Ride-to-Health: The Impact of Ridesharing on Patients' Emergency Care Access

Abstract

Transportation has been one of the obstacles preventing people from timely and appropriate access to healthcare. Emergency Department (ED), which provides around-the-clock care for illnesses and injuries, including life-threatening ones, is known as the "safety net" of the healthcare system. It would be interesting to investigate whether ridesharing platforms, as an alternative transportation option outside private cars, public transit, and ambulance, alleviate the transportation concern, especially for the access to ED services. This paper empirically examines how the entry of Uber, an online ridesharing platform, influences patients' access to emergency care. We leverage the sequential entries of Uber in different counties in California as a natural experiment setting and use the staggered difference-in-differences model to estimate this impact. We find a positive impact of Uber's entry on the number of high-severity ED visits. This impact is smaller for EDs that provide more comprehensive care, treat more uninsured patients, and are located in smaller areas. From ED utilization's perspective, Uber's entry decreases the number of low acuity ED visits, affects patients' ED selection by allowing them to travel to EDs beyond the closest ones, increases the patient waiting time, but overall reduces the mortality in ED. Our findings have important managerial and policy implications and contribute to the growing stream of research on the social effects of sharing economy.

Keywords: *ridesharing platform, emergency care, natural experiment, difference-in-differences, look-ahead propensity score matching*

1. Introduction

The growth of on-demand digital platforms in the sharing economy, such as Uber and Airbnb, has tremendous potential to affect the economy and society and has been increasingly discussed in academic research and media.[1] As a ridesharing platform, Uber started with its first trip in San Francisco in 2010 and now offers its services in more than 10,000 cities[2] worldwide, generating billions in revenue annually and reaching a market capitalization value as high as almost $75 billion.[3] Using mobile technology, users can now book a ride to their destination at the tap of a button anytime and anywhere, making ridesharing services easier to access than other public transportations such as buses or taxis that may have temporospatial restrictions. However, despite their business success, the social impacts of ridesharing platforms are not always positive. For example, while academic research has documented the reductions in violent crimes (Park et al. 2021), alcohol-related motor vehicle fatalities (Greenwood and Wattal 2017), and traffic congestion (Li et al. 2016) after Uber's entry, it has also been observed that the entry of the Uber platform leads to decreases in entrepreneurial activities (Burtch et al. 2018) and earnings of taxi drivers (Cramer and Krueger 2016).

Within the domain of societal impacts of ridesharing, industry experts and academic researchers have started discussing the impact of Uber on healthcare access, given its potential in alleviating the transportation barrier. The transportation barrier in this context is defined as the lack of access to transportation, particularly private transportation, in the form of ownership of a vehicle or through acquaintance with a vehicle owner. This barrier can lead to "no-shows" or missed medical appointments, delayed care, or low healthcare utilization (Drake et al. 2020, Guidry et al. 1997). It is particularly concerning that the transportation barrier tends to be more severe for minority demographic groups (Richardson et al. 2021), populations with lower income, and the underinsured/uninsured (Syed et al. 2013). While the role of public transportation in alleviating the concern of the transportation barrier may be

[1] Uber, Airbnb and consequences of the sharing economy: Research roundup: https://journalistsresource.org/economics/airbnb-lyft-uber-bike-share-sharing-economy-research-roundup/
[2] Use Uber in cities around the world: https://www.uber.com/global/en/cities/
[3] Market capitalization of Uber (UBER): https://companiesmarketcap.com/uber/marketcap/

insignificant (Giambruno et al. 1997) or adverse (Rittner and Kirk 1995), healthcare providers have been considering ridesharing as a potential solution given its capability to provide transportation on demand. For example, Uber has started collaborating with healthcare providers under the initiative of Uber Health[4] in 2017, with the objective of breaking down the transportation barrier for those who need help and providing improved access to healthcare. Healthcare providers have also started implementing policies that involve collaborating with transportation providers,[5] initially on a pilot basis, with the objective of reducing no-show rates at medical appointments, especially in patient groups with a more significant transportation barrier.[6] Some studies have tried to examine the effects of these initiatives on healthcare providers' cost savings (Rochlin et al. 2019) and refugee women's transportation access (Vais et al. 2020). However, whether Uber can break down the transportation barrier to improve healthcare access remains an open question.

We contribute to this ongoing discussion by focusing on the ridesharing platform's role in alleviating the transportation barrier to Emergency Department (ED) services. ED is an essential part of healthcare as it provides around-the-clock care for illnesses and injuries, including life-threatening ones (Hsia et al. 2018), and serves as the "safety net" of the healthcare system that provides medical services to all patients, including low-income and uninsured patients who may lack access to other healthcare providers (Felland et al. 2008). Even with the urgent nature of emergency care, ED visits are also significantly influenced by the transportation barrier, causing delays in treatment, even in severe medical conditions.[7] The ambulance service, although providing transportation access under emergent conditions, may not be a viable option to break down the transportation barrier given its high cost (Courtemanche et al. 2019, Moskatel and Slusky 2019, Tsega and Cho 2019) and its unpredictable availability and time-to-arrival

[4] Care begins with getting there: https://www.uberhealth.com/
[5] Healthcare ridesharing activity surges; focuses on improving care, reducing costs: https://www.healthleadersmedia.com/innovation/healthcare-ridesharing-activity-surges-focuses-improving-care-reducing-costs
[6] Our sickle cell clinic was struggling with no-shows. So we called an Uber.: https://www.bmc.org/healthcity/population-health/our-clinic-was-struggling-no-shows-so-we-called-uber
[7] Woman feared she couldn't afford ambulance after her leg was trapped by a subway train: https://www.cnn.com/2018/07/03/health/subway-accident-insurance-fear-trnd/index.html

(Berger 2017) due to demand fluctuation, e.g., as recently observed during the Covid-19 pandemic.[8] While ridesharing is considered an affordable on-demand transportation option with the potential to break down the transportation barrier (Birmingham et al. 2021), whether it has a tangible effect in improving emergency care access has never been systematically examined. This question is especially important for high-severity cases, given the significant consequences of delayed treatment.[9] This motivates our first research question: *Does the entry of Uber, as a typical ridesharing platform, affect the number of high-severity ED visits?*

The entry of a ridesharing platform may not influence all hospitals equally. Hospitals vary in their capability of handling severe and complex cases, location, existing patient load and capacity level, and the composition of different patient groups that vary in their sensitivity to the transportation barrier, their acceptability and accessibility to the new ridesharing option, and their utilization of this new option. It is thus important for us to examine not only the overall impact of Uber's entry but also how this impact varies for different types of hospitals to help us understand what types of hospitals and patient groups receive the most impact (Chaiyachati et al. 2018) from the availability of this new transportation option. Hence, our second research question is: *How do hospital characteristics moderate the impact of Uber on the number of high-severity ED visits?*

If the entry of Uber influences the number of ED visits differently at different hospitals, it may subsequently affect the resource redistribution at both intra-ED and inter-ED levels. For example, with the entry of Uber, patients would now have the flexibility to select from an expanded set of nearby EDs based on criteria such as the quality, reputation, or busyness of an ED, in addition to the distance to the ED. For

[8] COVID spike causing ambulance shortage and long 911 wait times in Pasco County, fire chief says: https://www.wfla.com/news/pasco-county/spike-in-covid-hospitalizations-causing-ambulance-shortage-and-long-911-wait-times-in-pasco-county-fire-chief-says/

[9] Some people may choose to delay treatment needed at emergency care facing a significant transportation barrier, when not recognizing the severity of their conditions. While the avoidance of ED visits does not always lead to catastrophic results, some, especially in high-severity cases, could result in fatal events. For example, for some people, certain symptoms involving abdominal pain or chest pain could be caused by non-life-threatening illness and may even subside without any medical intervention (e.g., gallbladder attack: https://www.hopkinsmedicine.org/health/conditions-and-diseases/what-causes-a-gallbladder-attack). For others, similar symptoms need immediate medical attention and require a comprehensive examination to rule out the possibility of life-threatening conditions. Delaying or avoiding ED visits in such cases can lead to severe consequences.

a given ED, an increase in patient numbers and thus in ED utilization may induce a longer waiting time in the ED and may lead to a deterioration in healthcare outcomes, if it does not have enough capacity to accommodate additional patients. Given that ED usage is of significant public concern, as highlighted in the Report to Congress[10], how the entry of Uber further influences the utilization of EDs is worth further investigation. Therefore, our next research question is: *how does Uber's entry influence patients' ED selections and ED utilization?*

Lastly, while we mainly focus on high-severity ED visits given their life-threatening consequential impact, we are also interested in exploring the effect of Uber's entry on other types of ED visits. For example, some low acuity visits could include non-emergent and "primary care treatable" conditions that can be avoided by having better access to primary care providers (Dowd et al. 2014, Enard and Ganelin 2013, Weinick et al. 2010). It would be interesting to examine whether such ED visits can be spared, leaving ED resources to more urgent situations, if the entry of Uber may improve not only the access to EDs but also that to primary care providers. Accordingly, our last research question is: *how does Uber's entry impact other types of ED visits?*

To empirically answer these four research questions, we use a dataset involving almost 300 hospitals from California, the most populated state in the United States. We collect annual hospital-level data of 15 years on the number of ED visits and ED characteristics and the corresponding county-level Uber entry information and county characteristics. We employ the difference-in-differences (DID) model with two-way fixed effects, by which we can design our research in the form of a quasi-experimental setup. We further corroborate the robustness of our results and address the potential concern over the endogeneity of Uber's entry decisions through a number of additional analyses. Utilizing the diversity of our dataset, we are also able to analyze the moderating effects of various hospital characteristics to understand the heterogeneous nature of the impact of ridesharing on emergency care access.

