per 100,000 population (a 1.8% decline). Though this figure is not statistically significant (maybe due to power limitations, since mortality changes are inherently more difficult to detect with more aggregated data), 41% of this population-level effect in deaths occurred from causes not amenable to ambulatory or emergency care, the same category for which inpatient mortality fell. This aligns with UPAs' effectiveness in improving outcomes for conditions that are best treated in hospital settings. Additionally, the other 59% of the reduction came from conditions amenable to emergency care, UPAs' primary focus.

A key empirical concern related to our hospital-level results is the possibility that there was a change in the risk profile of patients entering hospital following UPA opening. UPAs may divert less severe cases away from hospitals or reduce congestion in ways that alter the composition of admitted patients, potentially confounding improvements in hospital outcomes. We address this concern using a series of checks. We show that observable patient characteristics (age, gender, and income) do not change meaningfully after UPA openings, and that controlling for these characteristics leaves our estimates essentially unchanged. We also construct a diagnosis–age–sex severity index based on historical in-hospital mortality rates and find no evidence that the average severity of admitted patients shifts following UPA introduction. These results suggest that patient selection is unlikely to drive our findings.

We also address the potential concern that our estimates may be confounded by concurrent policies or political factors correlated with UPA adoption. We show that UPA openings do not coincide with changes in other layers of the health system, including primary care coverage, routine consultations, diagnostic exams, ambulance services, or hospital openings and closures. Our findings are also robust to excluding the city of Rio de Janeiro, varying hospital catchment areas, and accounting for political alignment between municipal and state governments, mayoral party affiliation, and other contemporaneous policies. Allowing for flexible, non-parametric city- or health-region-level trends also yields similar results.

This paper provides a comprehensive evaluation of introducing mid-tier emergency care units as free-standing facilities to address a critical gap between primary and tertiary care within a public health system. Most closely related to our work is a literature that has examined the expansion of retail clinics and urgent care centers (UCCs) in the United States and Mexico (Rubli, 2023; Allen et al., 2021; Alexander et al., 2019; Hollingsworth, 2014). While these studies focus on private-sector solutions for minor illnesses, UPAs differ in that they are public and treat a broader range of emergencies. We find that they are effective in reducing hospital congestion and improving hospital performance, without increasing overall utilization. We also extend the analysis to study service diversion and population-level mortality at the city level, finding weak evidence of an overall improvement.

Our work is also related to a broader literature that illustrates the perils of hospital congestion and consolidation. This literature has shown that capacity constraints affect physician behavior and quality of care (Hoe, 2022), that patient mortality rises when hospitals operate above capacity (Gutierrez and Rubli, 2021), that the health consequences of external shocks are amplified under tight supply (Guidetti et al., 2024), that demand-side expansions that are not accompanied by commensurate increases in effective capacity can worsen quality (Andrew and Vera-Hernández, 2024), and that hospital closures—often motivated by efficiency considerations—affect access to time-sensitive care (Avdic, 2016; Avdic et al., 2024; Hsia and Shen, 2019; Gujral and Basu, 2019; Buchmueller et al., 2006; Fischer et al., 2024; Carroll, 2022). We look at a reform that did the reverse. It was designed to expand capacity, reduce distance to emergency services and relieve congestion. Related work has examined "bringing facilities closer" the way that UPA did, but with a focus on expansion of access to primary health care through community-based health centers (Bailey and Goodman-Bacon, 2015; Bhalotra et al., 2019; Rocha and Soares, 2010). Our analysis thus contributes to the debate on the (de)centralization of public services and the trade-off between efficiency and equitable access (Brummet, 2014; Zhang et al., 2018; Mergele and Weber, 2020).

The remainder of the paper is structured as follows. Section 2 provides institutional background, while Section 3 outlines the conceptual framework. Section 4 describes the data and Section 5 the empirical strategy. Sections 6 and 7 present the results for hospital and city-level outcomes, respectively. Section 8 discusses robustness checks. Finally, Section 9 concludes with policy implications.

2 Institutional Background

2.1 The Brazilian Health System

In 1988, as Brazil returned to democracy, it established the constitutional right to universal, equitable, and comprehensive healthcare access. This led to the creation of the Unified Health System (*Sistema Único de Saúde*, SUS), a tax-funded, single-payer system that provides free-of-charge services at the point of care through both public and accredited private providers. Today, roughly 75% of Brazilians rely exclusively on the public health system, while about 25% hold private insurance (Rocha et al., 2021).

SUS has successfully expanded access to health services throughout the country, improved health outcomes, and reduced health inequalities (Castro et al., 2019; Bhalotra et al., 2019). Its expansion was closely linked to the Family Health Program (FHP), which shifted the focus from centralized hospital-based care to a community-driven model where primary care teams deliver preventive and basic healthcare directly to the population (Rocha and Soares, 2010). Despite significant progress, challenges persist, including inequalities in healthcare access, quality, and coordination. One prominent issue is hospital overcrowding, where emergency departments often handle cases that could be treated at other levels of care and reflect unmet needs in the broader health and social assistance systems (Bittencourt and Hortale, 2009). This was acknowledged by the federal government in the early 2000s as particularly disruptive for urgent care and emergency services (Brasil, 2002).

To alleviate hospital pressure and address dissatisfaction with the fragmented and scarce provision of urgent and emergency care in SUS, the federal government enacted the National Policy for Urgent Care (*Política Nacional de Atenção a Urgências*, PNAU) in 2003.[3] The PNAU reinforced previous regulatory attempts to expand and better coordinate urgent and emergency care services at the regional level (eg. Brasil, 2002). This led to introduction of new Emergency Care Units (*Unidades de Pronto Atendimento*, UPA24h), which serve as free-standing facilities designed to bridge the gap between primary and hospital services. The guidelines for establishing UPAs were formalized by the federal government in 2008, following the opening of the first units in the State of Rio de Janeiro in 2007.

2.2 UPA: Institutional Setting and Programme Roll-Out

UPAs (*Unidades de Pronto Atendimento*) are pre-hospital healthcare facilities designed to fill an intermediate role between primary and hospital care within local health systems. According to the Health Secretary of the State of Rio de Janeiro, UPAs were established to "provide quality healthcare to the neediest population and rescue them from death in the queues of overcrowded hospital corridors."[4]

[3] See Ordinance No. 1863/2003, which established the PNAU.

[4] Op-Ed in O Globo, 03/26/2009.

UPAs operate 24/7 and are equipped with X-ray machines, electrocardiography, basic clinical laboratories, and observation beds. They should accept all cases, but are equipped to handle conditions of basic to intermediate complexity and are particularly designed to provide qualified and resolutive care for acute or chronic clinical conditions, first aid to surgical and trauma cases, and medical consultations for cases of lower severity (Konder and O'Dwyer, 2016).

The scale of physical and human resources available to UPAs varies according to expected demand and location.[5] UPAs are publicly funded and managed by municipalities or states, with operational costs partially covered by the federal government, which provides monthly funds based on the size and infrastructure of the facility. Local governments complement these funds, and operations are increasingly delegated to Social Organizations (OS)—private, non-profit entities contracted to manage the facility's physical and human resources.

UPAs differ significantly from the retail clinics and urgent care centers (UCCs) commonly found in the U.S. in several key ways. First, UPAs are fully integrated into Brazil's universal public health system, offering free access to all citizens, whereas UCCs in the U.S. are typically private-sector initiatives, with many requiring out-of-pocket payments or insurance coverage, which can limit access. Second, UPAs provide more comprehensive emergency services, allowing them to handle a broader range of complex and acute cases (e.g. heart attacks and strokes) compared to UCCs, which typically focus on low-acuity, non-life-threatening conditions such as minor injuries, common colds, and routine medical needs (Alexander et al., 2019; Currie et al., 2023). In most US states, UCCs are considered physician's offices (Magnolfi et al., 2024).

In the Brazilian public health system, facilities do not compete for funding or patients. In particular, UPAs are not expected to compete with hospitals but rather to complement them. As shown in Section 6.6, we do not observe evidence of crowding out of physical or human resources in hospitals following the introduction of UPAs.[6,7]

UPAs are not mandatory gatekeepers for hospital admission but rather an additional, 24/7 point of entry into the emergency-care network. Patients may reach them either through self-directed walk-ins or via ambulances coordinated by the regional regulation center, which decides whether to transport the patient to the nearest UPA or directly to a hospital depending on case severity and available capacity (Ministry of Health, Nota Informativa nº 9/2024-CGURG/DAHU/SAES/MS).[8] From the patient's perspective, seeking care at a UPA is therefore a voluntary decision shaped by proximity, perceived urgency, and expectations about the type of care required, factors that help explain why even severe conditions may initially present at UPAs before referral to hospitals.

Upon arrival at a UPA, patients undergo a triage process and are classified by risk level, with severe cases treated first or referred to hospitals when necessary. Patients may be kept under observation

[5]Smaller facilities may occupy an area of 700m^2, have at least 2 doctors per shift and 7 beds, and are expected to cover an average of 150 visits per day. Larger facilities may occupy an area size greater than 1,300m^2, have at least 6 doctors and 15 beds, and are expected to cover more than 350 visits per day. These parameters have changed over time, but in general correlate with expected demand. More recently, for instance, Ordinance No. 10/2017 established eight size categories.

[6]During the analysis period, there was an expansion in medical schools and an increase in the supply of physicians and nurses thoughout the country, which helps explain where the new professionals needed to operate the UPAs came from. Between 2014 and 2016, the number of physicians per 1,000 people increased from 1.4 to 2.0 (Scheffer, 2023).

[7]The public and private systems are largely segmented, though emergency care may overlap as patients seek the nearest facility. While our data do not capture private utilization, this segmentation makes significant crowding-out effects unlikely.

[8]Administrative data do not record how many patients arrive by ambulance. Routing decisions are made by the SAMU regulation center rather than by patients or family members, based on case severity, and network capacity.

for up to 24 hours for diagnostic elucidation or clinical stabilization, and referred afterwards to a hospital if the case is not solved (O'Dwyer et al., 2013).

Systematic evidence on the types of services provided by UPAs compared to hospital emergency departments is limited. Our analysis of administrative data from Rio de Janeiro (RJ) helps characterize service delivery. Appendix Table A.1 compares the total number and distribution of ambulatory procedures performed in hospital emergency departments in 2006 (before the first UPA opened) and 2016. The data reveal that UPAs perform a higher proportion of clinical procedures, including doctor appointments, nursing care, and emergency consultations (79.4%) compared to hospitals (47.4%). Conversely, hospitals provide more diagnostic procedures (34.9% vs. 20.0%) and offer a wider array of specialized services. Nonetheless, UPAs still account for a significant share of diagnostic and other services typically provided by hospitals. In 2016, UPAs were responsible for approximately 42.9% (30 million) of all ambulatory procedures conducted in RJ when combining the total from both UPAs and hospital emergency departments.

The State of Rio de Janeiro was a forerunner in the introduction of UPAs. A possible reason is that, in the mid-2000s, it had one of the lowest primary care coverage among the Brazilian capitals, hospital capacity was under continuous stress and emergency departments were overloaded (Sousa and Hamann, 2009; Bittencourt and Hortale, 2009). By 2016, 459 UPAs were operating across Brazil, with 68 located in RJ. Figure 1a illustrates the rapid expansion of UPAs in the state, reaching nearly 50 units in 2010, and then stabilizing just below 70 units from 2014 onwards. The share of municipalities with at least one UPA in RJ reached 32% in 2016, significantly higher than the 6% observed in the rest of the country.[9]

3 Conceptual Framework

The introduction of UPAs altered the set of options available to patients seeking healthcare within the SUS. To organize how patients may re-sort across levels of care after UPAs are introduced, we adapt the conceptual framework of Alexander et al. (2019) to the institutional features of Brazil's health system. This framework makes explicit how individuals choose among primary care units (PHC), UPAs, hospital emergency departments, and the outside option of no care, and clarifies the conditions under which the introduction of UPAs can reshuffle demand across these tiers.

Before UPAs were introduced, patients choosing where to seek care faced a relatively simple two-tier structure. For a given episode, each individual evaluates the perceived value of care at a PHC unit, at a hospital emergency department, or at home by forgoing care. This perceived value reflects both perceptions of health needs and clinical considerations (how well each facility can treat the condition) and non-clinical factors (such as travel time, waiting time, familiarity with the provider, and the implicit or explicit costs of seeking care). For low-severity conditions, PHC units may generally offer the highest value. They are geographically close and capable of treating routine or moderately urgent issues. For high-severity conditions, however, hospitals provide substantially greater benefits because they offer specialized diagnostics, surgery, intensive care, and 24-hour coverage. PHC units, on the other hand, are open only in business hours and typically offer programmed visits. Under this pre-UPA system, patients sort into PHC or hospitals based on a single threshold level of severity. Below that threshold, PHC dominates. Above it, hospitals dominate, while for very mild cases, both options may be dominated by the choice to seek no care at all.

[9] Percentage obtained from CNES data.

The introduction of UPAs adds a new option between PHC and hospitals. Unlike private retail clinics, in high-income settings, UPAs in Brazil operate 24/7, provide laboratory and imaging services, and have the capacity to stabilize patients presenting with emergent but not highly complex conditions. These characteristics imply that the perceived value of UPAs may increase with severity more steeply than that of PHC, but still remains below that of hospitals for highly complex cases and emergencies. In graphical terms, UPAs introduce a new perceived-value curve that crosses the PHC curve at an intermediate severity level and eventually intersects the hospital curve at a higher severity level. As a result, the single severity threshold of the pre-UPA environment splits into two. A first threshold at which UPAs become preferable to PHC, and a second threshold at which hospitals become preferable to UPAs.

Figure 2 illustrates this structure. At low levels of severity, PHC remains the dominant option because its proximity and ability to resolve mild conditions provide greater value than either UPAs or hospitals. As severity increases, however, PHC's value stabilizes, while the value of UPAs rises sharply, reflecting the usefulness of rapid diagnostics, walk-in availability, and the capacity to stabilize emergent cases. This creates a region in which UPAs become the preferred provider. At even higher severity levels, hospital emergency departments become strictly more attractive because they can deliver advanced, resource-intensive treatments that UPAs cannot provide. Thus, the severity space is partitioned into three regions: low-severity cases best handled in PHC, moderate-severity emergent cases for which UPAs are most appropriate, and high-severity emergencies for which hospitals remain dominant.

Although the stylized figure abstracts from many operational considerations, it captures important determinants of sorting. The relative position and slope of each perceived-value curve depend on geographic access, expected waiting time, diagnostic and treatment capacity, and patients' beliefs about the type of care they will need and will receive. Travel time and distance favor PHC and UPAs over hospitals. Expected delays in emergency departments make UPAs particularly attractive for emergent but non-complex cases. And clinical expectations shape how individuals perceive their needs along the severity continuum. In addition, UPAs may generate referrals back to PHC after stabilizing patients or diagnosing unmanaged chronic conditions, creating feedback loops between levels of care. Finally, institutional features such as ambulance regulation protocols can influence sorting by directing certain patients to UPAs rather than hospitals depending on medical assessment and logistical considerations rather than patients' perceptions.

This conceptual structure yields several implications for how UPA openings may change utilization patterns. First, because UPAs dominate PHC and remain dominated by hospitals only at intermediate severity levels, the introduction of UPAs should draw a substantial number of emergent but not highly complex patients away from hospitals. This reduces the demand for medium-complexity procedures and emergency-sensitive admissions in hospitals without affecting the volume of high-severity care. Second, the effect on PHC is theoretically ambiguous. UPAs may divert some urgent visits away from PHC, but they may also identify conditions that require ongoing management and refer patients back to primary care. The net effect thus depends on local factors such as patient familiarity with PHC. Finally, the framework suggests that effects on foregone care should be limited for low-severity conditions, since PHC already dominates UPAs in that region.[10]

[10]However, UPAs may still reduce foregone care for individuals who perceive PHC as insufficiently responsive or who delay seeking treatment until their condition becomes urgent.

By making explicit how patients weigh their options along the severity dimension, this framework clarifies the mechanisms through which UPAs can alter the flow of patients across the health system. It also highlights how improvements in access at the intermediate level can relieve pressure on hospitals without fundamentally altering patterns of high-severity care.

4 Data

This section outlines the data sources, samples, and variables used in our analysis, followed by a discussion on the classification of conditions amenable to ambulatory and emergency care. Further details are provided in Appendix D.

4.1 Hospital-Level Indicators

We constructed longitudinal data on hospitals and UPAs by linking four administrative datasets from the Brazilian Ministry of Health (MS/Datasus). First, we used the National Register of Health Establishments (CNES), which provides comprehensive information on all health facilities, including their location, types of services, and available human and physical resources from 2005 onwards. This dataset allowed us to identify and precisely geocode the location of all 68 UPAs that opened during the study period and the 116 hospitals with emergency rooms (ER) in Rio de Janeiro (RJ). It also enabled us to identify the opening dates of each UPA.

Data on hospital admissions funded by the public health system (SUS), covering both public hospitals and private facilities accredited by the government, were obtained from the National Hospital Information System (SIH). This dataset includes detailed information on patient demographics, hospitalization causes (ICD-10 codes), outcomes (discharge or death), municipality of residence, admission dates, and the facility code. Each hospitalization and death was classified according to Alfradique et al. (2009) and Vashi et al. (2019), which categorize conditions as amenable to ambulatory or emergency care. Section 4.3 provides further details on these classifications and their application in our study.

We also used data from the National Ambulatory Information System (SIA), which covers all outpatient care services funded by SUS, including diagnostics, observation, consultations, treatment, interventions, and rehabilitation services.[11] Data on inpatient mortality were drawn from hospital records (SIH), while population-level mortality data were sourced from the National Mortality Information System (SIM). The SIM database records all deaths registered in Brazil, detailing the deceased's demographics, cause of death (ICD-10), and location of death.

The CNES, SIH, SIA, and SIM microdata enabled us to compute resource and production indicators as well as health outcomes at the hospital-by-quarter level between 2005 and 2016. Appendix Table A.2 presents descriptive statistics for the baseline period (2005Q1 to 2007Q1), just before the first UPA was established in RJ.

4.2 City-Level Indicators

At the city level, our analysis draws on data from the ambulatory system (SIA), the vital statistics records (SIM) and the Primary Care Information System (SIAB), creating a balanced panel of quar-

[11] SIA provides microdata at the procedure level. Due to changes in procedure codes over time, we analyze the total number of procedures and categorize them as basic, medium, and high-complexity procedures.

terly data that covers all 92 cities in Rio de Janeiro from 2005 to 2016. These data sources provide comprehensive insights into both mortality patterns and primary care coverage across the state.

The SIM data allowed us to identify the location of deaths—whether they occurred at home, on the street, or in health facilities such as UPAs and hospitals. This information, combined with ICD codes for the cause of death and demographics, enabled us to calculate mortality rates by both cause and location, as well as to examine mortality patterns by age, gender, and race. SIA also gives us the exact health facility in which procedures were performed and permits the computation of procedures rates by location.[12]

In addition, we utilized SIAB data to compute Family Health Program (FHP) coverage, primary care consultations, prescribed exams, and measures of registered patients. To gain insight into other layers of the health system, we collected information on the availability of SUS ambulance services from CNES and tracked hospital openings and closures using SIH and CNES data.

Controls. Controls in the hospital and city-level analyses include: (i) city GDP per capita (Brazilian Institute of Geography and Statistics, IBGE); (ii) Bolsa Família transfers (former Ministry of Social Development, MDS); (iii) dummies indicating the political party of the incumbent mayor and whether the mayor and state governor were politically aligned (Superior Electoral Court, TSE); and (iv) a dummy for cities affected by severe rains and landslides in 2011. Appendix Table A.3 provides summary statistics for all city-level variables during the baseline period (2005Q1 to 2007Q1). As explained in the following section, because controls like GDP are potentially endogenous, we present estimates with and without them.

4.3 Classification of Conditions Sensitive to Ambulatory and/or Emergency Care

We classify deaths and hospitalizations according to whether the condition is amenable to ambulatory and emergency care following Alfradique et al. (2009) and Vashi et al. (2019), respectively. We combined these classifications to create four categories for analysis: (a) conditions amenable to both ambulatory and emergency care; (b) conditions sensitive only to ambulatory care; (c) conditions sensitive only to emergency care; (d) conditions that are not amenable to either ambulatory or emergency care. Figure D.1 illustrates these four categories and the share of hospitalizations associated with each during the baseline period (2005/Q1-2007/Q1). Figure D.2 further details these categories and the main conditions within each group.

Conditions amenable to both ambulatory and emergency care include acute complications from diabetes, bacterial pneumonia, stroke, asthma, and chronic obstructive pulmonary disease (COPD) — cases that can be managed by ambulatory care but may require emergency attention if neglected. Conditions amenable only to ambulatory care include non-emergent conditions such as infectious gastroenteritis, urinary tract infections, and congestive heart failure. Conditions that are sensitive only to emergency care include heart attacks, accidents, poisoning, and viral or unidentified pneumonia. These tend to be inevitable and severe conditions for which emergency care is needed. Finally, conditions not amenable to either ambulatory or emergency care, and therefore most suited to hospital care, include, but are not limited to, childbirth, cancer, digestive system diseases (diverticulitis, hernia, Crohn's disease, cirrhosis, and others) and diseases of veins and arteries (atherosclerosis,

[12] Population data used to construct the mortality and procedure rates per capita at the city level come from the Brazilian Institute of Geography and Statistics (IBGE).

aneurysm, thrombophlebitis, varicose veins, and others).

5 Empirical Strategy

5.1 Empirical Model

To investigate the impacts of UPA opening on hospital and city-level outcomes, we take advantage of the policy's staggered implementation across locations in a difference-in-differences strategy. As shown in Goodman-Bacon (2021), when the timing of treatment varies, the usual fixed effect estimator recovers a weighted average of all possible pairs of the underlying DiD estimator. Extending their work, de Chaisemartin and D'Haultfœuille (2020) demonstrate that when treatment effects are heterogeneous across time and units, some of these weights might be negative. We use the dynamic estimator proposed by de Chaisemartin and D'Haultfoeuille (2022), which provides unbiased estimates under treatment effect heterogeneity.

In our setting, the unit of observation g is either a general hospital with ER or a city observed in quarter t. We define $D_{g,t-\ell}$ as a treatment indicator that switches from 0 to 1 when an UPA is opened in period $t-\ell$ in the hospital or city unit. Our purpose is to identify the contemporaneous ($\ell = 0$) and dynamic ($\ell > 0$) average treatment effects across cells $(g, t-\ell)$ that sequentially received treatment such that $D_{g,t-\ell-1} = 0$ and $D_{g,t-\ell} = 1$ for any pair of consecutive time periods $t-\ell-1$ and $t-\ell$.

The de Chaisemartin and D'Haultfoeuille (2022) estimator uses groups whose treatment status is stable to infer the trends that would have affected switchers if their treatment had not changed. Formally, let A_g =min{t: $UPA_{gt} = 1$} be the quarter in which the hospital or city is treated by an UPA, and $A_g = \infty$ for the never treated. We compute the family $\hat{\tau}_\ell^{ATT} \geq 0$ of dynamic treatment effects, one corresponding to each distance $\ell \geq 0$:

$$\hat{\tau}_\ell^{\text{ATT}} = \sum_t^T \omega_{t,\ell} \left[\sum_{\{g:A_g=t-\ell\}} \frac{Y_{g,t} - Y_{g,t-\ell-1}}{\#\{g : A_g = t-\ell\}} - \sum_{\{g:A_g>t\}} \frac{Y_{g,t} - Y_{g,t-\ell-1}}{\#\{g : A_g > t\}} \right] \tag{1}$$

where the term $Y_{g,t}$ refers to a hospital or city outcome, and $w_{t,\ell}$ are weights capturing the relative size of the group of hospital or cities treated by an UPA in each panel quarter t for a fixed ℓ.[13] Notice that the term in brackets is simply a DiD estimator comparing outcome evolution from period $t-\ell-1$ to t in groups that become treated in $t-\ell$ (first difference) and in groups that are still untreated at t (second difference).[14] The period of analysis runs from two and a half years previous to treatment to four years after, on a quarterly basis. We will report in tables the averages of the dynamic estimates $\hat{\tau}_\ell^{ATT}$ computed over the quarters after treatment, and event-study plots covering the entire period.

As standard in this framework, hospital or city fixed effects account for unobservable factors that vary across establishments or locations but remain constant over time, such as climate, geography, and initial health infrastructure. Quarter fixed effects control for time-specific shocks that affect all hospitals or cities simultaneously, capturing influences like seasonality in disease patterns or political cycles. Additionally, a generalization of equation 1 allows for the inclusion of covariates. We

[13] With the exception of mortality conditional on admission, occupation and average hours worked, we apply the inverse hyperbolic sine to all hospital outcomes, so the coefficients are interpreted as (approximate) fractional changes. The city outcomes are measured in per capita rates.

[14] The first and second DiD terms are assumed to be 0 if $\#\{g : A_g = t-\ell\} = 0$ or $\{g : A_g > t\} = 0$.

introduce city-time varying controls to adjust for local economic conditions, welfare coverage, and political dynamics, such as changes in the city's GDP or shifts in political leadership. [15]

While these time-varying controls help adjust for confounding factors, they are potentially endogenous and could influence both the treatment and outcomes of interest. Including these controls helps isolate the causal impact of UPA openings, but we also report results without these covariates to address concerns about potential endogeneity.

Standard errors are clustered at the hospital or city level to account for potential serial correlation and heteroscedasticity in the error terms. In the hospital-level analysis, we further refine our approach by clustering errors for hospitals located in close proximity to each other, defined as those less than one kilometer apart—corresponding to the 25th percentile of the distribution of distances between hospitals. This approach addresses spatial correlation, which may lead to biased standard errors if hospitals in the same area experience similar shocks or spillover effects.

Equation 1 allows one to consider outcome trends in not-yet-treated and never-treated hospitals or cities as a counterfactual for the trends that we would have seen in treated groups if they had not started receiving the treatment. Under a parallel trends assumption, $\widehat{\tau}_{\ell}^{ATT}$ is an unbiased estimator of the average treatment effect among switchers, at the time they switch. Our finding that the estimates are robust to the inclusion of covariates and trends mitigates the concern that our results are driven by differential trends across switchers and non-switchers. We also rely on placebo estimators defined by de Chaisemartin and D'Haultfoeuille (2022) to directly assess the plausibility of the underlying parallel trends assumption. Their test for pre-trends differs from the standard event study pre-trends test (Autor, 2003), which has been shown to be invalid when treatment effects are heterogeneous (Sun and Abraham, 2021).

A potential concern is that UPAs may have been introduced earlier in areas with worse hospital or city outcomes, which could result in our findings reflecting a catch-up effect rather than the true impact of UPAs. If this were the case, one could expect convergence to begin before the UPA openings, manifesting as differential pre-trends. Nevertheless, to assess how serious any dynamic endogeneity may be, we follow Galiani et al. (2005) and Rocha and Soares (2010) and model the hazard of UPA adoption as a function of municipality and hospital characteristics, in levels and changes. See Tables C.1 and C.2.

Our analysis shows that baseline hospital and city characteristics and past shocks are not predictive of the timing of UPA adoption, suggesting that endogeneity concerns related to these factors are limited. However, political alignment between city and state governments and the presence of SUS ambulance service are significant predictors of UPA adoption, which is consistent with the state government's role in promoting UPAs and the requirement for cities to have ambulance services to implement a UPA.[16] To address these potential confounders, we replicated our main results including these variables as controls, both directly and interacted with the treatment variable. The robustness checks presented in Tables C.3-C.5 show that our results remain consistent and are similar to those from our main specifications.

[15]The city-time varying controls include gross domestic product per capita, Bolsa Família coverage, an indicator for cities affected by severe rains and landslides in 2011, dummies for the political party in power in each city, and a dummy indicating alignment between city and state governments. The alignment dummy helps control for potentially confounding effects from other policies driven by political alignment.

[16]Primary care (FHP) coverage, the proportion of the population receiving Bolsa Família and inpatient deaths show a negative but very weak correlation with UPA adoption, with hazard ratios close to one.