[10] The issues are highlighted in the Report to Congress, 2021 on the Trends in the Utilization of Emergency Department Services, 2009-2018: https://aspe.hhs.gov/sites/default/files/migrated_legacy_files//199046/ED-report-to-Congress.pdf

We find a significantly positive impact of Uber's entry on ED visits of the highest severity level. Ridesharing platforms thus contribute to society by improving patients' access to emergency care in the most severe medical emergencies. The effect is significantly larger for the subgroup of hospitals that are less comprehensive (e.g., with relatively inferior trauma-handling capabilities, not having teaching affiliation, or providing only basic emergency medical services), hospitals that serve a relatively smaller proportion of uninsured patients, or hospitals that are located in large and medium metropolitan counties. These results raise the concern of whether the benefits to emergency care access from ridesharing services are effectively distributed to those who face the transportation barrier the most.

In addition, we find that Uber's entry redistributes the healthcare resources in several aspects. First, it is encouraging to observe more ED resources allocated to severe cases, indicated by a significant negative impact of Uber's entry on ED visits belonging to the lowest severity level. Second, our empirical analysis shows that patients have more flexibility in choosing EDs beyond location restrictions. Last but not least, probably due to the increased number of severe cases, we also find an increase in the average patient waiting time in ED. However, we believe that Uber's entry has an overall positive impact on emergency care as it ultimately leads to lower mortality in ED, even with an increased number of high-severity cases treated and a longer waiting time.

This study contributes to the literature on the societal impact of the sharing economy by providing the first large-scale empirical findings on the impact of a ridesharing platform's entry on emergency care access. Our results have important practical implications and provide empirical evidence that encourages healthcare providers, ridesharing platforms, and policymakers to initiate collaborative programs at a population level to improve patient access to emergency care. While regulating the sharing economy, policymakers should consider the benefits to healthcare access from ridesharing and facilitate distributing these benefits to patients who are more economically vulnerable and face a more significant transportation barrier to emergency care.

The remainder of the paper is structured as follows. Section 2 discusses the streams of literature that our paper is related to and the unique contributions of our research. Section 3 describes the empirical models and the data used in our research. Section 4 presents the results of our analysis through which we answer our research questions. In Section 5, we perform robustness checks to substantiate the validity of our main results. Finally, in Section 6, we conclude our findings and discuss their implications.

2. Literature review

This research contributes to the stream of literature that empirically examines the impact of information systems (IS) on healthcare access. Information technologies (IT) have demonstrated different socioeconomic effects, including effects related to health care. For example, using electronic health records (EHR) has shown a significant negative association with ED visit numbers and hospitalization rates through a cumulative effect across preventive care pathways (Reed et al. 2013). Similarly, "electronic visits" by patients to the physician's office have improved primary care continuity (Bavafa et al. 2018). Other benefits of implementing health IT applications for patient care include increase in hospitals' adherence to standard guidelines on length of stay (Oh et al. 2018). On the other hand, EHR adoption can increase the costs of the adopting hospital, although it simultaneously reduces the costs of neighboring hospitals through information and patient sharing (Atasoy et al. 2018). The focus of our research is on Uber, an online platform, and its effect on emergency care. As Uber is a ridesharing platform and not a healthcare-related platform, its effect on healthcare outcomes would be indirect and can be intriguing.

Our paper also relates to the literature studying the effect of transportation modes on patients' access to healthcare. As discussed in the introduction, transportation is a critical barrier to healthcare access, particularly for underprivileged groups (Drake et al. 2020, McConnell et al. 2020, Syed et al. 2013). One of the reasons is the lack of private transportation (Guidry et al. 1997) or the inconvenience of public transportation (Rittner and Kirk 1995). Our research is related to this field as ridesharing platforms provide an alternative option of transportation services, and it remains to be seen whether they can fill in the transportation gap in healthcare access, especially emergency care access.

The stream of research most related to our paper examines the socioeconomic impacts of ridesharing. Uber's economic effects studied in the literature include affecting the automobile industry by reducing the total number of automobile registrations (Sengupta et al. 2021) and increasing the number of new automobile registrations (Gong et al. 2019). From a societal aspect, the observed effects of Uber's entry into a geographic location include reductions in the number of sexual assaults (Park et al. 2021), traffic congestion (Li et al. 2016), motor vehicle fatalities due to driving under the influence (Greenwood and Wattal 2017), entrepreneurial activities (Burtch et al. 2018), and the earnings of taxi drivers (Cramer and Krueger 2016). We examine the impact of Uber's entry on the healthcare-related outcome of ED visits. Emergency care is the most critical medical service provided to the general population, especially when it involves the most severe conditions that could have an immediate risk to a patient's life. This critical role that EDs play in society underscores how any potential effect of ridesharing on emergency care access would result in an important societal impact.

In the stream of literature that links ridesharing platforms with healthcare access, researchers have investigated the impact of adopting ridesharing services as a medical transportation option for visits to non-emergency care providers, often through collaborations between healthcare providers and ridesharing firms. Based on a review of academic literature and media articles, a study has found that ridesharing is becoming a part of patients' transportation choices for non-emergency care access (Wolfe and McDonald 2020). On the contrary, other studies suggest that the uptake of ridesharing services is low even when provided complimentarily and does not decrease missed primary care appointments among 786 Medicaid patients in their facility (Chaiyachati et al. 2018). Thus, the findings have been contradictory and inconclusive, likely because they are based on small-scale pilot studies.[11] Moreover, the scope of these papers does not include any impact on ED visits. Considering the differences in the nature of these two types of services, findings from non-emergency care visits may not apply to ED visits. Therefore, the impact of ridesharing platforms on emergency care access for the general population remains an open question.

To our knowledge, we are the first paper that empirically investigates how the entry of a ridesharing platform affects ED visits. Some studies show that the introduction of ridesharing has resulted in a decrease

[11] Chaiyachati et al. (2018) acknowledge as one of their limitations, that their study population may not have been interested in ridesharing.

in psychiatric patients' waiting time for their discharge transport from an ED in a collaborative initiative in their facility (Blome et al. 2020) or a decrease in the per capita ambulance usage based on voluntarily-reported emergency transportation records (Moskatel and Slusky 2019). However, neither shorter discharge transport waiting time nor lesser ambulance usage has a clear relationship with the number of ED visits and measures the level of emergency care access. Other studies show that ridesharing-related awareness among ED patients may exist only to a limited extent, as only 5% of the 500 surveyed patients have used ridesharing for traveling home after discharge from their facility (Tomar et al. 2019), which may indicate limited impacts of ridesharing platform's entry on ED visits. In addition to the unsettled conclusions, we note that these findings of the ridesharing's usage for emergency care are obtained from a small study cohort in single healthcare facilities or from databases using voluntarily-reported emergency transportation records, which may raise concerns about the robustness and the generalizability of the results.[12] Different from previous studies, our work adopts a rigorous empirical methodology and includes almost all ED patients in the most populous state in the United States. We contribute to the literature by empirically examining the causal impact of ridesharing on ED visits for the first time and expanding the research scope from pilot studies to the general population across large and diverse geographies. Our findings provide the first large-scale empirical evidence on how access to ridesharing services affects the transportation barrier to healthcare, particularly emergency care. We also present additional findings on how ED characteristics moderate the impact of ridesharing on ED visits and the impact of ridesharing on patients' ED selection and ED utilization.

3. Background and Data

In this section, we describe the data that we use to answer our research questions. We first gather the information on Uber's entry into different locations from Uber's webpage and blog articles on Uber's newsroom and confirm the entry dates using related online news articles.

[12] Tomar et al. (2019) point out that their study subjects significantly differed from the overall ED population in terms of gender and age.

We then collect the number of ED visits and ED- and hospital-related information in the state of California, United States, from its Department of Health Care Access and Information (HCAI). California requires every hospital to file its annual utilization data for its licensed services, including ED services, and the state "indirectly prohibits" the operation of freestanding EDs through its state regulations.[13] Thus, this HCAI dataset includes the utilization information for all EDs in California. Specifically, we get hospital-level ED visits data from the hospital utilization datasets, the demographic composition of patient visits, the insurance information, and the ED mortality from the ED characteristics datasets, and the financial information of the hospitals from the annual financial datasets. All the datasets are available on the website of HCAI.

Our dataset initially comprises information from 584 hospitals from 57 counties in California, spanning 2005 to 2019. The starting year of our analysis is 2005, 5 years before Uber started as a company, and the end year is 2019, the latest year with complete data available at the time of analysis. Following the literature (Hsia et al. 2012, Lambe et al. 2002), we apply several filters to our initial dataset. Each year, we include only the hospitals for which the facility is operating, and the license status is active throughout the year. In addition, we include only "general acute care" hospitals that provide "general medical/surgical" services and "basic" or "comprehensive" licensed emergency medical service (EMS), have consistent reporting of ED visits, and have at least one ED visit recorded in every year in our sample. After applying these filters, the number of hospitals in our sample drops to 284, located in 48 counties. We consider hospitals as our unit of analysis because it allows us to capture the heterogeneity at a finer granularity than the county-level analysis and explore potentially different consumer behaviors in different hospitals.

ED visits are categorized into different severity levels based on HCAI.[14] There are five different severity levels from the highest to the lowest: severe-with-threat, severe-without-threat, moderate, low/moderate, and minor. ED visits on the highest severity level (referred to as *severe-with-threat* by HCAI)

[13] Freestanding Emergency Departments: Do They Have a Role in California. https://www.chcf.org/wp-content/uploads/2017/12/PDF-FreestandingEmergencyDepartmentsIB.pdf

[14] This severity categorization scheme has been also adopted by other government agencies for their ED utilization reporting such as Florida's Agency for Health Care Administration (AHCA).

are often associated with medical conditions that are the most urgent, pose an immediate significant threat to the life or physiologic function of the patient (e.g., active gastrointestinal bleeding), and require a comprehensive examination and medical decision-making of the highest complexity. The lowest severity levels of ED visits include *low/moderate* visits that require problem-focused examination and medical decision-making of low complexity (e.g., a minor injury with localized pain and swelling) and *minor* visits that require straightforward medical decision-making (e.g., removing sutures from a healed laceration).[15] We use these data to answer our research questions about ridesharing's impact on the most severe and least severe ED visits.

To fully understand the impact on EDs, we further collect additional data from several sources. First, to study the moderating effect of hospital locations, we supplement the HCAI data with the rural-urban designation for each county from the U.S. Department of Agriculture (USDA).[16] The USDA classification contains multiple categories for counties based on their population and their adjacency to metro areas. We also obtain county-level macroeconomic data such as gross domestic product (GDP) from the Bureau of Economic Analysis, population and median household income from the Census Bureau, land area required for calculating population density from the California State Association of Counties, and unemployment rates from the Bureau of Labor Statistics. Second, we compile data on patient waiting time in EDs from the Centers for Medicare & Medicaid Services (CMS) to examine the impact on ED utilization. Third, we obtain patients' residential ZIP codes and their ED visit frequencies from the HCAI Patient Origin/Market Share dataset to study the impact on patients' ED selections. Based on the latitude and longitude for every ZIP code from the ZIP code distance database of the National Bureau of Economic Research, we calculate an estimated traveled distance for each ED visit. Finally, we collect data on visits to primary care clinics and other clinic-related information from the Clinic Utilization datasets of HCAI to

[15] Other ED visit categories are severe-without-threat visits that are associated with severe conditions but without the immediate danger to the patient's life (e.g., an older adult having pain and difficulty moving due to a fall-related injury to her hip) and moderate visits that are less severe in nature but require detailed examination and medical decision-making of moderate complexity (e.g., an ankle injury leading to difficulty in standing).

[16] We also re-run our analysis with the National Center for Health Statistics (NCHS) categorization, and our results hold.

study the potential spillover from primary care visits to low-severity ED visits.

The description of our main variables and their summary statistics are in Table 1 and Table 2, respectively. The description and summary statistics of the other variables are in Table A1 and Table A2 of the online appendix, respectively.

4. Empirical Analysis

We consider Uber's entry as the treatment in the natural experiment setting. We identify Uber as the ridesharing platform in our study because it dominates the global ridesharing market and has preceded its competitors in entering most of the locations in the United States. As Uber sequentially enters different counties over time, we can use the staggered DID framework (Burtch et al. 2018) to examine the effect of Uber's entry by exploiting the temporal and geographical variations in Uber's entry. We will further corroborate our results with additional robustness analyses in Section 5.

4.1. Main effect of Uber's entry on high-severity ED visits

To address our first research question, we examine the impact of our treatment variable, *Uber*, on the number of severe-with-threat ED visits, at the hospital-year level. The main empirical model is:

$$Y_{it} = \alpha_i + \delta_t + \beta Uber_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (1)$$

where the dependent variable, Y_{it}, is the log-transformed number of severe-with-threat ED visits to hospital i in year *t*. The main independent variable of interest is $Uber_{it}$, which is a dummy variable that takes a value of 1 for the year when Uber enters the county of a particular hospital and the subsequent years for that hospital, and 0 otherwise. In any given year between 2005 and 2019, we consider the hospitals located in the counties that Uber has entered as treated hospitals and those located in counties without Uber as control hospitals. That is, we consider Uber's entry as the treatment with the treatment time varying by county and thus by the hospitals within the county. The coefficient of $Uber_{it}$ thus captures the treatment effect by effectively comparing the difference between the number of severe-with-threat ED visits for treated hospitals before and after Uber's entry to the same difference for control hospitals.

In our regression model, we include observable hospital-level time-varying characteristics that can affect ED visits into our model as control variables, captured by X_{it}.[17] Following prior literature (Hsia et al. 2012), we include the demographic profile of patients and the financial and infrastructural characteristics of a hospital that may change over time, which are the percentage of patients belonging to different gender, age, race, and insurance payer groups, the number of patients, gross operating revenue, other operating revenue, the licensed EMS level (comprehensive or basic), the level of trauma handling capability (trauma center level), a dummy denoting whether the hospital has teaching status, and the number of services provided 24-hours-a-day by its ED. In addition, hospital fixed effects α_i and time (year) fixed effects δ_t are included in the regression to control for unobserved time-invariant hospital factors and temporal effects. The error terms ε_{it} are clustered at the hospital level to account for correlation within hospitals.

The main empirical results are reported in Table 3. The estimated coefficient of the dummy for Uber's entry suggests a significantly positive effect of Uber's presence on the number of severe-with-threat ED visits, potentially due to the breaking down of the transportation barrier to ED access. Specifically, the presence of Uber in a county, leads to an average of 19% increase in the number of severe-with-threat ED visits to hospitals in that county compared to those visits to hospitals in counties without Uber's presence. This result answers our first research question.

4.2. Heterogeneous treatment effects by Uber's entry

While the overall impact of Uber's entry on severe-with-threat ED visits is positive, its effect may vary in hospitals with different characteristics, which can act as moderating variables. To explore the heterogeneous treatment effects of Uber on hospitals, which is our second research question, we follow the literature (Babar and Burtch 2020, He et al. 2022) and add interaction terms between Uber's entry variable and the moderating variables to our main regression model as described in Equation (2):

$$Y_{it} = \alpha_i + \delta_t + \beta_1 Uber_{it} + \beta_2 Uber_{it} * M_{it} + \beta_3 M_{it} + \beta_4 X_{it} + \varepsilon_{it} \tag{2}$$

Due to the multicollinearity concern, we add the interaction terms one at a time, except when multiple moderating variables correspond to the same hospital characteristic, such as the percentage of patients in

[17] We take the natural log transformation of the control variables that have skewed distributions.

different payer groups or dummies denoting metropolitan categories of counties. We denote the moderating variables and the other covariates by M_{it} and X_{it} in the regression model, respectively. There are mainly three different types of moderating variables: hospital classification, patient composition, and location.

We first consider hospitals' designation, including teaching affiliation, trauma center level, and licensed EMS level.[18] As shown in the results in Table 4, we find that the coefficients of the interaction terms are significantly negative for variables related to teaching affiliation, comprehensive licensed EMS (the highest level of EMS), and level-I trauma center designation (the highest trauma-handling capability). These results suggest that the positive impact of Uber's entry on severe-with-threat ED visits is likely to be larger for hospitals that provide relatively less comprehensive care. We speculate that hospitals with teaching affiliation, level-I trauma center designation, and comprehensive licensed EMS could already be facing a saturation of capacity for serving severe-with-threat ED visits because of their better treatment capability and quality of care (Ayanian and Weissman 2002, Sewalt et al. 2021). The access to Uber may have provided patients not only the convenience to travel but also the flexibility to switch to other less crowded hospitals for such visits.

Next, we investigate how hospitals with different compositions of patients may receive different impacts. Specifically, we consider the percentage of uninsured patients and a dummy variable to identify hospitals having a considerably large representation of patients who are uninsured or are covered under Medicaid (known as Medi-Cal in California) as "safety net" hospitals.[19] Overall, we consistently find a significantly negative moderating effect of the interactions with the percentage of uninsured patients and the "safety net" dummy variable. These results suggest that the positive impact of Uber's entry is likely to be comparatively larger for hospitals with a relatively lower percentage of uninsured patients. Low-income

[18] We also tried using other hospital characteristics as moderating variables, such as the number of beds, total staff, the number of operating rooms, and the number of ambulance diversion hours, but we did not find significant results.

[19] Following the definition by the U.S. Department of Health and Human Services, we define those hospitals as "safety net" where at least one of the following three criteria are met: at least 30% of the visits are with Medicaid, at least 30% of the visits are from uninsured patients, or a combined patient pool of Medicaid and uninsured contributes to at least 40% of the visits.

groups, who are more likely to be uninsured,[20] may not own a smartphone or credit card to access ridesharing services or may often not know how to access such services because they are not technology-savvy (Grahn et al. 2020, Tomar et al. 2019, Young and Farber 2019). Therefore, we speculate that ridesharing platforms may have less popularity and are possibly less accessible among the uninsured group.

The last moderating variable of interest is the rural-urban classification of counties where the hospitals are located. We find that the coefficients of the interaction terms are significantly positive for hospitals located in large and medium metropolitan counties, which are the most populated counties in the USDA categorization. This result could be explained by both the stronger demand for ridesharing services in cities with larger populations (Sengupta et al. 2021, Yu and Peng 2020) and the greater availability of driver-partners and cars (Mitra et al. 2019) in these cities. These results answer our second research question.