Having established that the timing of UPA openings is quasi-random, the main threats to identification in our design are endogenous risk-based selection into hospitals (which affects only the hospital-level results) and the potential influence of other time-varying events that are correlated with UPA openings and the outcomes. We address these issues in our empirical approach, as discussed in the Introduction and elaborated further in the results section. We will show that our results are robust to including non-parametric trends to account for broader regional dynamics, employing alternative definitions of hospital catchment areas, excluding hospitals with incomplete or inadequate data, and removing the capital city of Rio de Janeiro from the analysis due to its unique characteristics compared to the rest of the state.

5.2 Hospital Catchment Area

In the hospital-level analysis, treatment is defined by whether a hospital experiences the opening of a UPA within its catchment area, which is the geographic region and population from which the hospital draws its patients. Accurately specifying a hospital's catchment area is crucial as it captures the majority of the hospital's patient flow while excluding regions that contribute with random variation (DC and Wang, 2015; Gilmour, 2010). Although factors such as perceived quality of care and waiting times influence patient choice (Capps et al., 2003; Gowrisankaran et al., 2015; Ho, 2006; Raval et al., 2017), distance to the nearest facility, particularly for emergency services, is often the dominant factor. For example, Gowrisankaran et al. (2015) find that a five-minute increase in travel time to a hospital can reduce demand by 17% to 41% in the US, underscoring the importance of proximity. Consequently, hospital catchment areas are commonly defined based on distance and travel time.[17]

We define hospital catchment areas using circular buffers centered on each hospital's precise latitude and longitude coordinates. This approach reflects competition among healthcare providers, as overlapping catchment areas capture shared patient populations (Cooper et al., 2018). Our benchmark catchment radius is set at 4.5 kilometers, reflecting the median distance patients traveled to the nearest emergency department before the first UPA opened in RJ. To assess the robustness of our results, we also examine alternative distances in Section 8. We geocoded the locations of all hospitals with emergency services and all UPAs between 2005 and 2016, calculating the median distance to the nearest facility from each census tract, weighted by population size, using HERE maps for route measurements.[18] Our analysis accounts for hospitals that opened or closed during the study period. Additional methodological details are provided in Appendix Section D. Figure 3 illustrates the 4.5 km catchment areas for each hospital alongside the locations of UPAs, which may or may not fall within these areas. Figure 1b shows the evolution of the share of hospitals with an UPA in their catchment area, reaching 45% by 2016.

6 Results: Access to Emergency Services and Hospital Outcomes

6.1 Access to Emergency Health Services

Using the geocoded locations of all UPAs and hospitals with emergency services—jointly referred to as ER facilities—we calculated population-weighted mean and median distances from census tracts to the nearest facility in each city. Distances were measured in both kilometers and travel time, with

[17] For a review of methods used to estimate catchment areas, see DC and Wang (2015).

[18] Route data sourced from HERE maps: https://www.here.com/

the latter estimated as nighttime driving time by car (at midnight, when traffic is minimal). This measure captures potential access to emergency care for the overall population, rather than realized distances based on patient visits, which could be affected by selection into care.

We find that the opening of UPAs substantially improved access to emergency care in RJ, as illustrated in Figures 4a and 4b. Figure 4c shows that, on average, UPAs became the nearest ER facility for 50% of the population once the policy roll-out was complete. We also provide separate estimates for the city of Rio de Janeiro, which saw the opening of 30 UPAs during the study period and is the largest city in the state. Consistent with expectations, the impact of UPAs on access to ER services is more pronounced in Rio city.

Table 1 presents OLS estimates on these population-weighted average distances and travel times from census tracts using quarterly city-level observations from 2005–2016. Controlling for city and quarter fixed effects (column 3), the presence of an UPA is associated with a significant reduction in the median distance to an ER by 2.1 km. This represents a substantial 27.3% decrease relative to the baseline mean of 7.7 km. In terms of travel time, the median time to the nearest ER decreases by 3.3 minutes from a baseline average of 14.4 minutes, a reduction of 23%. Additionally, the share of the population for whom the nearest ER is a UPA increases to 36% on average.

6.2 Outpatient Procedures

Consistent with the policy goal of reducing pressure on hospitals, we analyze the impact of UPA openings on outpatient procedures. Table 2 presents estimates of equation 1 with and without controls. Unless specified otherwise, we focus on the results from the most comprehensive specification.[19]

Our results indicate that the opening of an UPA leads to a significant and persistent 30% reduction in outpatient procedures conducted in hospitals, including those in emergency rooms. This reduction is primarily driven by medium-complexity procedures, which account for 50% of all outpatient cases and suggests that UPAs effectively absorb less severe cases that would otherwise add to hospital workloads. These findings align with the broader goal of UPAs to relieve hospitals by managing cases that are less critical and do not require full hospital resources.[20]

To verify that the decline in hospital outpatient procedures was picked up by UPAs, we analyzed city-level data on ambulatory procedures per capita, categorized by facility and displayed in Table A.7. While the number of outpatient procedures per capita at hospitals declines by 0.29, the number at UPAs increases by 0.39. The net change was a modest decline of 0.18 (or 3.5%), which is not statistically significant. This suggests that the total volume of outpatient care did not increase following the introduction of UPAs. Instead, the evidence points to a substitution effect, with UPAs stepping in to absorb a portion of the hospital's caseload.

[19] Results including non-parametric trends were moved to the appendix, following comments received.

[20] Alexander et al. (2019) found that proximity to retail clinics in the U.S. is associated with a 4% to 12% reduction in ER use for preventable minor acute conditions. However, the comparison is limited due to the differing contexts of retail clinics in the U.S. versus UPAs in Brazil.

6.3 Hospital Admissions

We now turn to a detailed analysis of how UPAs influence hospital admissions. The second panel of Table 2 indicates an overall downward trend in hospital admissions, though the total effect is not statistically precise. However, when admissions are broken down by cause, we find a significant 37% reduction in admissions for conditions that are amenable to ambulatory care alone and a 24% decline for conditions sensitive to both ambulatory and emergency care, aligning with the policy's intent to shift manageable cases to UPAs. In contrast, admissions for conditions requiring hospital-level care and not suitable for ambulatory or emergency treatment show no significant change, reaffirming that these cases remain central to hospital operations. This suggests that UPAs may be effectively managing ambulatory-care-sensitive conditions, preventing their progression to more severe cases requiring hospitalization. Together, these ambulatory conditions represent about a quarter of baseline hospital admissions, highlighting the significant potential for UPAs to reduce hospital caseloads by addressing and better treating less severe conditions.

Further analysis of admissions by type, as shown in column 3 of Table 5 and Figure 7, reveals a clear reorientation in hospital care, characterized by a 25% increase in surgical and obstetric admissions and a 27% decline in clinical and other admissions. This pattern suggests that hospitals are redistributing their resources towards more advanced services, such as surgeries and complex medical interventions. This shift in focus seems to be enabled by the reduced volume of less critical cases, which are increasingly managed by UPAs. Consequently, UPAs not only help decrease the overall hospital caseload but also allow hospitals to enhance their capacity to deliver more specialized and complex care.

Figures 5 and 6 provide flexible coefficient plots, illustrating that pre-trends for treated versus control hospitals do not significantly differ in the ten quarters preceding UPA openings. The observed declines in outpatient procedures and admissions persist through sixteen quarters following the UPA openings, and these results are stable across specifications.

6.4 Patient Profile and Selection into Hospital

Before turning to the effects on mortality and hospital performance, we examine whether improvements in hospital outcomes could reflect changes in patient composition rather than improvements in care. Specifically, the opening of UPAs may have altered the risk profile of patients admitted to hospitals. For instance, UPAs could have diverted less severe cases away from hospitals, but they might also have reduced congestion and encouraged the admission of non-urgent patients with lower ex-ante mortality risk. Both possibilities imply that observed changes in hospital performance could, in principle, reflect compositional rather than quality effects.

To assess this empirically, we first analyze patient demographics, including age, gender, and income (see Table 3, and Appendix Figure B.1 for the corresponding coefficient plots).[21] The results show no significant or meaningful changes in these demographic and income characteristics following UPA openings.

Next, we include controls for the age, gender, and income composition of admitted patients in each

[21] The indicators are calculated by averaging the socioeconomic characteristics of patients at the hospital-by-quarter level. Average income is derived from the patient's residential zip code (available in SIH), matched to census-tract income per capita data from the 2010 Population Census.

hospital–quarter cell. This approach allows us to adjust directly for changes in the patient mix that could bias our estimates of hospital quality. The inclusion of these controls leaves the results virtually unchanged. UPA openings continue to be associated with significant improvements in hospital outcomes. The corresponding estimates are reported in Table C.3, which summarizes the robustness checks at the hospital level.

In addition, we implement a complementary approach to capture potential selection on unobserved severity. We construct a severity index based on historical in-hospital mortality rates by diagnosis, age, and sex, following Aguilar-Gomez et al. (2025) and Hoe (2022). Using the universe of hospital admissions and deaths in Rio de Janeiro, we define severity as the state-level in-hospital mortality rate for each 3-digit ICD-10 diagnosis category, conditional on age and sex. This measure is assigned to each patient and aggregated to the hospital–quarter level. We then re-estimate our difference-in-differences specification using this severity index as the outcome. As shown in Figure B.2, we find no evidence that the average severity of admitted patients changes following the introduction of UPAs.

Taken together, these findings support the interpretation that changes in patient composition are not driving our results. The evidence indicates that the improvements in hospital outcomes stem from gains in hospital performance.

6.5 Hospital Deaths and Performance

We now explore how these changes in hospital demand and admission profile translate into hospital performance and patient outcomes. The lower panel of Table 2 reveals a 22% reduction in total hospital deaths following the opening of a UPA. This reduction encompasses both emergency room and inpatient deaths. The decline in death counts is observed across all four categories of admission causes, and the event study plots in Figures 5c and 8 show no pre-trends, strengthening the causal interpretation.

However, this reduction may simply reflect a shift in demand towards UPAs. To better understand hospital performance, we evaluate inpatient deaths as a proportion of admissions (see Table 5). The inpatient death rate decreases by 0.8 percentage points, or 13% of the baseline rate. Interestingly, this decline is stronger and statistically significant only for conditions not amenable to either ambulatory or emergency care—the category where admissions did not decrease.

When we break the data down by type of admission, the most substantial reductions are seen in intensive care settings. Additionally, the reduction in deaths is especially significant on weekdays, when hospitals typically experience peak demand. As shown in Figure 9b, this reduction begins in the second year after UPA introduction, which aligns with the time needed for hospitals to adjust their operations and reallocate resources, as discussed in the next section.

We further analyzed the death rate within 24 hours of admission as a rough measure of the effectiveness of emergency care for patients admitted in critical condition. This metric also shows a significant decline of 0.35 percentage points (column 4), indicating improved emergency response and patient management. Detailed coefficient plots for these results are provided in Figure 9

Overall, these findings suggest that the reduction in admissions for less severe, ambulatory-care-sensitive conditions allowed hospitals to dedicate more resources and attention to critical patients, ultimately leading to better outcomes for those requiring hospital-level care. This conclusion is supported by evidence from the next section, which shows an increase in resources dedicated to inpatient care.

6.6 Reallocation of Hospital Resources

The upper panel in Table 4 shows that the number of health professionals at hospitals did not change significantly following UPA openings.[22] However, we observe a statistically significant increase in the average hours worked by health professionals in inpatient services, coupled with a decrease in hours devoted to other activities, which include administrative and ambulatory tasks. As illustrated in Figure 12 this adjustment is persistent over time.

Regarding hospital infrastructure, our analysis shows an increase in the amount of medical equipment, which, combined with fewer admissions, suggests that there was more equipment available per patient. However, we do not observe significant changes in the number of hospital beds or the bed occupancy rate.[23] Coefficient plots for these outcomes are provided in Figure 13.

Although these findings are not definitive on their own, they support the notion that reduced emergency department caseloads allow hospitals to redirect human resources from administrative and ambulatory roles to inpatient care, while also enhancing physical capital. This reallocation likely contributes to improved quality of inpatient services, as hospitals can better focus their resources on more complex patient needs.[24]

7 Results: Population-Level Health Outcomes

While UPAs have effectively reduced hospital caseloads and inpatient mortality, the ultimate policy objective is to improve overall population health. To evaluate whether the observed reduction in hospital deaths reflects a true decrease in mortality or merely a shift in where deaths occur, we turn to city-level mortality data, disaggregated by cause and location.

Table 6 shows a modest 1.8% (or 3 per 100,000 people) decline in overall city-level mortality following the introduction of UPAs. However, this reduction is not statistically significant, potentially due to the inherent difficulty in detecting small changes in mortality rates with limited statistical power. The event study plot in Figure 10 reinforces the validity of our identification strategy, as there is no

[22]Since UPAs were staffed with professionals, this implies an overall increase in healthcare personnel per capita rather than a redistribution of existing staff. This is consistent with the rapid expansion of the medical workforce in Brazil, where the number of physicians per 1,000 people grew from 1.4 in 2005 to 2.0 in 2016 (Scheffer, 2023)

[23]Note that bed-occupancy rates are unlikely to be an accurate measure of hospital congestion. National data show that public hospitals often operate at average occupancy below the 75% benchmark recommended by the Brazilian National Health Agency (ANS). These low figures reflect structural inefficiencies and resource shortages rather than a lack of demand or slack in infrastructure (Botega et al., 2020; TCU, 2015). A diagnostic study by the Federal Court of Accounts (TCU, 2015) found that 64% of hospitals reported frequent overcrowding. Chronic ER congestion is also widely documented, with many units operating beyond their physical and staffing capacity, leading to patients waiting on stretchers or receiving care in corridors (Bittencourt and Hortale, 2009; O'Dwyer et al., 2017). In this context, UPA openings likely relieved pressure on hospital ERs, enabling a reallocation of personnel and resources toward more complex inpatient care.

[24]An alternative explanation for the observed increase in hospital equipment is that local governments may have simultaneously expanded funding for hospitals in areas where UPAs were built. We observe no evidence of systematic investments of this kind. Administrative records and policy documents indicate that the UPA rollout did not coincide with hospital investment initiatives at either the state or municipal level. Our results remain consistently unchanged when we control for the expansion of other health policies, including expansion of the Family Health Program (FHP) and the Mobile Emergency Service (SAMU), which were the main federal programs affecting the supply of primary and emergency care at the time. They are similarly robust to allowing for flexible, city-level non-parametric trends. Taken together, the evidence suggests that the increase in hospital equipment reflects equilibrium adjustments to the relief of overcrowding rather than alternative sources of funding.

evidence of divergent trends in mortality before UPA openings between cities that did and did not receive a UPA.[25]

To directly assess the potential displacement of deaths, we leverage vital statistics that record deaths by location. Table 6 reveals strong evidence of displacement: hospital deaths decrease by 19.7 per 100,000 following UPA openings, but deaths in UPAs and other health facilities increase by 14.5 per 100,000.[26] This shift is expected, given that UPAs were newly created facilities, absorbing cases that would otherwise have been treated in hospitals. When accounting for deaths across all settings—homes, streets, and other locations—the net decrease in overall mortality amounts to 3 per 100,000 people. The changes in hospital and UPA deaths are persistent over the four years of follow-up, as shown in Figure 11.

Notably, the reduction in hospital mortality is concentrated among conditions not amenable to either ambulatory or emergency care—the same conditions for which hospital admissions did not decline. For these cases, we observe a significant net decline of 7.6 deaths per 100,000 inhabitants. This reduction is partly offset by an increase of 4.7 deaths in UPAs, resulting in a net decrease of 1.4 deaths per 100,000 in this category, which accounts for 41% of the total net reduction in deaths. These findings are consistent with the earlier results on improvements in hospital performance for more complex conditions. The remaining 59% of the reduction came from conditions amenable to emergency care, aligning with UPAs' primary focus.

In addition, Table A.8 examines whether the effects of UPA openings on population mortality differ across demographic groups. We estimate separate models by age, race, gender, and education. Across all subpopulations, the estimated coefficients are statistically indistinguishable from zero and provide little evidence of systematic patterns for any particular demographic group. These effects should also be interpreted with caution, as statistical power is limited when disaggregating mortality into finer subgroups.

Finally, Tables A.9 and A.10 provide further breakdowns of death rates by location and specific causes of death, revealing that displacement patterns are widespread across most causes. However, it is important to interpret these disaggregated results with caution, as the statistical power is limited. For nearly every cause, deaths in hospitals decrease, while most of the increase in deaths outside hospitals occurs in UPAs. Given that no deaths occurred in UPAs before their creation, the figures for deaths in UPAs (column 3) reflect only the magnitude and distribution of deaths by cause after the units became operational.

8 Robustness Checks

We have already presented results that explicitly model the timing of UPA openings, documenting that pre-trends in outcomes are not significantly different between treated and untreated units (hospitals or cities). These findings provide reassurance that C.6 trends do not precede UPA implementation. In addition, we examined whether UPA openings altered the selection of patients into

[25]When comparing hospital-level and city-level results, it's important to note that, here, hospital outcomes include all hospitals in each city, while fewer than half of these hospitals experienced a UPA opening in their catchment area. This difference should be kept in mind when comparing hospital-level and city-level results.

[26]The event study plot for deaths in other locations shows a temporary increase immediately after UPA openings, which reverts to baseline levels. Informal conversations with local policymakers suggest that this blip might result from initial miscoding in the SIM and CNES registers during the first months after UPAs were introduced, as these were new units in the system. If correct, this temporary increase may reflect UPA-related deaths incorrectly attributed to other locations.

hospitals, and no significant changes were found.

We next address the concern that UPA openings may have coincided with other local reforms or investments, potentially confounding the estimated effects. This concern is particularly relevant given the role of political factors in the allocation of UPAs. We therefore examine whether cities adopting UPAs experienced concurrent changes elsewhere, especially within the health system, that could plausibly drive our results.

Specifically, we explore whether UPA openings affected primary care services or other layers of the public health system. UPAs might have substituted for or complemented basic healthcare services, influenced the provision of ambulance services, or coincided with hospital openings or closures. As shown in Table 7 and Figure B.3, we find no statistically significant changes in primary care coverage (Family Health Program, FHP), routine consultations, physician consultations, prescribed exams, or the registration and follow-up of diabetic patients following the opening of a UPA. Similarly, UPA openings are not associated with changes in SUS ambulance services or the opening or closure of public hospitals.

Our baseline specification already controls for political alignment between city and state governments and for the mayor's party affiliation, with no material effect on the results. Moreover, since political alignment and the presence of SUS ambulance services are predictive of UPA adoption in our hazard analysis, we additionally re-estimate our main specifications controlling for these factors and allowing them to interact with treatment. These estimates are very similar to those from the baseline specification.

We also conduct a series of additional robustness checks that further address the possibility of confounding policies or differential local trends. First, we address the concern that the capital city of Rio de Janeiro may be driving the results for the entire state. To test this, we exclude the 13 hospitals in Rio (for the hospital analysis) and the city of Rio (for the city-level analysis) from our sample.[27]

Second, we examine the sensitivity of our results to alternative definitions of hospital catchment areas, varying the radius from 4.5 km (the median distance) to 6.5 km (the mean distance), and to sample restrictions that exclude hospitals with incomplete data in at least one dimension. We also estimate specifications that include controls for potentially endogenous health system variables—such as primary healthcare coverage, SUS ambulance services, and hospital openings and closures—which were excluded from the main analysis due to endogeneity concerns.

Third, we allow for greater flexibility in local dynamics by estimating specifications with city- or health region–level non-parametric time trends, which absorb location-specific shocks that could be correlated with both UPA placement and outcomes. Finally, we perform a conventional difference-in-differences analysis using a two-way fixed effects regression as a robustness check.

The results of these robustness tests are presented for hospital outcomes (Table C.3), the population-level results (Tables C.4 and C.5) and for the additional checks on health system changes (Table C.6). Across these tests, we observe consistent and statistically stable patterns, reinforcing the reliability of

[27]Since no UPAs were established in neighboring regions during the analysis period, it is unlikely that Rio de Janeiro residents would cross state lines for emergency services. Although individuals typically prefer closer facilities for urgent care, it is possible that some residents in bordering regions might use RJ-based UPAs as their nearest option. However, access to basic and intermediate-complexity emergency care in Brazil is typically organized and financed within state boundaries, making such cross-border utilization rare, regional spillovers limited, and unlikely to affect our estimates.

our findings.

9 Conclusions

This paper provides, to the best of our knowledge, the first comprehensive empirical evaluation of the introduction of free-standing, 24/7 emergency care centers within a publicly funded health system. Following the opening of UPA in the vicinity of a hospital, we identify substantial declines in hospital caseload driven by ambulatory-sensitive conditions, and a change in the composition of admissions towards those requiring more complex care. We also document an improvement in patient survival rates in intensive care and for conditions best suited to hospital treatment. Overall, the evidence indicates that UPAs eased pressure on hospitals allowing them to focus on critical care services.

While we observe a decline in deaths that occur in hospitals, there was some displacement of deaths to UPAs and, as a result, a modest, if any, improvement in population level mortality. Yet, consistent with our hospital-level analysis, the results suggest that population mortality declines are concentrated in causes not amenable to ambulatory or emergency care and that are best treated in hospitals. UPAs may have additionally contributed to aspects of system-wide efficiency that we do not measure, for instance, the timeliness and appropriateness of care that is visible in outcomes less extreme than mortality, including patient travel time and waiting times.

A full cost-effectiveness analysis is beyond the scope of this paper, as we lack information on variable costs across facilities and within hospitals. Nonetheless, aggregate spending figures provide a sense of relative magnitudes. The creation and operation of UPAs involved expenditures equivalent to roughly 5.6–14.2 percent of hospital spending.[28,29] These figures should be interpreted cautiously, but they suggest that UPAs represent a non-negligible yet limited share of total hospital expenditures. Policymakers must weigh both observable and potential gains from the introduction of UPAs against these direct costs as well as the opportunity costs of alternative investments. Future research with more granular cost and utilization data will be essential to quantify these broader fiscal and welfare effects.

Our findings can be viewed as a proof of concept that creating an additional facility with expertise that lies between that of outpatient clinics and hospital emergency departments can improve hospital outcomes. Under the institutional conditions of our empirical setting, the introduction of a mid-tier of emergency facilities reshaped patient sorting and relieved pressure on overburdened hospitals, thereby contributing to improvements in hospital performance. In that sense, our results are potentially relevant globally, as countries face increasing demand for emergency care and the challenge of managing time-sensitive conditions like sepsis, stroke, asthma, COPD, and AMI (Gujral and Basu, 2019). Hospital closures and ER overcrowding are common issues, even in higher-income countries, where efforts to provide emergency services outside hospitals, such as urgent care centers in Eng-

[28]The range is based on administrative spending data from the 2014 Fiscal Transparency Bulletin of the Rio de Janeiro State Finance Secretariat and bed-capacity figures from the CNES registry. Using the OECD's System of Health Accounts framework, we compared total UPA management expenditures (R$339 million for 25 UPAs) with alternative estimates of total public hospital spending in Rio de Janeiro derived from both national SUS data and state fiscal accounts, yielding ratios between 5.6 and 14.2 percent.

[29]A natural question concerns whether our findings extend beyond Rio de Janeiro. While Rio is among the more developed Brazilian states, its hospitals experienced severe and persistent emergency department overcrowding during our study period. National evidence indicates that congestion is widespread across the country rather than a peculiarity of Rio (TCU, 2015). Moreover, although UPAs were initially introduced as a state-level policy in Rio, their perceived success led to subsequent nationwide expansion. These facts suggest that our estimates are plausibly informative about the role of UPAs in other Brazilian settings, particularly where baseline hospital capacity is more constrained.

land, have struggled due to poor integration with existing systems (Timmins, 2007; Hsia et al., 2011; Torjesen, 2013; Avdic, 2016). In developing countries, where overcrowded hospitals and fragmented health systems are more common, timely treatment for life-threatening emergencies has not been a priority even though a significant burden of disease arises from time-sensitive conditions (Razzak and Kellermann, 2002).

At the same time, our analysis does not speak to the relative merits of alternative supply-side policies—such as expanding hospital emergency departments, strengthening primary care, or improving ambulance regulation—nor to the long-run sustainability of adding new tiers to the system. We therefore do not claim that other health systems should necessarily adopt UPAs, but rather that this experience offers a valuable policy alternative to consider in settings facing similar congestion challenges. In considering the relevance of our analysis to other settings, it is also important to note that introducing an additional tier affects both capacity and sorting, and it therefore does not automatically resolve congestion. In a multi-tier system, patients may continue to sort into higher levels of care unless gatekeeping, service capacity, and incentives align. Identifying when such interventions are most effective, and how they compare with other ways of expanding capacity or improving coordination, remains an important direction for future work.

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Main Tables

Table 1: Distance and Travel Time to Closer ER and % Population Closer UPA

	UPA			Mean at
	(1)	(2)	(3)	Baseline
Median Route (km)	-4.480***	-1.962***	-2.102**	7.73
	(0.805)	(0.661)	(0.852)	
Median Time (Min)	-6.108***	-3.423***	-3.320***	14.44
	(1.118)	(0.883)	(1.073)	
Mean Route (km)	-4.538***	-1.738***	-1.873**	9.17
	(0.751)	(0.592)	(0.772)	
Mean Time (Min)	-6.340***	-2.906***	-2.837***	16.46
	(1.055)	(0.753)	(0.952)	
% Population Closer to UPA	40.940***	43.650***	35.737***	0.00
	(4.081)	(3.973)	(4.373)	
Observations	4416	4416	4416	-
Munic FE	No	Yes	Yes	-
Time FE	No	No	Yes	-

Notes: This tables shows the results of regressing route and time measures (mean and median averaged at the municipality level) to the closest ER on the moment UPAs were introduced in each city. It also depicts the coefficients of a similar regression on the percentage of the population living closer to an UPA than to other ERs facilities. Municipality fixed effects were included in column (2) and quarter-year fixed effects in column (3). Baseline refers to the period 2005/Q1-2007/Q1, before the introduction of the first UPA in RJ. Routes are measured in kilometers and time in minutes. Standard errors clustered at the municipality level in all specifications. *** p<0.01, ** p<0.05, * p<0.1. We used HERE maps to calculate the distance/time from each census tract to the closest ER (weighted by population) by car at midnight.

Table 2: Hospital Demand and Total Mortality, Hospital-Level Estimates

	Specifications (1)	(2)	Mean at Baseline
Ambulatory Procedures			
Total	-0.289*** (0.059)	-0.300*** (0.061)	76.09
Basic Health Care	0.235 (0.338)	0.240 (0.345)	27.97
Medium Complexity	-0.309*** (0.080)	-0.302*** (0.080)	38.34
High Complexity	0.377 (0.257)	0.352 (0.259)	0.28
Hospital Admissions			
Total	-0.063 (0.071)	-0.072 (0.072)	723.25
Amenable to Ambulatory & Emergency Care	-0.207 (0.138)	-0.236* (0.142)	79.29
Amenable to Ambulatory Care Only	-0.346*** (0.119)	-0.378*** (0.124)	96.29
Amenable to Emergency Care Only	-0.055 (0.116)	-0.018 (0.126)	158.84
Non-Amenable to Ambulatory or Emergency Care	0.000 (0.082)	-0.022 (0.088)	388.84
Total Deaths			
Total	-0.226*** (0.061)	-0.218*** (0.062)	100.38
Amenable to Ambulatory & Emergency Care	-0.301*** (0.068)	-0.277*** (0.073)	13.53
Amenable to Ambulatory Care Only	-0.173** (0.076)	-0.179** (0.078)	16.95
Amenable to Emergency Care Only	-0.204*** (0.073)	-0.166* (0.087)	29.70
Non-Amenable to Ambulatory or Emergency Care	-0.132* (0.069)	-0.160** (0.078)	40.21
Hospital & Time FE	Yes	Yes	-
Controls	No	Yes	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are the IHS of hospitals' ambulatory procedures, hospital admissions, and total deaths, with coefficients interpreted as approximate fractional changes. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The dependent variables are the IHS of hospitals' ambulatory procedures, hospital admissions, and total deaths, with coefficients interpreted as approximate fractional changes. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS. Baseline values for ambulatory procedures are presented in thousands.