4.3. Impact on patients' ED selection and ED utilization

In this section, we investigate the broader impacts of Uber's entry on emergency care. First, an ambulance usually transports a patient to the nearest ED available unless diverted (Shen and Hsia 2015).[21] However, with ridesharing, patients could have the choice to select EDs based on their quality, reputation, and busyness, in addition to their proximity. Therefore, from the heterogeneous treatment effects analysis in Section 4.2, we speculate that the access to Uber provides patients not only the convenience to travel but also the flexibility to switch to different hospitals. Second, a significant increase in the number of ED visits could lead to an over-utilization of ED and longer patient waiting time at ED, which is often associated with a deterioration in emergency care outcomes (Shen and Lee 2019, Spaite et al. 2002). Accordingly, the increase in the number of severe-with-threat ED visits due to Uber's entry, as observed in our main analysis in Section 4.1, may lead to a concern about ED utilization. Therefore, given the two considerations, it is

[20] Health insurance coverage and income levels for the U.S. noninstitutionalized population under age 65, 2001. https://meps.ahrq.gov/data_files/publications/st40/stat40.pdf

[21] Ambulance diversion happens when the ambulance is denied entry by the nearest ED due to overcrowding. Reducing Ambulance Diversion in California: Strategies and Best Practices. https://www.chcf.org/wp-content/uploads/2017/12/PDF-ReducingAmbulanceDiversionInCA.pdf

important to run additional analyses to answer our third research question of how Uber's entry influences patients' ED selection and ED utilization.

4.3.1. Travel Distance Analysis

We explore the impact of Uber's entry on patients' ED selection by examining their travel distances to EDs. The HCAI dataset reports the distribution of ED patients' ZIP codes for each hospital.[22] By examining all pairs of ED and patient ZIP codes, we collect the number of visits to different EDs for each patient ZIP code. Then we use the following Equation (3) to calculate the distance between each pair of ED ZIP code and patient ZIP code by converting ZIP codes to latitudes and longitudes:[23]

$$d = 3963 * \arccos\left[\sin\left(\frac{latitude_1}{57.2958}\right) * \sin\left(\frac{latitude_2}{57.2958}\right) + \cos\left(\frac{latitude_1}{57.2958}\right) * \cos\left(\frac{latitude_2}{57.2958}\right) * \cos\left(\frac{longitude_1}{57.2958} - \frac{longitude_2}{57.2958}\right)\right] \quad (3)$$

We consider four distance intervals (0-5 miles, 5-10 miles, 10-25 miles, and over 25 miles).[24] For each distance interval, we calculate the number of ED visits that have a travel distance within the interval and the proportion of such ED visits over all ED visits from the same patient ZIP code. Then, we run an analysis on the level of patient ZIP code and use a regression model similar to that in Equation (1), where *i* now denotes a patient ZIP code instead of a hospital as in our earlier analyses. In two sets of analyses, we use the number and the proportion of ED visits calculated earlier for a patient ZIP code *i* as our dependent variable Y_{it}, respectively. The treatment variable $Uber_{it}$ denotes Uber's entry at the patient ZIP code level, derived from the county-level entry information. For the control variables X_{it}, we use the macroeconomic variables of the county to which the patient ZIP code belongs, including GDP, population density, mean household income, and unemployment rates. We also include patient ZIP code fixed effects α_i and the time (year) fixed effects δ_t.

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[22] Due to limited data availability, the timeline of the HCAI dataset is 2012 to 2019, which is shorter than the timeline of 2005 to 2019 in our main analysis in Section 4.1.
[23] Source: "Distance to Nearest Hospital" Files, NAMCS and NHAMCS (1999 to 2009). https://www.cdc.gov/nchs/data/ahcd/distance_to_nearest_hospital_file.pdf
[24] We select these distance intervals based on approximately the four quartiles of travel distances from patient ZIP codes to their visited EDs.

From the results in Table 5 and Table 6, we find a significant positive impact of Uber's entry on the number of visits and the proportion of visits to EDs 10-25 miles away. On the contrary, we find a significantly negative impact on the proportion of visits to closely located EDs within 5-10 miles and to EDs more than 25 miles away, although the number of visits to EDs more than 25 miles away increases. Accordingly, after Uber's entry, patients are visiting EDs located farther away, and this change in patients' ED selection is primarily restricted within 25 miles. We speculate that Uber enables patients to travel longer distances to hospitals they select based on specific characteristics such as quality of care, reputation, or busyness of the ED, instead of solely based on their proximity. The decrease in the proportion of ED visits more than 25 miles away can be explained by the proportionally much larger increase in the number of visits within 10-25 miles than the increase in the number of visits to more than 25 miles. These results suggest that ridesharing helps patients overcome location restrictions and provides them more flexibility in choosing EDs.

4.3.2. ED utilization analysis

To measure ED utilization, we use the CMS data on the average patient waiting time at the ED and the average patient waiting time in the queue.[25] The first measure denotes the average[26] time patients spent in the ED before leaving from the visit, while the second metric captures the average time patients spent in the ED before they were seen by a healthcare professional. The regression model we use is similar to the model in Equation (1), where the dependent variables Y_{it} are the two waiting time measures in two separate estimations, while other variables remain the same as in our main analysis in Section 4.1. From the results in Table 7, we find that Uber's entry leads to an increase in both waiting times. This is probably due to the sheer increase in the number of severe-with-threat ED visits, as such visits require a comprehensive

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[25] Due to limited data availability, the timeline of the waiting time data is 2013 to 2019, which is shorter than the timeline of 2005 to 2019 in our main analysis in Section 4.1. Unlike the HCAI ED dataset, not all hospitals report waiting times to CMS, which further reduces our sample size for this analysis, and the reported waiting time is based on a sample of ED visits.

[26] According to CMS, the data reported is the median time, but is referred to as the "average" for ease of understanding. We use the term "average time" in this study to be consistent with CMS. https://data.cms.gov/provider-data/topics/hospitals/timely-effective-care

examination and medical decision-making of the highest complexity and may require a longer stay at the ED. The increased waiting times may lead to a deterioration in emergency care outcomes and thus may raise concerns about Uber's impact on ED utilization (Shen and Lee 2019, Spaite et al. 2002). To address this concern, we further examine Uber's potential impact on emergency care outcomes in the following subsection. We choose to use mortality in ED,[27] which has been used in the literature (Baker and Clancy 2006), as the measure for the emergency care outcome.[28]

4.3.2.1. Analysis of mortality in ED

To analyze the impact of Uber's entry on the emergency care outcome, we collect mortality data of EDs from the HCAI dataset and perform the analysis at the level of hospital-year using a regression model similar to Equation 1 with the dependent variable Y_{it} being the number of deaths that occurred during the ED visit at hospital i in year t. We keep the covariates and the fixed effects identical to those used in our main analysis in Section 4.1.

From our results in Table 8, we find that Uber's entry leads to a significant decrease in the number of deaths that occurred during the ED visit. Interestingly, this positive effect is observed despite the significant increase in the number of severe-with-threat ED visits, which is expected to not only aggravate the already long waiting time at the ED but also increase mortality. We speculate that, as the entry of a ridesharing platform helps break down the transportation barrier, patients do not have to delay or defer their ED visits for severe conditions, which they could have done due to high costs or the shortage of ambulance transportation. This positive influence may triumph over the negative impact caused by longer waiting time at ED, leading to an overall reduction in mortality. This result supports the overall positive societal impact of Uber's entry on emergency care.

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[27] Following HCAI classification, we define ED mortality as the number of deaths that occur before the patient leaves the ED. Episodes of dead-on-arrival at the ED or cases where the patient dies after admission into the hospital are not included. https://hcai.ca.gov/wp-content/uploads/2020/10/EDAS-Disposition-Nov-2021-published.pdf

[28] Some studies have shown that the number of deaths after ED discharge that are directly related to ED visits is extremely small, and it is problematic to establish the contribution of ED visits to deaths after admission into hospitals (Baker and Clancy 2006).

4.4. Effect of Uber's entry on ED visits of other severity levels

Having observed the effects of Uber's entry on severe-with-threat ED visits, we next explore the impact on ED visits of other severity levels, which answers our final research question. Out of the remaining severity levels, we combine the minor and low/moderate levels because of the sparsity of observations and denote the sum as "low acuity." This combined reporting method has been used by Florida's Agency for Health Care Administration (AHCA) and was used by California's HCAI before 2002. We estimate the model at the hospital-year level similar to that in Equation (1). For each of the remaining severity levels (i.e., severe-without-threat, moderate, and low acuity), we run a separate regression with Y_{it} denoting the number of ED visits in the focal severity level to hospital i in year t. The treatment variable, the control variables, and the fixed effects remain the same as in our main analysis in Section 4.1.

The empirical results for low acuity ED visits are reported in Table 9,[29] and we observe a significantly negative impact. Specifically, the presence of Uber in a county leads to an average 9% decrease in the number of low acuity ED visits to hospitals in that county compared to the number of visits to hospitals in counties without Uber's presence.

It might seem counter-intuitive that Uber's entry leads to a decrease in low acuity ED visits, as one might expect the result to be in the same direction as that for severe-with-threat ED visits due to better access to emergency care. However, we speculate that Uber's entry also improves patients' access to other healthcare resources, including primary care providers. Such improvement might lead to a reduction in ED visits of the lowest severity level, as previous medical literature has reported that such ED visits are often "preventable" with timely primary care (Dowd et al. 2014, Enard and Ganelin 2013, Weinick et al. 2010). We provide evidence supporting this speculation in the following subsection.

4.4.1. Effect of Uber's entry on primary care visits

To provide evidence for our speculation, we analyze the impact of Uber's entry on the number of visits to

[29] We do not find any significant impact of Uber's entry on moderate and severe-without-threat ED visits.

primary care clinics in California.[30] We perform the analysis on the clinic-year level using a model similar to Equation (1). The dependent variable Y_{it} denotes the number of visits to primary care clinic i in year t; X_{it} denotes the characteristics of primary care clinics; and α_i denotes clinic fixed effects. We apply filters to our dataset of primary care clinics based on their operating status, services, etc.[31] From the results in Table 10, we find that Uber's entry does indeed lead to an increase in the number of visits to primary care clinics. This finding supports our speculation that Uber's entry improves the utilization of healthcare resources in general by improving patients' access to primary care and enabling EDs to reallocate resources to more severe cases.

5. Robustness checks

In this section, we perform robustness analyses to corroborate our main findings. Our first three analyses address the concern that the decision of Uber's entry into a location containing a hospital could be non-random and driven by factors that influence ED visits, introducing a selection bias and affecting our results. First, we use the *leads-and-lags* model to test the parallel trend assumption that is important for the validity of the DID method. Second, we re-run our main regression model after matching treated and control hospitals based on their pre-treatment characteristics. Third, we directly model Uber's entry decision into a county on the county's characteristics and lagged ED visit numbers. In the next analysis, we control for possible confounding effects of major policy implementation in the healthcare sector in California that coincide with the timeline of the sequential rollout of Uber. Finally, we rule out the possibility that the estimated relationship between Uber's entry and ED visit numbers comes from spurious correlations by performing random implementation or the placebo test.

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[30] Primary care clinics include "community and free clinics that provide primary care services to the uninsured and the underinsured groups in their local communities". https://hcai.ca.gov/data-and-reports/healthcare-utilization/clinic-utilization/

[31] Filters include whether the clinic is in operation at any time through the whole year, has an active license, offers medical services, has at least one physician available at the clinic, and has at least one visit recorded in every year of its operation.

5.1. Leads-and-lags model

We first use the *leads-and-lags* model to test the parallel trend assumption that is important for the validity of the DID method (Chen et al. 2022).

$$Y_{it} = \alpha_i + \delta_t + \sum_j \beta_j \, Entry_{it}(j) + \gamma X_{it} + \varepsilon_{it} \quad (4)$$

In this model, instead of $Uber_{it}$, we include a set of time dummies $Entry_{it}(j)$ that captures whether year t is the jth year from the entry of Uber into the county of treated hospital i. The suffix j takes negative values, zero, or positive values depending on whether the year t is before, in, or after the year of Uber's entry. We follow the previous literature (Burtch et al. 2018) to consider $Entry_{it}(-1)$, i.e., the 1-year pre-entry dummy, as the baseline. We combine all the dummies for 3-year-or-later post-entry periods into one because of the insufficient sample size for these periods, and we combine dummies for 7-year-or-earlier pre-entry periods for the same reason. The results in Figure 1, Figure 2, and Table 11 suggest that all pre-entry year dummies are insignificant, which supports the parallel trend assumption for the DID model that we have used to examine the impact of Uber on ED visits.

5.2. Look-ahead Propensity Score Matching

The next measure we take to address the concern of selection bias driven by possible differences between the treated and control hospitals is to re-run the main regression model after matching treated and control hospitals based on their pre-treatment characteristics using the Look-Ahead Propensity Score Matching (LA-PSM) method (Bapna et al. 2018). As described in the literature (Jung et al. 2019), the dynamic LA-PSM technique is specifically designed for the staggered DID model, and it is more suitable than the traditional PSM method in a scenario where the treatment is sequentially rolled out and eventually applies to almost all the units, as in the situation of the sequential launch of Uber across different locations. In such cases, an insufficient number of units are never treated to be used as the control group for the traditional PSM method. In addition, the hospitals that are treated later tend to be more similar in characteristics to early treated hospitals than those that are never treated, thus serving as a better, more comparable control group. Therefore, for each year within the timeline of this study, we use LA-PSM to match treated hospitals based on their pre-entry characteristics with "late adopters" hospitals that will be treated in a later year.[32] We are able to match 158 pairs of treated and control hospitals, comprising 226 unique hospitals. Based on the results of *t*-tests on the characteristics of the treated and control groups after matching, as reported in Table A3, the difference between the two groups is insignificant for all covariates, indicating that the matched dataset is balanced on hospital characteristics and that the treated hospitals are comparable to the matched control hospitals. We then re-estimate our regression model in Equation (1) using the matched sample and report the results in Column (1) of Table 12. The results based on the matched sample are quantitively similar to our main findings from the full sample (reported in Table 3). We also re-estimate the analyses we have used to answer other research questions using the matched sample. The results reported in Table 12 (Columns (2)-(3)) and Table 13 are all consistent with those obtained using the full sample.

5.3. Uber's endogenous entry decision

Our third measure to address the concern of whether the observed results are potentially driven by Uber's endogenous entry decision is to model this decision directly. As mentioned earlier, Uber may decide to enter a county based on its unobservable characteristics. These characteristics may correlate with the number of ED visits, leading to the results that we observe. To further address this concern, we follow prior literature (Burtch et al. 2018) to directly examine Uber's decision to enter a county using a logit model. We perform the analysis on a county-level as Uber is more likely to make the entry decision based on county-level characteristics. We aggregate our original hospital-year panel data to a county-year dataset and use the following logit model:

$$\ln\left(\frac{Uber_{it}}{1-Uber_{it}}\right) = \delta_t + \beta Y_{it} + \alpha X_{it} + \varepsilon_{it} \tag{5}$$

We denote the probability of Uber's entry into county i in year t as $Uber_{it}$. We run three separate estimations using the following quantities (after log transformation) as the predictor Y_{it}: the number of

[32] The variables used for matching are the total number of patients, other operating revenue, the number of beds, the number of services, gross patient revenue, the number of staff, and the number of operating rooms, using their 3-year lagged average values.

severe-with-threat ED visits, low acuity ED visits, and all ED visits in the immediately preceding year.[33] In X_{it}, we control for the county-level macroeconomic variables, including GDP, population density, unemployment rates, and median household income. We also control for the search intensity values of the keyword "Uber" on Google, collected from Google Trends, as a measure of Uber's popularity in the local place. Following existing literature (Burtch et al. 2018), we drop observations for the years after Uber's entry.

Our results in Table 14 show that Uber is not significantly more or less likely to enter counties with a larger pre-entry number of severe-with-threat, low acuity, or total ED visits, with all the coefficients of the ED visit-related predictors being insignificant. These results address the concern of Uber's endogenous entry decision, and we can consider that Uber's entry into a county is not influenced by the existing number of ED visits in the county.

5.4. Controlling for major policy implementation in the healthcare sector

During Uber's sequential rollout in California, two major healthcare policies were implemented: the Patient Protection and Affordable Care Act (ACA) (also known as "Obamacare") in 2013 and the Medicaid expansion under ACA in 2014.[34] While these policy implementations are statewide and expected to affect both treated and control counties in our analysis, we re-estimate our main regression by further controlling for the possible effect of the policy implementations on the number of ED visits that may vary across counties with different sizes of the eligible beneficiary population. Specifically, we denote every county by the dummy variable set $county_c$. We use three year-dummy variables: $year2013_t$ and $year2014_t$ to capture the implementation of ACA and Medicaid expansion, respectively, and $post2014_t$ to capture the combined long-term effects of these two policies for the period after 2014. We include interaction terms

[33] We did not put all the three predictors together in the same regression because of the multicollinearity issue.
[34] ACA was formally implemented in California with the first enrollment under the name of Covered California in 2013, and California adopted Medicaid expansion at the beginning of 2014.
Covered California is Open for Business: https://www.coveredca.com/newsroom/news-releases/2013/10/01/Covered-California-Is-Open-for-Business/
California and the ACA's Medicaid expansion: https://www.healthinsurance.org/medicaid/california/

between $county_c$ and each of the three year-dummy variables in Equation (6).

$$Y_{it} = \alpha_i + \delta_t + \lambda_1(year2013_t * county_c) + \lambda_2(year2014_t * county_c) + \lambda_3(post2014_t * county_c) + \beta Uber_{it} + \gamma X_{it} + \varepsilon_{it} \qquad (6)$$

The results show that our results on the impact of Uber's entry on severe-with-threat and low acuity ED visits still hold after controlling for the county-specific policy implementation effects, as observed in Table 15.

5.5. Random implementation (placebo) tests

Finally, we perform a random implementation test to confirm that our main results are not driven by chance or spurious relationships from serial correlation (Bertrand et al. 2004) in our outcome variables. Following literature (Chen et al. 2022), we reallocate the treatment variable of Uber's entry in our sample to randomly selected hospitals through the counties of their locations, thus modeling a placebo experiment. We re-estimate our DID model for severe-with-threat and low acuity ED visits and capture the coefficients of our placebo treatment, replicating the process 10,000 times. Then we perform *t*-tests to examine whether the average of the estimated coefficients of the reallocated Uber's entry dummies is significantly different from zero. We conduct the placebo test for both full and matched samples. This test helps us assess the possibility of any spuriousness of the significant results observed in our main analysis arising due to autocorrelation in our dependent variable, e.g., change in the number of ED visits is a natural trend rather than the result of Uber's entry.

Our results in Table 16 show that the estimated mean coefficient of the randomly assigned treatment dummies is not significantly different from zero for either severe-with-threat or low acuity ED visits. This test confirms that our results are not observed by accident and are not driven by spurious relationships in the dependent variables.