Table 3: UPA Effects on Inpatient Profile, Hospital-Level Estimates

	Average Income (1)	% Female (2)	Average Age (3)	% 65+ Years (4)
Total	-15.812	0.641	-0.738*	-0.898
	(25.281)	(0.530)	(0.423)	(0.628)
Amenable to Ambulatory/Emergency Care				
Amenable to Ambulatory & Emergency Care	-30.868	-1.764	-0.063	-0.394
	(32.311)	(1.692)	(1.010)	(1.494)
Amenable to Ambulatory Care Only	-1.119	0.547	-0.925	-0.952
	(30.883)	(1.632)	(0.806)	(1.284)
Amenable to Emergency Care Only	-26.456	-0.589	-0.813	0.911
	(31.941)	(0.796)	(0.946)	(1.190)
Non-Amenable to Ambulatory or Emergency Care	-18.951	0.651	-0.964*	-1.378
	(28.905)	(1.038)	(0.523)	(0.907)
Hospital & Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean at Baseline	1168.23	55.80	43.08	23.76

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables relate to inpatients' income, gender, and age, and are displayed by causes amenable and non-amenable to ambulatory and emergency care. Average income was determined by linking patients' zip codes to census tract data from the 2010 Census. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS. Baseline values for ambulatory procedures are presented in thousands.

Table 4: Human Resources, Infrastructure and Occupancy Measures, Hospital-Level Estimates

	Human Resources					
	No. Professionals (1)	No. Physicians (2)	No. Other Prof. (3)	Avg. Hrs Worked (4)	Avg Hrs Worked Inpatient (5)	Avg Hrs Worked Other (6)
UPA	0.006	0.027	0.020	-1.435	1.513***	-2.949**
	(0.040)	(0.042)	(0.062)	(1.162)	(0.539)	(1.258)
Mean at Baseline	264.33	83.97	180.36	26.73	1.91	24.82
	Beds					
	Total Hosp Beds (7)	Surgical Hosp Beds (8)	Clinical Hosp Beds (9)	ICU Hosp Beds (10)	Other Hosp Beds (11)	Amb + Emerg Beds (12)
UPA	-0.021	0.010	-0.026	-0.020	-0.102*	-0.074
	(0.026)	(0.035)	(0.047)	(0.079)	(0.060)	(0.066)
Mean at Baseline	120.90	36.55	40.40	11.16	32.79	16.65
	Equipments					
	Total Equipments (13)	Diagnosis Equipments (14)	Graphics Methods (15)	Optical Methods (16)	Life Saving (17)	Other Equipments (18)
UPA	0.111**	0.010	0.100*	-0.053	0.105	0.156***
	(0.050)	(0.027)	(0.054)	(0.054)	(0.070)	(0.055)
Mean at Baseline	99.93	6.30	4.66	3.43	74.89	10.65
	Occupancy					
	Occupancy Rate (\%) (19)	No. Days $\geq$ 85\% Occup. (20)	No. Days $\geq$ 100\% Occup. (21)	Bed Turnover Rate (22)	-	-
UPA	0.129	-2.517	-0.545	0.023		
	(2.627)	(2.215)	(0.368)	(0.132)	-	-
Mean at Baseline	41.58	5.36	0.53	2.23		
Hospital & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). Average hours worked relate to all professionals in the establishment. Diagnostic equipment includes X-rays, mammographs, CT scanners, MRI, and ultrasound machines. Graphics method equipment consists of electrocardiographs and electroencephalographs. Optical methods cover devices such as endoscopes, laparoscopes, and surgical microscopes, among others. Life-saving equipment includes defibrillators, ventilators, and bag valve masks, among others. We used the IHS of all human resources, beds, and equipment variables, except those related to average hours worked, so results can be interpreted as approximate fractional changes. The occupancy rate, the number of days hospital capacity is above 85%, the number of days capacity is above 100%, and the bed turnover rate are constructed based on the total number of inpatient beds, the number of hospital admissions, and their duration per quarter. The daily occupancy rate (number of inpatients divided by the number of beds) is averaged over each quarter. Bed turnover is calculated as the number of discharges (including deaths) divided by the number of beds in the hospital. All variables are sourced from CNES. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among geographically close hospitals. ***p<0.01, **p<0.05, *p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS.

Table 5: UPA Effects on Inpatient Outcomes, Hospital-Level Estimates

	Hosp Admissions	Inpatient Deaths	% Inpatient Deaths	%24h Inpatient Deaths	Hosp Adm Mean at
	(1)	(2)	(3)	(4)	Baseline
Total					
	-0.072	-0.249***	-0.813*	-0.348***	723.25
	(0.072)	(0.088)	(0.455)	(0.121)	
Amenable to Ambulatory/Emergency Care					
Amenable to Ambulatory & Emergency Care	-0.236*	-0.213*	0.300	-0.311	79.29
	(0.142)	(0.127)	(1.128)	(0.608)	
Amenable to Ambulatory Care Only	-0.378***	-0.389***	-0.859	-0.328	96.29
	(0.124)	(0.144)	(0.639)	(0.292)	
Amenable to Emergency Care Only	-0.018	-0.224**	-1.249	-0.397	158.84
	(0.126)	(0.108)	(0.975)	(0.364)	
Non-Amenable to Ambulatory or Emergency Care	-0.022	-0.260**	-1.137*	-0.526**	388.84
	(0.088)	(0.111)	(0.636)	(0.220)	
Type of Admission					
Surgical + Obstetric	0.248**	0.046	-0.187	-0.097	375.03
	(0.101)	(0.107)	(0.382)	(0.131)	
Clinical	-0.273***	-0.242**	-0.450	-0.420	274.4
	(0.085)	(0.097)	(0.912)	(0.297)	
Other	-0.267**	-0.129	-0.797	-0.142	73.82
	(0.133)	(0.090)	(0.505)	(0.158)	
ITU	0.094	-0.032	-8.299***	-2.162**	32.56
	(0.105)	(0.098)	(2.509)	(0.916)	
Day of the Week					
Weekday	-0.061	-0.253***	-0.998**	-0.405***	571.57
	(0.070)	(0.085)	(0.465)	(0.125)	
Weekend	-0.112	-0.208*	-0.102	-0.306	151.68
	(0.085)	(0.116)	(0.751)	(0.409)	
Hospital & Time FE	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	-
Mean at Baseline	723.25	52.24	6.35	1.33	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The first two dependent variables analyzed are the IHS of admissions and inpatient deaths, with coefficients interpreted as approximate fractional changes. Note that column 1 repeats the information from the second panel (column 4) of Table 2. Subsequent variables include total inpatient deaths conditional on admissions and inpatient deaths occurring within 24 hours, also conditional on total admissions, both expressed as percentages. Results are presented by causes amenable and non-amenable to ambulatory and emergency care, types of beds (surgical, obstetric, clinical, and other), and day of the week (weekday and weekend). Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS.

Table 6: Deaths per 100,000 by Cause and Location
City-Level Estimates

	Total	Location: Hospital	UPA	Other Health Facility	Household	Street	Other	Mean at Baseline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Total								
	-2.989	-19.710***	12.487***	1.878*	0.694	-0.595	2.029	169.31
	(4.001)	(5.079)	(2.493)	(0.980)	(1.248)	(0.844)	(1.668)	
Amenable to Ambulatory/Emergency Care								
Amenable to Ambulatory & Emergency Care	-1.206	-3.840***	1.579***	0.294	0.262	0.034	0.463**	22.4
	(1.229)	(1.373)	(0.338)	(0.209)	(0.291)	(0.040)	(0.216)	
Amenable to Ambulatory Care Only	0.443	-3.512**	2.521***	0.433*	0.203	0.068	0.645*	25.81
	(1.395)	(1.492)	(0.542)	(0.254)	(0.452)	(0.131)	(0.356)	
Amenable to Emergency Care Only	-0.812	-4.798***	4.268***	0.809*	-0.894	-0.617	0.292	52.85
	(2.172)	(1.619)	(0.908)	(0.454)	(0.886)	(0.779)	(0.763)	
Non-Amenable to Ambulatory or Emergency Care	-1.414	-7.561***	4.118***	0.342	1.123	-0.080	0.629	68.25
	(2.373)	(2.351)	(0.817)	(0.492)	(0.835)	(0.188)	(0.608)	
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Mean at Baseline	169.31	124.66	0	4.48	24.76	8.83	5.47	

This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are deaths per 100,000 people by cause and across six different locations: hospitals, UPAs, other health facilities, households, streets, and other places. The city-level results are not directly comparable to the hospital results shown earlier because the latter includes only hospitals with an ER. Additionally, the hospital analysis models the impact of an UPA opening within 4.5 km of the hospital, whereas the city analysis considers an UPA opening anywhere in the city, resulting in a much broader "catchment" area. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in rates per 100,000 inhabitants.

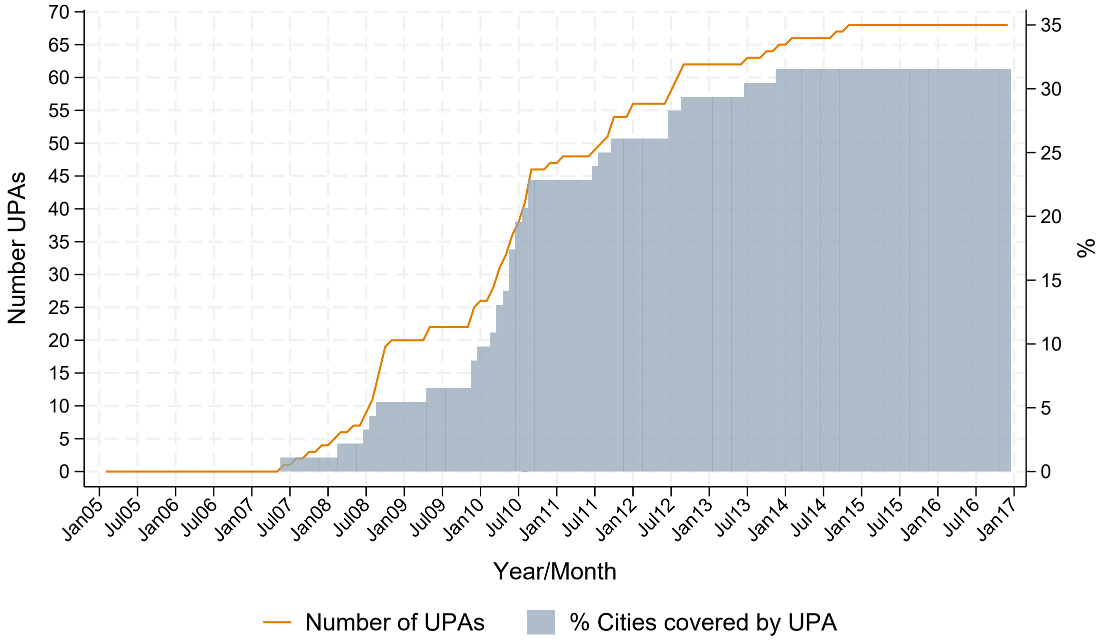
Table 7: UPA Effects on Local Health Systems

	Primary Care		
	% FHP Coverage (1)	Routine Consultations (2)	Physician Consultation (3)
UPA	-1.936	22.031	30.305
	(1.613)	(34.071)	(29.317)
Mean at Baseline	50.50	125.47	182.50
	Primary Care		
	Exams Prescribed (4)	Registered Diabetics (5)	% Diabetics Followed Up (6)
UPA	31.210	4.493	2.293
	(42.981)	(5.809)	(2.222)
Mean at Baseline	72.19	47.62	94.94
	Other Health System Layers		
	SUS Ambulance Service (7)	Net New Hospitals (8)	SUS Hospital Beds (9)
UPA	0.006	-0.042	-1.328
	(0.068)	(0.062)	(18.663)
Mean at Baseline	0.11	0.01	383.82
Hospital & Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

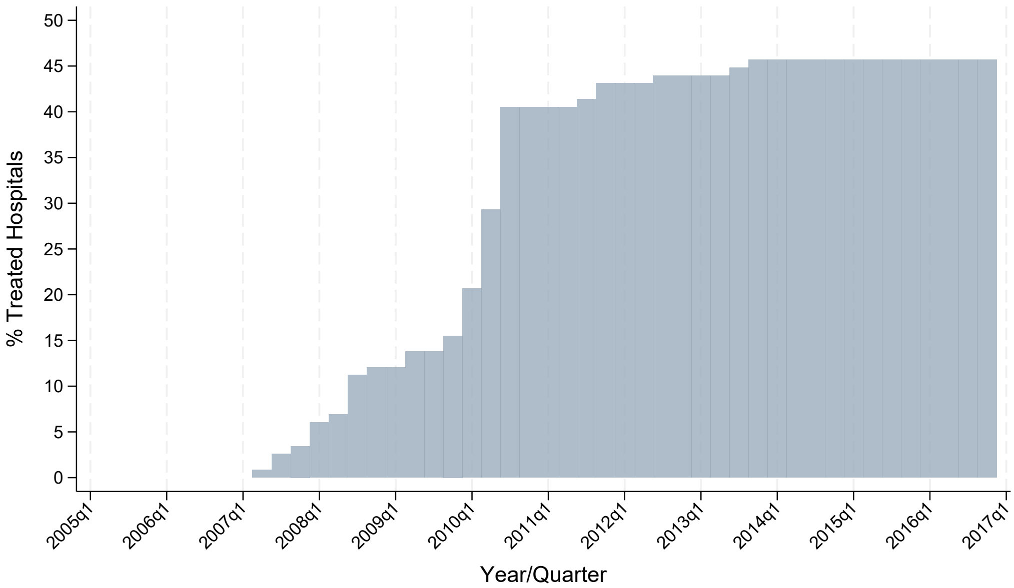
Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables related to the primary care sector are: (1) Family Health Program coverage; (2) routine consultations performed per 1,000 inhabitants; (3) consultations performed by physicians per 1,000 inhabitants; (4) exams prescribed per 1,000 inhabitants; (5) registered diabetics per 1,000 inhabitants; and (6) percentage of registered diabetics receiving follow-up care. Dependent variables related to other layers of the health system include: (7) presence of the SUS ambulance service; (8) net number of new SUS general hospitals with ERs (opened minus closed); and (9) SUS hospital beds per 1,000 inhabitants. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and has the same metric as the corresponding variable.

Main Figures

Figure 1: UPAs - RJ (2005-2016)



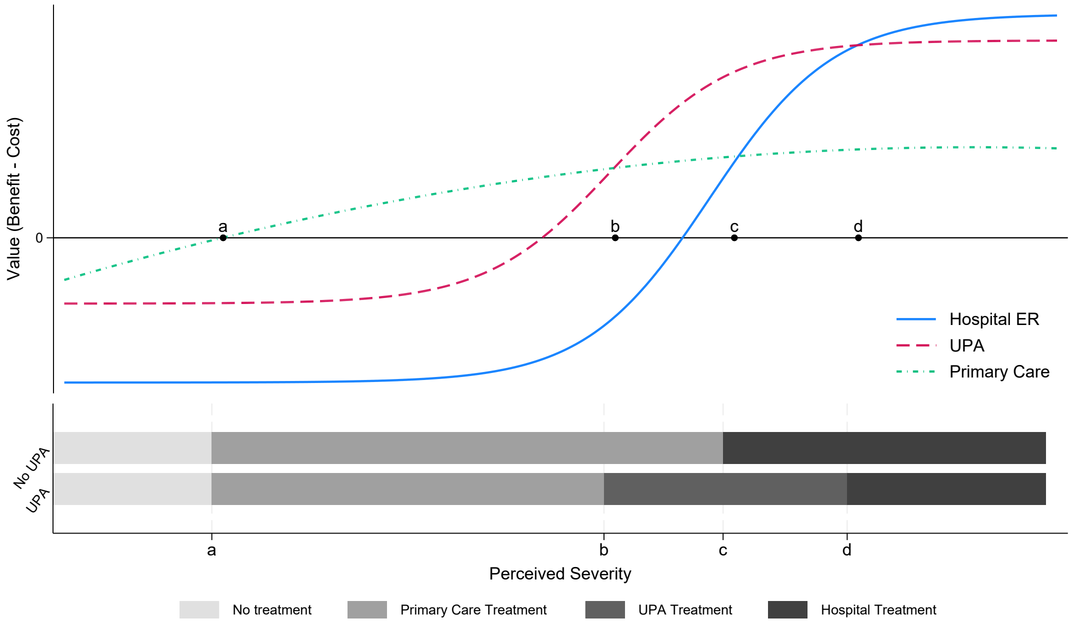
(a) Number of UPAs and % of Cities Covered by an UPA



(b) Percentage of Treated Hospitals

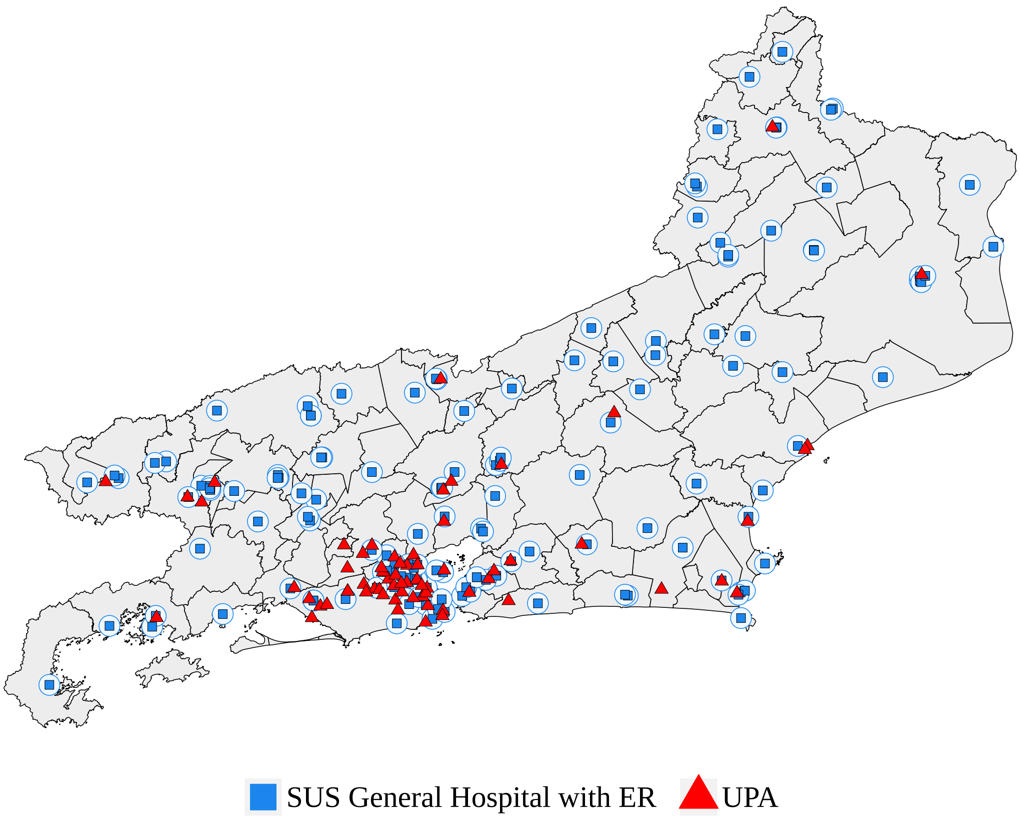
Notes: Panel (a) displays the number of UPAs and the percentage of cities covered by at least one UPA in the state of Rio de Janeiro between 2005 and 2016. The state comprises 92 cities. Panel (b) shows the percentage of general SUS hospitals with emergency rooms that received an UPA within their 4.5 km catchment area during the same period. The total number of hospitals in our sample is 115.

Figure 2: Conceptual Framework



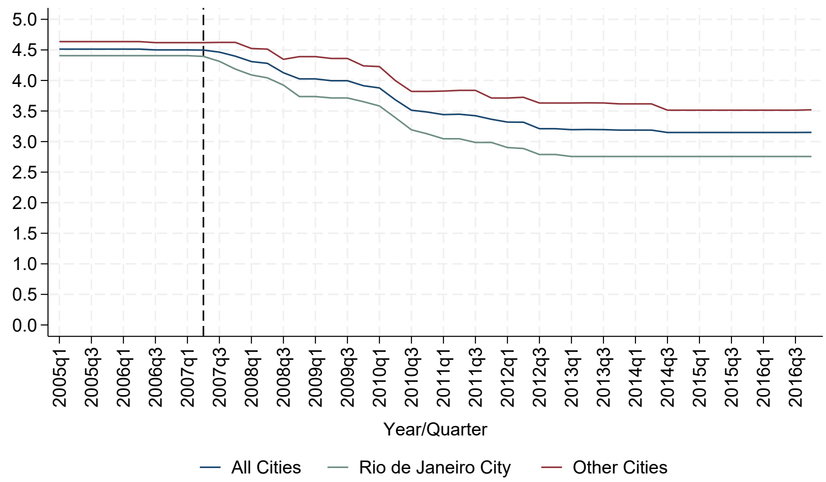
Notes: This graph depics how the value of treatment varies with perceived illness severity across different care settings. The top panel plots the net value of care (benefits minus costs) for primary care, UPAs, and hospitals. The bottom panel illustrates where patients of varying severities choose to seek care in scenarios with and without a UPA.

Figure 3: State of Rio de Janeiro: Cities, Emergency Care Providers and Hospital Catchment Areas

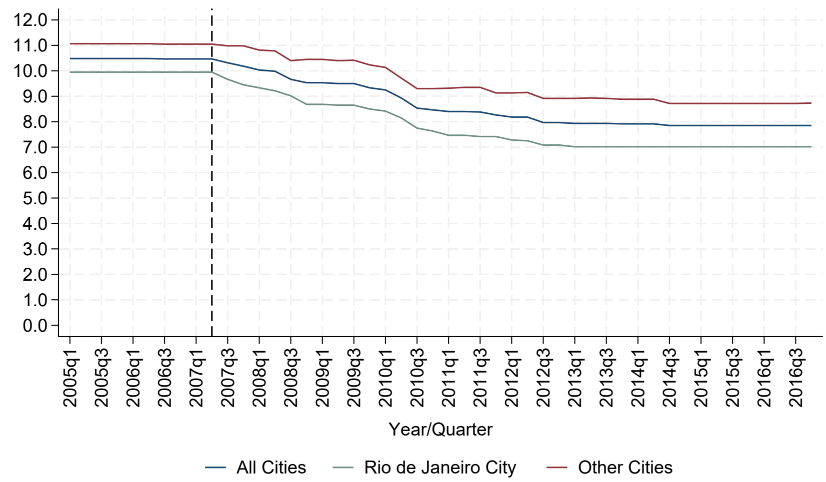


Notes: This map of Rio de Janeiro shows SUS general hospitals with emergency rooms as blue squares and UPAs as red triangles. Hospitals' catchment areas are depicted as blue circles with a 4.5 km radius. Municipal borders are also shown as delimiters on the map. The 4.5 km radius was determined based on the median distance traveled by patients to the nearest ER before the implementation of UPAs.

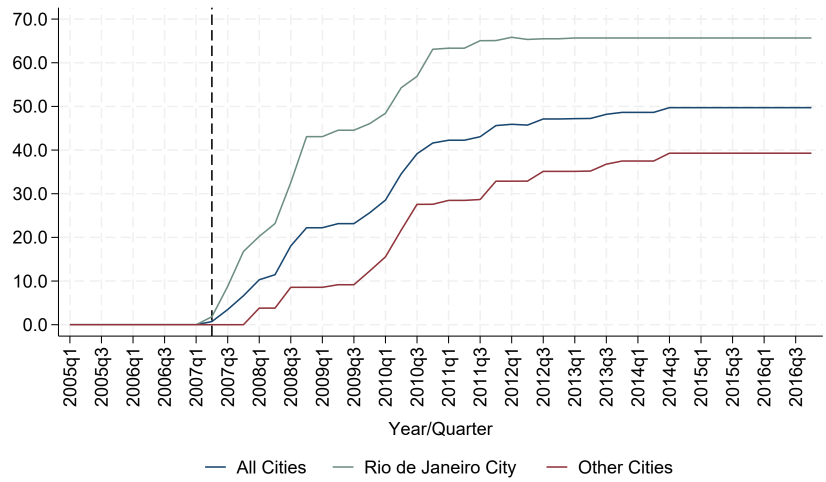
Figure 4: Distance and Travel Time to Closer ER and % Population Closer UPA



(a) Median Distance to Closest ER



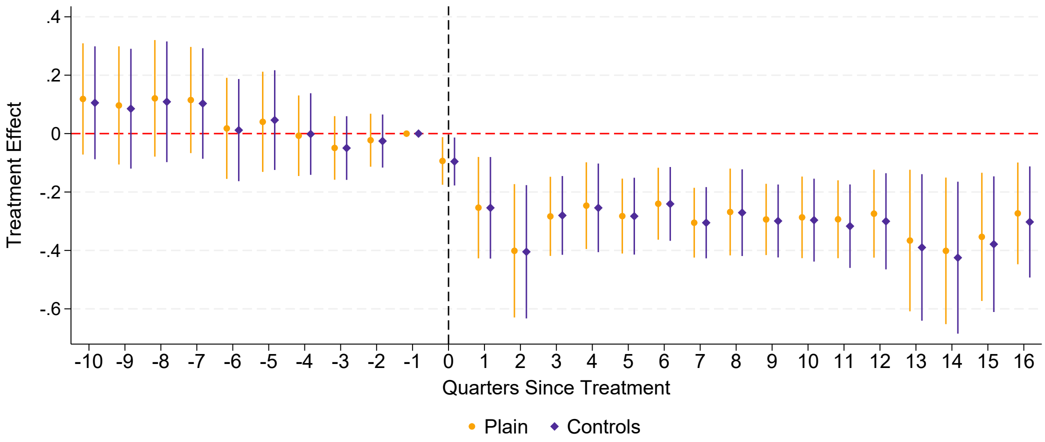
(b) Median Travel Time to Closest ER



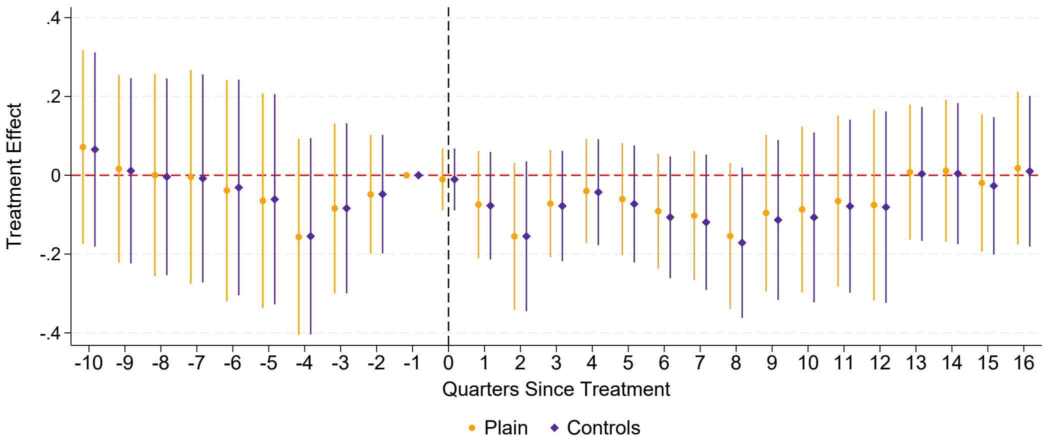
(c) % Population Closer to UPAs

Notes: This graph illustrates how (a) the median distance and (b) the median travel time to the closest emergency room (ER) evolved from 2005 to 2016 in the state of Rio de Janeiro. Panel (c) shows the percentage of the population living closer to an UPA over time. The dashed black line indicates the quarter when the first UPA was inaugurated in the state (2007-Q1). Distances and travel times from each census tract to the nearest ER were calculated using HERE maps, weighted by population, and measured by car at midnight.