6. Conclusion, discussion, and implications

In this paper, we contribute to the ongoing discussion on the ridesharing platform's role in improving healthcare access by focusing on emergency care, a critical component of the healthcare system in the United States. We specifically focus on ED visits of the highest severity level (severe-with-threat ED visits) that may suffer from life-threatening consequences of delayed access to emergency care. By leveraging Uber's sequential entries into different counties of California, we design our research in the form of a quasi-experimental setup and apply the DID model to establish causal relationships. We find that Uber's entry has a significantly positive impact on severe-with-threat ED visits. This result suggests that a ridesharing platform could break down the transportation barrier to emergency care access, enabling timely care for high-severity medical emergencies that the patient may have delayed or deterred due to the prohibitive costs or shortage of emergency medical transportation. We have conducted a number of robustness checks to demonstrate the robustness of our results, including validating the parallel trend assumption of the DID model, performing matching for the control and treated hospitals, testing for the endogeneity of Uber's entry decision, controlling for healthcare policies, and implementing a placebo test.

In addition, we have found substantial heterogeneity in the impacts among hospitals with different characteristics. The impact is smaller for hospitals that have teaching affiliations and provide more comprehensive emergency care and better trauma care. As these hospitals could already be facing a saturation of their service capacity, Uber may enable patients to switch to less crowded hospitals. We also find that the impact is smaller for hospitals that serve large proportions of uninsured and Medicaid patients and for hospitals not located in large or medium metropolitan counties. These results can be explained by the heterogeneity in ridesharing service access and ride availability.

Furthermore, we find that Uber's entry may successfully redistribute healthcare resources on both inter- and intra-hospital levels. We find that after Uber's entry, patients tend to choose EDs that are farther away, and their probability of visiting an ED with a minor issue is lower, likely because of the increased access to primary care providers, as shown by our results. Although the average ED waiting time increases as a result of the increased number of severe ED visits, we observe a significant reduction in ED mortality. Together, these findings support an overall positive societal impact of Uber's entry on emergency care.

Our study makes significant contributions to the academic literature. First, to our knowledge, this is the first paper that provides large-scale empirical findings about the causal impact of a ridesharing platform's entry on emergency care access. Previous empirical papers investigating the impact of ridesharing on healthcare-related outcomes have mostly looked at non-emergency care visits as the outcome (Chaiyachati et al. 2018, Wolfe and McDonald 2020). These studies are often based on localized pilot studies and present inconsistent findings. In terms of emergency care, a few papers have investigated the impact of ridesharing's entry on ambulance usage and patients' discharge transport waiting time in ED, using data obtained from small study cohorts in single healthcare facilities or voluntarily reported data (Blome et al. 2020, Moskatel and Slusky 2019, Tomar et al. 2019). In addition to the contradictory findings, their results do not evaluate ridesharing's impact on patients' emergency care access. In contrast, this paper directly measures the impact of Uber's entry on patients' emergency care access by examining the number of ED visits for the first time and includes the general population of California across large and diverse geographies. Moreover, we present additional findings on the moderating effects of various ED characteristics and the impact on patients' ED selection and ED utilization. Second, our work contributes to the IS literature on the societal impact of the sharing economy (Burtch et al. 2018, Greenwood and Wattal 2017, Li et al. 2016) by showing that the introduction of a ridesharing platform improves patients' access to emergency care measured by high-severity ED visits. This improved access to one of the most critical medical services, which treat life-threatening conditions, leads to important societal contributions, including timely access to emergency care, expanded hospital choices beyond location restrictions, and reduced ED mortality.

Our study also presents a wide range of important managerial and policy-level implications. First, our results show that Uber has partially fulfilled the need for transportation to ED with lower cost and better availability, which helps break the transportation barrier for patients to access emergency care services, especially in severe cases. At the same time, we note that taking Uber rides to ED in severe medical conditions may lead to undesired consequences since they are not equipped to provide necessary care during transportation as ambulances are (Berger 2017). Considering the potential risk of Uber rides to ED, we suggest that the government provides better public education or training to emergency responders to evaluate appropriate transportation options in different medical emergencies. In addition, policymakers can provide better reimbursement and capacity planning to make ambulances affordable and accessible in severe medical emergencies. Second, we show that Uber, by offering an additional transportation option, could help redistribute patient demand across hospitals and reduce ED mortality even when the number of high-severity ED visits increases. Therefore, how to leverage the benefits of demand redistribution warrants further thoughtful consideration in making regulation decisions on emergency transportation. Third, our findings on the effects of Uber on low-severity ED visits and primary care visits encourage policymakers to incentivize patients to prevent ED visits with minor issues by receiving care from primary care providers to improve the utilization of ED resources. Similar to some existing efforts to improve access for primary care patients, this may require collaborative programs at a population level among healthcare providers, ridesharing platforms, and policymakers. Lastly, we observe that Uber's impacts have accrued less to the economically vulnerable and geographically disadvantaged population, which calls for attention to best utilize these services for those in need. Policymakers may consider providing education and assistance programs to facilitate the usage of ridesharing services among these population groups.

Our paper is subject to limitations and leaves opportunities for future research. First, our results are drawn based on data from California, the most populated state in the United States. The richness of the data allows us to examine not only the effect of Uber's entry on ED visits at different severity levels but also how the effect varies with hospitals' characteristics. We expect our results to shed light on the effects of ridesharing services on emergency care access beyond California, which can be confirmed by future research with data from different geographical locations. Second, while our analyses on ED utilization and patients' ED selection provide explorative evidence that contributes to the analysis of resource redistribution at intra- and inter-ED levels, future research with individual patient-level data can further examine individual patients' choices and provide more nuanced suggestions. Finally, while we examine Uber as an independent service provider, which already shows promising positive effects in improving emergency care access, it would be interesting to further explore the effects of policy interventions in this domain, e.g., through collaborative programs such as Uber Health, on emergency care access.

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Figure 1: Parallel trend assumption test for severe-with-threat ED visits (*leads-and-lags* model)

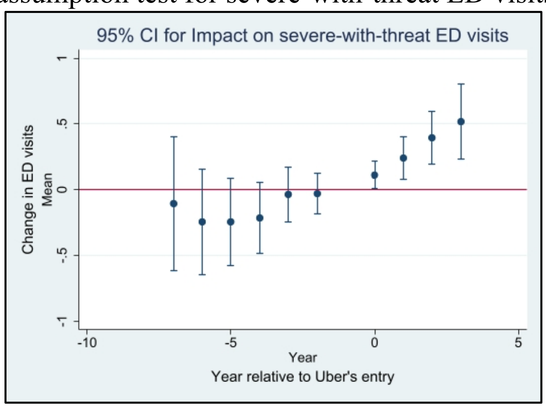

Figure 2: Parallel trend assumption test for low acuity ED visits (*leads-and-lags* model)

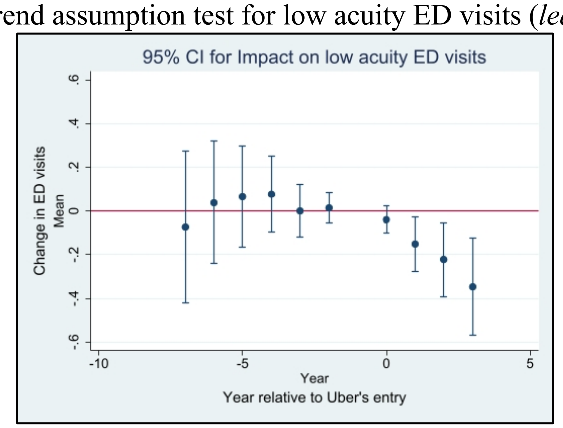

Table 1: Description of key variables (used in our main analysis in Section 4.1)

Variable	Description
$Uber_{it}$	Presence of Uber: = 1 if Uber is present in county of hospital *i* in year *t* = 0 otherwise
$Entry_{it}(j)$	Time dummy to measure the chronological distance from Uber's entry = 1 if year *t* is the j^{th} year from the entry of Uber in county of hospital *i* = 0 otherwise
Severe-with-$threat_{it}$	ED visits under the severity level of Severe-with-threat of hospital *i* in year *t*
% $Male_{it}$	Percentage of male patients over total patients of hospital *i* in year *t*
% $Female_{it}$	Percentage of female patients over total patients of hospital *i* in year *t*
% $White_{it}$	Percentage of White patients over total patients of hospital *i* in year *t*
% $Black_{it}$	Percentage of Black patients over total patients of hospital *i* in year *t*
% Asian-Pacific $Islander_{it}$	Percentage of Asian and Pacific Islander patients over total patients of hospital *i* in year *t*
% Native $American_{it}$	Percentage of Native American patients over total patients of hospital *i* in year *t*
% $Hispanic_{it}$	Percentage of Hispanic patients over total patients of hospital *i* in year *t*
% $Age(0\text{-}19)_{it}$	Percentage of patients aged 0-19 over total patients of hospital *i* in year *t*
% $Age(20\text{-}39)_{it}$	Percentage of patients aged 20-39 over total patients of hospital *i* in year *t*
% $Age(40\text{-}59)_{it}$	Percentage of patients aged 40-59 over total patients of hospital *i* in year *t*
% $Age(>60)_{it}$	Percentage of patients aged 60- over total patients of hospital *i* in year *t*
% Medi-Cal_{it}	Percentage of Medi-Cal patients over total patients of hospital *i* in year *t*
% $Medicare_{it}$	Percentage of Medicare patients over total patients of hospital *i* in year *t*
% Private $insurance_{it}$	Percentage of privately insured patients over all patients of hospital *i* in year *t*
% $Uninsured_{it}$	Percentage of uninsured patients over total patients of hospital *i* in year *t*
Gross $revenue_{it}$	Total gross revenue (patient charges) of hospital *i* in year *t*
Other $revenue_{it}$	Total other operating revenue (grants from government and private sources) of hospital *i* in year *t*
Total $patients_{it}$	Total number of patients visiting hospital *i* in year *t*
$Services(24)_{it}$	Total number of services offered 24 hours a day at hospital *i* in year *t*
EMS $stations_{it}$	Total number of emergency medical stations at hospital *i* in year *t*
Total $staff_{it}$	Total staff measured by full time equivalents (FTEs) at hospital *i* in year *t*
Operating $rooms_{it}$	Total number of operating rooms at hospital *i* in year *t*
$Teaching_{it}$	Dummy that denotes whether hospital *i* is a "teaching hospital" in year *t*
Trauma center level I_{it}	Dummy if hospital *i* has a trauma center designation of Level I in year *t*
Trauma center level II_{it}	Dummy if hospital *i* has a trauma center designation of Level II in year *t*
Trauma center level III_{it}	Dummy if hospital *i* has a trauma center designation of Level III in year *t*
Trauma center level IV_{it}	Dummy if hospital *i* has a trauma center designation of Level IV in year *t*