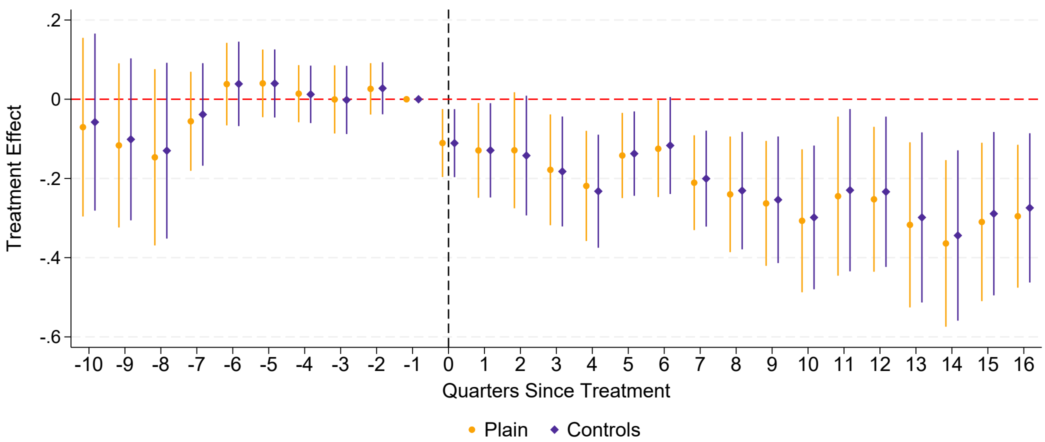
Figure 5: Event Study - Hospitals' Demand and Deaths



(a) Total Ambulatory Procedures



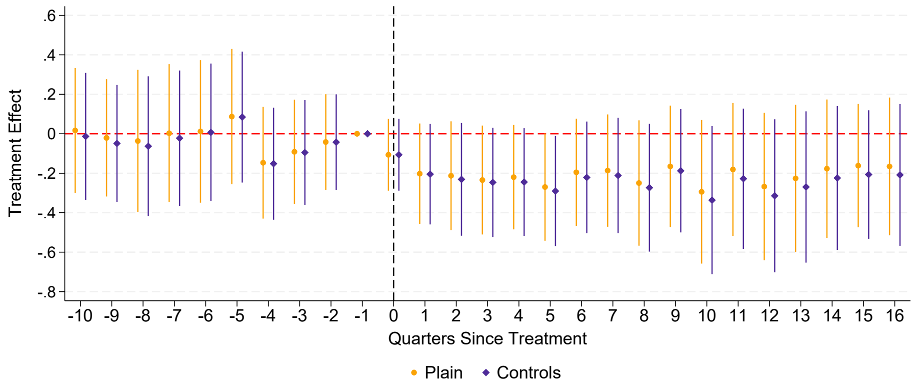
(b) Total Hospital Admissions



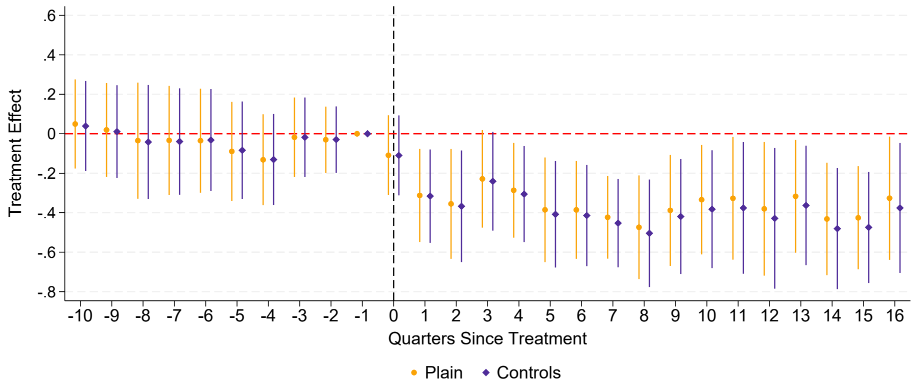
(c) Total Deaths

This graph presents the dynamic and placebo DID estimators for the effect of UPA on the IHS of hospitals' (a) total ambulatory procedures, (b) total hospital admissions, and (c) total deaths. The coefficients can be interpreted as approximate fractional changes. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

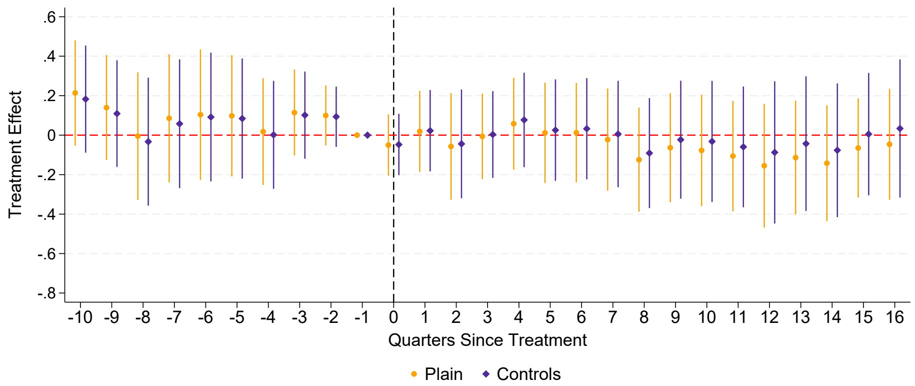
Figure 6: Event Study - Hospital Admission by Different Conditions



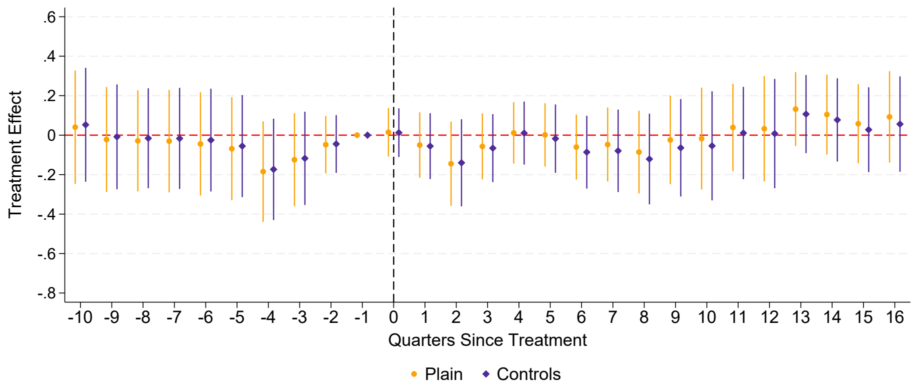
(a) Amenable to Ambulatory & Emergency Care



(b) Amenable to Ambulatory Care Only



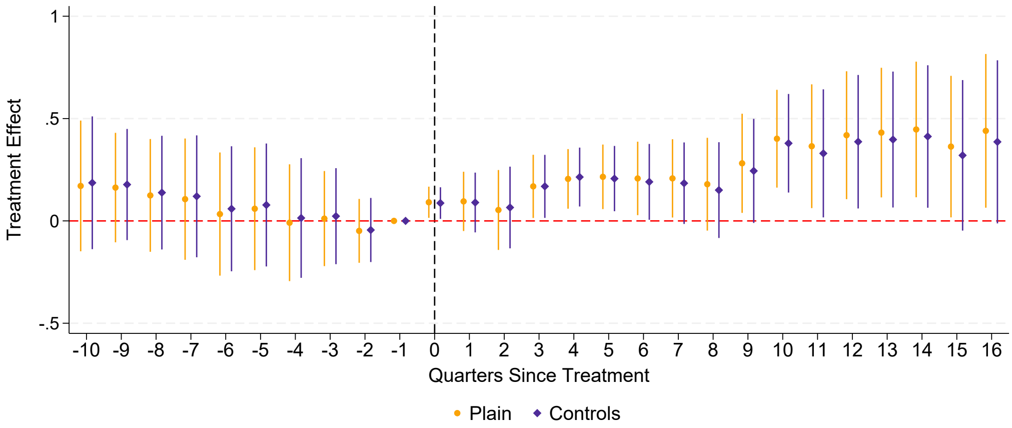
(c) Amenable to Emergency Care Only



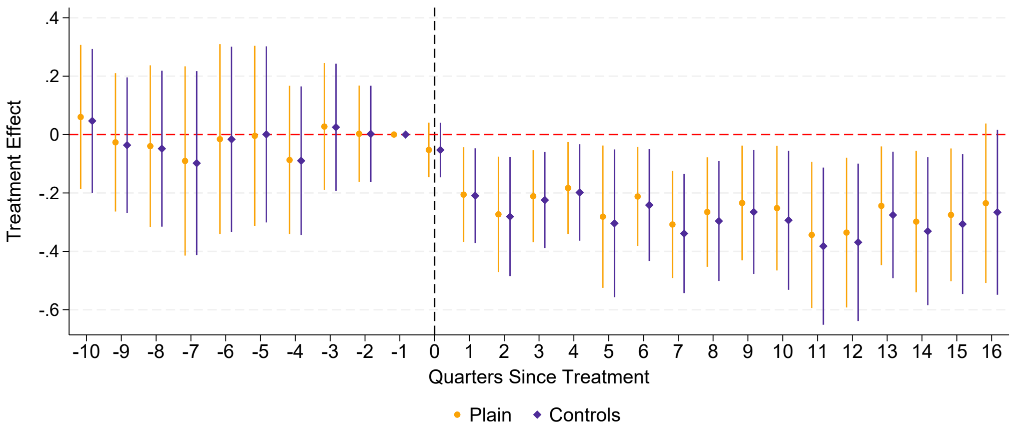
(d) Non-Amen. to Ambulatory or Emerg. Care

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on the IHS of hospital admissions categorized by different conditions: (a) admissions amenable to both ambulatory and emergency care, (b) admissions amenable to ambulatory care only, (c) admissions amenable to emergency care only, and (d) admissions non-amenable to either ambulatory or emergency care. The coefficients can be interpreted as approximate fractional changes. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

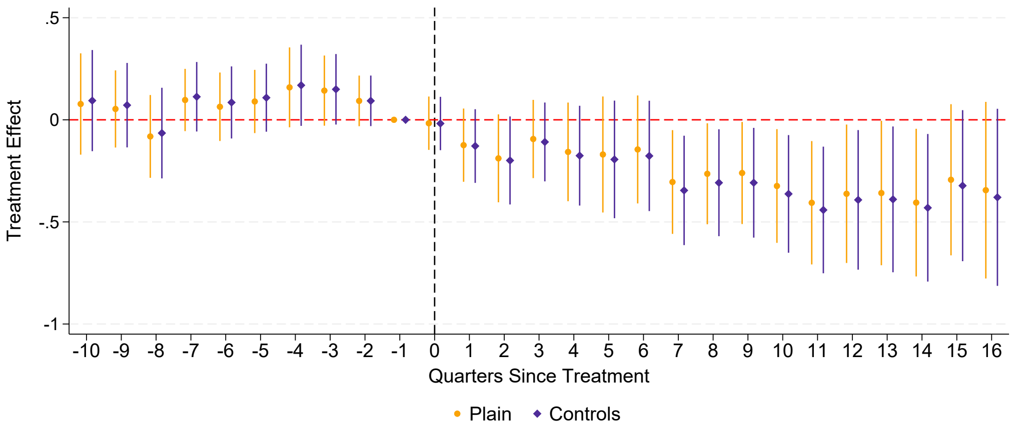
Figure 7: Event Study - Hospital Admission by Type



(a) Surgical + Obstetrics



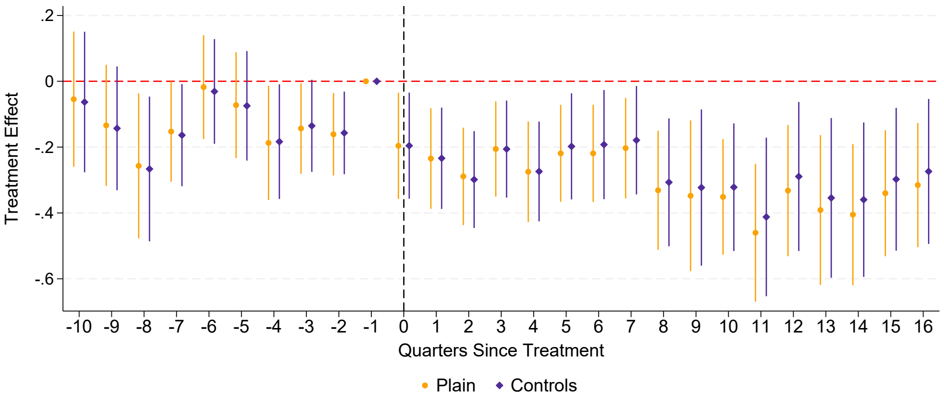
(b) Clinical



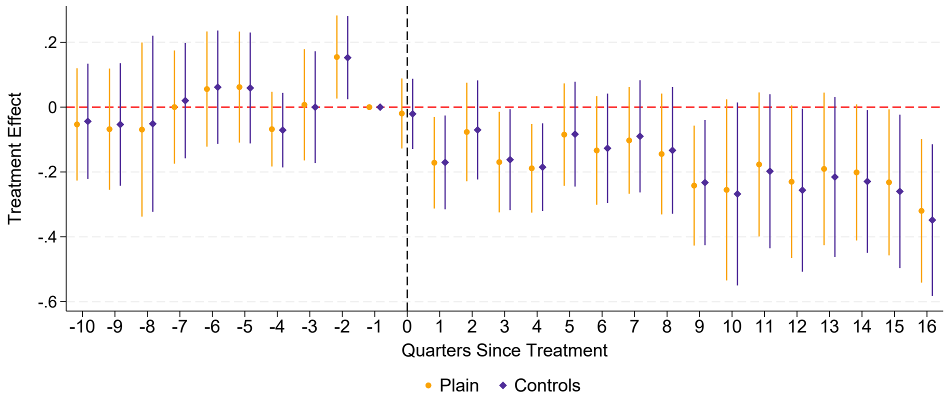
(c) Other

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on the IHS of hospital admissions categorized by different types: (a) sugical and obstetric (b) clinical, and (c) other. The coefficients can be interpreted as approximate fractional changes. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

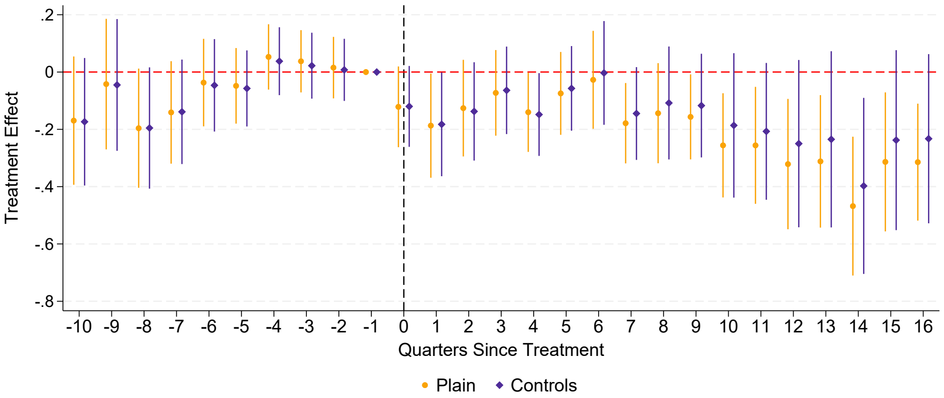
Figure 8: Event Study - Total Hospital Deaths by Different Conditions



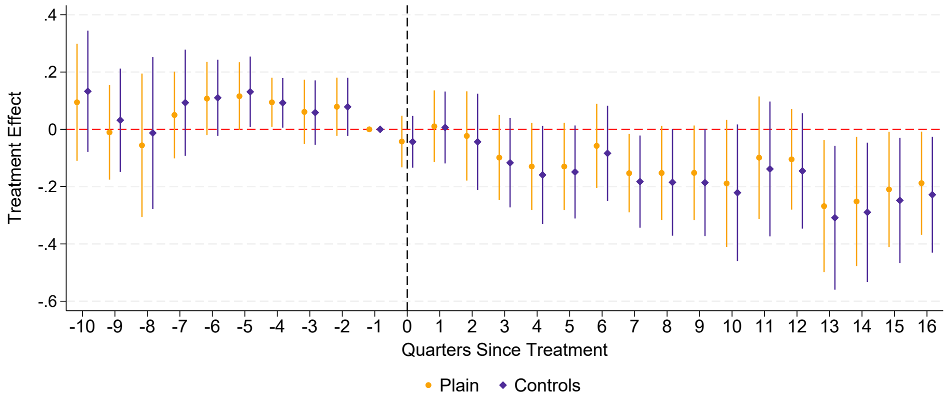
(a) Amenable to Ambulatory & Emergency Care



(b) Amenable to Ambulatory Care Only



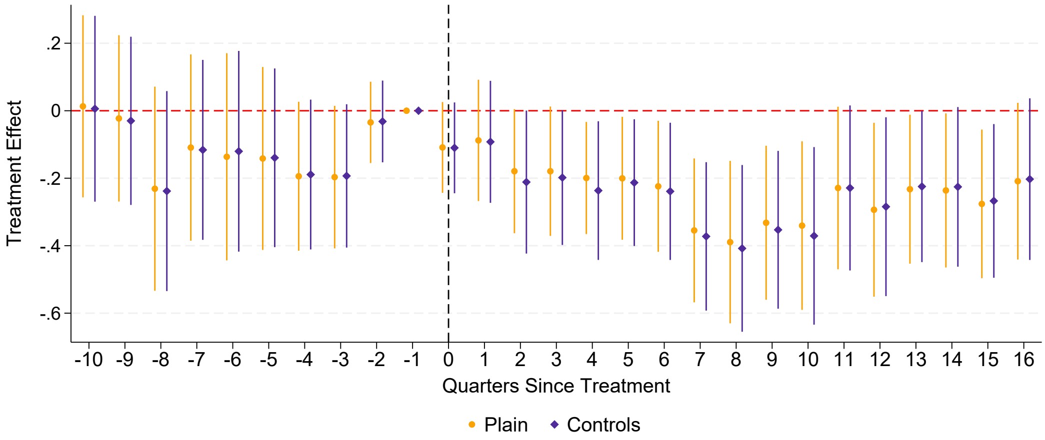
(c) Amenable to Emergency Care Only



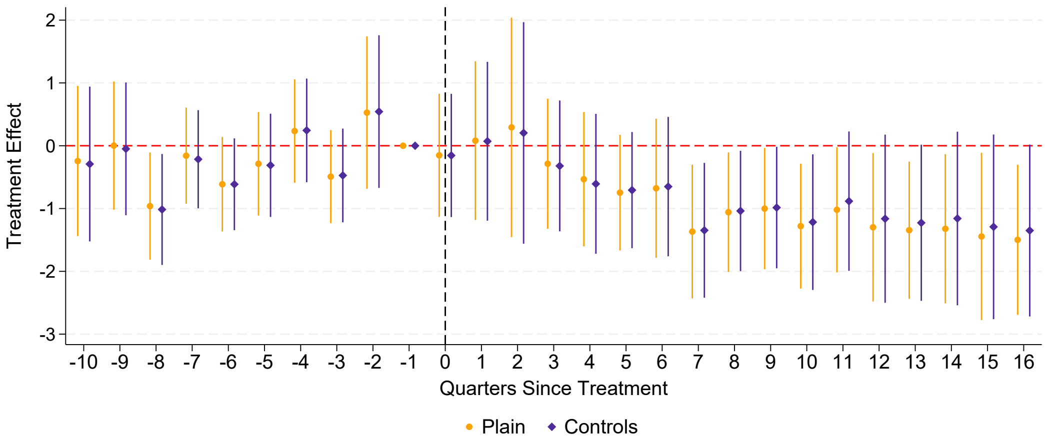
(d) Non-Amen. to Ambulatory or Emergency Care

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on the IHS of total hospital deaths categorized by different conditions: (a) deaths amenable to both ambulatory and emergency care, (b) deaths amenable to ambulatory care only, (c) deaths amenable to emergency care only, and (d) deaths non-amenable to either ambulatory or emergency care. The coefficients can be interpreted as approximate fractional changes. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

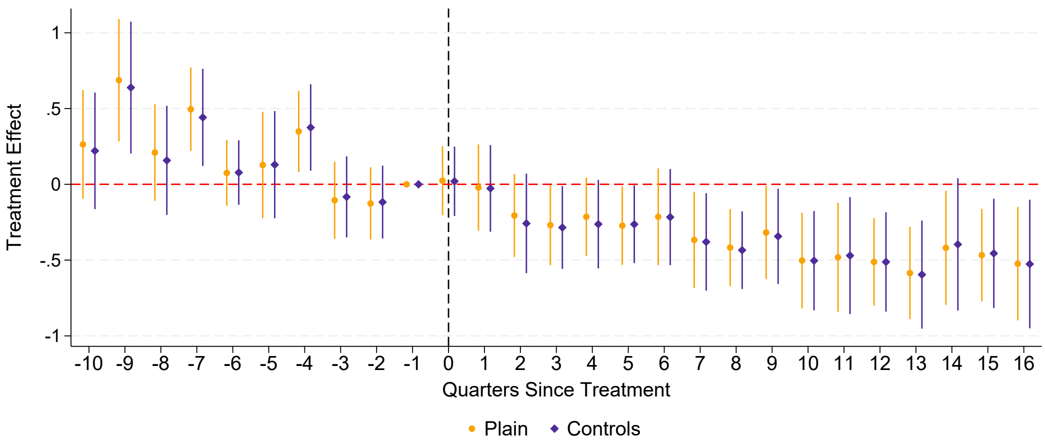
Figure 9: Event Study - Inpatient Measures



(a) Inpatient Deaths



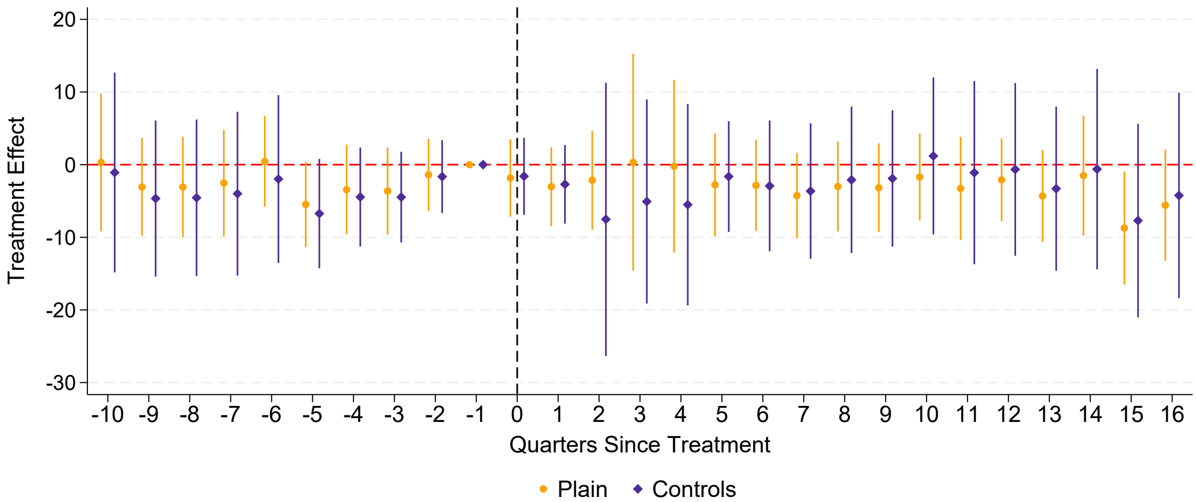
(b) % Inpatient Deaths



(c) % 24h Inpatient Deaths

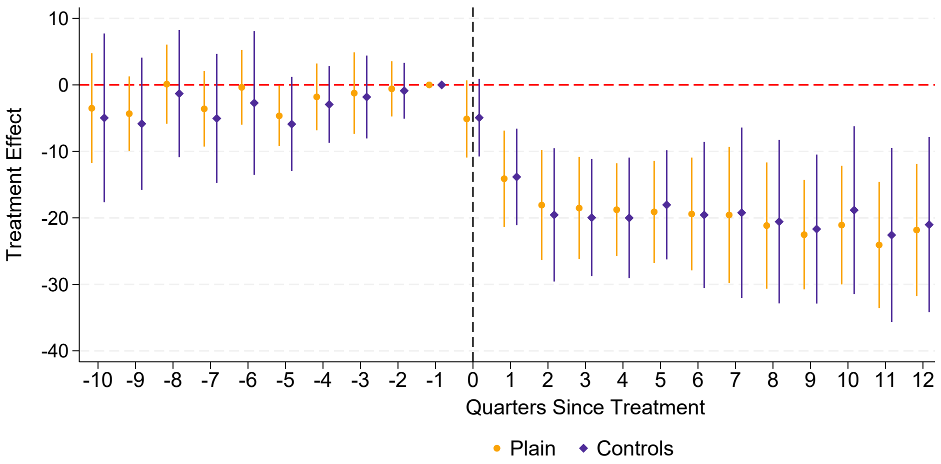
Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on (a) the IHS of inpatient deaths, (b) deaths conditional to admission (%) and (c) deaths within 24h conditional on admission (%). Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

Figure 10: Event Study – Total Deaths per 100,000, Municipality-Level Estimates

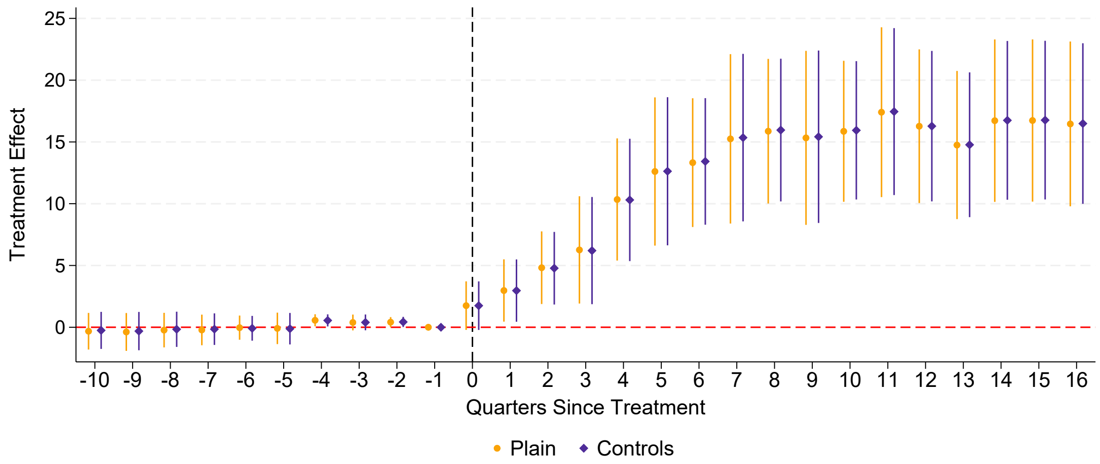


Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPAs on deaths per 100,000 people, measured at the municipality level. Treatment is defined as the presence of an UPA within the municipality. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered at the municipality level.

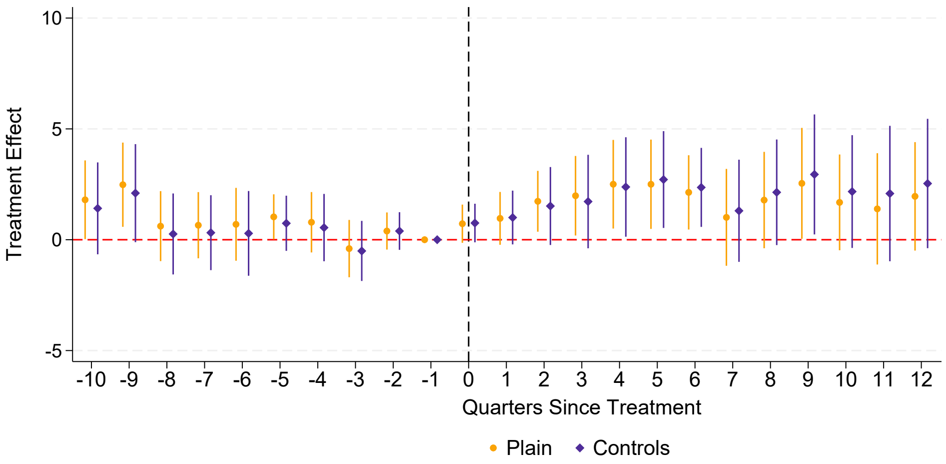
Figure 11: Event Study - Deaths per 100,000 by Location, Municipality-Level Estimates



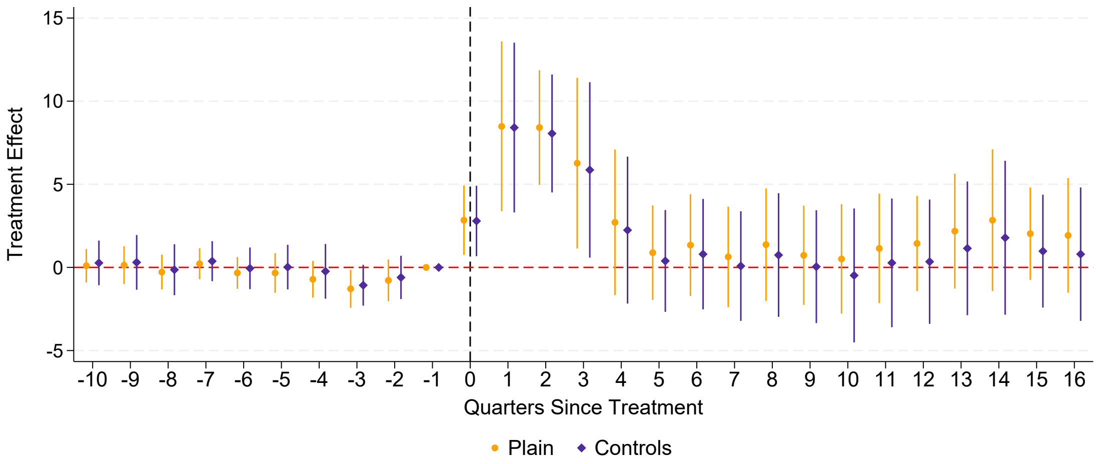
(a) Hospital



(b) UPA



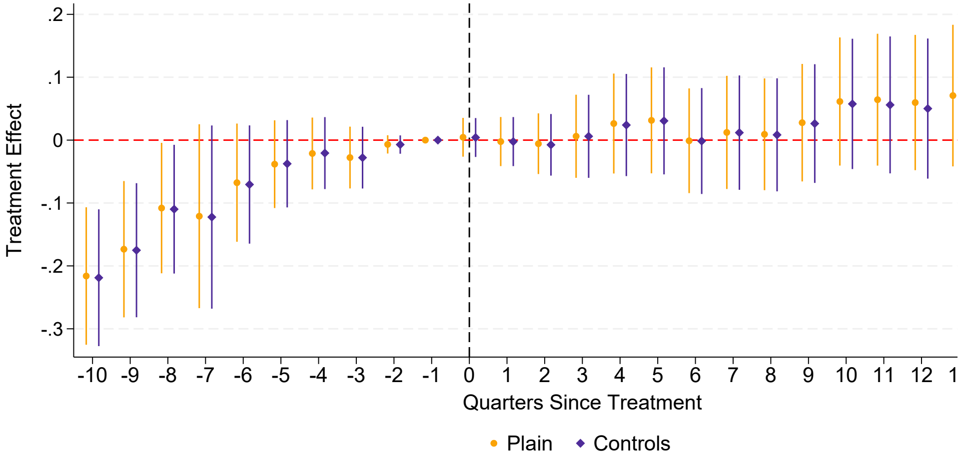
(c) Other Health Facility



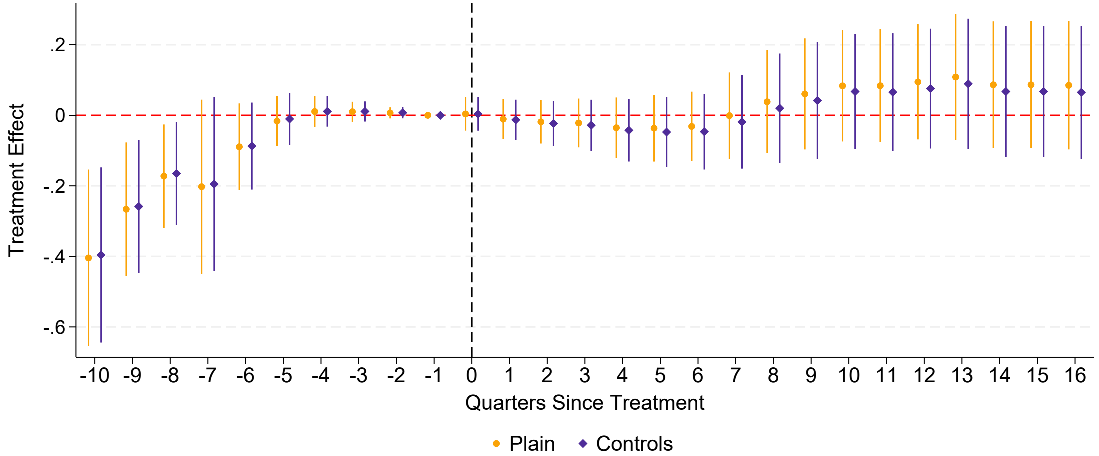
(d) Other Location

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPAs on deaths per 100,000 people, measured at the municipality level, across four different locations: (a) Hospital, (b) UPA, (c) Other Health Facilities, and (d) Other Locations. Treatment is defined as the presence of an UPA within the municipality. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered at the municipality level.

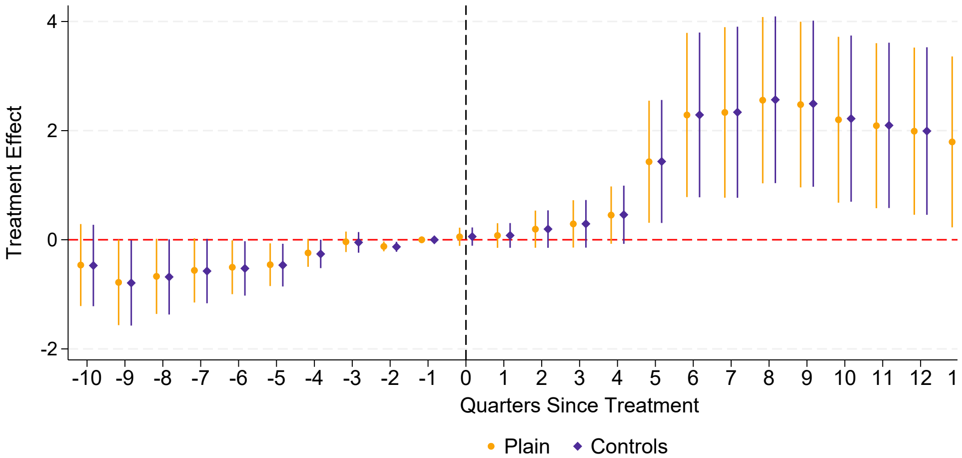
Figure 12: Event Study - Human Resources



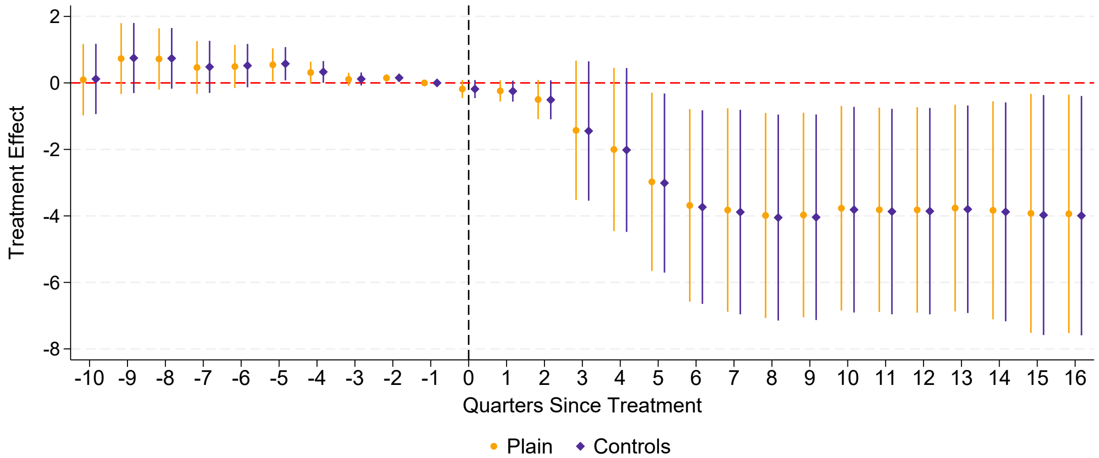
(a) N. Physicians



(b) N. Non-Physicians



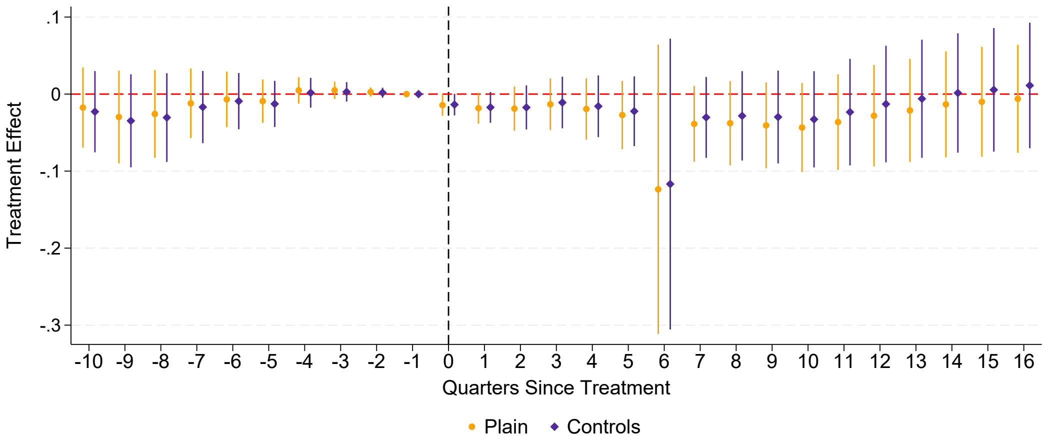
(c) Average Hours Worked - Inpatients



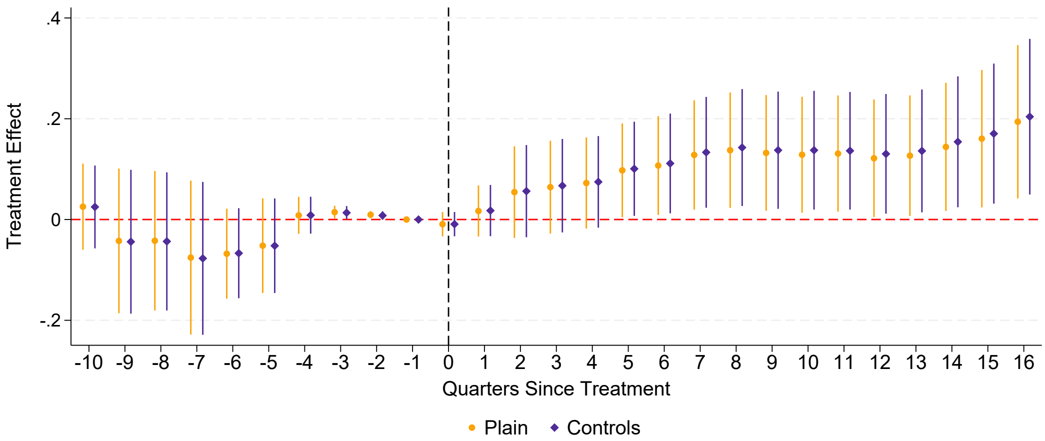
(d) Average Hours Worked - Other Activities

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on (a) the IHS number of physicians, (b) the IHS number of non-physicians, (c) the average hours worked with inpatients, and (d) the average hours worked on other activities. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

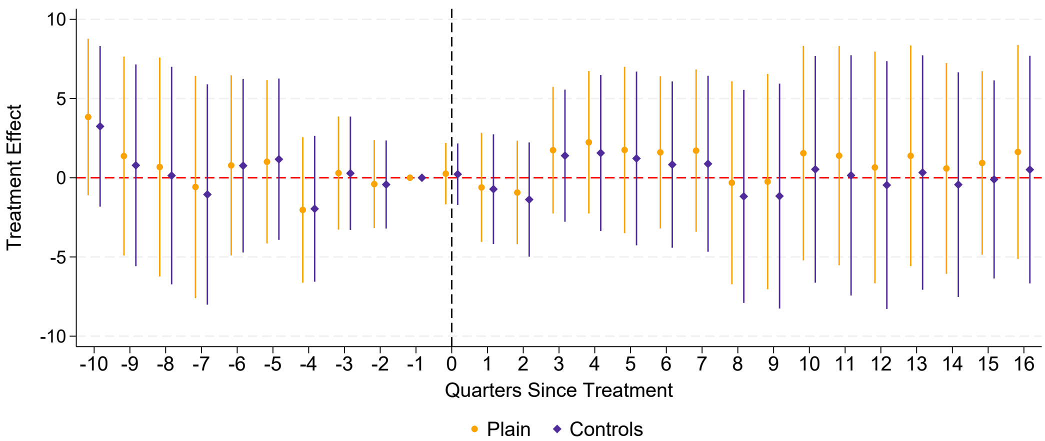
Figure 13: Event Study - Infrastructure



(a) Total Hospital Beds



(b) Total Equipments



(c) % Occupation Rate

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPA on the IHS total number of (a) hospital beds, (b) hospital equipment, and (c) occupancy rate. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other.

Appendix Tables and Figures

A Supplementary Tables

Table A.1: Ambulatory Procedures - Hospital ER and Clinics vs. UPAs

	Number of Procedures			% of Total in Each Group/Subgroup		UPA % of Total 2016
	Hospital 2006 (1)	Hospital 2016 (2)	UPA 2016 (3)	Hospital 2006 (4)	UPA 2016 (5)	(3)/[(2)+(3)] (6)
1. Health Promotion Procedures	**121376**	**94937**	**18769**	**0.36**	**0.06**	**16.51**
2. Diagnostic Procedures	**11821358**	**18015941**	**5900762**	**34.87**	**20.01**	**24.67**
2.1. Extraction of sample cells/tissues (biopsy and other forms)	518919	679232	751381	1.53	2.55	52.52
2.2. Clinical laboratoy tests	7585947	13120114	3138328	22.38	10.64	19.30
2.3. Pathological Anatomy and Cytopathology	126705	58819	0	0.37	0.00	0.00
2.4. X-rays	2750007	2245108	720970	8.11	2.44	24.31
2.5. Ultrasound, Tomography & MRI exams	267332	554546	695	0.79	0.00	0.13
2.6. Nuclear Medicine in Vivo	604	2699	0	0.00	0.00	0.00
2.7. Endoscopy	40653	36561	0	0.12	0.00	0.00
2.8. Other diagnostic methods	531191	1318863	1289389	1.57	4.37	49.43
3. Clinic Procedures	**16058324**	**20081730**	**23415687**	**47.37**	**79.39**	**53.83**
3.1. Consultations & Follow Up Appointments	15622958	18974339	23384373	46.08	79.28	55.21
3.1.1. Appointment with doctors/college degree professionals	3863789	4644232	2936913	11.40	9.96	38.74
3.1.2. Worker's Health	1	5	0	0.00	0.00	0.00
3.1.3. Urgency Pre-Hospital Care	9454	2659	2731	0.03	0.01	50.67
3.1.4. Other consultations with doctors/college degree professionals	9	23973	3666	0.00	0.01	13.26
3.1.5. Home Care	7980	2391	272	0.02	0.00	10.21
3.1.6. Emergency (in general)	3961517	7181488	8137474	11.68	27.59	53.12
3.1.7. Rehabilitation	3945	13520	0	0.01	0.00	0.00
3.1.8. Psychosocial Care	0	4040	0	0.00	0.00	0.00
3.1.9. Elderly Care	0	0	0	0.00	0.00	-
3.1.10. Nursing Care	7776213	7101944	12303317	22.94	41.71	63.40
3.1.11. Burned Patients	50	81	0	0.00	0.00	0.00
3.1.12. Endocrine, metabolic and nutritional diseases	0	0	0	0.00	0.00	-
3.1.13. Consultation in other specialties	0	0	0	0.00	0.00	-
3.1.14. Palliative Care	0	8	0	0.00	0.00	0.00
3.2. Physiotherapy	0	458673	1103	0.00	0.00	0.24
3.3. Clinical Treatments (other specialties)	196413	326509	1364	0.58	0.00	0.42
3.4. Oncology	37296	167298	0	0.11	0.00	0.00
3.5. Nephrology	56426	48703	0	0.17	0.00	0.00
3.6. Hemotherapy	86302	85776	0	0.25	0.00	0.00
3.7. Dentistry	51435	14760	28841	0.15	0.10	66.15
3.8.Treatment of injuries, poisoning	0	0	0	0.00	0.00	-
3.9. Specialized Therapies	7494	5672	6	0.02	0.00	0.11
3.10. Birth	0	0	0	0.00	0.00	-
4. Surgical Procedures	**1302472**	**1021392**	**145089**	**3.84**	**0.49**	**12.44**
4.1 Small & Skin Surgeries	1043113	964305	122703	3.08	0.42	11.29
4.2. Other Surgeries	259359	57087	22387	0.77	0.08	28.17
5. Transplant Procedures	**2487**	**1776**	**0**	**0.01**	**0.00**	**0.00**
6. Medicines	**0**	**0**	**0**	**0.00**	**0.00**	**-**
7. Prostheses, Orthoses and Special Materials	**2351**	**25558**	**0**	**0.01**	**0.00**	**0.00**
8. Complimentary Ambulatory Health Actions Performed	**597**	**603**	**14932**	**0.00**	**0.05**	**96.12**
9. Not Defined	**4594188**	**0**	**0**	**13.55**	**0.00**	**-**
Total Ambulatory Procedures	**33903153**	**39241936**	**29495239**	**100.00**	**100.00**	**42.91**

Notes: This table presents the total number and percentage distribution of ambulatory procedures performed in UPAs and SUS general hospitals with ERs in the state of Rio de Janeiro. Total procedures were calculated for hospitals in 2006 and 2016, and for UPAs in 2016. The data, sourced from SIA-SUS, is categorized into eight major groups of procedures (health promotion, clinical, diagnostic, surgical, transplant, medicines, OPSM, and complementary ambulatory health actions) plus an undefined category. The last column shows the share of total procedures performed by UPAs in these establishments in 2016.

Table A.2: Hospital Summary Statistics (baseline period 2005Q1-2007Q1)

	Mean (1)	Std Dev (2)	Min (3)	Max (4)	Data Source (5)
Ambulatory Procedures (in thousands)					
Total	74.6	90.9	0.0	650	SIA
Basic Health Care	36.0	154.8	0.0	2697	SIA
Medium Complexity	36.1	43.7	0.0	299	SIA
High Complexity	0.3	1.2	0.0	14	SIA
Hospital Admissions					
Total	706.1	700.8	0.0	4396	SIH
Amenable to Ambulatory & Emergency Care	85.4	79.9	0.0	500	SIH
Amenable to Ambulatory Care Only	96.0	88.3	0.0	495	SIH
Amenable to Emergency Care Only	160.2	202.4	0.0	1150	SIH
Non-Amenable to Ambulatory or Emergency Care	364.6	416.3	0.0	2590	SIH
Total Deaths					
Total	102.3	152.7	0.0	879	SIM
Amenable to Ambulatory & Emergency Care	14.6	20.3	0.0	105	SIM
Amenable to Ambulatory Care Only	17.1	26.8	0.0	173	SIM
Amenable to Emergency Care Only	30.0	49.4	0.0	258	SIM
Non-Amenable to Ambulatory or Emergency Care	40.6	61.4	0.0	370	SIM
Inpatient Deaths					
Total	50.6	74.7	0.0	537	SIH
Amenable to Ambulatory & Emergency Care	11.0	16.7	0.0	114	SIH
Amenable to Ambulatory Care Only	7.7	11.0	0.0	84	SIH
Amenable to Emergency Care Only	20.5	35.8	0.0	252	SIH
Non-Amenable to Ambulatory or Emergency Care	11.3	19.1	0.0	142	SIH
Other Hospital Measures					
% Hospital Inpatient Deaths	6.3	5.3	0.0	34.1	SIH
% Hospital inpatient deaths within 24h of admission	1.3	1.4	0.0	9.5	SIH
Bed Occupancy Rate (%)	40.7	24.9	0.0	104.9	SIH-CNES
No. of days when capacity is over 85%	5.6	16.3	0.0	92	SIH-CNES
Human Resources & Infrastructure					
No. Professionals	252.3	502.8	2	5682	CNES
No. Physicians	80.5	120.8	2	1290	CNES
Avg. hrs/week worked per SUS professional	26.9	9.1	8	99	CNES
No. Hospitalization Beds	118.6	117.0	0	942	CNES
No beds for obs in amb and emerg structure	16.3	19.4	0	116	CNES
Total Equipment	88.7	190.8	1	2338	CNES

Notes: This table provides summary statistics for the main variables used in the hospital-level analysis during the baseline period (2005Q1-2007Q1), along with their sources. The sample includes 116 hospitals. Variables are measured at the hospital-quarter level. Data sources listed in column 5 are detailed in Appendix D.

Table A.3: City Summary Statistics (baseline period 2005-2007Q1)

	Mean (1)	Std Dev (2)	Min (3)	Max (4)	Data Source (5)
Local Deaths per 100,000 Inhabitants by Cause					
Total	172.1	38.1	29.5	357.3	SIM
Amenable to Primary and Emergency Care	23.3	12.8	0.0	102.2	SIM
Amenable to Primary Care Only	27.2	12.4	0.0	84.3	SIM
Amenable to Emergency Care Only	53.8	17.4	0.0	152.7	SIM
Non-Amenable to Primary or Emergency Care	67.8	22.5	0.0	201.0	SIM
Local Deaths per 100,000 inhabitants by Location					
Hospital	126.4	34.4	29.5	268.0	SIM
UPA	0.0	0.0	0.0	0.0	SIM
Other Health Facility	4.9	11.6	0.0	110.0	SIM
Household	27.0	13.8	0.0	112.5	SIM
Street	8.8	6.6	0.0	40.0	SIM
Other	4.5	5.2	0.0	38.1	SIM
Health System					
% FHP Coverage	50.5	37.7	0.0	100.0	DAB
Routine Consultation	95.5	133.2	0.0	3111.8	SIAB
Physician Consultations	180.1	133.7	0.0	698.9	SIAB
Exams Prescribed	64.4	91.2	0.0	1763.0	SIAB
Diabetics Registered	42.1	25.0	0.0	114.4	SIAB
Diabetics Followed-up	92.2	18.7	0.0	100.0	SIAB
SUS Ambulance Service	0.1	0.3	0.0	1.0	CNES
SUS Hospital eds per 100,000 inhabitants	374.1	518.1	0.0	3665.5	CNES
Controls					
GDP Per Capita (2010 reais)	24682.2	43354.7	37.0	328499.5	IBGE
Dummy if City Party = State Party	0.1	0.3	0.0	1.0	TSE
PBF: Value (R$) per 1,000 people	1958.2	1006.2	0.0	5322.4	MSD

Notes: This table provides summary statistics for the main variables used in the municipality-level analysis during the baseline period (2005Q1-2007Q1), along with their sources. The sample includes 92 cities. Variables are measured at the city-quarter level. Data sources listed in column 5 are detailed in Appendix D.

Table A.4: UPA Effects on Inpatient Outcomes: By Specific Causes (Part 1), Hospital-Level Estimates

	Hosp Admissions	Inpatient Deaths	% Inpatient Deaths	%24h Inpatient Deaths	Hosp Adm Mean at
	(1)	(2)	(3)	(4)	Baseline
Total					
	-0.072	-0.249***	-0.813*	-0.348***	723.25
	(0.072)	(0.088)	(0.455)	(0.121)	
Amenable to Ambulatory \& Emergency Care					
Total	-0.236*	-0.213*	0.300	-0.311	79.29
	(0.142)	(0.127)	(1.128)	(0.608)	
Diabetes Mellitus-Acute	-0.189	-0.162*	-0.178	0.471	14.61
	(0.129)	(0.087)	(1.521)	(0.696)	
Bacterial Pneumonia	0.066	0.062	4.405	-0.391	14.89
	(0.134)	(0.074)	(3.103)	(1.215)	
Stroke/Cerebral Infaction	-0.318**	-0.091	1.616	-0.595	15.64
	(0.148)	(0.114)	(1.846)	(0.684)	
Asthma \& COPD	-0.189	-0.162*	-0.178	0.471	14.61
	(0.129)	(0.087)	(1.521)	(0.696)	
Other	-0.207*	-0.094	-1.589	-1.293	34.15
	(0.114)	(0.124)	(2.325)	(1.929)	
Amenable to Ambulatory Care Only					
Total	-0.378***	-0.389***	-0.859	-0.328	96.29
	(0.124)	(0.144)	(0.639)	(0.292)	
Gastroenteritis	-0.206	-0.092**	-3.765***	0.234	9.46
	(0.135)	(0.044)	(0.801)	(0.491)	
Urinary Tract Infection	-0.081	-0.127*	-0.462	-0.288	12.97
	(0.109)	(0.075)	(1.125)	(0.644)	
Congestive Heart Failure	-0.323**	-0.210**	0.208	-1.555	14.48
	(0.126)	(0.105)	(2.028)	(1.022)	
Cellulitis \& Erysipelas	-0.131	0.031	0.104	-0.385	10.39
	(0.133)	(0.052)	(1.014)	(0.689)	
Other	-0.431***	-0.352***	-0.681	-0.051	48.99
	(0.117)	(0.115)	(0.993)	(0.319)	
Hospital & Time FE	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	-
Mean at Baseline	723.25	52.24	6.35	1.33	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The first two dependent variables analyzed are the IHS of hospital admissions and inpatient deaths. Columns 3 and 4 show total inpatient deaths and inpatient deaths occurring within 24 hours, both conditional on total admissions and measured as percentages. Results are displayed by specific causes within each of the four emergency/ambulatory care groups constructed (see Appendix D for more details on the selection and construction of these groups and subgroups). Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS.

Table A.5: UPA Effects on Inpatient Outcomes: By Specific Causes (Part 2), Hospital-Level Estimates

	Hosp Admissions	Inpatient Deaths	% Inpatient Deaths	%24h Inpatient Deaths	Hosp Adm Mean at
	(1)	(2)	(3)	(4)	Baseline
Total					
	-0.072	-0.249***	-0.813*	-0.348***	723.25
	(0.072)	(0.088)	(0.455)	(0.121)	
Amenable to Emergency Care Only					
Total	-0.018	-0.224**	-1.249	-0.397	158.84
	(0.126)	(0.108)	(0.975)	(0.364)	
External Causes	-0.149	-0.166*	-1.968*	0.206	72.32
	(0.092)	(0.091)	(1.047)	(0.376)	
AMI	-0.316***	-0.180*	-0.436	-4.121	8.82
	(0.119)	(0.105)	(3.422)	(2.669)	
Pneumonia (Except Bacterial)	-0.011	-0.168	-2.152	0.160	24.71
	(0.138)	(0.125)	(2.105)	(0.502)	
Other	0.052	-0.124	-1.488	-0.417	53
	(0.125)	(0.100)	(1.760)	(0.726)	
Non-Amenable to Ambulatory or Emergency Care					
Total	-0.022	-0.260**	-1.137*	-0.526**	388.84
	(0.088)	(0.111)	(0.636)	(0.220)	
Cancer	-0.086	-0.132	-5.234*	-0.293	15.71
	(0.164)	(0.125)	(3.091)	(0.951)	
Digestive	0.016	-0.026	-0.368	-0.072	51.63
	(0.118)	(0.086)	(0.719)	(0.291)	
Delivery	0.245**	0.258**	-0.661	-0.264	118.68
	(0.105)	(0.113)	(0.899)	(0.385)	
Diseases of Veins \& Arteries	0.206*	0.012	-1.545	-0.654	15.25
	(0.124)	(0.086)	(1.705)	(0.662)	
Other	-0.066	-0.242*	-0.775	-0.342	202.82
	(0.086)	(0.133)	(0.698)	(0.230)	
Hospital & Time FE	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	-
Mean at Baseline	723.25	52.24	6.35	1.33	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The first two dependent variables analyzed are the IHS of hospital admissions and inpatient deaths. Columns 3 and 4 show total inpatient deaths and inpatient deaths occurring within 24 hours, both conditional on total admissions and measured as percentages. Results are displayed by specific causes within each of the four emergency/ambulatory care groups constructed (see Appendix D for more details on the selection and construction of these groups and subgroups). Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS.