Table 2: Summary statistics of key variables (used in our main analysis in Section 4.1)

Variable	Observations	Mean	Std. dev.	Min.	Max.
$Uber_{it}$	3848	0.43	0.50	0	1
$Severe\text{-}with\text{-}threat_{it}$	3848	6893	6914	0	48160
% $Male_{it}$	3848	0.46	0.03	0.22	0.65
% $Female_{it}$	3848	0.54	0.03	0.21	0.63
% $White_{it}$	3848	0.48	0.24	0.00	0.98
% $Black_{it}$	3840	0.09	0.10	0.00	0.65
% Asian-Pacific $Islander_{it}$	3834	0.05	0.06	0.00	0.68
% Native $American_{it}$	3769	0.01	0.03	0.00	0.73
% $Hispanic_{it}$	3846	0.34	0.22	0.00	0.95
% $Age(0\text{-}19)_{it}$	3848	0.26	0.10	0.03	1.00
% $Age(20\text{-}39)_{it}$	3848	0.31	0.05	0.00	0.45
% $Age(40\text{-}59)_{it}$	3848	0.25	0.04	0.00	0.44
% $Age(>60)_{it}$	3848	0.19	0.07	0.00	0.45
% $Medi\text{-}Cal_{it}$	3840	12142	11558	2	91417
% $Medicare_{it}$	3835	6256	4574	1	41467
% Private $insurance_{it}$	3838	11526	9916	1	67002
% $Uninsured_{it}$	3823	4721	5173	1	107789
Gross $revenue_{it}$ ($ mn)	3848	1060	1440	0	20300
Other $revenue_{it}$ ($ mn)[35]	3848	9	26	-2	375
Total $patients_{it}$	3848	36465	21102	2801	143619
$Services(24)_{it}$	3848	5	2	0	7
EMS $stations_{it}$	3848	24	15	1	116
Total $staff_{it}$	3848	1363	1423	52	12328
Operating $rooms_{it}$	3848	10	7	0	51
$Teaching_{it}$	3848	0.09	0.29	0	1
Trauma center level I_{it}	3848	0.05	0.21	0	1
Trauma center level II_{it}	3848	0.12	0.33	0	1
Trauma center level III_{it}	3848	0.04	0.20	0	1
Trauma center level IV_{it}	3848	0.02	0.14	0	1

Table 3: Impact of Uber's entry on severe-with-threat ED visits – main model

Variables	Log (Severe-with-threat)
$Uber_{it}$	0.176**
	(0.072)
Observations	3462
R-squared (within)	0.175

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital fixed effects and year fixed effects are included. Covariates included: % Male, % Age(0-19), % Age(20-39), % Age(40-59), % Age(>60), % White, % Black, % Asian-Pacific Islander, % Hispanic, %Medi-Cal, %Medicare, % Private insurance, % Uninsured, Total patients, Gross revenue, Other revenue, Services(24), ED license level, Trauma center level, Teaching.

[35] Other (operating) revenue can have offsetting entries when grant funds are used to cover direct expenses (salaries, supplies, non-capital goods) or the depreciation expense of any capital project (construction, repair, renovation), which might lead to negative values.

Table 4: Moderating effects of ED characteristics on Uber's impact on severe-with-threat ED visits

Variables	Log (Severe-with-threat)	Log (Severe-with-threat)	Log (Severe-with-threat)	Log (Severe-with-threat)	Log (Severe-with-threat)	Log (Severe-with-threat)
$Uber_{it}$ * $Teaching_{it}$	-0.620***					
	(0.237)					
$Uber_{it}$ * Trauma center level I_{it}		-0.944***				
		(0.274)				
$Uber_{it}$ * $Comprehensive_{it}$			-0.867**			
			(0.395)			
$Uber_{it}$ * % $Uninsured_{it}$				-2.874**		
				(1.158)		
$Uber_{it}$ * Safety-net ED_{it}					-0.278**	
					(0.132)	
$Uber_{it}$ * Large $metro_{it}$						0.372*
						(0.198)
$Uber_{it}$ * Medium $metro_{it}$						0.591***
						(0.206)
Observations	3462	3462	3462	3471	3502	3462
R-squared (within)	0.182	0.183	0.181	0.190	0.162	0.180

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects and all other covariates from Table 3 are included.

Table 5: Impact of Uber's entry on the number of visits to hospitals at different distances

	(1)	(2)	(3)	(4)
Variables	**Log (# 0 – 5 mi)**	**Log (# 5 – 10 mi)**	**Log (# 10 – 25 mi)**	**Log (# > 25 mi)**
$Uber_{it}$	0.042	0.015	0.095***	0.032***
	(0.033)	(0.029)	(0.024)	(0.012)
Observations	11988	11988	11988	11988
R-squared (within)	0.004	0.024	0.056	0.187

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at patient ZIP code level in parentheses; ZIP and year fixed effects, and county covariates: GDP, population density, unemployment, and median household income are included.

Table 6: Impact of Uber's entry on the proportion of visits to hospitals at different distances

	(1)	(2)	(3)	(4)
Variables	**% 0 – 5 mi**	**% 5 – 10 mi**	**% 10 – 25 mi**	**% > 25 mi**
$Uber_{it}$	0.005	-0.005*	0.006*	-0.006*
	(0.003)	(0.003)	(0.004)	(0.003)
Observations	11988	11988	11988	11988
R-squared (within)	0.003	0.004	0.006	0.011

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at patient ZIP code level in parentheses; ZIP and year fixed effects, and all county covariates from Table 5 are included.

Table 7: Impact of Uber's entry on waiting time

	(1)	(2)
Variables	**Total waiting time**	**Queue waiting time**
$Uber_{it}$	9.055*	5.418***
	(5.124)	(1.858)
Observations	929	613
R-squared (within)	0.089	0.198

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects and all other covariates from Table 3 are included.

Table 8: Impact of Uber's entry on mortality in ED

Variables	**Log (Died)**
$Uber_{it}$	-0.050*
	(0.026)
Observations	3434
R-squared (within)	0.108

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects and all covariates from Table 3 are included.

Table 9: Impact of Uber's entry on low acuity ED visits

Variables	**Log (Low acuity)**
$Uber_{it}$	-0.099**
	(0.049)
Observations	3462
R-squared (within)	0.119

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects and all covariates from Table 3 are included.

Table 10: Impact of Uber's entry on visits to primary care clinics

Variables	**Log (Total visits)**
$Uber_{it}$	0.102***
	(0.030)
Observations	8018
R-squared (within)	0.126

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at clinic level in parentheses; clinic and year fixed effects are included. Covariates: number of physicians, % of different demographic groups (sex, age, race, ethnicity, poverty, insurance), dummies for second language, clinic financials.

Table 11: Impact of Uber's entry on severe-with-threat and low acuity ED visits – leads and lags model

	(1)	(2)
Variables	**Log (Severe-with-threat)**	**Log (Low acuity)**
$Entry_{it}$(-7-)	-0.105	-0.074
	(0.261)	(0.178)
$Entry_{it}$(-6)	-0.244	0.038
	(0.204)	(0.143)
$Entry_{it}$(-5)	-0.244	0.066
	(0.170)	(0.118)
$Entry_{it}$(-4)	-0.216	0.077
	(0.138)	(0.089)
$Entry_{it}$(-3)	-0.035	-0.000
	(0.106)	(0.062)
$Entry_{it}$(-2)	-0.030	0.014
	(0.080)	(0.036)
$Entry_{it}$(0)	0.112**	-0.039
	(0.052)	(0.032)
$Entry_{it}$(+1)	0.241***	-0.151**
	(0.083)	(0.064)
$Entry_{it}$(+2)	0.395***	-0.223**
	(0.103)	(0.086)
$Entry_{it}$(+3+)	0.517***	-0.348***
	(0.145)	(0.114)
Observations	3462	3462
R-squared (within)	0.182	0.128

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects and all other covariates from Table 3 are included.