Table A.6: UPA Effects on Inpatient Outcomes by Elective/Emergency Admissions, Hospital-Level Estimates

	Hosp Admissions	Inpatient Deaths	% Inpatient Deaths	%24h Inpatient Deaths	Hosp Adm Mean at
	(1)	(2)	(3)	(4)	Baseline
Total					
	-0.072	-0.249***	-0.813*	-0.348***	723.25
	(0.072)	(0.088)	(0.455)	(0.121)	
Type of Admission					
Elective	0.269	-0.010	-1.357**	-0.452	68.95
	(0.227)	(0.099)	(0.535)	(0.363)	
Emergency	-0.021	-0.168*	-0.801	-0.327**	584.65
	(0.108)	(0.098)	(0.599)	(0.162)	
Hospital & Time FE	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	-
Mean at Baseline	723.25	52.24	6.35	1.33	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The first two dependent variables analyzed are the IHS of hospital admissions and inpatient deaths. Columns 3 and 4 show total inpatient deaths and inpatient deaths occurring within 24 hours, both conditional on total admissions and measured as percentages. Results are presented by elective and emergency admissions. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample includes 116 hospitals. Standard errors are clustered among hospitals that are geographically close. ***p<0.01, **p<0.05, *p<0.1. Baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in levels instead of IHS.

Table A.7: Ambulatory Procedures Per Capita by Location, City-Level Estimates

		Location				
	Total (1)	Hospital (2)	UPAs (3)	FHP (4)	Other Health Facilty (5)	Mean at Baseline
All	-0.181 (0.416)	-0.294* (0.178)	0.386*** (0.075)	-0.105 (0.255)	-0.168 (0.174)	5.04
City & Time FE	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	-
Mean at Baseline	5.04	1.11	0	2.5	1.44	-

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are ambulatory procedures performed per capita across four different locations: hospitals, UPAs, establishments with basic healthcare programs (FHP/ACS/NASF), and other health facilities. The city-level results are not directly comparable to the hospital results shown earlier because the latter includes only hospitals with an ER. Additionally, the hospital analysis models the impact of an UPA opening within 4.5 km of the hospital, whereas the city analysis considers an UPA opening anywhere in the city, resulting in a much broader "catchment" area. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in rates per 100,000 inhabitants.

Table A.8: Deaths per 100,000 by Cause and Demographics
City-Level Estimates

		Age					Gender		Race		Years of Schooling				
	Total (1)	0 to 4 (2)	5 to 17 (3)	18 to 44 (4)	45 to 64 (5)	65+ (6)	Female (7)	Male (8)	White (9)	Non-White (10)	0 to 3 (11)	4 to 7 (12)	8 to 11 (13)	12+ (14)	Mean at Baseline
Total															
	-2.989 (4.424)	-0.178 (0.505)	-0.581 (0.404)	-1.462 (1.304)	-0.673 (2.032)	-0.095 (2.955)	-1.590 (1.962)	-1.462 (3.647)	-3.163 (2.784)	1.760 (2.230)	-0.487 (2.751)	-2.679 (2.098)	0.063 (1.365)	0.243 (0.663)	169.31
Amenable to Ambulatory/Emergency Care															
Amenable to Ambulatory & Emergency Care	-1.206 (1.358)	0.051 (0.044)	0.012 (0.039)	-0.162 (0.174)	-0.664 (0.675)	-0.442 (1.099)	-0.711 (0.902)	-0.501 (0.667)	-0.769 (1.011)	0.008 (0.741)	-0.370 (0.774)	-0.644 (0.537)	-0.568 (0.355)	0.110 (0.179)	22.4
Amenable to Ambulatory Care Only	0.443 (1.468)	-0.086 (0.107)	0.003 (0.095)	0.287 (0.320)	0.629 (0.608)	-0.389 (0.907)	-0.348 (0.913)	0.789 (1.170)	-0.333 (1.088)	0.997 (1.025)	0.361 (1.049)	-0.284 (0.636)	-0.296 (0.318)	-0.032 (0.195)	25.81
Amenable to Emergency Care Only	-0.812 (2.117)	-0.122 (0.267)	-0.495 (0.369)	-1.445 (0.910)	-1.275 (1.054)	2.525* (1.323)	1.505 (1.060)	-2.365 (1.840)	0.198 (1.365)	-0.568 (1.288)	1.355 (1.232)	-1.550 (1.064)	0.247 (0.666)	-0.255 (0.364)	52.85
Non-Amenable to Ambulatory or Emergency Care	-1.414 (2.411)	-0.020 (0.398)	-0.101 (0.190)	-0.141 (0.723)	0.637 (1.026)	-1.788 (1.819)	-2.036 (1.481)	0.616 (1.700)	-2.259 (1.501)	1.323 (1.440)	-1.833 (1.630)	-0.201 (1.025)	0.680 (0.753)	0.419 (0.406)	68.25
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Mean at Baseline	169.31	6.23	2.00	24.87	42.48	93.73	69.85	99.44	97.39	65.92	61.16	35.92	15.21	6.98	-

This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are deaths per 100,000 people by cause and age, gender, race and years of schooling. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in rates per 100,000 inhabitants.

Table A.9: Deaths per 100,000 by Specific Causes and Location, City-Level Estimates (Part 1)

		Location						
	Total (1)	Hospital (2)	UPA (3)	Other Health Facility (4)	Household (5)	Street (6)	Other (7)	Mean at Baseline
Total								
	-2.989	-19.710***	12.487***	1.878*	0.694	-0.595	2.029	169.31
	(4.001)	(5.079)	(2.493)	(0.980)	(1.248)	(0.844)	(1.668)	
Amenable to Ambulatory & Emergency Care								
Total	-1.206	-3.840***	1.579***	0.294	0.262	0.034	0.463**	22.40
	(1.229)	(1.373)	(0.338)	(0.209)	(0.291)	(0.040)	(0.216)	
Diabetes Mellitus-Acute	-0.401	-0.831	0.231***	0.052	0.031	0.009	0.106*	4.81
	(0.606)	(0.625)	(0.088)	(0.062)	(0.125)	(0.010)	(0.057)	
Bacterial Pneumonia	0.057	-0.053	0.083**	-0.005	0.013	0.005	0.015	0.80
	(0.209)	(0.155)	(0.034)	(0.039)	(0.109)	(0.006)	(0.024)	
Stroke/Cerebral Infaction	0.090	-0.950*	0.615***	0.044	0.224	0.012	0.145	7.86
	(0.546)	(0.527)	(0.153)	(0.121)	(0.215)	(0.018)	(0.089)	
Asthma \& COPD	-0.401	-0.831	0.231***	0.052	0.031	0.009	0.106*	4.81
	(0.606)	(0.625)	(0.088)	(0.062)	(0.125)	(0.010)	(0.057)	
Other	-0.951	-2.005***	0.650***	0.203**	-0.006	0.009	0.197**	8.93
	(0.825)	(0.767)	(0.137)	(0.093)	(0.172)	(0.028)	(0.100)	
Amenable to Ambulatory Care Only								
Total	0.443	-3.512**	2.521***	0.433*	0.203	0.068	0.645*	25.81
	(1.395)	(1.492)	(0.542)	(0.254)	(0.452)	(0.131)	(0.356)	
Gastroenteritis	0.128	0.045	0.013	0.033	0.024	0.009	0.004	0.21
	(0.120)	(0.105)	(0.021)	(0.042)	(0.061)	(0.013)	(0.004)	
Urinary Tract Infection	0.162	-0.333	0.305***	0.061	0.026	-0.005	0.108**	1.41
	(0.365)	(0.364)	(0.086)	(0.054)	(0.052)	(0.004)	(0.046)	
Congestive Heart Failure	-0.765	-0.948**	0.242***	0.086	-0.104	-0.016	-0.054	2.88
	(0.725)	(0.483)	(0.066)	(0.103)	(0.123)	(0.013)	(0.095)	
Cellulitis \& Erysipelas	0.007	0.020	-0.012	-0.011	0.008	0.000***	0.002	0.07
	(0.124)	(0.116)	(0.022)	(0.018)	(0.008)	(0.000)	(0.007)	
Other	0.912	-2.297	1.973***	0.265	0.250	0.080	0.586**	21.23
	(1.602)	(1.475)	(0.417)	(0.233)	(0.470)	(0.132)	(0.278)	
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Mean at Baseline	169.31	124.66	0	4.48	24.76	8.83	5.47	

Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are deaths per 100,000 people by cause and across six different locations: hospitals, UPAs, other health facilities, households, streets, and other places. The city-level results are not directly comparable to the hospital results shown earlier because the latter includes only hospitals with an ER. Additionally, the hospital analysis models the impact of an UPA opening within 4.5 km of the hospital, whereas the city analysis considers an UPA opening anywhere in the city, resulting in a much broader "catchment" area. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in rates per 100,000 inhabitants.

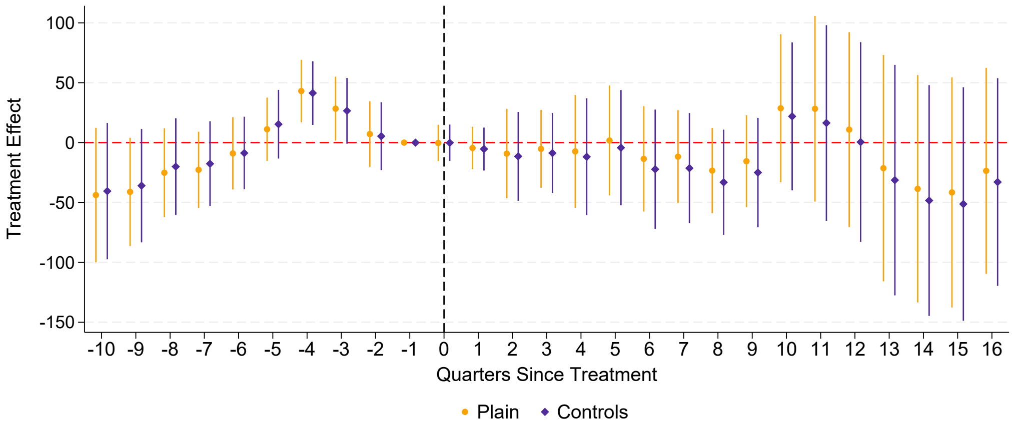
Table A.10: Deaths per 100,000 by Specific Causes and Location, City-Level Estimates (Part 2)

		Location						
	Total (1)	Hospital (2)	UPA (3)	Other Health Facility (4)	Household (5)	Street (6)	Other (7)	Mean at Baseline
Total								
	-2.989	-19.710***	12.487***	1.878*	0.694	-0.595	2.029	169.31
	(4.001)	(5.079)	(2.493)	(0.980)	(1.248)	(0.844)	(1.668)	
Amenable to Emergency Care Only								
Total	-0.812	-4.798***	4.268***	0.809*	-0.894	-0.617	0.292	52.85
	(2.172)	(1.619)	(0.908)	(0.454)	(0.886)	(0.779)	(0.763)	
External Causes	-2.631	-2.098***	0.607***	0.091	-0.359	-0.657	-0.327	20.29
	(1.893)	(0.673)	(0.183)	(0.075)	(0.776)	(0.769)	(0.533)	
AMI	0.601	-1.464	1.823***	0.283	-0.536**	0.100	0.401	14.54
	(1.268)	(1.050)	(0.364)	(0.253)	(0.254)	(0.127)	(0.317)	
Pneumonia (Except Bacterial)	-0.183	-1.670*	1.132***	0.187	0.043	-0.035	0.141	5.7
	(0.740)	(0.878)	(0.253)	(0.167)	(0.092)	(0.028)	(0.089)	
Other	1.401	0.435	0.706***	0.247**	-0.042	-0.025	0.077	12.32
	(0.876)	(0.879)	(0.207)	(0.107)	(0.230)	(0.058)	(0.126)	
Non-Amenable to Ambulatory or Emergency Care								
Total	-1.414	-7.561***	4.118***	0.342	1.123	-0.080	0.629	68.25
	(2.373)	(2.351)	(0.817)	(0.492)	(0.835)	(0.188)	(0.608)	
Cancer	0.298	-0.987	1.027***	0.023	-0.059	0.016	0.264	26.06
	(1.469)	(1.523)	(0.271)	(0.152)	(0.325)	(0.035)	(0.164)	
Digestive	-0.514	-0.793*	0.182***	0.011	0.211	-0.086	-0.042	4.84
	(0.453)	(0.422)	(0.052)	(0.057)	(0.199)	(0.135)	(0.068)	
Delivery	-0.038	-0.039	0.001	0.001***	0.000***	0.000	-0.002	.01
	(0.026)	(0.025)	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)	
Diseases of Veins \& Arteries	-0.109	-0.226	0.040**	-0.009	0.029	0.010	0.049**	1.26
	(0.299)	(0.287)	(0.020)	(0.025)	(0.041)	(0.011)	(0.024)	
Other	-1.161	-5.741***	2.908***	0.306	0.971	-0.010	0.408	37.34
	(1.742)	(1.550)	(0.593)	(0.347)	(0.770)	(0.188)	(0.468)	
City & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Mean at Baseline	169.31	124.66	0	4.48	24.76	8.83	5.47	

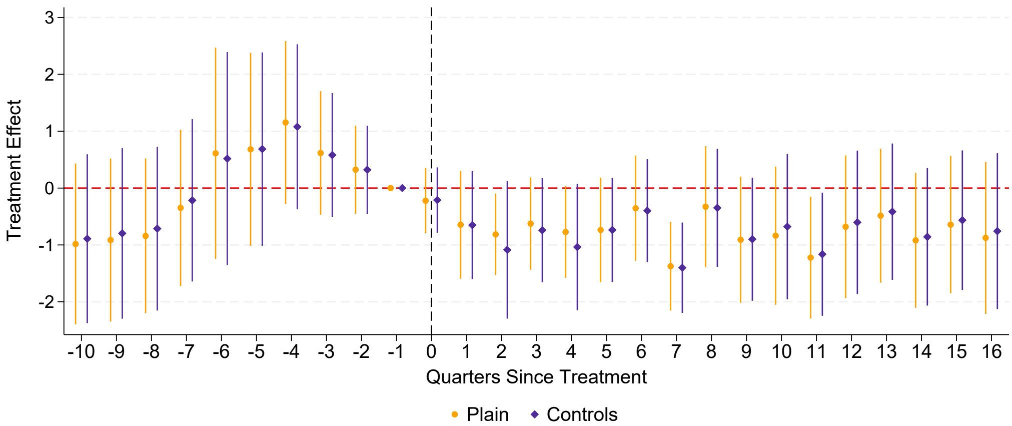
Notes: This table displays the weighted average of the dynamic two-way fixed effects estimators proposed by de Chaisemartin and D'Haultfoeuille (2022). The dependent variables are deaths per 100,000 people by cause and across six different locations: hospitals, UPAs, other health facilities, households, streets, and other places. The city-level results are not directly comparable to the hospital results shown earlier because the latter includes only hospitals with an ER. Additionally, the hospital analysis models the impact of an UPA opening within 4.5 km of the hospital, whereas the city analysis considers an UPA opening anywhere in the city, resulting in a much broader "catchment" area. Controls include city GDP, Bolsa Família transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. The sample consists of 92 municipalities. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1. The baseline refers to 2007/Q1, the quarter before the introduction of the first UPA in Rio de Janeiro, and is measured in rates per 100,000 inhabitants.

B Supplementary Figures

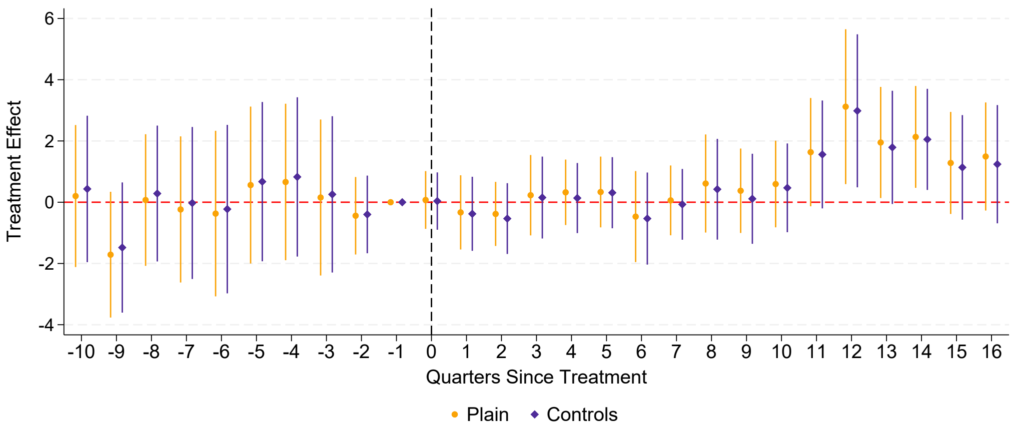
Figure B.1: Event Study - Inpatient Profile



(a) Mean Income



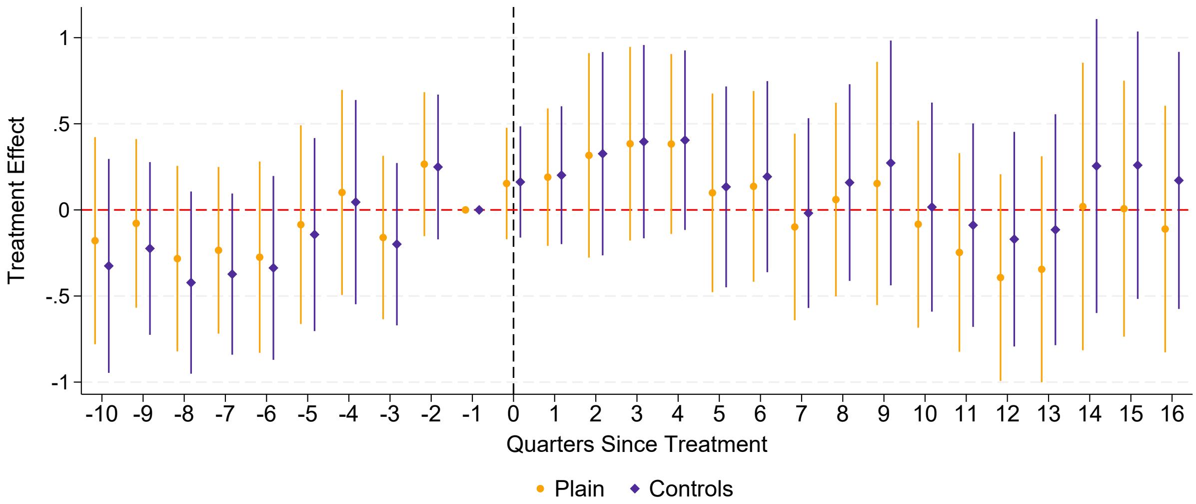
(b) Age



(c) % Female

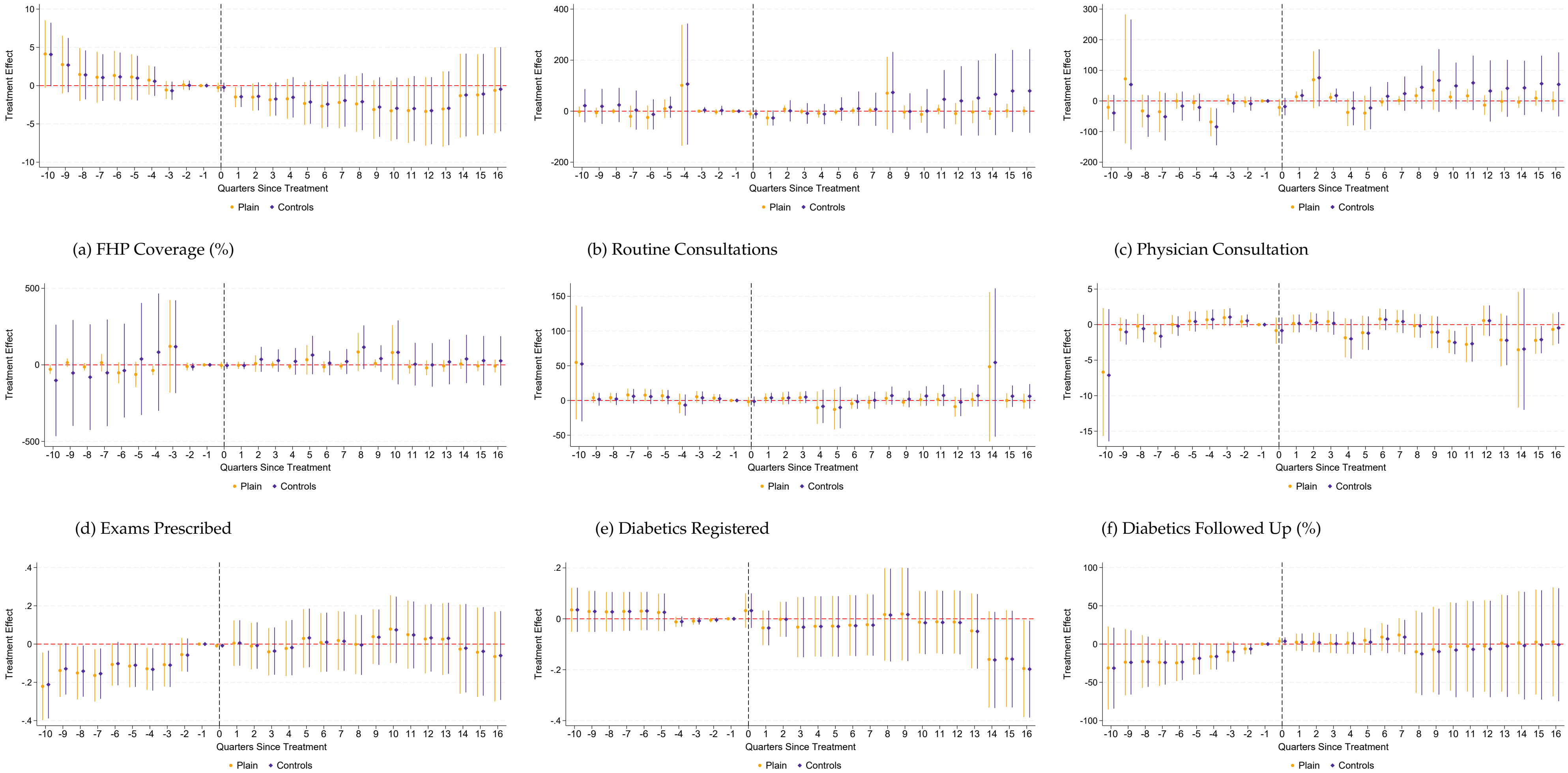
Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPAs on the average income, age, and gender of hospital inpatients. Treatment is defined as the presence of an UPA within a 4.5 km catchment area of the hospital. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, the political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered among hospitals that are geographically close to each other..

Figure B.2: Event Study – Total Predicted Deaths per 100,000, Municipality-Level Estimates



Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPAs on predicted mortality per 100,000 people, measured at the municipality level. Treatment is defined as the presence of an UPA within the municipality. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered at the municipality level.

Figure B.3: Event Study - Health System, Municipality-Level Estimates



(a) FHP Coverage (%)
(b) Routine Consultations
(c) Physician Consultation
(d) Exams Prescribed
(e) Diabetics Registered
(f) Diabetics Followed Up (%)
(g) SUS Ambulance Service
(h) Net New General Hospitals w/ ER
(i) SUS Hospital Beds

Notes: This graph presents the dynamic and placebo DID estimators for the effect of UPAs on on various components of primary care and other layers of the health system: (a) Family Health Program coverage; (b) routine consultations performed per 1,000 inhabitants; (c) consultations performed by physicians per 1,000 inhabitants; (d) exams prescribed per 1,000 inhabitants; (e) registered diabetics per 1,000 inhabitants; (f) percentage of registered diabetics receiving follow-up care. Variables related to other layers of the health system include: (g) SUS ambulance service; (h) net number of new SUS general hospitals with ERs (opened minus closed); (i) SUS hospital beds per 1,000 inhabitants. Vertical bars represent 95% confidence intervals (CIs) around the coefficients. Results from two different specifications are shown: the first is a basic specification without any controls, and the second includes the following controls: city GDP, Bolsa Família Program transfers (R$) per 1,000 inhabitants, political party in power, political alignment with the State government, and a dummy variable indicating cities that experienced severe rainfall and landslides in 2011. Standard errors are clustered at the municipality level.

C Further Robustness Results

Table C.1: Hazard Estimation of the Probability of Receiving an UPA, City-Level, 2005-2016

	Hazard Ratio		
	(1)	(2)	(3)
Variables Measured in the First Period			
Deaths Amenable to Amenable to Amb & Emerg Care	0.978	0.971	0.961
	(0.017)	(0.019)	(0.025)
Deaths Amenable to Amb Care Only	1.002	1.004	1.003
	(0.013)	(0.014)	(0.021)
Deaths Amenable to Emerg Care Only	1.010	1.012	0.983
	(0.014)	(0.013)	(0.013)
Deaths Non-Amenable to Amb or Emerg Care	1.017	1.016	1.001
	(0.011)	(0.011)	(0.012)
FHP Coverage	0.982**	0.980***	0.981**
	(0.006)	(0.006)	(0.008)
SUS Ambulance Service	15.529***	13.911***	42.715***
	(7.704)	(7.059)	(36.465)
SUS Hospital Beds per 100,000	0.999	1.000	1.001
	(0.001)	(0.001)	(0.000)
GDP Per Capita	1.000	1.000*	1.000
	(0.000)	(0.000)	(0.000)
Bolsa Familia Transfer per Capita	0.999**	0.999**	0.999**
	(0.000)	(0.000)	(0.000)
Alignment with the Governor	3.222***	1.494	9.840**
	(1.257)	(0.867)	(9.585)
Time-Varying Mortality (per 100,000 people)			
Δ_{t-4} Deaths Amenable to Amenable to Amb & Emerg Care		1.005	1.006
		(0.010)	(0.012)
Δ_{t-4} Deaths Amenable to Amb Care Only		1.005	1.013
		(0.008)	(0.010)
Δ_{t-4} Deaths Amenable to Emerg Care Only		1.009	1.010
		(0.007)	(0.010)
Δ_{t-4} Deaths Non-Amenable to Amb or Emerg Care		0.993	0.992
		(0.005)	(0.009)
Public Policy and Health Related Time-Varying Measures			
Δ_{t-4} FHP Coverage		0.988	0.986
		(0.011)	(0.017)
Δ_{t-4} SUS Ambulance Service		2.767**	2.333*
		(1.235)	(1.081)
Δ_{t-4} SUS Hospital Beds per 100,000		1.003	1.005
		(0.003)	(0.003)
Socioeconomic and Political Time-Varying Measures			
Δ_{t-4} GDP Per Capita		1.000	1.000
		(0.000)	(0.000)
Δ_{t-4} Bolsa Familia Transfer per Capita		1.000**	0.999**
		(0.000)	(0.000)
Δ_{t-4} Alignment with the Governor		1.345	1.762
		(1.082)	(1.614)
Health Region FE	No	No	Yes
N	3,317	2,949	2,949

Notes: This table shows the hazard estimation where municipalities leave the sample when they receive an UPA. The first column shows a model with the following variables measures in the first period: death rate by different conditions, FHP coverage, SAMU presence, SUS hospital beds per 100,000, GDP per capita, Bolsa Família transfer (R$) per 1,000, and political alignment with the State government. The second column adds the change in the same variables lagged in one year. Municipality level observations.