Table 12: Impact of Uber's entry on severe-with-threat ED visits, mortality in ED, and low acuity ED visits (matched sample)

	(1)	(2)	(3)
Variables	**Log (Severe-with-threat)**	**Log (Died)**	**Log (Low acuity)**
$Uber_{it}$	0.098*	-0.056**	-0.096**
	(0.059)	(0.023)	(0.044)
Observations	4166	4149	4166
R-squared (within)	0.162	0.067	0.093

Note: *** p<0.01, ** p<0.05, * p<0.1.
Robust standard errors clustered at hospital level in parentheses; hospital fixed effects and year fixed effects are included. Covariates included: % Male, % Age(0-19), % Age(20-39), % Age(40-59), % Age(>60), % White, % Black, % Asian-Pacific Islander, % Hispanic, % Medi-Cal, % Medicare, % Private insurance, % Uninsured, ED license level, Trauma center level, Teaching.

Table 13: Moderating effects of ED characteristics on Uber's impact on severe-with-threat ED visits (matched sample)

Variables	**Log (Severe-with-threat)**	**Log (Severe-with-threat)**	**Log (Severe-with-threat)**	**Log (Severe-with-threat)**	**Log (Severe-with-threat)**	**Log (Severe-with-threat)**
$Uber_{it}$ * $Teaching_{it}$	-0.560**					
	(0.251)					
$Uber_{it}$ * Trauma center level I_{it}		-0.951***				
		(0.356)				
$Uber_{it}$ * $Comprehensive_{it}$			-0.999*			
			(0.573)			
$Uber_{it}$ * % $Uninsured_{it}$				-2.196*		
				(1.189)		
$Uber_{it}$ * Safety-net ED_{it}					-0.274**	
					(0.120)	
$Uber_{it}$ * Large $metro_{it}$						0.541***
						(0.160)
$Uber_{it}$ * Medium $metro_{it}$						0.705***
						(0.161)
Observations	4166	4166	4166	4170	4201	4166
R-squared (within)	0.168	0.174	0.167	0.175	0.158	0.171

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital fixed effects and year fixed effects and all other covariates from Table 12 are included.

Table 14: Analysis on endogeneity of Uber's entry decision using the logit model

	(1)	(2)	(3)
Variables	**Uber**	**Uber**	**Uber**
Lagged log (Severe-with-threat)$_{it}$	-0.335		
	(0.370)		
Lagged log (Low acuity)$_{it}$		-0.680	
		(0.648)	
Lagged log (Total ED)$_{it}$			-1.051
			(0.793)
Observations	194	194	194

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at county level in parentheses, year fixed effects are included. County-related covariates included: GDP, Population, Population density, Unemployment, Median household income, and Uber's search intensities from Google Trends.

Table 15: Impact of Uber's entry on ED visits controlling for county-year interaction effects

	(1)	(2)	(3)	(4)
	Full sample		**Matched sample**	
Variables	**Log (Severe-with-threat)**	**Log (Low acuity)**	**Log (Severe-with-threat)**	**Log (Low acuity)**
Uber$_{it}$	0.263**	-0.165**	0.193**	-0.139**
	(0.115)	(0.076)	(0.092)	(0.061)
Observations	3462	3462	4166	4166
R-squared (within)	0.234	0.197	0.247	0.198

Note: *** p<0.01, ** p<0.05, * p<0.1
Robust standard errors clustered at hospital level in parentheses; hospital and year fixed effects, interaction terms between counties and year dummies, and all other covariates from Table 3 (for the full sample) or Table 12 (for the matched sample) are included.

Table 16: Random implementation (placebo) test

	(1)	(2)	(3)	(4)
	Full sample		**Matched sample**	
Estimation	**Log (Severe-with-threat)**	**Log (Low acuity)**	**Log (Severe-with-threat)**	**Log (Low acuity)**
Mean of random coefficient	-0.0005	0.0007	-0.0000	-0.0003
Std. dev. of random coefficient	0.0009	0.0006	0.0007	0.0005
Replications	10000	10000	10000	10000
t-statistic	-0.6415	1.2928	-0.0345	-0.4856
p-value	0.5212	0.1961	0.9725	0.6272

Online Appendix

Table A1: Description of other variables

Variable	Description
Low acuity$_{it}$	ED visits under the severity levels of Minor and Low/Moderate of hospital *i* in year *t*
Moderate$_{it}$	ED visits under the severity level of Moderate of hospital *i* in year *t*
Severe-without-threat$_{it}$	ED visits under the severity level of Severe-without-threat of hospital *i* in year *t*
Comprehensive$_{it}$	Dummy whether the ED of hospital *i* is licensed as Comprehensive in year *t*
Basic$_{it}$	Dummy whether the ED of hospital *i* is licensed as Basic in year *t*
Safety-net$_{it}$	Dummy whether hospital *i* is classified as "safety net" in year *t*
Large metro$_{it}$	Dummy if hospital *i*'s county is classified as large metropolitan in year *t*
Medium metro$_{it}$	Dummy if hospital *i*'s county is classified as medium metropolitan in year *t*
Small metro$_{it}$	Dummy if hospital *i*'s county is classified as small metropolitan in year *t*
Micropolitan$_{it}$	Dummy if hospital *i*'s county is classified as micropolitan in year *t*
Noncore metro$_{it}$	Dummy if hospital *i*'s county is classified as noncore metropolitan in year *t*
Total waiting time$_{it}$	Total waiting time at the ED of hospital *i* in year *t*, measured in minutes
Queue waiting time$_{it}$	Waiting time in the queue at the ED of hospital *i* in year *t*, in minutes
# 0-5 mi$_{it}$	Number of patients visiting EDs within 0-5 miles from ZIP code *i* in year *t*
# 5-10 mi$_{it}$	Number of patients visiting EDs within 5-10 miles from ZIP code *i* in year *t*
# 10-25 mi$_{it}$	Number of patients visiting EDs within 10-25 miles from ZIP code *i* in year *t*
# >25 mi$_{it}$	Number of patients visiting EDs outside 25 miles from ZIP code *i* in year *t*
% 0-5 mi$_{it}$	Percent of patients visiting EDs within 0-5 miles from ZIP code *i* in year *t*
% 5-10 mi$_{it}$	Percent of patients visiting EDs within 5-10 miles from ZIP code *i* in year *t*
% 10-25 mi$_{it}$	Percent of patients visiting EDs within 10-25 miles from ZIP code *i* in year *t*
% >25 mi$_{it}$	Percent of patients visiting EDs outside 25 miles from ZIP code *i* in year *t*
Died$_{it}$	Number of patients who died during the ED visit at hospital *i* in year *t*
Total visits$_{it}$	Total number of visits to primary care clinic *i* in year *t*
GDP$_{it}$	Gross domestic product of county/state *i* in year *t* in million US dollars
Population$_{it}$	Population of county *i* in year *t* in thousands
Population density$_{it}$	Population density of county *i* in year *t* in persons per square mile
Median income$_{it}$	Median household income of county *i* in year *t* in US dollars
Unemployment$_{it}$	Unemployment rate of county *i* in year *t* in percent
Google trends$_{it}$	Search intensities of the keyword "Uber" on Google in county *i* in year *t*

Table A2: Summary statistics of other variables

Variable	Observations	Mean	Std. dev.	Min.	Max.
Low acuity$_{it}$	3848	9650	8780	0	130481
Moderate$_{it}$	3848	14657	11289	0	92305
Severe-without-threat$_{it}$	3848	10377	7494	0	68694
Comprehensive$_{it}$	3848	0.03	0.17	0	1
Basic$_{it}$	3848	0.97	0.17	0	1
Safety-net$_{it}$	3848	0.61	0.49	0	1
Large metro$_{it}$	3848	0.69	0.46	0	1
Medium metro$_{it}$	3848	0.20	0.40	0	1
Small metro$_{it}$	3848	0.05	0.21	0	1
Micropolitan$_{it}$	3848	0.05	0.21	0	1
Noncore metro$_{it}$	3848	0.02	0.13	0	1
Total waiting time$_{it}$	1131	169	45	61	444
Queue waiting time$_{it}$	802	32	19	0	117
# 0-5 mi$_{it}$	13749	3335	5475	0	40514
# 5-10 mi$_{it}$	13749	1808	3396	0	39747
# 10-25 mi$_{it}$	13749	1301	2706	0	45646
# >25 mi$_{it}$	13749	407	660	0	10966
% 0-5 mi$_{it}$	13749	0.30	0.35	0.00	1.00
% 5-10 mi$_{it}$	13749	0.21	0.27	0.00	0.98
% 10-25 mi$_{it}$	13749	0.28	0.32	0.00	1.00
% >25 mi$_{it}$	13749	0.20	0.31	0.00	1.00
Died$_{it}$	3804	59	44	1	310
Total visits$_{it}$	11411	14515	15771	0	123993
GDP$_{it}$ ($ mn)	707	48100	100000	730	727000
Population$_{it}$ (‘000)	707	795	1546	18	10100
Population density$_{it}$	707	826	2592	2	18756
Median income$_{it}$ ($)	707	58798	17438	32724	135234
Unemployment$_{it}$	707	8.4	4.3	2.1	29.4
Google trends$_{it}$	640	14	19	0	59

Table A3: LA-PSM *t*-test result

Pre-treatment variable	Treated	Control	*t*-statistics	*p*-value
Log(Total patients$_i$)	10.261	10.297	0.526	0.599
Log(Other revenue$_i$)	12.420	13.011	1.045	0.297
Log(EMS stations$_i$)	3.058	3.032	-0.381	0.704
Services(24)$_{it}$	4.773	4.910	0.781	0.435
Log(Gross revenue$_i$)	17.390	18.211	1.067	0.287
Log(Total staff$_i$)	6.883	6.924	0.465	0.642
Log(Operating rooms$_i$)	2.196	2.240	0.722	0.471