Table C.2: Hazard Estimation of the Probability of Receiving an UPA, Hospital-Level, 2005-2016

	Hazard Ratio		
	(1)	(2)	(3)
Variables Measured in the First Period			
Ambulatory Procedures	1.000	1.000**	1.000
	(0.000)	(0.000)	(0.000)
Hospital Admissons	1.001	1.001*	1.001
	(0.001)	(0.001)	(0.001)
Total Deaths	1.003	1.004*	1.004
	(0.002)	-0.002	(0.003)
Inpatient Deaths	0.983***	0.985**	0.984**
	(0.005)	(0.006)	(0.007)
% Inpatient Deaths	1.080	1.079	1.091
	(0.056)	(0.057)	(0.072)
No. Professionals	1.002**	1.001	1.001
	(0.001)	(0.001)	(0.001)
Total Hospital Beds	1.002	1.000	1.001
	(0.002)	(0.002)	(0.002)
Total Equipments	1.000	0.997	0.996
	(0.002)	(0.003)	(0.004)
Occupancy Rate (%)	1.016	1.013	1.015
	(0.011)	(0.012)	(0.012)
Patient Mean Household Income	1.001	1.001	1.001
	(0.001)	(0.001)	(0.001)
Patient Mean Age	1.012	1.006	1.001
	(0.035)	(0.045)	(0.048)
Patient % Female	1.025	1.020	1.018
	(0.025)	(0.029)	(0.027)
Time-Varying Hospital Outcomes			
Δ_{t-4} Ambulatory Procedures		1.000	1.000
		(0.000)	(0.000)
Δ_{t-4} Hospital Admissions		1.001	1.001
		(0.001)	(0.001)
Δ_{t-4} Total Deaths		1.000	1.000
		(0.005)	(0.005)
Δ_{t-4} Inpatient Deaths		0.991	0.991
		(0.006)	(0.006)
Δ_{t-4} % Inpatient Deaths		1.080	1.067
		(0.052)	(0.061)
Time-Varying Hospital Characteristics			
Δ_{t-4} No. Professionals		1.000	1.000
		(0.001)	(0.001)
Δ_{t-4} Total Hospital Beds		0.988*	0.988
		(0.007)	(0.008)
Δ_{t-4} Total Equipments		0.998	0.997
		(0.005)	(0.005)
Δ_{t-4} Occupancy Rate (%)		1.001	1.006
		(0.013)	(0.015)
Health Region FE	No	No	Yes
N	3,653	2,795	2,795

Notes: This table shows the hazard estimation where hospitals leave the sample when they receive an UPA in the 4.5km catchment area. The first column shows a model with the following variables measured in the first period: ambulatory procedures, hospital admissions, inpatient deaths, inpatient deaths conditional on admission (%), number of professionals working in the hospital, total hospital beds, total equipments, occupancy rate (%), patient mean household income, age and gender. The second column adds the change in the same variables lagged in one year. The last column adds municipality fixed effects. Hospital-level observations.

Table C.3: Hospitals' Outcomes, Hospital-Level Robustness Checks

		Robustness								
	Main Sample (1)	Excluding RJ City (2)	6.5km Catch. Area (3)	Hospitals w/ Adequate Data (4)	Health System Controls (5)	Adoption Model Controls (6)	Non-parametric Trend (7)	Normal DD (8)	Demographic Controls (9)	Mean at Baseline
Ambulatory Procedures										
Total	-0.300***	-0.356***	-0.251***	-0.212***	-0.304***	-0.303***	-0.266***	-0.369***	-0.287***	76.09
	(0.061)	(0.068)	(0.063)	(0.063)	(0.063)	(0.063)	(0.084)	(0.108)	(0.102)	
Basic Health Care	0.240	0.179	0.309	0.239	0.200	0.199	0.307	0.338	0.242	27.97
	(0.345)	(0.340)	(0.320)	(0.357)	(0.351)	(0.350)	(0.409)	(0.484)	(0.378)	
Medium Complexity	-0.302***	-0.341***	-0.273***	-0.220***	-0.310***	-0.311***	-0.221**	-0.547***	-0.298**	38.34
	(0.080)	(0.092)	(0.083)	(0.083)	(0.079)	(0.080)	(0.103)	(0.127)	(0.123)	
High Complexity	0.352	0.321	0.421*	0.452*	0.353	0.350	0.099	1.043***	0.367	0.28
	(0.259)	(0.317)	(0.244)	(0.255)	(0.256)	(0.257)	(0.261)	(0.359)	(0.279)	
Inpatient Measures: Amenable to Ambulatory & Emergency Care										
Hosp Admissions	-0.236*	-0.196	-0.188	-0.186	-0.238*	-0.238*	-0.171	-0.205	-0.197	79.29
	(0.142)	(0.163)	(0.132)	(0.146)	(0.143)	(0.143)	(0.155)	(0.177)	(0.147)	
Total Deaths	-0.277***	-0.332***	-0.220***	-0.261***	-0.268***	-0.273***	-0.182	-0.236***	-0.265***	13.53
	(0.073)	(0.082)	(0.080)	(0.076)	(0.080)	(0.076)	(0.111)	(0.071)	(0.086)	
Inpatient Deaths	-0.213*	-0.182	-0.206	-0.174	-0.253	-0.253	-0.192	-0.225*	-0.184	11.44
	(0.127)	(0.124)	(0.136)	(0.131)	(0.160)	(0.160)	(0.149)	(0.136)	(0.122)	
% Inpatient Deaths	0.300	-0.082	-0.341	0.424	0.085	0.029	-0.306	-0.493	0.238	11.36
	(1.128)	(0.974)	(1.521)	(1.067)	(1.267)	(1.339)	(1.490)	(0.911)	(1.275)	
% 24h Inpatient Deaths	-0.311	-0.711	-0.251	-0.476	-0.699	-0.628	-0.225	-0.519*	-0.482	2.05
	(0.608)	(0.779)	(0.579)	(0.611)	(0.825)	(0.769)	(0.639)	(0.312)	(0.658)	
Inpatient Measures: Amenable to Ambulatory Care Only										
Hosp Admissions	-0.378***	-0.353**	-0.351***	-0.342***	-0.406***	-0.403***	-0.368***	-0.333*	-0.351***	96.29
	(0.124)	(0.138)	(0.127)	(0.126)	(0.139)	(0.137)	(0.133)	(0.176)	(0.124)	
Total Deaths	-0.179**	-0.181*	-0.168**	-0.178**	-0.176**	-0.174**	-0.015	-0.223***	-0.184**	16.95
	(0.078)	(0.094)	(0.075)	(0.075)	(0.079)	(0.079)	(0.128)	(0.084)	(0.083)	
Inpatient Deaths	-0.389***	-0.341**	-0.367**	-0.324**	-0.415**	-0.404***	-0.288*	-0.241*	-0.358***	7.78
	(0.144)	(0.142)	(0.170)	(0.143)	(0.166)	(0.156)	(0.156)	(0.132)	(0.128)	
% Inpatient Deaths	-0.859	-0.571	-0.846	-0.253	-0.967	-0.822	-0.161	-0.324	-0.662	6.89
	(0.639)	(0.719)	(0.759)	(0.618)	(0.771)	(0.631)	(0.734)	(0.633)	(0.789)	
% 24h Inpatient Deaths	-0.328	-0.291	-0.328	-0.308	-0.160	-0.157	-0.107	-0.387**	-0.314	1.3
	(0.292)	(0.239)	(0.318)	(0.308)	(0.200)	(0.200)	(0.246)	(0.178)	(0.232)	
Inpatient Measures: Amenable to Emergency Care Only										
Hosp Admissions	-0.018	0.065	-0.020	0.019	-0.025	-0.031	-0.049	-0.168	0.016	158.84
	(0.126)	(0.135)	(0.122)	(0.128)	(0.122)	(0.120)	(0.145)	(0.175)	(0.145)	
Total Deaths	-0.166*	-0.160*	-0.138*	-0.139	-0.166*	-0.165*	-0.168	-0.182*	-0.127	29.7
	(0.087)	(0.090)	(0.077)	(0.092)	(0.088)	(0.088)	(0.126)	(0.093)	(0.087)	
Inpatient Deaths	-0.224**	-0.120	-0.219**	-0.193*	-0.265***	-0.267***	-0.182	-0.264*	-0.181*	20.81
	(0.108)	(0.114)	(0.101)	(0.112)	(0.100)	(0.100)	(0.139)	(0.144)	(0.105)	
% Inpatient Deaths	-1.249	-0.354	-1.446	-1.188	-1.741*	-1.697*	-0.226	-1.691	-1.017	10.67
	(0.975)	(1.042)	(0.898)	(1.032)	(0.949)	(0.933)	(0.976)	(1.152)	(0.967)	
% 24h Inpatient Deaths	-0.397	-0.203	-0.015	-0.367	-0.519	-0.471	-0.319	-0.645*	-0.332	2.71
	(0.364)	(0.362)	(0.301)	(0.369)	(0.358)	(0.362)	(0.483)	(0.375)	(0.402)	
Inpatient Measures: Non-Amenable to Ambulatory or Emergency Care										
Hosp Admissions	-0.022	0.128	-0.029	0.026	-0.023	-0.024	-0.044	0.043	-0.006	388.84
	(0.088)	(0.087)	(0.095)	(0.088)	(0.090)	(0.090)	(0.090)	(0.154)	(0.085)	
Total Deaths	-0.160**	-0.097	-0.148*	-0.118	-0.162**	-0.162**	-0.056	-0.205**	-0.115	40.21
	(0.078)	(0.078)	(0.089)	(0.074)	(0.079)	(0.079)	(0.084)	(0.095)	(0.088)	
Inpatient Deaths	-0.260**	-0.260**	-0.222**	-0.200*	-0.266**	-0.274**	-0.374**	-0.144	-0.226*	12.21
	(0.111)	(0.121)	(0.110)	(0.113)	(0.108)	(0.109)	(0.164)	(0.140)	(0.117)	
% Inpatient Deaths	-1.137*	-1.934***	-0.962	-0.784	-1.204**	-1.256**	-1.264*	-0.551	-0.806	3.3
	(0.636)	(0.648)	(0.682)	(0.641)	(0.588)	(0.577)	(0.737)	(0.632)	(0.547)	
% 24h Inpatient Deaths	-0.526**	-0.805***	-0.458*	-0.456**	-0.558***	-0.590***	-0.666***	-0.378***	-0.428**	0.48
	(0.220)	(0.234)	(0.240)	(0.195)	(0.200)	(0.191)	(0.217)	(0.137)	(0.210)	
Hospital & Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-

Notes: This table shows different robustness checks related to the main hospitals' outcomes studied. In the first column, we have our main specification, in which we excluded hospitals with bad SIA and/or SIH data. The second column shows results when we exclude 13 hospitals from Rio de Janeiro City. Column 3 shows the results when we consider a 6.5km radius (mean distance traveled in the baseline to closest ER). Column 4 keeps only hospitals that have adequate data in both SIA and SIH, leaving us with 108 hospitals. Column 5 includes the following health-related controls: FHP coverage, the existence of SAMU ambulance program, number of general hospitals with ER that opened and closed inside the hospitals' catchment area, expansion of hospital ER through CER, and private health insurance coverage. Column 6 includes as controls variables that were consistently significant in the adoption model (solo and interacted with the treatment dummy): SAMU presence, FHP coverage, Bolsa Família transfer (R$) per 1,000, and political alignment with the State government. Column 7 shows the results with non-parametric trends at the city-level. Column 8 shows the results using the traditional two-way fixed effect estimator. Finally, column 9 show the results including the following patient demographics: age, gender and mean income. All results also include the following controls: cities' GDP, Bolsa Família transfer (R$) per 1,000, political party in government, political alignment with the State government, and a dummy indicating cities that suffered from heavy rains and the collapse of hills in 2011. Municipality-specific time (quarter/year) trends were also introduced (except for the traditional DD robustness). Dependent variables are the IHS, except for the % inpatient deaths. Baseline refers to the period 2005/Q1-2007/Q1, before the introduction of the first UPA in RJ, and has the same metric as its corresponding variable.

Table C.4: Total Deaths per 100,000, City-Level Robustness Estimates

	Treatment Effect				Mean at
	(1)	(2)	(3)	(4)	Baseline
Main Specification	-2.287 (3.039)	-2.256 (4.982)	-4.146 (4.039)	-7.023 (7.232)	176.63
Robustness					
Excluding RJ City	-2.245 (3.077)	-2.456 (5.275)	-4.078 (3.529)	-7.702 (6.931)	176.28
Health System Controls	-2.287 (3.039)	-2.038 (5.119)	-4.146 (4.039)	-5.860 (7.921)	176.63
Adoption Model Controls	-2.287 (3.039)	-1.941 (5.122)	-4.146 (4.039)	-6.382 (7.417)	176.63
Traditional DD	-2.194 (2.483)	-2.711 (2.468)	-3.243 (2.356)	-2.986 (2.645)	176.63
City & Time FE	Yes	Yes	Yes	Yes	-
Controls	No	Yes	No	Yes	-
Trend	No	No	Yes	Yes	-

Notes: This table shows robustness checks related to the outcome total deaths per 100,000 inhabitants analysed at the city-level. In the first row, we have our main specification. The second excludes Rio de Janeiro city and the third includes the following health-related controls: FHP coverage, presence of SAMU ambulance program, number of general hospitals with ER that opened, closed expanded their ER thorough CER and private health insurance coverage. The fourth row includes as controls variables that were consistently significant in the adotion model (solo and interacted with the treatment dummy): SAMU presence, FHP coverage, Bolsa Família transfer (R$) per 1,000, and political alignment with the State government. The fifth row shows the results using the traditional two-way fixed effect estimator. In all results, the following controls are introduced in columns (2) and (4): cities' GDP, Bolsa Família transfer (R$) per 1,000, political party in government, political alignment with the State government and a dummy indicating cities that suffered from heavy rains and the collapse of hills in 2011. Health region specific time (quarter/year) trends were introduced in columns (3) and (4). Main sample is composed of 92 cities. Standard errors clustered at the city level in all specifications. *** p<0.01, ** p<0.05, * p<0.1. Baseline refers to the period 2005/Q1-2007/Q1, before the introduction of the first UPA in RJ, and is measured in rates per 100,000 inhabitants.

Table C.5: Deaths per 100,000 by Cause and Location
City-Level Robustness Estimates

		Location						
	Total (1)	Hospital (2)	UPA (3)	Other Health Facility (4)	Household (5)	Street (6)	Other (7)	Mean at Baseline
Main Specification								
Total	-2.989	-19.710***	12.487***	1.878*	0.694	-0.595	2.029	169.31
	(4.001)	(5.079)	(2.493)	(0.980)	(1.248)	(0.844)	(1.668)	
Amenable to Ambulatory & Emergency Care	-1.206	-3.840***	1.579***	0.294	0.262	0.034	0.463**	22.4
	(1.229)	(1.373)	(0.338)	(0.209)	(0.291)	(0.040)	(0.216)	
Amenable to Ambulatory Care Only	0.443	-3.512**	2.521***	0.433*	0.203	0.068	0.645*	25.81
	(1.395)	(1.492)	(0.542)	(0.254)	(0.452)	(0.131)	(0.356)	
Amenable to Emergency Care Only	-0.812	-4.798***	4.268***	0.809*	-0.894	-0.617	0.292	52.85
	(2.172)	(1.619)	(0.908)	(0.454)	(0.886)	(0.779)	(0.763)	
Non-Amenable to Ambulatory or Emergency Care	-1.414	-7.561***	4.118***	0.342	1.123	-0.080	0.629	68.25
	(2.373)	(2.351)	(0.817)	(0.492)	(0.835)	(0.188)	(0.608)	
Excluding RJ City								
Total	-0.915	-18.563***	12.941***	1.637*	0.963	-0.499	2.481	168.94
	(3.018)	(4.372)	(2.563)	(0.913)	(1.184)	(0.799)	(1.573)	
Amenable to Ambulatory & Emergency Care	-1.101	-3.734***	1.635***	0.287	0.295	0.017	0.402**	22.43
	(0.958)	(1.058)	(0.339)	(0.208)	(0.293)	(0.035)	(0.198)	
Amenable to Ambulatory Care Only	1.430	-2.748*	2.676***	0.445*	0.316	0.122	0.593*	25.79
	(1.684)	(1.597)	(0.540)	(0.248)	(0.522)	(0.106)	(0.359)	
Amenable to Emergency Care Only	-0.445	-4.828***	4.423***	0.654**	-0.918	-0.559	0.707	52.72
	(1.996)	(1.531)	(0.929)	(0.327)	(0.865)	(0.730)	(0.677)	
Non-Amenable to Ambulatory or Emergency Care	-0.800	-7.253***	4.207***	0.252	1.270*	-0.078	0.779	68
	(2.328)	(2.310)	(0.852)	(0.526)	(0.762)	(0.155)	(0.567)	
Health System Controls								
Total	-2.629	-18.764***	12.809***	1.600*	0.117	-1.085	2.528*	169.31
	(3.657)	(4.742)	(2.501)	(0.942)	(1.631)	(1.143)	(1.460)	
Amenable to Ambulatory & Emergency Care	-1.191	-3.710***	1.634***	0.241	0.241	0.016	0.391*	22.4
	(1.108)	(1.196)	(0.341)	(0.203)	(0.337)	(0.036)	(0.200)	
Amenable to Ambulatory Care Only	0.832	-2.850*	2.712***	0.393	-0.229	0.136	0.632*	25.81
	(1.448)	(1.633)	(0.540)	(0.248)	(0.718)	(0.139)	(0.328)	
Amenable to Emergency Care Only	-1.673	-5.282***	4.349***	0.673*	-1.082	-1.109	0.684	52.85
	(2.964)	(1.877)	(0.905)	(0.361)	(1.082)	(1.115)	(0.681)	
Non-Amenable to Ambulatory or Emergency Care	-0.597	-6.922***	4.114***	0.293	1.188	-0.128	0.821	68.25
	(2.634)	(2.543)	(0.819)	(0.531)	(0.791)	(0.159)	(0.532)	
Adoption Model Controls								
Total	-2.218	-19.280***	12.695***	1.501	0.957	-0.643	2.384	169.31
	(3.605)	(4.665)	(2.470)	(0.917)	(1.235)	(0.806)	(1.507)	
Amenable to Ambulatory & Emergency Care	-1.233	-3.799***	1.621***	0.318	0.215	0.019	0.394**	22.4
	(1.128)	(1.227)	(0.335)	(0.202)	(0.310)	(0.037)	(0.200)	
Amenable to Ambulatory Care Only	0.780	-3.239**	2.620***	0.441*	0.182	0.137	0.598*	25.81
	(1.372)	(1.422)	(0.521)	(0.251)	(0.447)	(0.137)	(0.342)	
Amenable to Emergency Care Only	-0.826	-4.863***	4.339***	0.583*	-0.865	-0.710	0.587	52.85
	(2.296)	(1.677)	(0.902)	(0.324)	(0.876)	(0.771)	(0.653)	
Non-Amenable to Ambulatory or Emergency Care	-0.939	-7.378***	4.115***	0.159	1.425	-0.088	0.805	68.25
	(2.382)	(2.273)	(0.816)	(0.578)	(0.972)	(0.161)	(0.525)	
Non-parametric Trend								
Total	-2.424	-16.174***	12.811***	-0.309	-0.120	-0.671	1.932*	169.31
	(3.470)	(4.773)	(2.154)	(0.778)	(1.190)	(0.576)	(1.099)	
Amenable to Ambulatory & Emergency Care	-0.892	-2.910***	1.710***	-0.047	-0.063	0.010	0.431***	22.4
	(0.983)	(0.933)	(0.285)	(0.417)	(0.355)	(0.029)	(0.155)	
Amenable to Ambulatory Care Only	1.188	-2.115	2.735***	0.335*	-0.232	0.078	0.314	25.81
	(1.900)	(2.083)	(0.510)	(0.203)	(0.454)	(0.131)	(0.359)	
Amenable to Emergency Care Only	-0.485	-4.553***	4.449***	0.210	-0.721	-0.578	0.615	52.85
	(1.889)	(1.292)	(0.828)	(0.362)	(1.336)	(0.598)	(0.426)	
Non-Amenable to Ambulatory or Emergency Care	-2.236	-6.596***	3.918***	-0.808*	0.896	-0.181	0.572	68.25
	(2.600)	(2.407)	(0.727)	(0.452)	(0.917)	(0.131)	(0.444)	
Normal DD								
Total	-2.830	-19.566***	14.206***	-2.789	3.571***	-0.586	2.254*	169.31
	(2.668)	(4.914)	(3.381)	(1.699)	(0.861)	(0.457)	(1.342)	
Amenable to Ambulatory & Emergency Care	-0.008	-2.481***	1.689***	-0.080	0.501***	0.033	0.316***	22.4
	(0.521)	(0.664)	(0.410)	(0.222)	(0.170)	(0.026)	(0.121)	
Amenable to Ambulatory Care Only	0.435	-3.977***	3.007***	-0.307	1.210***	-0.001	0.494**	25.81
	(0.748)	(0.992)	(0.702)	(0.361)	(0.380)	(0.049)	(0.244)	
Amenable to Emergency Care Only	-0.430	-5.515***	4.681***	-0.893*	0.977**	-0.436	0.661	52.85
	(1.288)	(1.575)	(1.077)	(0.515)	(0.393)	(0.426)	(0.527)	
Non-Amenable to Ambulatory or Emergency Care	-2.826*	-7.593***	4.829***	-1.509**	0.883	-0.183	0.783	68.25
	(1.576)	(2.139)	(1.236)	(0.676)	(0.546)	(0.139)	(0.563)	
Mean at Baseline	169.31	124.66	0	4.48	24.76	8.83	5.47	

Notes: This table shows robustness checks related to deaths per 100,000 inhabitants for different causes and locations at the city level. The first block shows results for our main specification. The second excludes Rio de Janeiro city and the third includes the following health related controls: FHP coverage, presence of SAMU ambulance program, number of general hospitals with ER that opened, closed expanded their ER thorough CER and private health insurance coverage. The fourth panel includes as controls variables that were consistently significant in the adotion model (solo and interacted with the treatment dummy): SAMU presence, FHP coverage, Bolsa Família transfer (R$) per 1,000, and political alignment with the State government. The last panel shows the results using the traditional two-way fixed effect estimator. All results also include the following controls: cities' GDP, Bolsa Família Program transfer (R$) per 1,000, political party in government, political alignment with the State government and a dummy indicating cities that suffered from heavy rains and the collapse of hills in 2011. Health region specific time trends (quarter/year) were included (except for the traditional DD robustness). The city level results are not directly comparable with the hospital results shown earlier because the former include only hospital with an ER. Also the hospital analysis models impact of an UPA opening within 4.5km of the hospital whereas the city analysis involves an UPA opening anywhere in the city, so the "catchment" area is much broader. Main sample is composed of 92 cities. Standard errors clustered at the city level in all specifications. *** p<0.01, ** p<0.05, *p<0.1. Baseline refers to the period 2005/Q1-2007/Q1, before the introduction of the first UPA in RJ, and is measured in rates per 100,000 inhabitants.

Table C.6: Health System, City-Level Robustness Estimates

	% FHP Coverage (1)	Ambulance Program (2)	Net New Hospitals (3)
Main Specification	-2.408	-0.003	-0.040
	(2.793)	(0.017)	(0.104)
Robustness			
Excluding RJ City	-2.457	-0.003	-0.032
	(2.601)	(0.014)	(0.087)
Traditional DD	-4.152	-0.024*	0.096
	(2.752)	(0.012)	(0.179)
City & Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Mean at Baseline	60.26	0.20	0.00

Notes: This table shows robustness checks related to the health system analysis at the city level. The first block shows results for our main specification. The second one excludes Rio de Janeiro city and the third shows the results using the traditional two-way fixed effect estimator. Controls are cities' GDP, Bolsa Família transfer (R$) per 1,000, political party in government, political alignment with the State government, and a dummy indicating cities that suffered from heavy rains and the collapse of hills in 2011. Health region specific time trends (quarter/year) were included in the first robustness, but not in the traditional DD. Dependent variables are: (1) Family Health Program coverage; (2) presence of SAMU ambulatory program; (3) number of new SUS general hospitals with ER (opened - close). The main sample is composed of 92 cities. Standard errors clustered at the city level in all specifications. *** p<0.01, ** p<0.05, * p<0.1. Baseline refers to the period 2005/Q1-2007/Q1, before the introduction of the first UPA in RJ, and is measured in rates per 100,000 inhabitants.

D Data Appendix

D.1 Conditions Amenable to Ambulatory and Emergency Care

The division of deaths and hospital admissions by conditions amenable and non-amenable to ambulatory and emergency care follow Alfradique et al. (2009) and Vashi et al. (2019), respectively. Alfradique et al. (2009) adapts the international ICD-10 list of conditions amenable to ambulatory care to the Brazilian context. These are conditions for which the need for hospitalization could have been avoided with adequate ambulatory and non-specialized care. High rates of admissions and deaths related to such conditions usually indicate the failure of the antecedent primary care and are used as an indirect indicator of its effectiveness. The description and codes related to these conditions can be found in Table D.1.

Table D.1: List of Conditions Amenable to Ambulatory Care

Condition Group	ICD-10 Codes
Preventable diseases due to immunization	A37; A36; A33 to A35; B26; B06; B05; A95; B16; G00.0; A17.0 A19; A15.0 to A15.3; A16.0 to A16.2, A15.4 to A15.9, A16.3 to A16.9, A17.1 to A17.9; A18; I00 to I02; A51 to A53; B50 to B54
Infectious Gastroenteritis and Complications	E86; A00 to A09
Anemia	D50
Nutritional deficiencies	E40 to E46; E50 to E64
Ear, nose, and throat infections	H66; J00; J01; J02; J03; J06; J31
Bacterial pneumonias	J13; J14; J15.3, J15.4; J15.8, J15.9; J18.1
Asthma	J45, J46
Pulmonary diseases	J20, J21; J40; J41; J42; J43; J47; J44;
Hypertension	I10; I11
Angina	I20
Heart Failure	I50; J81
Cerebrovascular diseases	I63 to I67; I69, G45 to G46
Diabetes mellitus	E10.0, E10.1, E11.0, E11.1, E12.0, E12.1; E13.0, E13.1; E14.0, E14.1; E10.2 to E10.8, E11.2 to E11.8; E12.2 to E12.8;E13.2 to E13.8; E14.2 to E14.8; E10.9, E11.9; E12.9, E13.9; E14.9
Epilepsies	G40, G41
Infection of the kidney and urinary tract	N10; N11; N12; N30; N34; N39.0
Infection of skin and subcutaneous tissue	A46; L01; L02; L03; L04; L08
Female pelvic organs inflammatory disease	N70; N71; N72; N73; N75; N76
Gastrointestinal ulcer	K25 to K28, K92.0, K92.1, K92.2
Diseases related to prenatal and delivery	O23; A50; P35.

Notes: Source for conditions amenable to ambulatory care: Ministry of Health Ordinance 221/2008. Link: https://bvsms.saude.gov.br/bvs/saudelegis/sas/2008/prt0221_17_04_2008.html

Vashi et al. (2019) provides a set of emergency care-sensitive conditions that are treated in most EDs, and represent common reasons for seeking emergency care. These are conditions for which timely, high-quality emergency care is expected to impact mortality and morbidity. However, contrary to conditions amenable to ambulatory care, higher rates of emergency care admissions are not an indicator of poor emergency care. Many acute illnesses and acute manifestations of chronic diseases are inevitable, and when they occur, the emergency care system should be able to rapidly identify and treat these episodes efficiently.

This classification was adapted to the Brazilian data by Isaacson et al. (2021), where the admissions selected for analysis were associated with at least one of the ICD-10 codes specified in Vashi et al. (2019). We follow the same procedure to classify deaths and hospitalizations sensitive to emergency care. Since the list is very comprehensive and detailed we reproduced only Vashi et al. (2019)'s main condition groups in Table D.2. Details about related ICD-10-CM codes can be found in their supplemental material.

Table D.2: List of Conditions Amenable to Emergency Care

Condition Group	
Abdominal, Lower Back, Pelvic & External Genitalia Injuries	Infectious Fasciitis
Acute Angle Closure Glaucoma	Stroke, not specified
Acute Appendicitis	Intracranial Injury
Acute Pancreatitis	Meningitis
Acute Respiratory Distress Syndrome	Moderate-Severe Burns and Corrosions
Alcohol Withdrawal	Myocardial Infarction
Anaphylaxis	Neck Injuries
Angina and Other Acute Ischemic Heart Disease	Other Cardiac Arrhythmia
Aortic Aneurysm and Dissection	Other Diseases of Intestine
Arterial Embolism and Thrombosis	Other Tachyarrhythmias
Asthma	Overdose/Poisonings
Chronic Obstructive Pulmonary Disease	Paralytic Ileus and Intestinal Obstruction wo Hernia
Cardiac Arrest and Severe Arrhythmias	Pericardial Disease, Endocarditis, and Myocarditis
Cerebral Infarction	Peritonitis
Cholecystitis and Perforation of the Gallbladder	Pneumonia
Complications of Cardiac & Vascular Prosthetic Devices/Grafts	Pneumothorax
Complications of Procedures	Postpartum Hemorrhage
Diabetes Mellitus-Acute	Pre-eclampsia/Eclampsia
Disorders of the Brain	Pulmonary Embolism
Early Complications of Trauma	Respiratory Failure
Ectopic Pregnancy	Sepsis & Systemic Inflammatory Response Syndrome
Encephalitis, Myelitis and Encephalomyelitis	Septic Arthritis
Environmental Exposures	Shock
Femur Fracture	Thoracic Injuries
Gastrointestinal Tract Bleeding and/or Perforation	Volume Depletion
Heart Failure	Intracranial Hemorrhage

Notes: Source for conditions amenable to emergency care: Vashi et al. (2019), supplemental material.

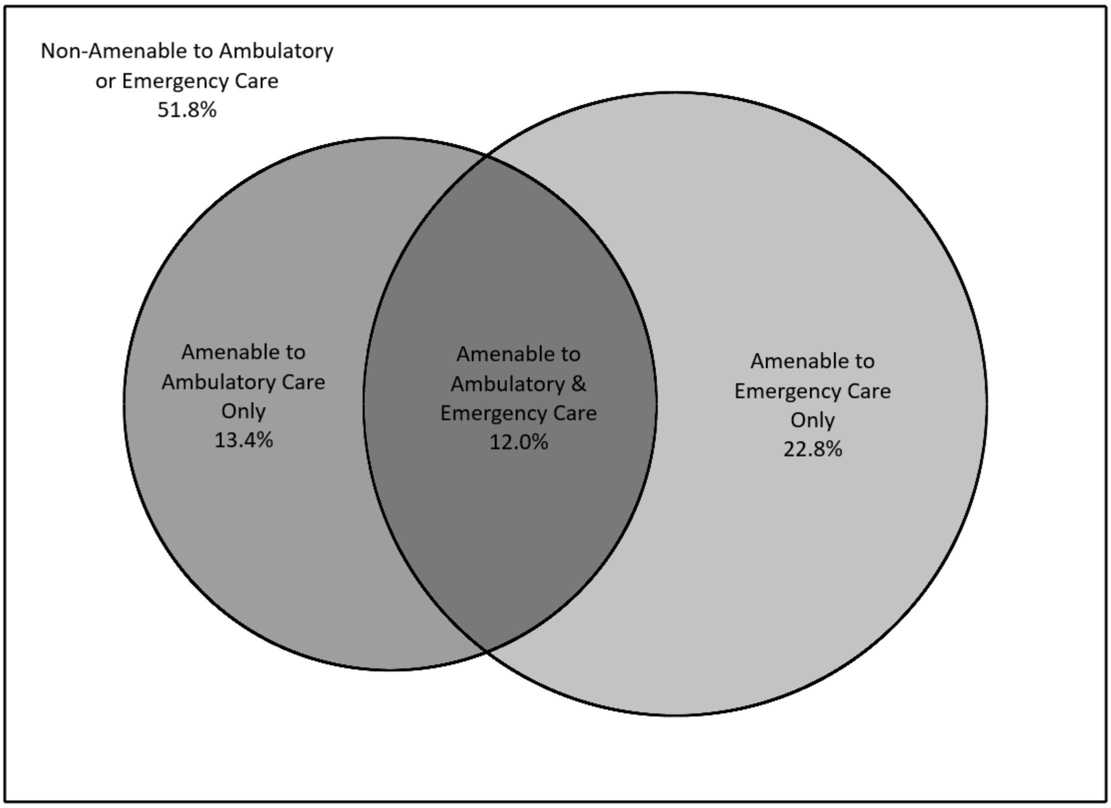
In this paper, we merged these two classifications and generated four categories that guided our analysis: (a) conditions amenable to both ambulatory and emergency care; (b) conditions sensitive only to ambulatory care; (c) conditions sensitive only to emergency care; (d) conditions that are not amenable to either ambulatory or emergency care. This division and the percentage of hospitalizations associated with them in the baseline (2005/Q1-2007/Q1) can be found in Figure D.1.

The first category, (a), includes conditions amenable to both ambulatory and emergency care such as acute complications in diabetes, bacterial pneumonia, stroke, asthma, and chronic obstructive pulmonary disease (COPD). This group is supposed to capture conditions that could usually be treated or prevented by good ambulatory care but, once unattended, lead to severe situations in which emergency care is needed.

The second group, (b), involves conditions that are amenable to ambulatory care but not emergent. These include infectious gastroenteritis, urinary tract infection, congestive heart failure, and cellulitis, among others. These are urgent and non-urgent situations that could be dealt with or prevented by appropriate basic healthcare.

The third group, (c), incorporates situations that are only sensitive to emergency care such as heart attacks, accidents, poisoning, and viral or unidentified pneumonia. These are mainly inevitable and severe conditions for which emergency care is needed.

Figure D.1: Venn Diagram

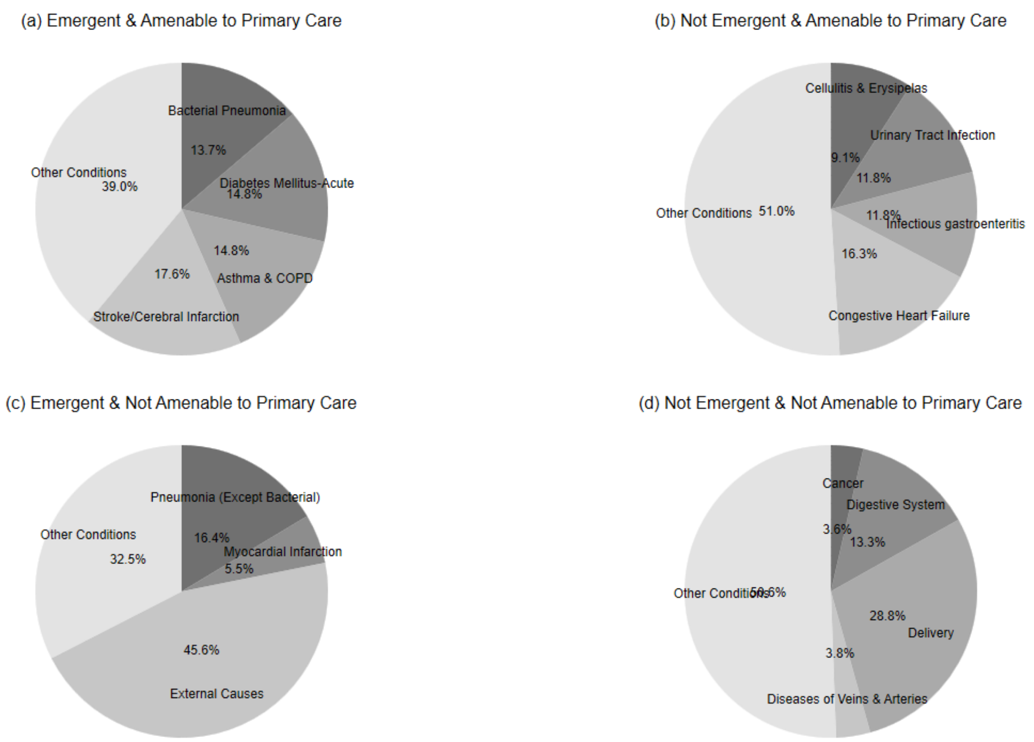


Notes: This graph shows the percentage of hospitalizations (SIH) due to conditions amenable to ambulatory and/or emergency care during the baseline period (2005/Q1 - 2007/Q1). The four categories displayed in the Venn diagram were created by merging conditions sensitive to ambulatory care, as identified by Alfradique et al. (2009), with conditions sensitive to emergency care from Vashi et al. (2019).

Finally, the fourth category, (d), is a group of conditions that could neither be treated in an ER nor prevented by good ambulatory care. For them, we expect hospital and specialized care to be more appropriate. This category includes, but is not limited to, the following conditions: (i) childbirth; (ii) cancer; (iii) digestive system diseases (diverticulitis, hernia, Crohn's disease, cirrhosis, and others); (iv) diseases of veins and arteries (atherosclerosis, aneurysm, thrombophlebitis, varicose veins, and others).

UPAs were designed as a free-standing emergency department and an intermediate point of access within local health systems, in between the primary and the hospital care layers. They are equipped to handle conditions of basic to intermediate complexity and are particularly designed to provide: i) qualified and resolutive care for acute or chronic clinical conditions; ii) first aid to surgical and trauma cases, and; iii) medical consultations for cases of lower severity (Konder and O'Dwyer, 2016). Therefore, since UPAs were designed to treat conditions sensitive to both ambulatory and emergency care, the proposed division will be particularly convenient to analyse our setting. Figure D.2 depicts these four categories and the main conditions that constitute them, considering hospitalizations in the baseline period (2005/Q1-2007/Q1).

Figure D.2: Conditions Distribution Within Each Group



Notes: This graph shows the percentage of hospitalizations (SIH) attributed to specific causes within each group of conditions amenable to ambulatory and/or emergency care during the baseline period (2005/Q1 - 2007/Q1). The categories displayed above were created by merging conditions sensitive to ambulatory care as identified by Alfradique et al. (2009) with conditions sensitive to emergency care from Vashi et al. (2019)

D.2 Hospital and City Databases

The primary sample used to analyze hospitals' performance contains all UPAs and SUS general hospitals with a 24h walk-in emergency department in Rio de Janeiro between 2005 and 2016. These facilities and their geographical location were identified with the help of two data sources: the National Register of Health Establishments (CNES) and the Brazilian Open Data Portal (dados.gov.br). CNES has information on every Brazilian health facility and their human resources, installed capacity, location and type of services provided, regardless of whether or not they provide care to SUS users. It is available since 2003 on a monthly basis, but gained a new version in 2005. The portal, on the other hand, started with the Access to Information Act in 2011 and aims to provide data and transparency on the most varied themes of public administration.

To identify the hospitals needed for this study, we started from the sample of all establishments in CNES that, at least once between 2005-2016, were classified as a general hospital and had hospitalization and urgency services. Through CNES and dados.gov.br, we also identified all UPAs inaugurated in the period and obtained the latitude and longitude of all establishments. Then, we double-checked the classification and operational status of each facility with the support of phone calls to managers and searches online, and by inspecting whether there existed interruption of service production based on information from SIH and SIA administrative datasets. Also, the location of some facilities were not accurate, so we inspected them using Google maps and fixed the ones that were not correct.

We observe that, between 2005 and 2016, there were 139 general hospitals with ER and SUS care in Rio de Janeiro and 68 UPAs started operating. One UPA was exclusively pediatric and removed from our analysis. Among the hospitals, 25 opened and/or closed in the period. These facilities were not included as units of analysis in our main specifications, but the opening or closure of hospitals was controlled for in robustness checks performed at the hospital and city-level analyses (Appendix Section C). Therefore, our main database comprises 114 hospitals. Treatment was defined by an UPA falling within a 4.5km radius of the hospital - the median distance traveled by patients to the closest ER before the inauguration of the first UPA in 2007. We also checked the sensitivity of our estimates to a catchment area with a 6.5km radius, which represents the mean distance traveled by patients before UPAs (Appendix Section C).

Not all the 114 SUS general hospitals with 24h emergency services in RJ had consistent records throughout the entire 2005-2016 period in SIA and/or SIH. Three hospitals in SIH had missing data in sequence for more than a year, even though records were being filled into SIA and SIM and we could not find any information that they were closed or interrupted their services during the same period. Therefore we excluded these hospitals from the sample used in the analyses on SIH outcomes. The same happened with six hospitals in SIA, and we followed a similar protocol. In Appendix Section C we provide robustness checks in which we exclude hospitals with problems of data in either SIH or SIA and keep an homogeneous sample of 108 hospitals in all analyses. Results remain very similar.

In the second part of this study, we investigated the effects that UPAs had on the local mortality rate as well as on local health systems. In this analysis we relied on the 92 cities of RJ, in a quarterly panel from 2005 to 2016. Treatment was defined by the introduction of an UPA in the city.

D.3 Distance to the Nearest ER

We used the geocoded location of all UPAs and hospitals with emergency services, to calculate the mean and the median distance to the closest facility from each census tract, weighted by population size, at the municipality-level. We estimated distance both in kilometers and in minutes, taken by car at midnight, when there is limited traffic. We were also able to estimate the share of inhabitants for whom the closest ER is an UPA. To measure the routes (in kilometers) we used HERE maps.[30] Hospitals that opened and closed were taken into consideration, and routes were recalculated once they started or stopped operating. The median and mean distance travelled by patients before the first UPA is introduced was 4.5km and 6.5km, respectively.

D.4 Outcome and Control Variables

Hospital-Level Outcome Variables. In the study of hospitals' production and performance, we focus on four groups of outcomes available from the Brazilian Ministry of Health information systems (MS/Datasus). The first one involves the ambulatory procedures performed at hospitals' ER and clinics. The goal is to see whether UPAs had the desired effect of reducing the pressure on hospitals' emergency departments. This data comes from the National Ambulatory Information System (SIA/Datasus), which contains administrative information on all outpatient care funded by SUS, including: diagnosis, observation, consultation, treatment, intervention, and rehabilitation services. SIA provides microdata at the procedure level, but many procedure codes have changed over time.

[30]Link: https://developer.here.com/

Because of severe compatibility issues, we analysed the total number of procedures and also examined them subdivided as basic, medium, and high-complexity procedures.

Then we investigate outcomes related to hospitalizations from the National System of Information on Hospitalizations (Datasus/SIH). Less congestion in hospitals' ERs might increase relative resources and improve hospital performance towards its inpatients. However, this depends on patient selection and hospital response. SIH contains administrative information at the hospitalization level. This data is managed by the Ministry of Health, which receives information about hospitalizations from public and private hospitals through standardized inpatient forms - AIHs (Autorização de Internação Hospitalar). It includes all hospital admissions funded by SUS. SIH provides us with many inpatient information such as cause (ICD-10) and type (clinical, surgical, other) of admission to the hospital, duration of stay, final outcome (discharge or death), and patient socioeconomic characteristics (municipality and zip code of residence, gender, and date of birth).

Third, we analyze if the introduction of UPAs produced any restructuring in hospitals' human resources and infrastructure. Data comes from CNES and comprises information on the total number of professionals, the average number of hours worked in ambulatory and inpatient services, the number of beds by type, and equipment available.

Finally, we examine hospitals' total mortality (not only inpatient) and rely on microdata from vital statistics collected by the National System of Mortality Records (SIM/Datasus). SIM contains data on every death registered in Brazil and includes the deceased's age, gender, municipality of residence, cause of death (ICD-10), and location of death. In SIM, the establishments' CNES codes were implemented only in 2006, so all our total mortality analyses at the hospital level started in 2006 instead of 2005.

All variables were organized quarterly and at the hospital-level from 2005Q1 to 2016Q4. Details on how they were defined and constructed can be found in Tables D.3 and D.4. With the exception of mortality conditional on admission, occupation and average hours worked, we apply the inverse hyperbolic sine to all hospital outcomes, so the coefficients are interpreted as (approximate) fractional changes. The classification of hospital admissions and deaths by conditions amenable and non-amenable to primary and emergency care followed the Alfradique et al. (2009) and Vashi et al. (2019), respectively. For more information on these two classifications and on how they were merged in our setting, see Appendix A.

City-Level Outcome Variables. We used microdata from the National Register of Health Establishments (CNES/Datasus) and the National System of Mortality Records (SIM/Datasus) to build a balanced panel of quarterly data at the city level. Our sample covered all of the 92 cities of RJ from 2005Q1 to 2016Q4. CNES enabled us to identify the exact timing of UPAs' opening in each city and to compute the number of hospital inpatient beds not funded by SUS. SIM allowed us to identify whether the death occurred at home, in the street or in different types of health facilities. We used this information, together with ICD for the cause of death, to compute mortality rates by cause and location. For more information on how conditions were classified into amenable to primary and emergency care, see Appendix A.

To study the effects on the primary healthcare system, we first computed the Family Health Program (FHP) coverage from data provided by the Ministry of Health's Primary Health Care Department (SAPS). Then, we worked with data from SIAB which provides information on primary care routine consultations, exams prescribed and measures of patients registered and followed up. Data in SIAB goes only until 2015. As for information related to other layers of the health system, we collected the presence of SUS ambulance services and the total number of hospital beds in CNES, and tracked the opening and closure of hospitals using SIH and CNES.

All city outcomes, with the exception of the FHP and the SAMU presence, are measured in per capita rates. Population data used to construct these rates at the city level comes from the Brazilian Institute of Geography and Statistics (IBGE). Details on how each variable was defined and constructed can be found in Table D.5.

Control Variables. Control variables used in both the hospital and city-level analyses are: (i) the amount transferred by the Bolsa Família Program per 1,000 inhabitants, which is the main conditional cash transfer program in Brazil implemented by the federal government and with data available from the Ministry of Citizenship (former Ministry of Social Development, MDS); (ii) dummies indicating the political party of the incumbent mayor and whether the mayor and the state governor were aligned in the same party for each period. These are from data provided by the Superior Electoral Court (TSE); (iii) annual city GDP per capita, from the Brazilian Institute of Geography and Statistics (IBGE); (iv) a dummy indicating cities that suffered from heavy rains and the collapse of hills in 2011. The share of the population covered by private health insurance from the National Supplementary Health Agency (ANS) is also used as a control in robustness checks. They were all computed at the municipality-year level. More details on how they were defined and constructed can be found in Table D.6

D.5 Data Sources and Download Links

CNES: ftp://ftp.datasus.gov.br/dissemin/publicos/CNES/
SIH: ftp://ftp.datasus.gov.br/dissemin/publicos/SIHSUS/
SIA: ftp://ftp.datasus.gov.br/dissemin/publicos/SIASUS/
SIM: ftp://ftp.datasus.gov.br/dissemin/publicos/SIM/
UPA: https://dados.gov.br/dataset/upa_funcionamento_cnes
TSE Data: https://cepesp.io/consulta/tse
SAMU: https://dados.gov.br/dataset/samu_cobertura
Family Health Program Coverage: https://egestorab.saude.gov.br/paginas/acessoPublico/relatorios/relHistoricoCoberturaAB.xhtml
GDP Data: https://sidra.ibge.gov.br/pesquisa/pib-munic/tabelas
Bolsa Família Coverage: https://dados.gov.br/dataset/bolsa-familia-misocial
Population Data: https://sidra.ibge.gov.br/tabela/6579
Health Insurance Data: http://www.ans.gov.br/anstabnet/cgi-bin/dh?dados/tabnet_02.def
2010 Census: https://www.ibge.gov.br/estatisticas/sociais/habitacao/9662-censo-demografico-2010.html?=&t=microdados
Lat/Lon CNES: https://dados.gov.br/dataset/cadastro-nacional-de-estabelecimentos-de-saude-cnes1/resource/b5a7acba-f3db-448c-a29e-ec9e48563a08?inner_span=True
Lat/Lon UPA: http://i3geo.saude.gov.br/i3geo/ogc.htm?temaOgc=upa_funcionamento_cnes](http://i3geo.saude.gov.br/i3geo/ogc.htm?temaOgc=upa_funcionamento_cnes
Shapefile - RJ Municipalities: ftp://geoftp.ibge.gov.br/organizacao_do_territorio/malhas_territoriais/malhas_de_setores_censitarios__divisoes_intramunicipais/censo_2010/setores_censitarios_shp/rj/
Shapefile - RJ Census Tract: ftp://geoftp.ibge.gov.br/organizacao_do_territorio/malhas_territoriais/malhas_de_setores_censitarios__divisoes_intramunicipais/censo_2010/
2010 Household Income Data at the Census Tract Level: https://www.ibge.gov.br/estatisticas/sociais/trabalho/9662-censo-demografico-2010.html?=&t=downloads

Table D.3: Hospital Outcomes - Definitions

Hospital-Level Outcomes	Definition/Observations	Source
Ambulatory Procedures	**IHS(Number of ambulatory procedures performed)** Complexity was defined based on variable PA_NIVCP. Procedures' code changed in 2008 from SIA Table to SIGTAP and were made compatible.	SIA
Hospital Admissions	**IHS(Number of hospital admissions)** ICD-10 codes related to each cause examined are explained in Appendix D.1. Weekday: Monday-Friday; Weekend: Saturday & Sunday, variable DT_INTER.	SIH
Inpatient Deaths	**IHS(Number of inpatient deaths)** ICD-10 codes related to each cause examined are explained in Appendix D.1.	SIH
Deaths Conditional on Hospital Admission	**(# Inpatient deaths / # hospital admissions) x 100** ICD-10 codes related to each cause examined are explained in Appendix D.1.	SIH
Deaths w/n 24h Conditional on Hospital Admission	**(# Inpatient deaths within 24h / # hospital admissions) x100** ICD-10 codes related to each cause examined are explained in Appendix D.1	SIH
Total Deaths	**IHS(Number of total deaths)** ICD-10 codes related to each cause examined are explained in Appendix D.1. Weekday: Monday-Friday; Weekend: Saturday & Sunday. Day: between 7am-18pm; Night: 19pm-6am, variable HORAOBITO.	SIM
Inpatient Income	**Average Inpatient Income** Information comes from linking inpatient zipcode with census tracts' average household income from the 2010 Census.	SIH & 2010 Census
Inpatient Age and Gender	**% female inpatients; average inpatient age; % inpatients in different age categories** Age categories created: 0-4years, 5-14yrears, 15-24years, 25-44years, 45-64years and 65+ years. ICD-10 codes related to each cause examined are are explained in Appendix D.1.	SIH
Professionals	**IHS(Number of professionals); IHS(Number of physicians); IHS(Number of non-physicians)** Information comes from CNES professionals' database (PF). This database has information on all health workers jobs per establishment on a monthly basis. Variable PF_CBO contains the professional's occupation code (CBO) and allow us to identify physicians and non-physicians. CBO 2002 with the description of each code can be found here: http://tabnet.datasus.gov.br/cgi/cnes/CBO%202002.htm	CNES - PF
Average Hours Worked	**Average Hours Worked by SUS professionals** Information comes from CNES professionals database (PF). This database has information on all health workers jobs per establishment on a monthly basis Variables NUMHR_H, NUMHR_A and NUMHR_O have the number of hours/week worked in hospital, ambulatory and other services, respectively. They are filled for SUS professionals. We investigate time spent with hospital services (NUMHR_H) against the other two categories merged together (NUMHR_A+NUMHR_O). This information is then averaged over the number of SUS professionals in the establishment.	CNES - PF
Inpatient Beds	**IHS(Number of total inpatient beds); IHS(Number of inpatient beds by type)** Information comes from CNES inpatient beds database (LT). Variables QT_EXIST and TP_LEITO were used. The first one contains the number of existing inpatient beds (SUS and non-SUS) and the second has the type of bed (surgical, clinical, ITU/ICU, obstetric, pediatric, other specialties and hospital-day). We look at the total number of inpatient beds and also by the following types: surgical, obstetric, clinical, ITU/ICU, and we aggregate pediatric, other specialties, and hospital-day into an "other" category.	CNES - LT

Notes: All variables were calculated at the hospital-quarter level.

Table D.4: Hospital Outcomes - Definitions

Hospital-Level Outcomes	Definition/Observations	Source
Ambulatory and Emergency Beds	**IHS(Number of ambulatory and emergency beds)** Information comes from CNES establishment database (ST). The number of beds for children and adult observation in emergency and ambulatory structure is provided by the sum of variables: QTLEIT05 + QTLEIT06 + QTLEIT07 + QTLEIT08 + QTLEIT19 + QTLEIT20 + QTLEIT21 + QTLEIT22.	CNES - ST
Equipments	**IHS(Number of total equipments); IHS(Number of equipments by type)** Information comes from CNES equipment database (EQ). We look at the total number of equipment available for use: QT_USO Variable TIPEQUIP characterizes equipment in eight groups: diagnostic imaging; optical methods; graphics methods; life saving; infrastructure, dentistry, audiology and other. We aggregate infrastructure, dentistry, audiology and other in an "other" category. Diagnostic imaging equipment includes x-rays, mammographs, CT scanner, MRI and ultrasound machines. Optical methods incorporates endoscopes, laparoscopes, surgical microscope, among others. Graphics method equipment comprises electrocardiograph and electroencephalograph. Life saving equipment involves defibrillators, ventilators, bag valve mask, among others.	CNES - EQ
Occupancy Rate (%)	**(# inpatients / # inpatient beds) x 100, calculated for each day and then averaged over the quarter** Number of inpatients comes from SIH and number of inpatient beds comes from CNES (LT).	SIH & CNES - LT
Number of days occupancy is $\geq$ 85%	**# days in the quarter-year in which the occupancy rate is above 85%** Occupancy is define as above and calculated for each day. Then the number of days in which we see a value above or equal to 85% is calculated.	SIH & CNES - LT
Number of days occupancy is $\geq$ 100%	**# days in the quarter-year in which the occupancy rate is above 100%** Occupancy is define as above and calculated for each day. Then the number of days in which we see a value above or equal to 100% is calculated.	SIH & CNES - LT
Bed Turnover Rate	**(# inpatient discharges (including deaths) / # inpatient beds)** Number of inpatients comes from SIH and number of inpatient beds comes from CNES (LT).	SIH & CNES - LT

Notes: All variables were calculated at the hospital-quarter level.

Table D.5: City Outcomes - Definitions

Municipality-Level Outcomes	Definition/Observations	Source
Ambulatory Procedures Per Capita	**(Number of ambulatory procedures performed / Population)** Complexity was defined based on variable PA_NIVCP. Procedures' code changed in 2008 from SIA Table to SIGTAP and were made compatible.	SIA
Total Deaths per 100,000 Inhabitants	**(Number of Deaths / Population) x 100,000** Population data comes from IBGE. ICD-10 codes related to each cause examined are in Table D.1 and Vashi et al. (2019) Location was mainly defined based on variable LOCOCOR from SIH, with the exception of deaths that occurred in UPAs. This location category was added by identifying UPAs CNES numbers.	SIM & IBGE
FHP Coverage (%)	**% Population covered in the municipality by the Family Health Program** Data on population coverage at the municipality level is provided by the Ministry of Health's Primary Health Care Department (SAPS)	SAPS
SUS Ambulance Service	**Presence of SUS Ambulance Program in the municipality** Dummy variable indicating if the municipality had mobile units in that period.	CNES-ST
Routine Consultations per 100,000 inhabitants	**(Number of Routine Consultations Performed in Primary Care / Population) x 100,000** Routine consultations come from SIAB and involve pre-natal and pediatric care and the following conditions: diabetes, hypertension, sexually transmitted diseases, leprosy, and tuberculosis. Population Data comes from IBGE.	SIAB & IBGE
Physician Consultations per 100,000 inhabitants	**(Number of Physician Consultations Performed in Primary Care / Population) x 100,000** Consultations performed by physicians in primary care. Information comes from SIAB. Population Data comes from IBGE.	SIAB & IBGE
Exams Prescribed per 100,000 inhabitants	**(Exams Prescribed in Primary Care / Population) x 100,000** Includes clinical pathology, radiodiagnostic, and cytopathological exams, ultrasounds, and other exams prescribed in primary care. Data comes from SIAB. Population Data comes from IBGE.	SIAB & IBGE
Diabetics Registered per 100,000 inhabitants	**(Number of registered people with diabetes in primary care / Population) x 100,000** Number of registered people with diabetes in primary care comes from SIAB. Population Data comes from IBGE.	SIAB & IBGE
Diabetics Followed-up (%)	**(Number of people with diabetes followed-up in primary care / Number of registered people with diabetes in primary care) x 100** Percent of registered people with diabetes in primary care that are regularly followed up. Data comes from SIAB.	SIAB

Notes: All variables were calculated at the city-quarter level.

Table D.6: Control Variables - Definitions

Controls	Definition/Observations	Source
Municipality Gross Domestic Product Per Capita	**Annual Municipality GDP / Population** Annual municipality GDP, GDP price deflator and population data are from IBGE. We computed the municipality GDP in 2010 reais and divided it by its population.	IBGE
Political Alignment	**Indicators of cities' political parties and state-city alignment** Data is from the Superior Electoral Court data repository, which was organized and made available by the Center for Politics and Economics in the Public Sector Studies (CEPESP/FGV). Through this database we constructed dummies indicating the political party of the incumbent mayor and whether the mayor and the state governor were aligned in the same party for each period.	TSE / CEPESP
Bolsa Família Program	**(Value of Bolsa Familia Program transfer (R$) per quarter / Population) x 1,000** This data is made available by the Ministry of Citizenship (former Ministry of Social Development, MDS) through the Brazilian Open Data Portal.	Brazilian Open Data Portal

Notes: All variables are defined at the city-year level.